Wiley
Journal of Engineering
Volume 2025, Article ID 7098166, 16 pages
https://doi.org/10.1155/je/7098166

WILEY

Research Article

Automated Carrot Harvesting Machine With YOLOv8 for Precision and Optimal Efficiency

Sadaf Zeeshan [1] **and Muhammad Ali Ijaz Malik** [2]

[1] *Mechanical Engineering Department, University of Central Punjab, Lahore, Pakistan*
[2] *School of Civil and Environmental Engineering, Faculty of Engineering and Information Technology, University of Technology Sydney, Ultimo, New South Wales, Australia*

Correspondence should be addressed to Muhammad Ali Ijaz Malik; muhammadaliijaz.malik@student.uts.edu.au

Received 10 March 2025; Revised 23 July 2025; Accepted 19 August 2025

Academic Editor: Giovanni Angiulli

Carrots are a key staple in Pakistan's agriculture, yet harvesting practices remain predominantly manual, resulting in high labor costs, inefficiencies, and considerable postharvest losses. The current study presents the design and fabrication of a cost-effective, intelligent carrot harvesting machine, modeled in SolidWorks and optimized for key operational parameters: claw belt speed of 4 m/s, roller speed of 1.2 m/s, and a taper angle of 26°, to maximize pick-up efficiency and minimize crop damage. A YOLOv8-based quality assessment model, trained on a region-specific annotated dataset of local carrot varieties, was integrated for real-time defect detection. The model achieved high accuracy (approximately 0.98), $F1$-score (approximately 0.95), and mAP@0.5 (approximately 0.94), ensuring the reliable sorting of high-quality produce. Laboratory evaluations demonstrated significant performance gains over manual harvesting methods in terms of speed (3–5 acres/day vs. 0.2–0.5 acres/day), efficiency (80%–92%), and reduced physical strain. These findings support the adoption of mechanized harvesting aligned with precision agriculture to enhance productivity, safety, and sustainability.

Keywords: accurate classification; agricultural machines; carrot harvesting; YOLO-based detection system

1. Introduction

Vegetables and fruits play a vital role in human health due to their rich nutrients like vitamin C, fiber, folate, and potassium. Over the last decade, the global fruit trade market has observed a growth of around 40%, thus rising from 45 to 63 million tonnes [1]. Pakistan's agricultural sector remains heavily reliant on traditional harvesting methods, particularly for vegetables such as carrots. This labor-intensive approach, often involving rudimentary tools, results in inefficiencies including suboptimal labor utilization, reduced crop yields, and elevated operational costs [2]. Such limitations are especially critical in the context of a rapidly growing population and increasing domestic and global demand for vegetables. The only potential solution for problems like labor-intensive harvesting, expensive manual labor, and time-consuming processes is the introduction of agricultural robots [3, 4]. The automated agricultural processes trends like harvesting [5], pruning [6], localized spraying [7], and computer-aided vision techniques for vegetable and fruit image detection [8, 9] mark the pathway toward the digital revolution in agriculture. While many countries have transitioned to mechanized agricultural practices, Pakistan's reliance on manual labor highlights a critical gap that undermines its competitiveness in international markets [10]. Introducing mechanized harvesting solutions is no longer optional but essential to modernize the sector, enhance productivity, and ensure sustainable growth in the global economy [11]. Carrots are a dietary staple in Pakistan and other developing economies [12]. They hold significant importance due to their nutritional value and contribution to food security. Being rich in essential vitamins and nutrients, carrots support the dietary needs of Pakistan's growing population. Moreover, Pakistan ranks as a notable producer of carrots, exporting to international markets and contributing significantly to agricultural GDP, accounting for approximately 20%–25% of the national economy [13]. However, inefficiencies in harvesting and postharvest handling not only result in high labor costs but also lead to substantial postharvest losses, limiting the profitability of this vital crop [14].

The agricultural sector in Pakistan has historically played a vital role in the nation's economy, with carrots being a significant contributor among vegetables, generating approximately $0.08 million. The exports are primarily classified under the category of fresh or chilled carrots and turnips (HS code 070610). Over the 3 years from 2017 to 2019, carrot exports increased marginally by 1.95%. The production growth rate is estimated to have changed, underscoring the need for enhanced mechanization and innovative solutions to improve both yield and quality [15]. This highlights an urgent need to adopt advanced carrot harvesting methods to increase efficiency, reduce postharvest losses, and meet both domestic and export demands effectively. The adoption of automated carrot harvesting machines could revolutionize Pakistan's agricultural sector. These systems reduce dependency on manual labor, minimize human error, and ensure timely harvesting, thus reducing spoilage and increasing yields [16]. For a country where agriculture is the backbone of rural livelihoods and food security, such advancements are essential to align with global standards and meet the growing demands of both local and international markets. Agricultural mechanization plays a critical role in the transition from traditional to modern agrarian economies, directly improving labor productivity, resource efficiency, and overall farm output. It plays a pivotal role in ensuring sustainable food security and in alleviating rural poverty. Manual harvesting typically requires 100–120 labor hours per hectare, making the process labor-intensive and time-consuming [17]. Appropriate mechanization has been shown to reduce human labor requirements on farms by 25%–30%, cut working time by 25%–35%, and decrease fertilizer usage by a similar margin [18]. Despite agriculture employing approximately 37.4% of Pakistan's total labor force [19], the sector remains undermechanized, limiting its capacity to meet the food demands of a rapidly growing population [20]. To fully harness the agricultural potential and address labor shortages and inefficiencies, there is an urgent need to accelerate the adoption of appropriate, scale-appropriate mechanization solutions across the farming landscape. Food security has emerged as one of the most pressing challenges in Pakistan, affecting millions of people across urban and rural areas. Despite being an agrarian economy, the country is experiencing an alarming food crisis, with 37% of the population classified as food insecure, according to the 2023 Global Hunger Index [21].

In addition to mechanization, sorting and grading of carrots play a pivotal role in ensuring market competitiveness. High-quality produce is essential for meeting export standards and consumer expectations. Advanced computer vision technologies, such as YOLO (You Only Look Once) and convolutional neural networks (CNNs), have emerged as powerful tools for automating sorting processes [22]. Khanna et al. [23] used an ensemble version of YOLOv8n called the fruit and vegetable detection network (FVDNet), which achieved a mean average precision (mAP) score of 0.82. Liu et al. [24] used the vanilla YOLO model for fruit yield estimation in guava orchards. They found that V-YOLO can rapidly detect the guavas with a detection speed 2.6 times higher than that of YOLOv10n. Gao et al. [25] applied improved YOLO v5s for tomato identification in the continuous working environment. The achieved results show that the recall rate and tomato detection precision of the YOLO v5s model are 82.42% and 92.08%, respectively. The mean absolute precision and recognition precision are improved by 1.29% and 2.72%, respectively, for the YOLOv5s model. Yuan et al. [26] used the integrated model named CNN_BiLSTM deep learning model, that is, a combination of a CNN and bidirectional long-short term memory neural network (BiLSTM) for the detection of the freshness of fruits. They achieved results with an accuracy of 97.76%. Khoiruddin and Tena [27] used a CNN to classify 36 different vegetables and fruits based on their color, texture, and shape. They achieved results with an accuracy of 97.31%. Hence, these detection systems enable the real-time identification and classification of carrots based on size, shape, and surface defects, ensuring uniformity and adherence to quality benchmarks [28]. By integrating such technologies into the harvesting workflow, Pakistan's agricultural sector can achieve a higher standard of efficiency and precision, addressing both domestic and international market requirements. Table 1 summarizes the recent technological advancements in carrot harvesting, sorting, grading, and yield prediction.

Recent advancements in automation and precision agriculture have demonstrated the effectiveness of machine learning and computer vision technologies in various aspects of carrot production, as shown in Table 1. The CNNs have been successfully applied in automatic sorting and quality assessment, achieving accuracy rates ranging from 98.7% to 99.82% (see Table 1). For instance, Ahmad et al. [29] achieved 99.43% accuracy in sorting, while Limiao et al. [30] reported a high accuracy of 99.82% using a deep learning model (CDDNet) for binary classification. Similarly, Hongfei et al. [31] employed CNNs to assess carrot quality based on appearance and achieved a classification accuracy of 98.7%. In addition to sorting, the prediction of carrot mass and volume has also been significantly enhanced by machine learning models. For example, Weijun et al. [32] utilized a stacked ensemble model (EM) and achieved an R^2 of 0.997, MAPE of 1.28%, and RMSE of 3.02. Wenqi et al. [34] applied a deep Fourier network (DFN), obtaining an R^2 of 0.9765 and RMSE of 0.0312 for volume prediction. Moreover, the use of object detection technologies like YOLOv5 and YOLOv4, combined with semantic segmentation techniques like DeepLabv3, has proven effective for detecting surface defects as well as estimating the physical characteristics of carrots. Wenqi et al. [34] reported 90.7% accuracy with YOLOv5 for harvesting and defect detection, while Sze-Teng et al. [36] managed to achieve high accuracy in estimating the length, width, and volume of carrots, with average errors of 1.85%, 2.51%, and 5.35%, respectively. Furthermore, predictive models like artificial neural networks (ANNs) and regression techniques have shown promise in forecasting carrot yield and quality. Piotr et al. [38]

TABLE 1: Recent studies on technological advancements in carrot harvesting, sorting, grading, and yield prediction.

Reference	Focus area	Technology	Key performance outcome
Ahmad et al. [29]	Automatic carrot sorting	CNN	99.43% accuracy
Limiao et al. [30]	Carrot grading	CDDNet (deep learning)	99.82% binary classification accuracy
Hongfei et al. [31]	Quality by appearance	CNN	98.70% accuracy, 98.34% sensitivity, 98.99% specificity
Weijun et al. [32]	Mass prediction	Stacked ensemble model	MAPE: 1.28%, RMSE: 3.02 g, R^2: 0.997
Weijun et al. [33]	Carrot grading	ELM	96.67% recognition accuracy
Wenqi et al. [34]	Harvesting & defect detection	YOLOv5	90.7% accuracy
Mustafa and Humar [35]	Volume prediction	Deep Fourier Network	R^2: 0.9765, RMSE: 0.0312
Sze-Teng et al. [36]	Carrot inspection	YOLOv4 + DeepLabv3	Length/width/volume error: 1.85%, 2.51%, 5.35%
Zhenhui et al. [37]	Rolling angle measurement	OPC + ICSM	High accuracy and efficiency
Piotr et al. [38]	Yield loss prediction	ANN	90.69% accuracy
Chan et al. [39]	Yield mapping	Random forest	R^2: 0.82, RMSE: 2.64 Mg/ha, MAE: 1.74 Mg/ha
de Lima et al. [40]	Yield and quality prediction	ANN	R^2: 0.68

demonstrated that ANNs could predict carrot root yield loss with 90.69% accuracy, while Chan et al. [39] employed random forest regression to predict carrot yield, achieving an R^2 of 0.82 and RMSE of 2.64 Mg ha^{-1}. Lastly, innovative methods for measuring the rolling angle of carrots, such as the outer profile curve (OPC) and improved cyclic shift method (ICSM), have been developed, offering high accuracy and efficiency, as demonstrated by Zhenhui et al. [37]. These findings underscore the growing potential of machine learning and computer vision in improving the efficiency and accuracy of carrot production processes.

While recent studies have demonstrated the successful application of deep learning models for carrot sorting, grading, and quality estimation, most of these efforts remain confined to controlled classification tasks or dataset-specific prediction models, with limited emphasis on real-world integration. Notably, previous work has not addressed the combination of intelligent defect detection with an optimized mechanical harvesting system tailored for practical deployment. Furthermore, most existing models rely on generic or publicly available datasets, which often fail to capture the morphological diversity of region-specific produce. Additionally, prior studies rarely explore the joint tuning of mechanical parameters (e.g., claw belt speed, roller speed, and taper angle) and seldom incorporate control strategies such as proportional–integral–derivative (PID) for maintaining operational consistency. This study addresses these limitations by introducing a unified, low-cost carrot harvesting solution that integrates a YOLOv8-based quality detection model, trained on a custom-annotated dataset of local carrot varieties, with an optimized mechanical design and PID controller to ensure reliable performance under varied field conditions.

The proposed system comprises a cost-effective, intelligent carrot harvesting machine combining a PID-controlled mechanical framework with an automated sorting mechanism powered by YOLOv8. The machine's harvesting efficiency is quantified based on output per acre, while the YOLOv8 model enables real-time classification of harvested produce, distinguishing high-quality carrots from defective ones, such as cracked or spoiled samples. The model's performance is validated using standard evaluation metrics: precision, recall, $F1$ score, and mAP, demonstrating robust detection capability following effective model training and convergence. The novelty of this work lies in its integration of regionally adapted computer vision with precision-optimized mechanical engineering. By using YOLOv8 on a locally trained annotated dataset, the system achieves context-aware detection accuracy superior to generic approaches. The harvesting mechanism operates at optimized parameters of claw belt speed, roller speed, and taper angle to minimize crop damage while maximizing efficiency. The addition of a PID controller ensures stable operation across varying conditions. These contributions altogether deliver a scalable, intelligent harvesting solution aligned with precision agriculture, offering meaningful advancement in root crop automation for resource-constrained agricultural economies.

2. Methodology

The experiment was conducted to evaluate the performance of an automatic carrot harvesting machine through a structured methodology that combined mechanical system design optimization, force optimization, soil interaction analysis, and vision-based carrot sorting. The approach integrated mechanical engineering principles with intelligent control systems and machine learning algorithms. This ensured precision, reliability, and crop protection under field conditions. The tensile strength of carrots was determined through controlled mechanical testing, which guided the calibration of a PID control system. To achieve optimal harvesting performance, the claw belt speed, roller speed, and taper angle were methodically varied and evaluated. These parameters directly influence the machine's ability to grip, lift, and transport carrots while minimizing mechanical damage. The claw belt speed was tested within a range of 3.5–4.5 m/s to assess the influence of sufficient pulling force and crop safety. Roller speed was varied between 1.0 and 1.5 m/s to

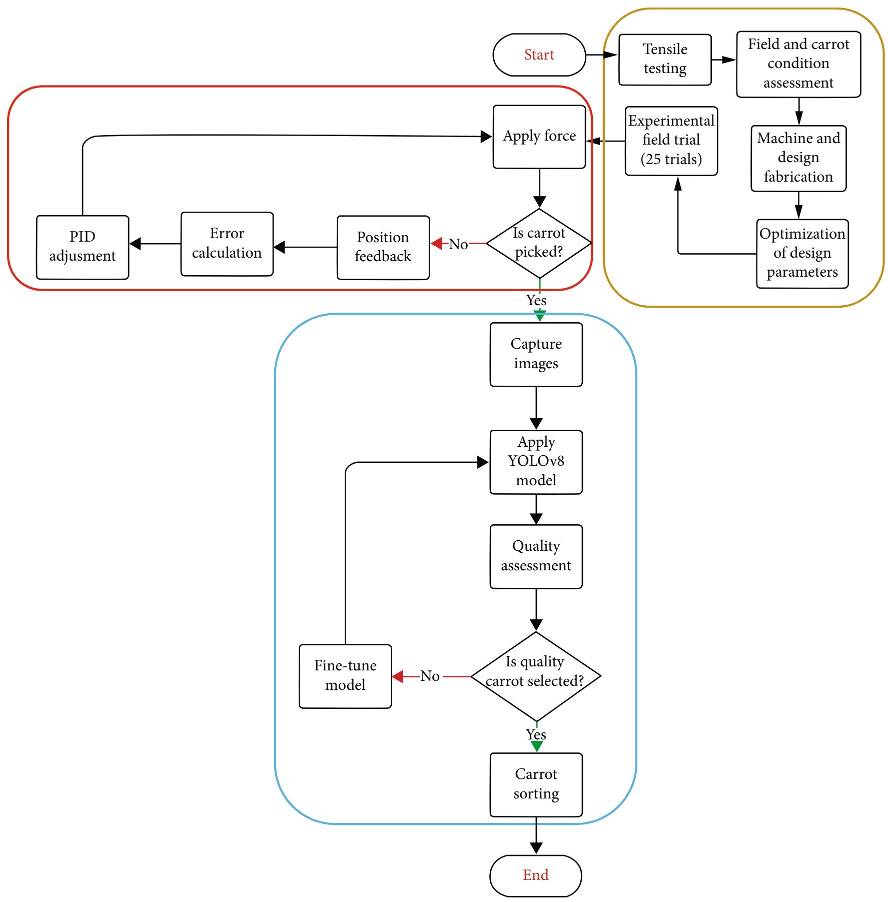

Figure 1: Flowchart of the carrot harvesting design and sorting methodology.

determine its effect on soil removal and lifting smoothness. Taper angles of 22°, 26°, and 30° were selected to represent different geometric configurations of the roller assembly, influencing the carrot's grip and trajectory during extraction. This system dynamically adjusted the gripping force applied by rubber belts to prevent breakage during extraction. The harvesting mechanism comprised driver and driven pulleys powered by a 96-W DC motor, tensioned via Teflon rollers to prevent slippage, and used angled rollers and claw belts to gently lift the carrots. Specialized pins were installed to improve soil separation, while a robust mild steel digging unit minimized extraction force by loosening the soil.

After extraction, stereo vision cameras captured high-resolution images of the harvested carrots. These images were processed in real time using a YOLOv8 detection framework. It was trained to distinguish between marketable and defective carrots based on shape, size, and visible deformities. A dataset of 280 annotated images of harvested carrots was created using stereo camera captures under natural lighting conditions to train and test the YOLOv8 model with a 70:30 ratio split. When detection accuracy required improvement, the model was fine-tuned iteratively using field-acquired data. Adaptive feedback from the PID controller adjusted roller and belt speeds accordingly, enhancing both operational efficiency and sorting precision. Field trials were carried out under controlled conditions to evaluate multiple operational parameters, including claw belt speed, roller speed, and taper angle. A total of 25 trials were conducted across 2–3 acres in loamy and sandy loam soils, with preirrigation and soil moisture control to ensure consistency. Performance was assessed in terms of harvesting efficiency, damage rate, sorting accuracy, and energy consumption. The insights obtained informed iterative design improvements, resulting in a machine optimized for carrot harvesting in Pakistani field conditions. Figure 1 illustrates the methodological sequence in a flowchart, beginning with the optimized design of the carrot harvesting machine (shown in yellow), followed by mechanical extraction (shown in red), and then real-time vision-based sorting (shown in blue). This comprehensive process demonstrated the potential for sustainable, labor-efficient carrot harvesting through the integration of smart agricultural technologies.

3. Design and Experimentation

3.1. Tensile Testing. Mechanical tensile testing is critical in optimizing carrot harvesting machines by providing essential data on the mechanical properties of carrots, such as elastic modulus, tensile strength, and fracture toughness. These insights allow for the design of harvesting mechanisms that apply precise forces and prevent carrot damage while reducing postharvest losses. Tensile test data guide the engineering of machine components that prevent breaking during the harvesting process, confirming their

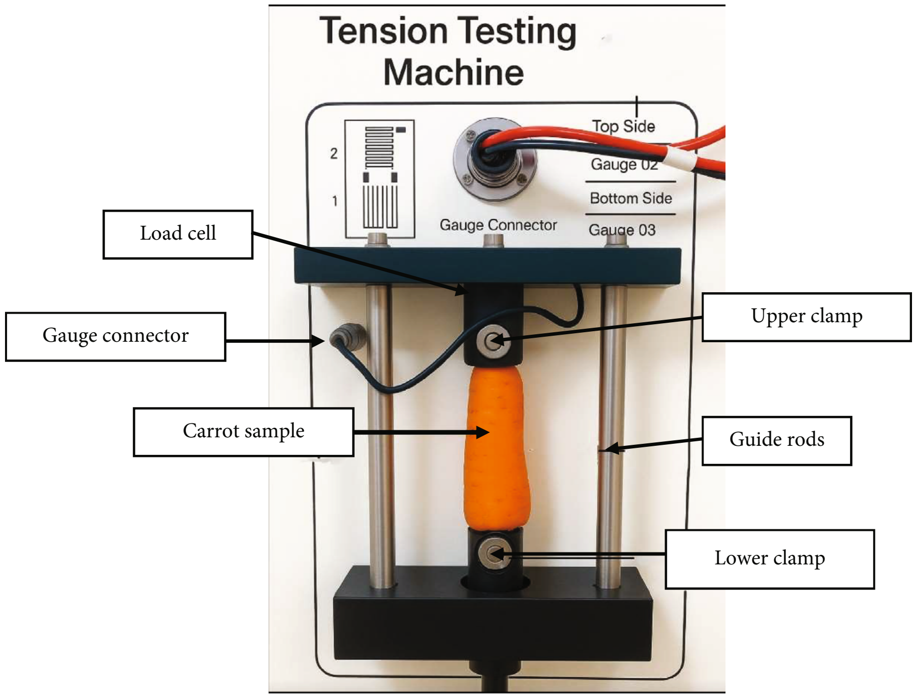

FIGURE 2: Tensile testing setup for measuring carrot tensile force.

structural integrity under stress. Additionally, the testing informs material selection for vital parts and ensures they can withstand operational loads. Figure 2 shows the tensile testing machine used to compute the tensile force required for effective carrot harvesting. Fresh carrots were selected and manually shaped into uniform cylindrical forms using a knife and sandpaper to minimize surface irregularities and ensure parallel gripping ends. Each specimen was trimmed to a gauge length of approximately 100 mm. Carrots with varying diameters were tested to study the effect of cross-sectional area on tensile strength. The average diameter of the specimens was measured using a Vernier Caliper and found to be approximately 20 mm. The specimens were clamped vertically between the upper and lower grips of the tensile machine, with particular attention to ensure proper axial alignment to avoid bending stresses. The machine was equipped with strain gauges and a load cell to record the force and elongation data. A constant crosshead speed of 5 mm/min was maintained until specimen failure. Based on multiple trials with shaped carrot samples of varying diameters, the average tensile force required to fracture the specimens was found to be approximately 70 N.

Furthermore, tensile testing accounts for the variability in carrot varieties, including differences in size, shape, and moisture content, enhancing the harvester's adaptability and efficiency. Table 2 summarizes the properties of carrots cultivated in the South Asian region, including data representative of crops from Pakistan, along with the computed tensile force by testing. Therefore, mechanical tensile testing is essential for creating advanced, damage-minimizing carrot harvesters that improve productivity and performance in diverse agricultural conditions.

TABLE 2: Properties of the carrot plant [41].

Properties	Average value
Length (cm)	10–15 ± 3
Diameter (mm)	30 ± 3.6
Mass (g)	85–100 ± 15
Volume (cm^3)	115 ± 15
Foliage length (mm)	50 ± 5
Tensile force (N)	70 ± 15

3.2. Soil Conditions. The soil conditions in Punjab, Pakistan, are generally favorable for carrot cultivation, primarily due to the region's fertile alluvial and loamy soils, which provide an ideal environment for root crops. The soil texture, often loamy or sandy loam, promotes good drainage, moisture retention, and aeration, allowing for optimal carrot root development. The pH of the soil, which typically ranges from 6.0 to 7.0, supports healthy carrot growth by facilitating nutrient uptake and reducing the risk of disease [42]. The region's well-developed canal irrigation system ensures a consistent water supply, essential for maintaining adequate soil moisture, particularly during the growing season [43]. However, excessive water or improper irrigation can lead to soil compaction, which can hinder root expansion and complicate harvesting. Additionally, while the soil is nutrient-rich, the management of organic matter is crucial for maintaining soil structure and preventing erosion [44]. Despite the generally favorable conditions, challenges such as salinity in certain areas can affect carrot growth, and soil compaction may arise in intensively cultivated fields [45]. Overall, the soil conditions in Punjab, when properly managed, support the successful cultivation and harvesting of high-quality carrots. Figure 3 shows mature carrots grown in Punjab, Pakistan, ready for harvest.

3.3. Experimental Setup. The experimental setup for evaluating the carrot harvesting machine was methodically structured to capture the influence of critical operational parameters on performance metrics such as harvesting efficiency and carrot damage. Tests were performed under both laboratory-controlled and field-representative conditions. A series of 25 experimental trials were conducted, varying claw belt speed (3.5–4.5 m/s), roller speed (1.0–1.5 m/s), and taper angle (22°, 26°, and 30°). The experimental matrix was designed to identify optimal settings that would maximize harvesting efficiency while minimizing mechanical damage to the carrots. Parameter ranges were determined from preliminary field observations and relevant literature to reflect practical operational limits under typical soil and crop conditions. The chosen claw belt and roller speeds span from minimal mechanical agitation to higher throughput levels. The selected taper angles represent varying degrees of carrot grip and guidance, enabling assessment of both conservative and aggressive harvesting geometries. The optimized parameters were then selected for further evaluation. The development of the carrot harvester involved a structured optimization process to enhance performance, efficiency, and durability. Key design parameters, including roller speed, taper angle, claw belt speed, and motor power consumption, were systematically evaluated under standardized field conditions. Similarly, the claw belt speed was examined at 3.5, 4.0, and 4.5 m/s to balance harvesting speed and mechanical stress on the tested carrots. The motor power requirement was set at 96 W to ensure compatibility with standard planting patterns while maintaining energy efficiency.

Figure 4 presents the CAD design of the carrot harvesting machine, developed using SolidWorks. Figure 4a illustrates the complete 3D model, providing a comprehensive view of the machine's overall structure and components. Figure 4b displays the top view, offering insights into the machine's layout and arrangement of key elements. Figure 4c presents the front view, highlighting the design features and operational aspects from a frontal perspective. Figure 4d shows the side view, detailing the machine's profile and structural configuration.

The automated carrot harvesting machine developed for this study comprises several integrated components designed for efficient and low-damage operation, with a total fabrication cost of Rs. 140,000 (≈$500). Key components of the machine include a claw belt mechanism with rubber claws and pulley-driven motion powered by a 96-W DC motor, and a roller assembly featuring Teflon-coated rollers set at a 26° taper angle for guiding and cleaning. A digging unit with a mild steel blade loosens soil to reduce pulling resistance, while the tensioning and alignment system with Teflon tension rollers ensures belt stability. A PID-controlled module adjusts motor torque in real time using load sensor feedback to prevent crop damage. The machine also integrates a stereo vision camera and YOLOv8-based

Figure 3: Carrot ready for harvesting in Punjab, Pakistan.

detection system for real-time carrot quality assessment and classification. Power is supplied by two lightweight 12-V lithium batteries (each weighing approximately 4 kg and with 20 Ah capacity), while 14-in. pneumatic tyres ensure smooth mobility over uneven agricultural terrain. Finally, a sorting conveyor system directs carrots into appropriate bins based on vision output, ensuring consistency with minimal manual handling, tailored for local farming needs.

Figure 5 shows the fabricated automatic carrot harvesting machine. Testing was conducted in conditions with loamy and sandy loam soils. Moisture levels were maintained between 15% and 25% to replicate optimal carrot growth conditions. Carrot spacing was kept at 0.3 m, and forward speed was maintained at 1.2 m/s for consistent operation across different plots. Performance metrics such as harvesting speed and efficiency were carefully recorded. The precision, accuracy, recall, and $F1$-score were used to ensure effective YOLOv8 model performance. This comprehensive testing approach provided valuable insights into the machine's mechanical performance, detection capabilities, and suitability for large-scale commercial carrot harvesting. Key soil parameters recorded during the experimentation are shown in Table 3. Soil type was classified by doing texture analysis, while moisture content was determined gravimetrically. The bulk density was measured using the core sampling method, while compaction was assessed through a cone penetrometer. The temperature was recorded using soil thermometers, and root zone depth was evaluated by manual excavation and profiling. The field was preirrigated 24 h before harvesting to maintain optimal soil looseness and reduce pulling resistance. This ensured consistency in evaluating machine performance, particularly in terms of extraction force, root damage, and sorting accuracy. These soil conditions provided a realistic and challenging environment to assess the adaptability of the machine's digging unit, claw belt grip, and PID force regulation under variable field textures.

3.4. Control System. The control system of the carrot harvesting machine is designed with an encoder-based feedback mechanism to ensure precise operation and efficient harvesting. The system uses encoders attached to the motors driving the rollers, claw belts, and other mechanical components. These encoders continuously monitor the rotational speed and position of each part, providing real-time data to the central processing unit (CPU). This feedback enables the

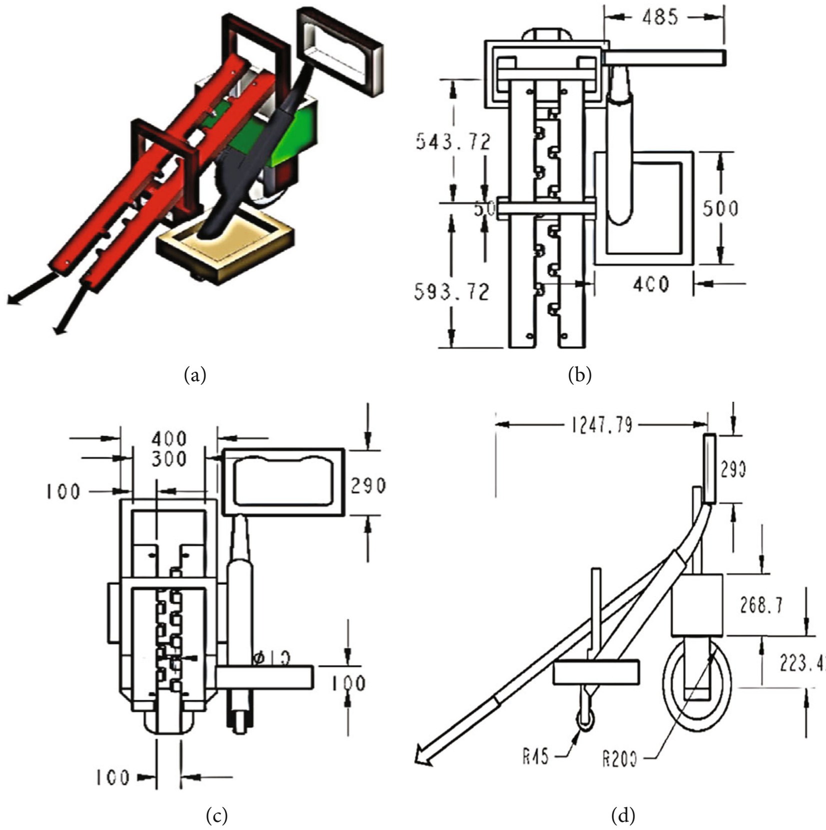

FIGURE 4: CAD diagram of carrot harvesting machine: (a) overall 3D model, (b) top view, (c) front view, and (d) side view of the harvesting machine.

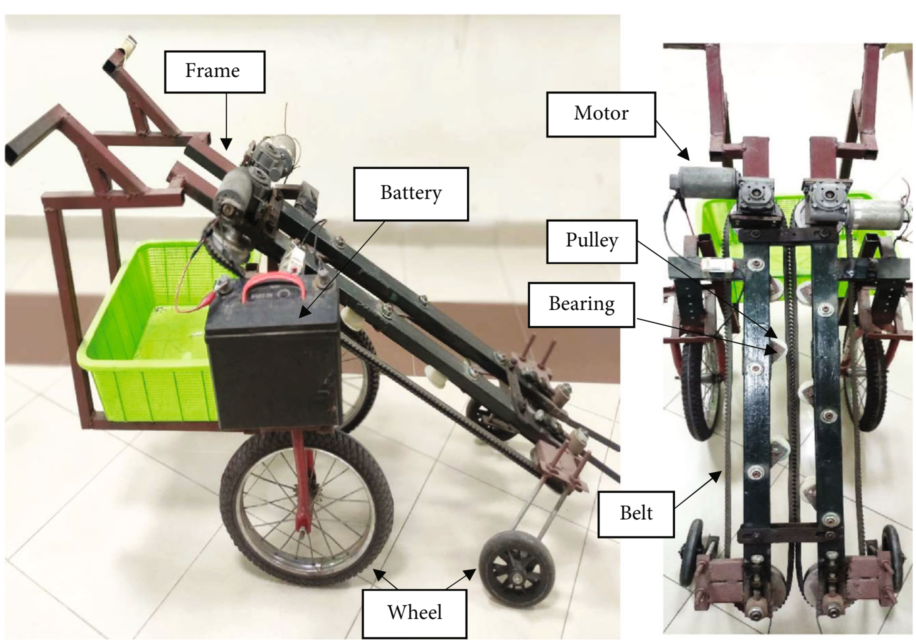

FIGURE 5: Prototype of a carrot harvesting machine.

implementation of a closed-loop control system, such as a PID controller, to dynamically adjust motor power and maintain optimal performance. As the machine operates, the control system continuously monitors the encoder data to regulate motor speed. This ensures that the rollers rotate at the correct speed to match the forward velocity of the machine, as the claw belts efficiently grip and pull the carrots without causing damage. In the event of soil irregularities or variations in carrot density, the encoder feedback allows the system to make real-time adjustments to prevent slippage or excessive force.

TABLE 3: Soil parameters at the time of testing.

Soil property	Value/range
Soil type	Loamy and sandy loam
Soil moisture content	18%–22%
Bulk density	1.3–1.5 g/cm^3
Soil temperature	22°C–26°C
Compaction (penetrometer)	1.2–1.8 MPa
Root zone depth	15–25 cm

TABLE 4: Hyperparameters of the YOLO v8 model.

Hyperparameters	Values
Epoch no.	100
Learning rate	0.01
Batch size	16
Confidence threshold	0.4
IoU threshold (NMS)	0.5
Dropout rate	0.5
Optimizer	Adam

3.5. Quality Carrot Detection. The YOLOv8 model was utilized for carrot detection and quality assessment using a specialized dataset of 280 annotated images, prepared with the LabelImg tool. The dataset was divided into training and testing sets in a 70:30 ratio to ensure a robust evaluation framework, and the hyperparameter configuration of the YOLO model was fine-tuned to optimize its performance for detecting and classifying the quality of carrots. The model was trained for 100 epochs, which provided sufficient iterations for meaningful patterns within the data. A learning rate of 0.01 was chosen to balance convergence speed and accuracy, while a batch size of 16 was employed to achieve an effective balance between computational efficiency and model performance. A confidence threshold of 0.4 was set to filter out low confidence predictions, thereby minimizing false positives (FPs), and the intersection over union (IoU) threshold for nonmaximum suppression (NMS) was configured at 0.5 to eliminate redundant bounding boxes, retaining only the most accurate ones. The dropout rate of 0.5 was applied to minimize overfitting by randomly deactivating neurons during training. The anchor boxes were customized to align with the specific dimensions and aspect ratios of the carrots in the dataset. The Adam optimizer was utilized for its adaptive learning rate capabilities, making it well suited for training on this relatively small dataset. Table 4 shows the hyperparameters at which the YOLOv8 model was trained.

The performance of the model was evaluated using key metrics, including true positives (TPs), FPs, true negatives (TNs), and false negatives (FNs). These metrics are essential for calculating performance parameters such as precision, recall, accuracy, and $F1$ score. A confusion matrix was generated to provide a comprehensive analysis of the model's classification performance. This offered insights into the balance between detection errors and correct predictions. This approach ensured that the fine-tuned YOLOv8 model delivered reliable and accurate detection and classification of carrot quality, facilitating a detailed evaluation of its effectiveness. Performance was evaluated using accuracy, precision, recall, and $F1$ score, which are defined as follows:

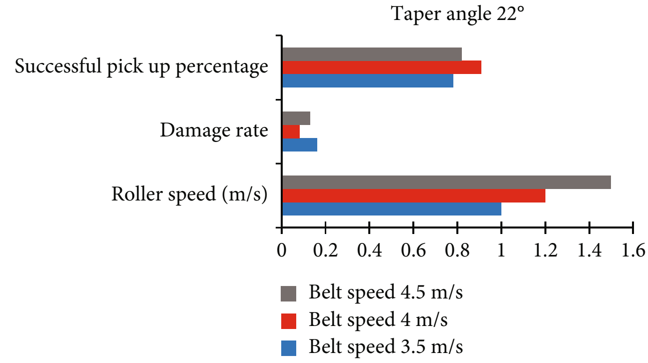

FIGURE 6: Carrot harvesting machine performance at taper angle 22°.

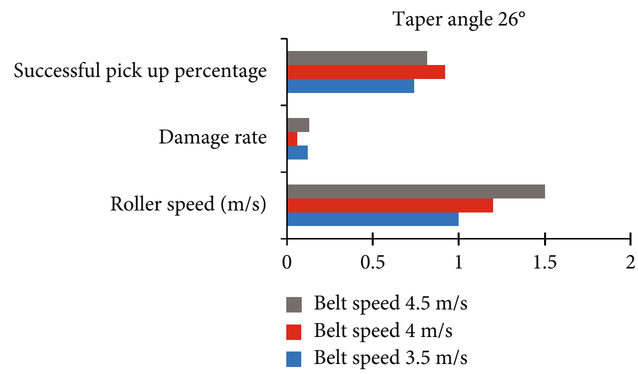

FIGURE 7: Carrot harvesting machine performance at taper angle 26°.

$$\textbf{Accuracy} = \frac{(\text{true positives} + \text{true negatives})}{\text{total carrot samples}},$$

$$\textbf{Precision} = \frac{\text{true positives}}{\text{true positives} + \text{false positives}},$$

$$\textbf{Recall} = \frac{\text{true positives}}{\text{true positives} + \text{false negatives}},$$

$$\textbf{F1 score} = 2 \times \frac{(\text{precision} \times \text{recall})}{\text{precision} + \text{recall}}.$$

The training performance was visualized through epoch-wise plots of precision as well as loss. The precision curve exhibited steady improvement, stabilizing near peak performance, while the loss curve showed a consistent decline. This indicated effective learning of the model. This fine-tuned YOLOv8 model demonstrated high precision in detecting carrot locations and orientations, facilitating the reliable separation of quality carrots from defective ones. These findings highlight YOLOv8's efficacy in agricultural automation, enabling real-time, high-accuracy operations.

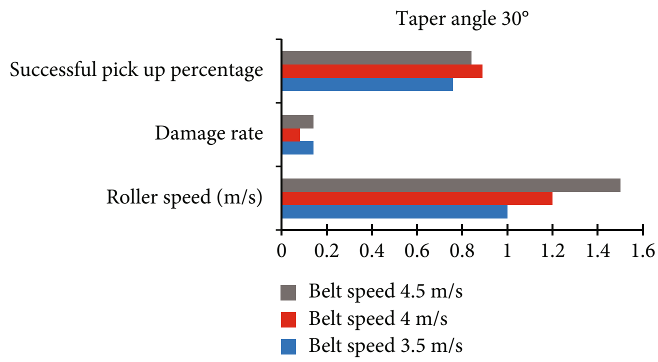

FIGURE 8: Carrot harvesting machine performance at taper angle 30°.

TABLE 5: Experimental setup and parameter optimization.

Test no.	Claw belt speed (m/s)	Roller speed (m/s)	Taper angle (°)	Harvesting efficiency (%)	Carrot damage (%)
1	3.5	1	22	84	11
2	4	1.2	22	87	9
3	4	1.2	26	**92**	**3**
4	4.5	1.5	26	89	7
5	4.5	1	26	83	13
6	3.5	1	22	80	14
7	3.5	1.3	30	78	6
8	4	1	26	88	8
9	4.5	1	30	85	10
10	4.5	1.3	30	82	12
11	3.5	1	22	85	10
12	3.5	1.2	26	89	7
13	4	1.3	26	91	6
14	4.5	1.2	26	89	6
15	4.5	1.5	30	80	15
16	3.5	1.3	22	78	16
17	3.5	1	30	86	8
18	4.5	1	26	86	9
19	4	1.5	26	87	7
20	4	1.2	26	90	9
21	3.5	1.2	26	88	8
22	4	1.2	30	87	7
23	3.5	1	26	87	8
24	4.5	1.2	30	81	13
25	4	1.2	22	**91**	**5**

4. Results and Discussion

The effect of different taper angles: 22°, 26°, and 30°, and belt speeds: 3.5, 4, and 4.5 m/s, was studied for three parameters mainly roller speed, successful pick-up percentage, and damage rate. Across all taper angles, roller speed increases with higher belt speeds, reaching its maximum at 4.5 m/s. The successful pick-up percentage follows a similar pattern, peaking at 4 m/s, while 3.5 m/s results in lower pick-up efficiency. The damage rate remains minimal under all conditions. However, a slightly higher damage rate is noted at 4.5 m/s. The results indicate that a belt speed of 4 m/s provides the optimal balance between maximizing pick-up efficiency and minimizing damage. Additionally, the taper angle influences overall performance, with the most effective results observed at 26°.

Figure 6 illustrates the impact of a 22° taper angle on roller speed, successful pick-up percentage, and damage rate for three different belt speeds: 3.5, 4, and 4.5 m/s. The roller speed increases with higher belt speeds, reaching its maximum at 4.5 m/s. The successful pick-up percentage also follows a similar trend, having a high efficiency of 91%,

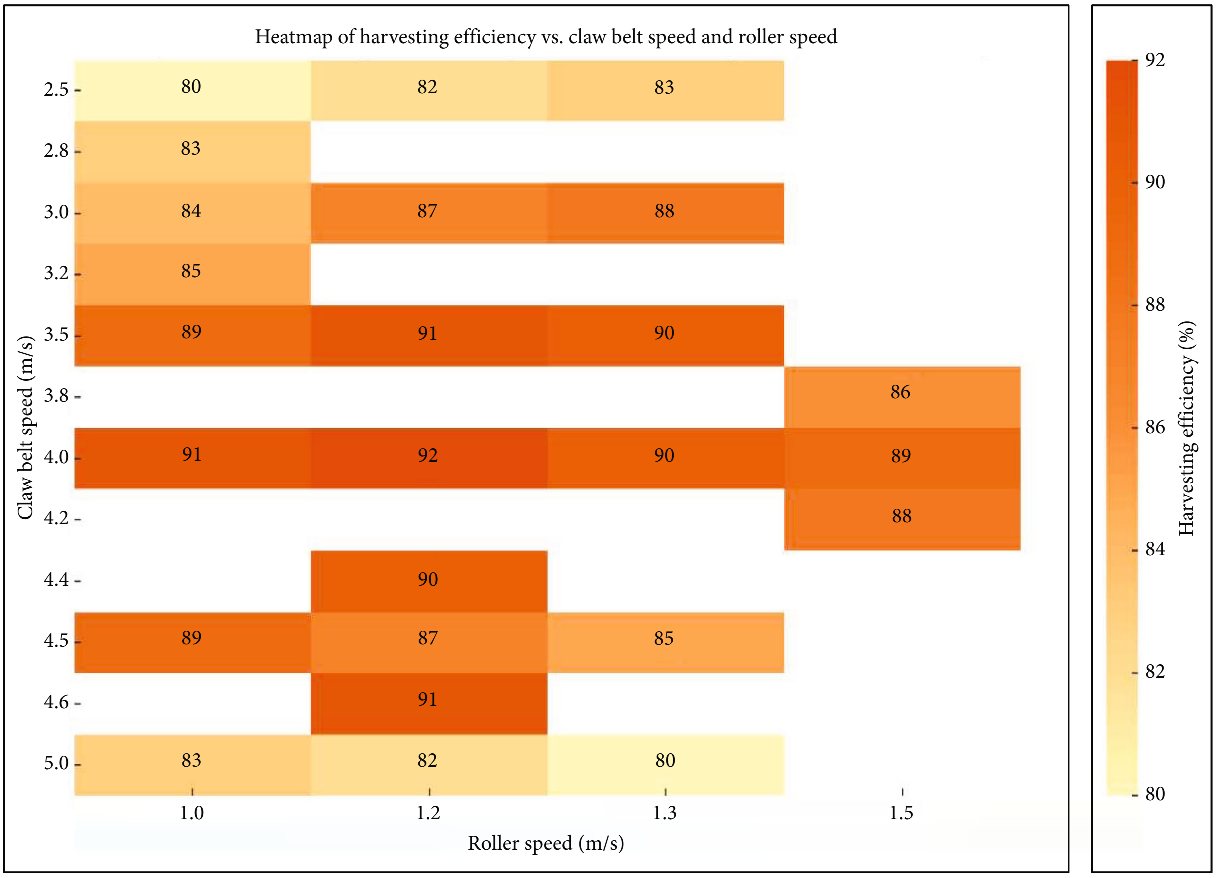

Figure 9: Heatmap showing the effect of claw belt speed and roller speed on carrot harvesting efficiency.

TABLE 6: Calculated carrot harvesting machine design parameters after optimization (shift to results).

Design parameters	Value
Roller speed—linear (m/s)	1.2
Taper angle (°)	26
Claw belt speed—linear (m/s)	4.0
Motor power requirement (W)	96.0
Power consumption (kW)	1.2
Forward speed (m/s)	1.2
Carrot spacing (m)	0.3

observed at 4 m/s, while the lowest pick-up rate corresponds to 3.5 m/s. The damage rate remains lowest at 4 m/s. These results suggest that while increasing the belt speed enhances roller speed and pick-up efficiency, excessively high speeds may contribute to a marginal increase in damage.

Figure 7 illustrates the impact of a 26° taper angle on roller speed, successful pick-up percentage, and damage rate for three different belt speeds: 3.5, 4, and 4.5 m/s. The minimum damage rate of 3% is achieved for a belt speed of 4 m/s. This speed also yields the best successful pick-up of 92%.

Figure 8 shows the impact of a 30° taper angle on roller speed, successful pick-up percentage, and damage rate for three different belt speeds: 3.5, 4, and 4.5 m/s. The most successful pick-up was observed at 4 m/s of 87% with an average damage rate of 7%, while the lowest was observed for 3.5 m/s of 78%.

Table 5 presents experimental readings used to optimize the carrot harvesting machine. It outlines the combinations of claw belt speed, roller speed, and taper angle tested across 25 trials, along with the resulting harvesting efficiency and crop damage rates.

The heatmap, shown in Figure 9, visually represents the effect of varying claw belt speed and roller speed on the harvesting efficiency of the machine. Each cell in the heatmap corresponds to a unique combination of these parameters, with color intensity indicating the resulting efficiency percentage. Darker shades (dark orange) represent higher efficiencies, while lighter shades indicate suboptimal performance. This visualization aids in identifying the optimal range of operating conditions for maximum harvesting efficiency with minimal damage.

Based on the experimental results, the optimized design parameters of the machine are mentioned in Table 6. The design parameters were optimized to roller speed of 1.2 m/s, taper angle of 26°, and claw belt speed of 4.0 m/s for efficient operation. The motor power requirement of 96 W, along with a forward speed of 1.2 m/s and carrot spacing of 0.3 m, ensured compatibility with standard planting patterns. These tests were conducted on a standardized setup, with rollers set to a linear speed of 1.2 m/s and motor power inputs continuously monitored to ensure operational

(a) (b)

Figure 10: Detection of quality carrots using YOLO. (a) All carrots detected (confidence: 0.58–0.87, no defects), and (b) quality carrots detected (confidence: 0.62–0.87), defects not detected.

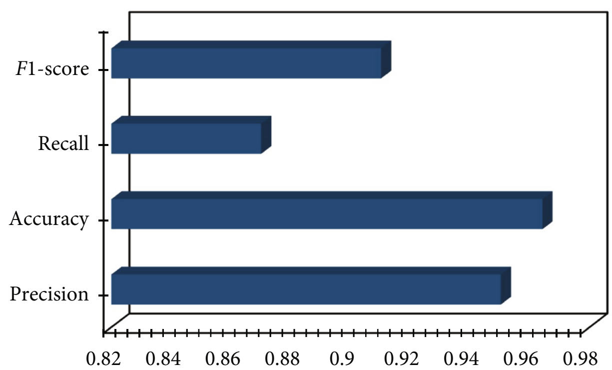

Figure 11: Performance metrics of the YOLO model.

efficiency. Additionally, the machine's power consumption was recorded at 1.2 kW.

Figure 10 shows the detection of quality carrots using the YOLOv8 model. Figure 10a shows that all carrots are detected with a confidence level of 0.58–0.87 and no defects. Figure 10b shows that quality carrots are detected with a confidence level of 0.62–0.87, while defective ones are not detected.

Figure 11 provides a comparative analysis of precision, accuracy, recall, and $F1$ score to evaluate the model's performance. Precision and accuracy exhibit the highest values, approaching 0.98, indicating the model's strong ability to correctly identify relevant instances and maintain an overall correct classification rate. The $F1$ score, a harmonic mean of precision and recall, is slightly lower than precision but remains close to 0.95, reflecting a balance between the model's precision and recall capabilities. Recall, which measures the model's ability to identify all relevant instances, is slightly above 0.9. Overall, the results demonstrate a robust performance, with high precision and accuracy contributing to an effective classification process.

Figure 12 demonstrates the precision of the YOLOv8 model during the training and validation phases for carrot detection, plotted against the number of epochs. Initially, both training and validation precision exhibit a rapid increase, reflecting the model's ability to learn features effectively from the dataset. At approximately 30 epochs, the precision for both datasets surpasses 0.8, indicating strong model performance in detecting carrots. Beyond 30 epochs, the training precision slightly outpaces validation precision. However, both curves converge near 90 epochs, achieving a precision close to 0.95 and reaching an optimal level of learning. Hence, the graph demonstrates the robustness and reliability of the YOLOv8 model in detecting carrots, with high precision. This is achieved for both the training and validation datasets over 100 epochs. This highlights the model's capacity to balance learning efficiency and accuracy for carrot detection tasks.

Figure 13 illustrates the loss of the YOLOv8 model during both the training and validation phases for carrot detection, plotted against the number of epochs. The loss decreases significantly after the 50th epoch for both the training and validation datasets, with minimum loss observed at the 100th epoch, after which the loss stabilizes. Overall, this behavior reflects good training dynamics, where the model learns effectively in the early stages and then stabilizes, making it good for testing and deployment without overfitting.

Figure 14 shows the relationship between the confidence threshold and precision for the YOLOv8 model. Confidence represents the model's certainty about detecting an object within an image, with higher values indicating a greater level of certainty. Precision, in turn, refers to the proportion of TP predictions (correct detections) relative to all positive predictions made by the model. As the confidence threshold increases from 0.1 to 0.9, precision improves, reflecting that the model becomes more selective and produces more accurate detections with higher confidence. The precision stabilizes at approximately 0.98 beyond a threshold of 0.7, signifying that further increases in confidence do not significantly enhance precision but help reduce FPs.

Figure 15 illustrates the trade-off between confidence and recall in model performance. Confidence represents the model's certainty in its predictions, while recall measures the proportion of actual positives correctly identified by the model. As confidence increases from 0.1 to 0.9, it is observed that recall decreases. This highlights the typical inverse relationship between these two metrics. Initially, lower confidence thresholds yield higher recall, indicating the model is

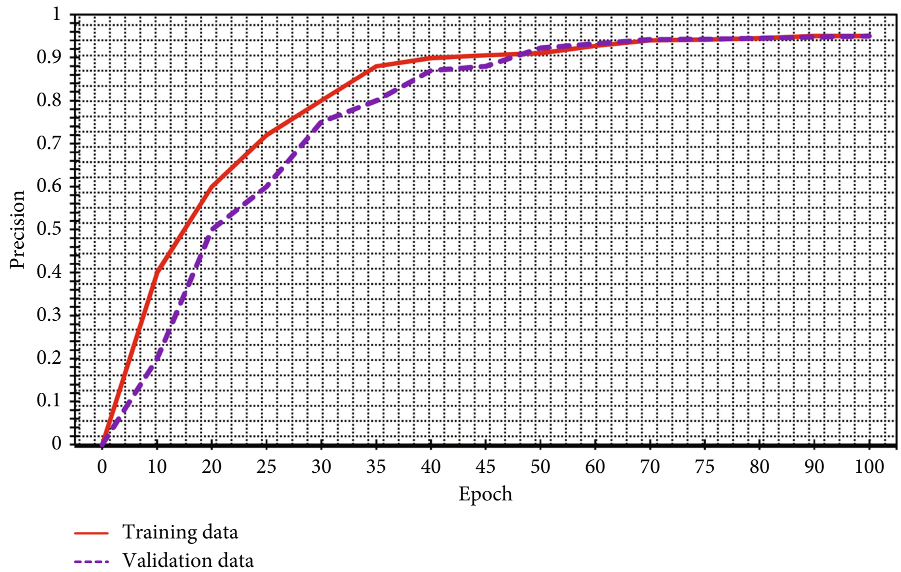

FIGURE 12: Precision with respect to epoch for the YOLO model.

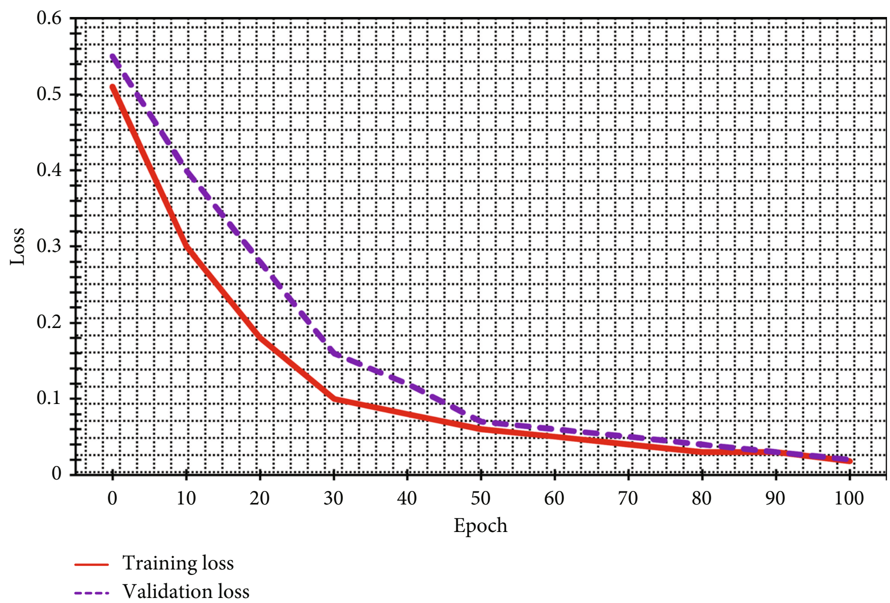

FIGURE 13: Loss with respect to epoch for the YOLO model.

more likely to classify TPs. However, as the confidence threshold rises, recall sees a decline, suggesting more stringent criteria for prediction, which reduces the number of TPs identified.

The model exhibited strong detection performance by achieving a mAP of approximately 0.94 at IoU 0.5 (mAP@0.5). These values indicate the model's ability to maintain high precision and recall across varying levels of localization strictness, ensuring reliable detection and classification of quality carrots. The high mAP scores further reflect the robustness of the model in distinguishing between quality and defective samples and hence reinforce its effectiveness in automation-driven harvesting applications.

Table 7 shows the comparison of the performance of manual carrot harvesting versus carrot harvesting machines. The comparison between conventional hand-picking and harvesting machines shows critical differences in performance parameters such as speed, efficiency, cost, scalability, and worker safety. The analysis is seen as favoring machine-based harvesting for large-scale and efficient operations. Harvesting machines demonstrate a superior speed of 3–5 acres per day, with an average harvesting time of approximately 2.88 h per acre. This significantly outpaces the 0.2–0.5 acres per day achieved through manual methods. Additionally, the harvesting efficiency of machines, mainly ranging from 80% to 92%, surpasses the 60%–80% efficiency of manual picking. This higher efficiency is attributed to the

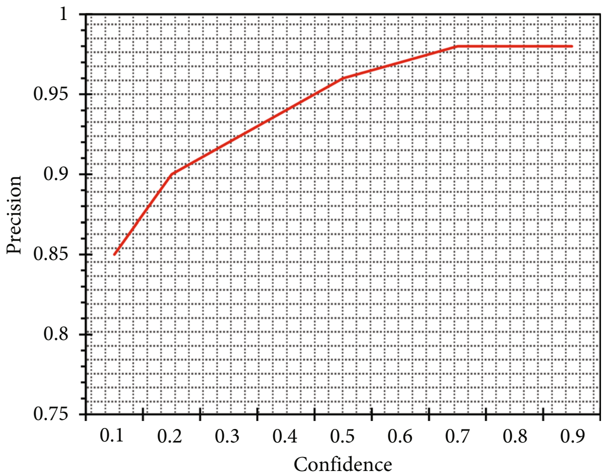

FIGURE 14: Model performance showing confidence with respect to precision.

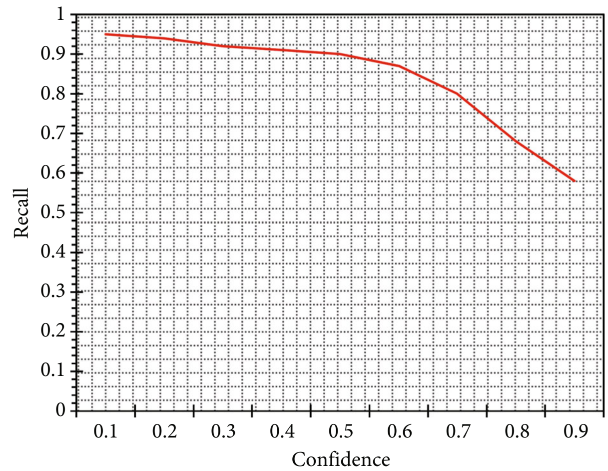

FIGURE 15: Model performance showing confidence with respect to recall.

precision and consistency of machines, which minimize crop losses under optimal field conditions, whereas manual methods are prone to human fatigue and error, increasing the likelihood of unharvested crops.

Figure 16 shows the comparison of harvesting efficiency using the conventional method and the carrot harvesting machine. Although the initial cost of harvesting machines is higher due to the expense of procurement and maintenance, this investment is offset by their scalability and ability to handle extensive operations. Machines can operate continuously with minimal downtime, providing a clear advantage for large-scale harvesting, whereas manual methods are limited by the availability and endurance of the labor force. Moreover, worker safety is significantly improved with machines, as they reduce the physical strain and risk of injuries associated with repetitive manual tasks. In contrast, manual harvesting poses long-term ergonomic risks and a higher likelihood of work-related injuries. In conclusion, the results strongly favor the adoption of harvesting machines for modern agricultural practices, particularly in large-scale farming. The increased speed, superior efficiency, enhanced scalability, and improved worker safety of machine-based methods outweigh the benefits of lower initial costs associated with manual harvesting. For sustainable and high-output farming, investing in harvesting machinery provides a practical and scientifically justified solution, aligning with the needs of precision agriculture and labor optimization.

The experimental outcomes of the current study provide substantial insights into the optimization of key design and operational parameters for a carrot harvesting machine. Specifically, the optimal configuration, comprising a claw belt speed of 4.0 m/s, a roller speed of 1.2 m/s, and a taper angle of 26°, demonstrated a successful pick-up rate of up to 92% and a minimal damage rate of mostly 6%–8%. These findings are consistent with and, in some aspects, improve upon previous studies reported in the literature, while also addressing critical shortcomings identified in earlier designs.

Bokai et al. [46], in their analysis of a clamping and conveying device for carrot harvesting, highlighted persistent challenges in reducing damage and leakage rates. Their findings reported average damage rates ranging from 3.5% to 9.9% for different varieties at varying clamping speeds (0.4–1.3 m/s). Although their best-case damage rates were slightly lower than those observed in our study (minimum of 6%), it is important to note that our design balances both high pick-up efficiency and operational simplicity in field deployment. Additionally, their design reported significant leakage issues, which our optimized system addressed through improved taper angle and synchronized belt–roller dynamics, reducing both crop escape and mechanical strain. The findings from Senthilkumar et al. [47] demonstrated a detopping efficiency of 98% and a damage rate of just 2% under optimized field conditions in hilly regions. While these outcomes indicate excellent machine performance, the actual field capacity was recorded at 0.028 ha/h (equivalent to roughly 0.7 acres/day), significantly lower than the 3–5 acres/day achieved by our machine. This reflects the suitability of our design for large-scale operations in plain terrains. Furthermore, the use of claw-based pick-up mechanisms in our study provides more versatile handling of diverse soil textures and planting configurations compared to fixed blade designs. A similar emphasis on reducing damage was presented in the study on the double-disc cutter design [48]. Their optimized system achieved a root and stem damage rate as low as 2.61%, yet this configuration involved complex cutter geometry and precise disc settings. While this advanced cutting system excels in reducing damage during detopping, it does not directly address the efficiency of pick-up or conveying, which our study specifically focuses on. Moreover, their detopping effectiveness (87%–89%) is comparable to the successful pick-up rates (88%–91%) recorded at a 26° taper angle and 4.0 m/s belt speed in our machine, suggesting our approach achieves competitive performance using fewer moving parts and lower energy requirements.

The optimized design parameters, specifically the roller speed of 1.2 m/s, claw belt speed of 4.0 m/s, and taper angle of 26°, are well complemented by the physical design

TABLE 7: Comparison of the performance of manual carrot harvesting vs. carrot harvesting machine.

Operational parameters	Conventional hand picking (based on 8 h/day)	Harvesting machine
Speed (acres/day)	0.2–05	3–5
Harvesting efficiency	60%–80%	80%–92%
Initial cost	Low	High
Scalability	Limited	High
Worker safety	High risk (physical strain)	Low risk

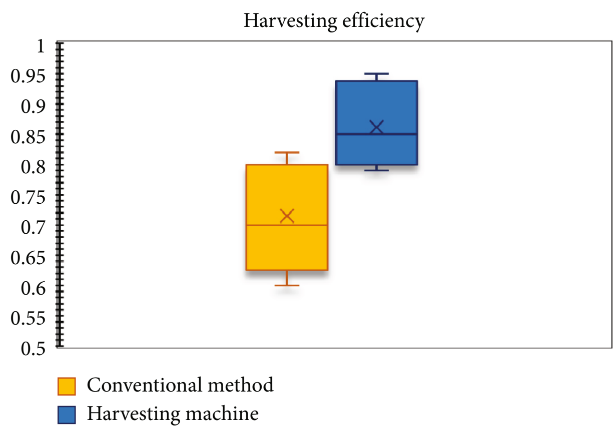

Figure 16: Comparison of carrot harvesting efficiency using the conventional method and the harvesting machine. X highlights the mean while the line signifies the median.

geometry of the harvesting system suggested by Gaadhe et al. [49]. The spatial configuration, including belt length, elevation, and tyne spacing, ensures synchronized interaction with typical carrot spacing observed in field conditions. This synergy between mechanical setup and experimental optimization enhances the overall reliability, efficiency, and crop protection performance of the harvester. The incorporation of YOLOv8 in our study introduces a significant advancement by enabling real-time detection of quality carrots. With a precision of 0.978, a recall of 0.912, and $F1$ score of 0.945, the model demonstrates strong performance in distinguishing quality produce from defective samples. These metrics surpass traditional image processing techniques used in earlier systems, offering an integrated solution for mechanical harvesting and AI-based quality grading. The model's mAP (mAP@0.5) of 0.94 is indicative of its robustness and practicality for deployment in postharvest automation. Moreover, the overall harvesting efficiency of our machine (80%–92%) outperforms the manual harvesting range (60%–80%), as shown in Table 5. This superiority in both speed and efficiency aligns well with modern agricultural needs for scalability and reduced labour dependency. Compared to conventional practices, our machine offers a balance of mechanical reliability, operational simplicity, and digital intelligence. Hence, while previous research has made valuable contributions to reducing damage rates and improving specific components of carrot harvesters, the present study offers a holistic approach that optimizes mechanical parameters in conjunction with AI-based quality detection. This integrated methodology ensures not only minimal crop loss and mechanical damage but also meets the scalability demands of commercial operations. The combination of optimized design parameters and smart detection thus contributes to a novel and practical advancement in the domain of automated root crop harvesting.

5. Conclusions

- Carrots are a key staple in Pakistan, and mechanizing their harvest is essential to meet rising demand and enhance agricultural efficiency and sustainability.
- A semiautomated, PID-controlled carrot harvesting machine was successfully designed and tested under Pakistani field conditions at the cost of Rs. 140,000 (≈\$500). It achieved a harvesting efficiency of 92% with less than 5% root damage.
- The machine harvested 3–5 acres per day, with an average harvesting time of approximately 2.88 h per acre, significantly outperforming manual methods (0.2–0.5 acres/day), while also reducing labor dependency and improving operational safety.
- The system demonstrated optimal mechanical performance at a taper angle of 26°, claw belt speed of 4.0 m/s, and roller speed of 1.2 m/s. Incorporation with a YOLOv8-based vision module enabled real-time classification and sorting of carrots with a mAP (mAP@0.5) of 94%, ensuring high detection accuracy.
- These outcomes support the adoption of precision agriculture and mechanized harvesting as viable, sustainable practices for improving productivity in developing regions.
- For future work, it is recommended to conduct extensive field testing across a wider range of regions to validate the results comprehensively. Furthermore, sensor fusion techniques can be explored and incorporated into the detection model to increase detection accuracy and optimize sorting efficiency.

Data Availability Statement

The data is available on reasonable request and with permission from the relevant institutions.

Conflicts of Interest

The authors declare no conflicts of interest.

Funding

No funding was received for this manuscript.

Acknowledgments

The authors would like to thank the University of Technology Sydney, University of Central Punjab, Lahore, and the Pakistan Engineering Council for supporting the current research.

References

[1] O. M. Lawal, "Real-Time Cucurbit Fruit Detection in Greenhouse Using Improved YOLO Series Algorithm," *Precision Agriculture* 25, no. 1 (2024): 347–359, https://doi.org/10.1007/s11119-023-10074-0.

[2] K. Imtiaz, F. Sehar, A. Bilal, et al., "Problems of Agriculture in Pakistan: An Insight Into Their Solution," *Pakistan Journal of Biotechnology* 19, no. 2 (2023): 73–83, https://doi.org/10.34016/pjbt.2022.19.2.73.

[3] V. Raja, B. Bhaskaran, K. Nagaraj, J. Sampathkumar, and S. Senthilkumar, "Agricultural Harvesting Using Integrated Robot System," *Indonesian Journal of Electrical Engineering and Computer Science* 25, no. 1 (2022): 152, https://doi.org/10.11591/ijeecs.v25.i1.pp152-158.

[4] N. Bharad and B. Khanpara, "Agricultural Fruit Harvesting Robot: An Overview of Digital Agriculture," *Plant Archives* 24, no. SI (2024): 154–160, https://doi.org/10.51470/PLANTARCHIVES.2024.v24.SP-GABELS.023.

[5] P. Gupta, P. Balas, and V. Bambhaniya, "Comparison Between Manual Harvesting and Mechanical Harvesting," *Journal of Scientific Research and Reports* 30, no. 6 (2024): 917–934, https://doi.org/10.9734/jsrr/2024/v30i62110.

[6] M. Mhamed, Z. Zhang, J. Yu, Y. Li, and M. Zhang, "Advances in Apple's Automated Orchard Equipment: A Comprehensive Research," *Computers and Electronics in Agriculture* 221 (2024): 108926, https://doi.org/10.1016/j.compag.2024.108926.

[7] K. Sharma and S. K. Shivandu, "Integrating Artificial Intelligence and Internet of Things (IoT) for Enhanced Crop Monitoring and Management in Precision Agriculture," *Sensors International* 5 (2024): 100292, https://doi.org/10.1016/j.sintl.2024.100292.

[8] C. Shen, R. Wang, H. Nawazish, B. Wang, K. Cai, and B. Xu, "Machine Vision Combined With Deep Learning–Based Approaches for Food Authentication: An Integrative Review and New Insights," *Comprehensive Reviews in Food Science and Food Safety* 23, no. 6 (2024): e70054, https://doi.org/10.1111/1541-4337.70054.

[9] T. Akter, T. Bhattacharya, J.-H. Kim, et al., "A Comprehensive Review of External Quality Measurements of Fruits and Vegetables Using Nondestructive Sensing Technologies," *Journal of Agriculture and Food Research* 15 (2024): 101068, https://doi.org/10.1016/j.jafr.2024.101068.

[10] A. Muhammad, "Mechanisms of Labour Exploitation: The Case of Pakistan," *International Journal of Law and Management* 62, no. 1 (2020): 1–21, https://doi.org/10.1108/IJLMA-07-2018-0145.

[11] A. Horst and S. Watkins, *Enhancing Smallholder Incomes by Linking to High Value Markets in Pakistan's Punjab and Sindh Provinces* (World Bank, 2022).

[12] I. Ali, R. Areeba, A. K. Ammar, K. Rabbia, A. Muhammad, and B. Reeja, "Exploring the Health Benefits and Utility of Carrots and Carrot Pomace: A Systematic Review," *International Journal of Food Properties* 27, no. 1 (2024): 180–193, https://doi.org/10.1080/10942912.2023.2301569.

[13] S. M. Shah, G. Liu, Q. Yang, M. Casazza, F. Agostinho, and B. F. Giannetti, "Sustainability Assessment of Agriculture Production Systems in Pakistan: A Provincial-Scale Energy-Based Evaluation," *Ecological Modelling* 455, no. 1 (2021): 109654, https://doi.org/10.1016/j.ecolmodel.2021.109654.

[14] T. Ruqaya, Q. Iqra, F. Salma, et al., "Artificial Intelligence in Cutting and Sorting of Fruits and Vegetables," in *Artificial Intelligence in the Food Industry* (CRC Press, 2025).

[15] A. Asif Ali and A. Naveed Wahid, "Comparative Analysis of Profitability of Major and Minor Crops in Pakistan," *Journal of the Saudi Society of Agricultural Sciences* 19, no. 7 (2020): 476–481, https://doi.org/10.1016/j.jssas.2020.09.001.

[16] A. Kumari, S. Singh, A. VP, et al., "Mechanization in Pre-Harvest Technology to Improve Quality and Safety," in *Engineering Aspects of Food Quality and Safety* (Springer International Publishing, 2023), 93–114, https://doi.org/10.1007/978-3-031-30683-9_5.

[17] S. K. Gaadhe and V. K. Tiwari, "Carrot Harvesting Methods: A Review," *International Journal of Plant and Soil Science* 34, no. 10 (2022): 7–16.

[18] M. Zeeshan, D. Satesh Kumar, T. Ahmed Ali, and Y. Zheng, "Adoption of Farm Mechanization for Improved Yield in Pakistan: A Comprehensive Review," *International Journal of Agriculture and Sustainable Development* 6, no. 4 (2024): 238–257.

[19] G. G. Mahmood, S. Liberatori, and F. Mazzetto, "Agricultural Mechanization Perspective in Pakistan: Present Challenges and Digital Future," *Agricultural Engineering* 56, no. 2 (2025): https://doi.org/10.4081/jae.2025.1636.

[20] N. Asghar, A. Afzal, and G. Hameed, "Future Food Demand for Pakistan: An Analysis," *Pakistan Social Sciences Review* 7, no. 3 (2023): 425–434.

[21] N. Azizullah, "Food Security Challenges in Pakistan Explained" 2025, *The Agricultural Economist*, Available: https://agrieconomist.com/food-security-challenges-in-pakistan-explained.

[22] T. Hongkun, W. Tianhai, L. Yadong, Q. Xi, and L. Yanzhou, "Computer Vision Technology in Agricultural Automation—A Review," *Information Processing in Agriculture* 7, no. 1 (2020): 1–19, https://doi.org/10.1016/j.inpa.2019.09.006.

[23] S. Khanna, C. Chattopadhyay, and S. Kundu, "Enhancing Fruit and Vegetable Detection in Unconstrained Environment With a Novel Dataset," *Scientia Horticulturae* 338 (2024): 113580, https://doi.org/10.1016/j.scienta.2024.113580.

[24] Z. Liu, J. Xiong, M. Cai, X. Li, and X. Tan, "V-YOLO: A Lightweight and Efficient Detection Model for Guava in Complex Orchard Environments," *Agronomy* 14, no. 9 (2024): 1988, https://doi.org/10.3390/agronomy14091988.

[25] G. Gao, C. Shuai, S. Wang, and T. Ding, "Using Improved YOLO V5s to Recognize Tomatoes in a Continuous Working Environment," *Signal, Image and Video Processing* 18, no. 5 (2024): 4019–4028, https://doi.org/10.1007/s11760-024-03010-w.

[26] Y. Yuan, J. Chen, K. Polat, and A. Alhudhaif, "An Innovative Approach to Detecting the Freshness of Fruits and Vegetables Through the Integration of Convolutional Neural Networks and Bidirectional Long Short-Term Memory Network,"

Current Research in Food Science 8 (2024): 100723, https://doi.org/10.1016/j.crfs.2024.100723.

[27] M. Khoiruddin and S. Tena, "Fruit and Vegetable Classification Using Convolutional Neural Network With MobileNetV2," *Journal of Applied Research in Computer Science and Information Systems* 2, no. 2 (2024): 203–210, https://doi.org/10.61098/jarcis.v2i2.197.

[28] R. S. Latha, G. R. Sreekanth, R. Rajadevi, et al., "Fruits and Vegetables Recognition Using YOLO," in *2022 International Conference on Computer Communication and Informatics (ICCCI)* (IEEE, 2022), 1–6, https://doi.org/10.1109/ICCCI54379.2022.9740820.

[29] J. Ahmad, M. Mohammad, M. Majid, and R. Petia, "Waste Management Using an Automatic Sorting System for Carrot Fruit Based on Image Processing Technique and Improved Deep Neural Networks," *Energy Reports* 7 (2021): 5248–5256.

[30] D. Limiao, L. Juan, and H. Zhongzhi, "Online Defect Detection and Automatic Grading of Carrots Using Computer Vision Combined With Deep Learning Methods," *LWT* 149 (2021): 111832.

[31] Z. Hongfei, D. Limiao, W. Dawei, G. Jiyue, N. Jiangong, and H. Zhongzhi, "Identifying Carrot Appearance Quality by Transfer Learning," *Journal of Food Process Engineering* 42, no. 6 (2019): e13187, https://doi.org/10.1111/jfpe.13187.

[32] X. Weijun, W. Shuo, Z. Zhaohui, C. Zhaoli, and Y. Deyong, "Developing a Stacked Ensemble Model for Predicting the Mass of Fresh Carrot," *Postharvest Biology and Technology* 186 (2022): 111848.

[33] X. Weijun, W. Fenghe, and Y. Deyong, "Research on Carrot Grading Based on Machine Vision Feature Parameters," *IFAC-PapersOnLine* 52, no. 30 (2019): 30–35, https://doi.org/10.1016/j.ifacol.2019.12.485.

[34] Z. Wenqi, S. Chao, S. Kai, W. Nuan, S. Xiaobo, and G. Pengxiang, "Surface Defect Detection System for Carrot Combine Harvest Based on Multi-Stage Knowledge Distillation," *Food* 12, no. 4 (2023): 793, https://doi.org/10.3390/foods12040793.

[35] N. Ö. Mustafa and K. Ö. Humar, "Developing a Deep Neural Network Model for Predicting Carrots Volume," *Journal of Food Measurement and Characterization* 15 (2021): 3471–3479.

[36] L. Sze-Teng, W. Yi-Liang, L. Gen-Bing, and Y. S. Gan, "Moving Towards Agriculture 4.0: An AI-AOI Carrot Inspection System With Accurate Geometric Properties," *Journal of Food Engineering* 357 (2023): 111632.

[37] S. Zhenhui, Z. Shuhe, C. Jianxiong, R. Jinbo, and M. M. Arcel, "Rolling Angle Measurement for Carrots Using Computer Vision and Improved Cyclic Shift Method," *Measurement* 235 (2024): 114917.

[38] R. Piotr, P. Przemysław, O. Andrzej, O. Ewa, and K. Ireneusz, "Artificial Neural Network Model for Predicting Carrot Root Yield Loss in Relation to Mechanical Heading," *Agriculture* 14, no. 10 (2024): 1755, https://doi.org/10.3390/agriculture14101755.

[39] F. W. Marcelo Chan, M. Leonardo Felipe, N. O. Pedro Medeiros, and M. José Paulo, "Carrot Yield Mapping: A Precision Agriculture Approach Based on Machine Learning," *Ai* 1, no. 2 (2020): 229–241, https://doi.org/10.3390/ai1020015.

[40] Y. K. de Lima Silva, C. E. A. Furlani, and T. F. Canata, "AI-Based Prediction of Carrot Yield and Quality on Tropical Agriculture," *AgriEngineering* 6, no. 1 (2024): 361–374, https://doi.org/10.3390/agriengineering6010022.

[41] V. Nithyalakshmi, "Evaluating Carrot (*Daucus carota* L.) Physical Properties and Static Coefficient of Friction for Equipment Design," *International Journal of Research in Agronomy* 7, no. 5 (2024): https://doi.org/10.33545/2618060X.2024.v7.i5g.729.

[42] P. Antonello, K. Prasada Rao, S. Annalisa, et al., "Challenges and Opportunities in the Sustainable Improvement of Carrot Production," *Plants* 13, no. 15 (2024): 2092, https://doi.org/10.3390/plants13152092.

[43] M. H. Bhatti, A. Sami, M. Z. Haider, et al., "Genetic Diversity of Vegetable Crops and Utilization in Food and Nutritional Security," in *Sustainable Utilization and Conservation of Plant Genetic Diversity* (Springer Nature Singapore, 2024), 171–197, https://doi.org/10.1007/978-981-99-5245-8_6.

[44] B. Humberto and L. Rattan, *Soil Conservation and Management* (Springer, 2nd edition, 2024).

[45] K. Iwona, L. Aneta, K.-C. Magdalena, et al., "Antioxidative and Osmoprotecting Mechanisms in Carrot Plants Tolerant to Soil Salinity," *Scientific Reports* 12, no. 1 (2022): 7266, https://doi.org/10.1038/s41598-022-10835-3.

[46] W. Bokai, H. Zhichao, W. Feng, and G. Fengwei, "Analysis and Evaluation of Harvest Quality Effectiveness of Carrot Clamping and Conveying Device," *Agriculture* 15, no. 3 (2025): 275, https://doi.org/10.3390/agriculture15030275.

[47] T. Senthilkumar, S. S. Imran, G. Manikandan, and R. S. Krishnan, "Development and Evaluation of a Power-Operated Carrot Harvester-Cum-Detopper for Hilly Regions," *Current Science* 127, no. 9 (2024): 1118, https://doi.org/10.18520/cs/v127/i9/1118-1123.

[48] W. Bokai, H. Zhichao, G. Fengwei, W. Feng, C. Mingzhu, and S. Yunjing, "Analysis and Evaluation of the Experimental Effect of Double-Disc Knife-Cutting Device for Carrot Combine Harvester," *Agriculture* 15, no. 7 (2025): 682, https://doi.org/10.3390/agriculture15070682.

[49] S. K. Gaadhe, S. K. Chavda, R. D. Bandhiya, D. K. Gojiya, and D. B. Chavda, "Optimizing Carrot Harvesting Machine Design: Incorporating Soil and Crop Parameters," *International Journal of Environment and Climate Change* 13, no. 10 (2023): 3680–3689, https://doi.org/10.9734/ijecc/2023/v13i103039.