

Article

Simulation-Based Evaluation of Vision-Based Adaptive Conveyor Speed Control Using Reel-Synchronous Onion Counting in a Self-Propelled Onion Collector

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Abstract

The stream of onions entering a self-propelled onion collector varies with field conditions, feeding density, and the transient lifting behavior of the onion–soil mass, whereas the collection conveyor is conventionally operated at a fixed speed, wasting hydraulic energy. This study proposes and evaluates, through field-calibrated simulation, a vision-based feed-forward conveyor speed control framework that couples reel-synchronous onion counting with variable-displacement pump control. To mitigate the periodic occlusion caused by the compact dual-conveyor structure, a frame-selection method synchronized with the detected conveyor position was implemented, and a YOLOv8n detector was trained and evaluated on 314 images extracted from 32 indoor and field source videos partitioned at the source-video level. On the independent test subset, the model achieved precision, recall, and mAP@0.5 of 0.952, 0.944, and 0.959, and the proposed counting method maintained count recovery ratios above 95% across all engine speeds in 45 independent field trials, outperforming fixed-period sampling and tracking-based baselines by 6.6 and 3.8 percentage points, respectively. An AMESim model of the fixed-displacement hydraulic system was calibrated and shown to be consistent with field measurements and was then used to evaluate the variable-displacement configuration. Net conveyor-related fuel savings (engine no-load consumption subtracted) were estimated at 14.3–18.7% under the field-identified constant transmission efficiency, with conservative estimates of 11.5–16.9% when partial-displacement efficiency losses were accounted for through an anchored loss model. These results demonstrate the feasibility of vision-based feedforward conveyor speed control and its potential for energy savings in bulb-crop collection.

Keywords: vision-based feedforward control; reel-synchronous onion counting; adaptive conveyor speed control; hydraulic simulation; machine vision; onion collector



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1. Introduction

Onion is one of the most widely cultivated horticultural crops worldwide and an important open-field vegetable crop in South Korea. Global onion production reached approximately 111 million tons in 2023 [1], whereas the onion cultivation area in South Korea was 17,677 ha in 2025 [2]. Onion is cultivated extensively and is recognized as a labor-intensive crop, particularly during harvesting and collection [3]. However, South Korean agriculture faces increasingly severe challenges related to population aging and labor shortages, with 55.8% of the farming population aged 65 years or older in 2024 [4]. Consequently, mechanization and automation have become increasingly important, particularly for labor-intensive operations such as onion harvesting and collection.

Despite this growing demand for mechanization, the agricultural environment in Northeast Asia, including South Korea, limits the widespread adoption of large-scale harvesting equipment. Because farmland is generally small and fragmented [5], compact harvesters and collection machines are more practical than large machines in terms of maneuverability and economic feasibility. However, these compact machines must provide sufficient conveying performance within limited vehicle dimensions. As a result, their working components are densely arranged, often requiring steep conveyor transfer paths. To prevent onion loss and improve conveying stability, a dual-conveyor system incorporating an upper auxiliary conveyor is commonly adopted. Although mechanically advantageous, this configuration periodically obscures onions on the lower conveyor, creating structural occlusion that degrades the performance of camera-based vision systems.

Deep learning-based vision techniques offer a promising approach for overcoming this limitation in agricultural applications. Recent studies have increasingly employed object detection models, particularly the YOLO family, for crop detection and yield estimation in wild blueberries [6], feed-quantity prediction in wheat combine harvesters [7], fruit counting [8], and grain flow detection in harvester-mounted systems [9]. However, recent reviews of object detection in precision agriculture and harvesting environments have consistently identified several factors that reduce detection reliability [10–13]. These include illumination variation, machine vibration, object overlap, background complexity, and structural occlusion. Therefore, accurately estimating onion inflow under field conditions requires more than improving detection accuracy; it also requires an observation strategy that selectively analyzes frames with minimal occlusion. In practical harvesting environments, determining when to perform detection is therefore as important as determining what to detect.

Reliable estimation of onion count can support not only monitoring but also adaptive control of machine components. Previous studies have shown that conveyor design parameters and operating speed significantly influence the performance of onion harvesting and conveying systems [14,15]. Likewise, the conveying demand of an onion collector varies with field conditions, loading density, and instantaneous onion count, making constant-speed operation susceptible to onion accumulation or unnecessary energy consumption under certain conditions [16,17]. Nevertheless, most conventional collectors employ fixed-displacement pumps because of their simple design, limiting conveyor speed adjustment under varying operating conditions. In contrast, hydraulic drive systems equipped with variable-displacement pumps enable continuous flow-rate regulation through swash-plate angle control, making them better suited for adaptive speed regulation under fluctuating loads. Recent studies have also demonstrated that hydraulic systems using variable-displacement pumps can improve speed matching and energy efficiency in agricultural machinery [18,19]. However, vision-based recognition and hydraulic speed control have largely been investigated independently, and few studies have used vision-derived onion counts directly as inputs for conveyor control in onion collectors. Moreover,

the periodic structural occlusion inherent to compact dual-conveyor systems has received little attention.

To address these research gaps, this study proposes a framework that integrates forward-view onion recognition, reel-synchronous onion counting, and vision-based feed-forward conveyor speed control for a self-propelled onion collector (hereafter, the collector). The objectives were to (1) develop a vision-based method that mitigates the periodic occlusion inherent to the compact dual-conveyor structure under field operating conditions, (2) establish a vision-based feedforward conveyor speed control strategy using the estimated onion count as the control input, and (3) evaluate the hydraulic performance and energy efficiency of the proposed strategy using a field-calibrated AMESim simulation model.

The main contributions of this study are summarized as follows:

- A reel-synchronous onion-counting strategy was developed for the collector, whose compact dual-conveyor structure periodically occludes the crops. Frames are selected at a consistent observation position using the detected conveyor position. The strategy maintained count recovery ratios above 95% in 45 independent field trials and outperformed fixed-period sampling and tracking-based counting by 6.6 and 3.8 percentage points, respectively, in an ablation comparison.
- A vision-based feedforward conveyor-speed control was formulated by coupling the reel-synchronous count with variable-displacement pump control. Its energy-saving potential was evaluated on a field-calibrated AMESim framework, yielding estimated net conveyor-related fuel savings of 14.3–18.7%, with conservative estimates of 11.5–16.9% when partial-displacement efficiency losses were accounted for.
- An integrated evaluation framework was established that links occlusion-specific crop counting to machine-side hydraulic energy assessment in a bulb-crop collector, and the resulting flow-on-demand control approach shows potential for transfer to other hydraulically driven working units.

2. Materials and Methods

2.1. Overview of Proposed Vision-Based Adaptive Conveyor Control System

Figure 1 compares the operating principles of the conventional collection system and the proposed vision-based adaptive control system. In the conventional system, onion inflow varies with field conditions but is not automatically estimated. Consequently, a fixed-displacement hydraulic pump supplies hydraulic power at a nearly constant rate, and the conveyor operates at a fixed speed regardless of fluctuations in onion inflow. This operating strategy may result in inefficient energy consumption under variable working conditions. In contrast, the proposed system estimates the onion count per reel segment through camera-based onion detection and counting, with a conveyor-position-based frame selection procedure mitigating the periodic occlusion caused by the upper conveyor. The estimated onion count is then used to adjust the displacement of the hydraulic pump and generate the conveyor speed command. As a result, the conveyor speed is adaptively regulated according to the estimated onion count, reducing unnecessary hydraulic power consumption and improving overall energy efficiency.

2.2. Self-Propelled Onion Collector

The collector shown in Figure 2 was used as the experimental platform to analyze bulb crop collection characteristics and onion inflow behavior at the collection unit. The crawler-type machine was equipped with an inclined front-end collection unit designed to continuously lift onions from the field surface and convey them rearward. The collection unit comprised a multistage conveying system that performed onion pickup using

rotary pickup components and subsequent transport through sequential conveyor elements. Downstream of the collection unit, a sorting unit received the conveyed onions for subsequent sorting and transfer. The collector was powered by a 25.4-kW diesel engine.

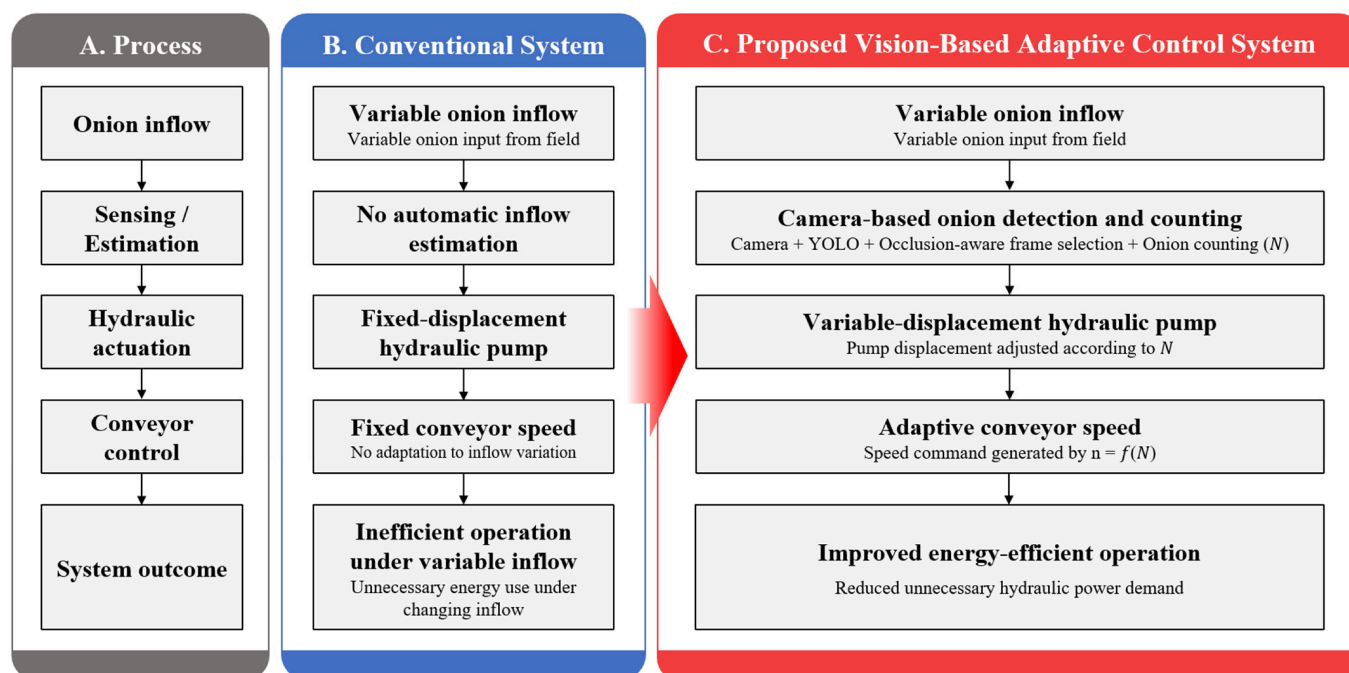


Figure 1. Comparison between conventional collection system and proposed vision-based adaptive control system.



Figure 2. Photographs of the self-propelled onion collector: (a) Side view showing the camera installation position; (b) View of the collection unit captured by the installed camera.

Table 1 summarizes the main specifications of the collector. This study focused on the inflow rate, inflow distribution, and internal conveying behavior within the front collection unit. Based on the machine configuration, an instrumentation system and a video acquisition system were established for the subsequent experiments.

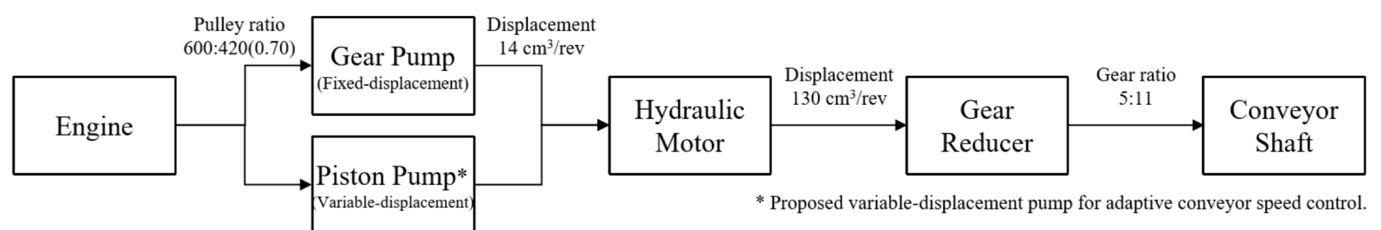
Table 1. Specifications of the self-propelled onion collector.

Parameter	Value
Dimensions (L × W × H) (mm)	5580 × 2205 × 2100
Engine rated power (kW)	25.4 @ 2600 rpm
Weight (kg)	3170
Collection unit width (mm)	1240
Track width (mm)	450 × 90
Track ground contact length (mm)	1580
Pulley reduction ratio	600:420 (0.70)
Hydraulic pump displacement for collection unit (cm ³ /rev)	14
Hydraulic motor displacement for collection unit (cm ³ /rev)	130
Gear reduction ratio	5:11 (0.46)
Rubber reel spacing (mm)	254

As shown in Figure 3, power was transmitted sequentially from the engine to the gear pump through the pulley system and then to the hydraulic motor, gear reducer, and conveyor shaft. In the conventional configuration, the collection unit was driven by a fixed-displacement gear pump, which did not permit active conveyor speed control. In the proposed configuration, the fixed-displacement gear pump was replaced with a variable-displacement swash-plate pump to enable adaptive conveyor speed control. Based on this power transmission path, the rotational speed of the upper and lower conveyor shafts, n_{conv} (rpm), was determined from the engine speed, pulley reduction ratio, pump and motor displacements, and gear reduction ratio:

$$n_{\text{conv}} = n_{\text{eng}} \times r_{\text{pulley}} \times \left(\frac{V_{\text{pump}}}{V_{\text{motor}}} \right) \times r_{\text{gear}} \quad (1)$$

where n_{eng} is the engine speed (rpm), r_{pulley} is the pulley reduction ratio, V_{pump} and V_{motor} are the pump and motor displacements (cm³/rev), respectively, and r_{gear} is the gear reduction ratio.

**Figure 3.** Power transmission path of the collection unit drive system.

Using an engine speed of 2600 rpm and the pulley reduction ratio, pump displacement, motor displacement, and gear reduction ratio listed in Table 1, the maximum rotational speed of both conveyor shafts was estimated to be approximately 89.1 rpm because the upper and lower conveyors rotated synchronously. The fixed-displacement pump served as the conventional reference because it was installed on the collector used in the field experiments, whereas the swash-plate pump of the proposed configuration was evaluated by simulation. Its displacement can be adjusted continuously over 0–14 cm³/rev through swash-plate angle control.

2.3. Experimental Setup for Hydraulic Load Measurement and Video Acquisition in Self-Propelled Collector

To quantitatively analyze the operating conditions of the collector and the onion inflow behavior at the collection unit, the instrumentation and video acquisition systems

summarized in Table 2 were configured simultaneously. The instrumentation system consisted of a pressure sensor, a flow sensor, a proximity sensor, a data acquisition (DAQ) system, and a PC for recording the collector's hydraulic operating parameters. In addition, a dedicated camera was installed to monitor the onion inflow and conveying behavior at the collection unit. The pressure sensor (HySense PR130, Hydrotechnik GmbH, Limburg, Germany) was installed in the hydraulic motor line to measure pressure variations in the hydraulic circuit during operation. The flow sensor (HySense QG100, Hydrotechnik GmbH, Limburg, Germany) was installed in the same hydraulic line to measure the hydraulic oil flow rate. A proximity sensor (BRQT100, Autonics Corporation, Busan, Republic of Korea) was used to measure the rotational speeds of both the collection unit and the engine. Reflective tape was attached to the gear shaft of the collection unit and the engine flywheel, and the rotational signals were detected using the proximity sensor. All sensor signals were recorded using an 8-channel DAQ system (MX840B, HBM, Darmstadt, Germany) at a sampling rate of 300 Hz and stored on a PC for subsequent analysis.

Table 2. Specifications of the sensors used in the collector instrumentation system.

Sensor	Parameter	Value
Pressure sensor (HySense PR130, Hydrotechnik)	Range (bar)	0–250
	Accuracy (%)	0.5 (± 1.25 bar)
	Non-linearity (%)	0.4 (± 1 bar)
Flow sensor (HySense QG100, Hydrotechnik)	Measurement range (L/min)	0.7–70
	Accuracy (%)	0.4 (± 0.3 L/min)
Proximity sensor (BRQT100, Autonics)	Detection distance (mm)	100
	Response time (ms)	≤ 1
DAQ (MX840B, HBM)	Channels	8
	Maximum sampling rate (Hz)	40,000

The video acquisition system employed a GoPro HERO12 camera (GoPro, San Mateo, CA, USA), the specifications of which are listed in Table 3. The camera was mounted on the front frame of the collection unit at a height of 1350 mm above the ground. Laterally, it was positioned along the centerline of the collection conveyor, approximately 620 mm from each side of the 1240-mm-wide conveyor. This configuration enabled the camera to capture onion inflow, accumulation, and conveying processes while maintaining a nearly symmetrical field of view across the conveyor width. Videos were recorded at a resolution of 4K (3840 $\times$ 2160 pixels) and a frame rate of 120 fps. The recorded videos were synchronized with the sensor measurements to analyze the relationship between onion inflow conditions and the hydraulic operating characteristics.

Table 3. Specifications of the camera used for video acquisition.

Parameter	Value
Image sensor	1/1.9" CMOS
Processor	GP2
Maximum photo resolution	27 MP (RAW + JPEG)
Video resolution & frame rate	5.3K 60 fps/4K 120 fps/2.7K 240 fps/1080p 240 fps
Color processing	HDR photo & video, 10-bit GP-Log
Image stabilization	HyperSmooth 6.0 (AutoBoost, 360° Horizon Lock)
Battery (mAh)	1720
Continuous recording time (min)	Approx. 70 @ 5.3K 60 fps/155 @ 1080p 30 fps
Dimensions (L $\times$ W $\times$ H) (mm)	71.8 $\times$ 50.8 $\times$ 33.6
Weight (g)	154

2.4. Field Test

Field experiments were conducted in an upland onion field located at 293-5, Cheongcheon-ri, Cheonggye-myeon, Muan-gun, Jeollanam-do, Republic of Korea (34°58'6.6" N, 126°27'18.2" E). The field was arranged in an eight-row planting configuration with row and plant spacings of 15 cm, reflecting local onion cultivation practices. Figure 4 illustrates the field operation sequence, from pre-stem cutting to onion collection after field drying. The collector was operated under actual field conditions to evaluate its collection performance. The experiments were conducted at three engine speeds (2000, 2300, and 2600 rpm), representing the practical operating range of the collector. The 2000 rpm condition was selected because it is the recommended minimum engine speed for the hydrostatic transmission (HST) travel system, whereas 2600 rpm corresponds to the rated engine speed. The intermediate speed of 2300 rpm was included to evaluate performance between these operating conditions. Throughout the experiments, the forward speed was maintained at 0.2 m/s. This speed provided stable operation by allowing onions to be lifted and conveyed without excessive accumulation, scattering, or interruption of the collection process. Forward speed directly affects the onion inflow rate, increasing the number of onions entering the collection unit per unit time as travel speed increases. It was therefore held constant to isolate the effects of engine speed on the hydraulic response and to provide consistent field-derived inflow data for the subsequent simulation-based evaluation. For the onion-counting evaluation, 15 independent collection trials were conducted at each engine speed, resulting in a total of 45 trials.



Figure 4. Overview of field operations during the onion field tests: (a) Before stem cutting; (b) After stem cutting; (c) After digging; (d) Collection after field drying (target operation).

Table 4 summarizes the soil conditions at the test site. Cone index measurements were obtained at 20 sampling locations selected using a random grid method. Soil texture was classified according to the USDA soil texture classification system based on the relative proportions of sand, silt, and clay [20]. These field conditions were considered representative of the environment used for field data acquisition and hydraulic model calibration.

Table 4. Field characteristics of the experimental evaluation of the collector.

Field	Soil Moisture Content (%)	Soil Texture	Cone Index (kPa)			
			0–5 cm	5–10 cm	10–15 cm	15–20 cm
Upland	32.14	Loam	316	581	776	1604

Table 5 summarizes the physical characteristics of the onion bulbs used in the field experiments. A total of 200 onion bulbs were sampled for measurement.

Table 5. Physical characteristics of the onion bulbs used in the field experiments.

Category	Max./Min.	Mean $\pm$ SD
Bulb height (mm)	109.0/80.0	92.7 $\pm$ 9.3
Bulb circumference (mm)	298.0/235.0	264.6 $\pm$ 18.6
Residual stem length (mm)	36.0/5.0	18.1 $\pm$ 11.1
Bulb weight (g)	363.8/181.5	263.1 $\pm$ 49.4

2.5. Object Recognition Model

2.5.1. Dataset and Model Training

To recognize onions on the conveyor during the collection process, an object detection-based model was developed. Figure 5 illustrates the overall workflow, including data acquisition, dataset preparation, preprocessing and augmentation, model training, validation, and testing/comparison. To represent both controlled and actual operating conditions, the dataset was constructed using images acquired from indoor and field experiments [21]. Indoor images were captured under controlled conditions, whereas field images were collected during actual collection operations. A total of 32 source videos (22 field and 10 indoor videos; approximately 66,400 field and 43,400 indoor raw frames) were recorded in dedicated field and indoor acquisition sessions, and video frames were extracted from these recordings. Because the onion-count update interval was 0.80–0.97 s under the tested field conditions, consecutive frames within an interval are visually redundant; frames were therefore screened using predefined conveyor-position and visibility criteria. Frames with unstable conveyor positions, severe occlusion, or poor visibility were excluded, resulting in 314 annotated original images. All 10 indoor videos were assigned to the training subset. Among the 220 training images, 46 (20.9%) were acquired indoors and 174 (79.1%) in the field, whereas the validation (63 images from 7 videos) and test (31 images from 3 videos) subsets consisted exclusively of field images. Two object classes, onion and conveyor, were defined. The onion class was used for reel-synchronous onion counting, whereas the conveyor class served as a dynamic reference for region-of-interest (ROI)-based frame selection. This approach enabled the selection of frames with relatively consistent conveyor positions, thereby reducing counting errors caused by the periodic occlusion of onions by the upper rubber-reel conveyor. Furthermore, combining indoor and field images allowed the dataset to capture variations in onion appearance, conveyor position, and partial occlusion encountered during operation.

The dataset was prepared using Roboflow (Version 1.0, Roboflow, Inc., Des Moines, IA, USA). To prevent information leakage from highly correlated consecutive frames, the dataset was partitioned at the source-video level: each of the 32 source videos was manually assigned in its entirety to a single subset, so that no video contributed frames to more than one subset. Videos were assigned such that the resulting image-level proportions approximated the commonly adopted 7:2:1 ratio [22–24], yielding 22, 7, and 3 videos (220, 63, and 31 images) in the training, validation, and test subsets, respectively. This partition prevents frame-level leakage, while domain-level diversity remains limited to the indoor and field acquisition sessions and is discussed in the limitations. Preprocessing included automatic image orientation and contrast enhancement using adaptive histogram equalization. Photometric data augmentation was applied only to the training subset after the split, adjusting saturation within $\pm 25\%$ and exposure within $\pm 10\%$ [25–27]; the training dataset was thereby expanded to 660 images. The training, validation, and test subsets contained 590/2223, 155/803, and 88/272 annotated conveyor/onion instances, respectively; these counts refer to the original images before augmentation, because photometric augmentation duplicates existing annotations rather than introducing new objects.

The per-image conveyor-instance density (2.5–2.8 per image) was consistent across the three subsets.

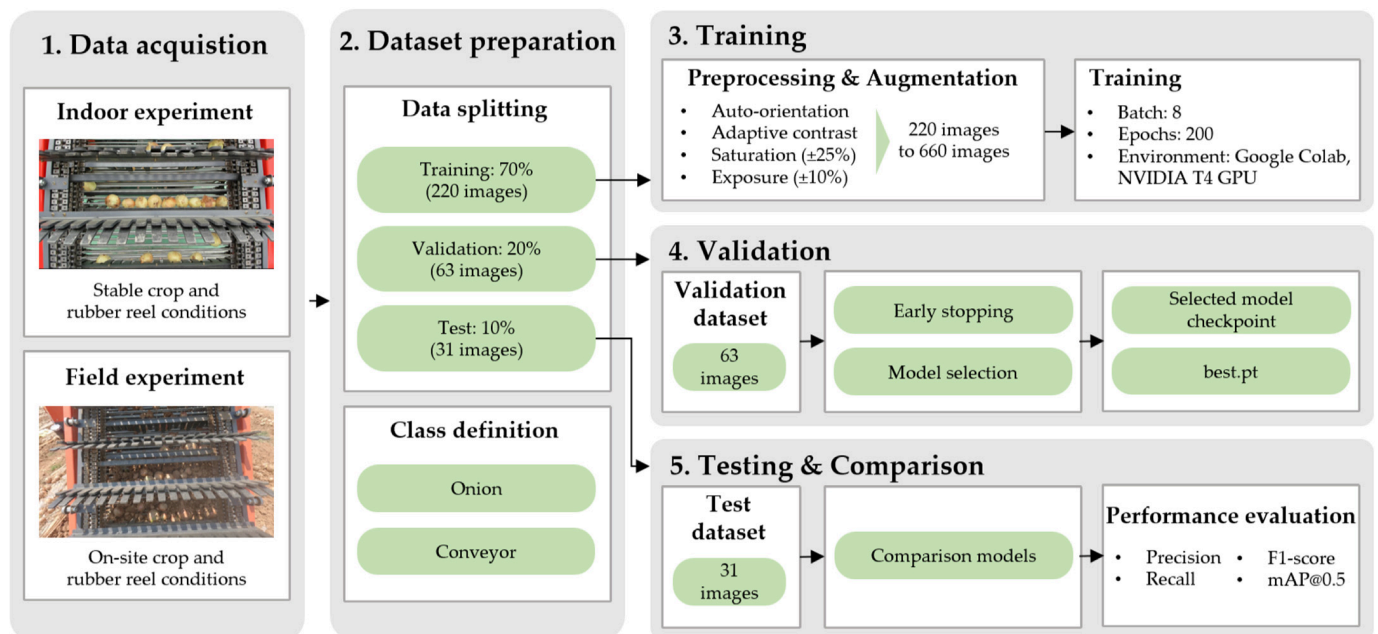


Figure 5. Object recognition workflow from dataset construction through preprocessing, model training, validation, and testing.

The Ultralytics YOLOv8n architecture was selected as the primary detection model because it provides a favorable balance between detection speed and accuracy, while the nano variant offers a lightweight architecture with a low computational cost. The model was trained in the Google Colab environment. The input image size, batch size, and number of training epochs were set to 1280×1280 pixels, 8, and 200, respectively. During inference, a confidence threshold of 0.25 was applied, and detections below this threshold were excluded from onion counting and conveyor-position-based frame selection. The software environment consisted of Python (version 3.12.12) and the PyTorch deep learning framework (version 2.9.0), and hardware acceleration was provided by an NVIDIA T4 GPU.

To quantitatively assess the effect of training-set size on detection performance, an additional learning-curve analysis was conducted using 25%, 50%, 75%, and 100% of the available training data. The subsets were constructed in a nested manner, such that each smaller subset was fully contained within the subsequent larger subset. The validation dataset and training conditions were maintained consistently across all four training-set sizes.

Although YOLOv8n was selected as the primary model, additional lightweight YOLO-based models were trained using the same dataset and computational environment for performance comparison. Early stopping was applied during training, and the representative performance of each model was determined using the epoch with the highest validation performance according to the default Ultralytics validation procedure.

Model performance was evaluated using precision, recall, mean average precision (mAP), and F1-score, which are widely used metrics for object detection [28,29]. Precision and recall were calculated from the numbers of true positives (TP), false positives (FP), and false negatives (FN):

$$\text{Precision} = \frac{TP}{TP + FP}, \quad (2)$$

$$\text{Recall} = \frac{TP}{TP + FN}. \quad (3)$$

The F1-score, which represents the harmonic mean of precision and recall, was calculated as

$$F_1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (4)$$

The mAP was calculated as the mean of the average precision values, obtained from the area under the precision–recall curve, across all classes:

$$\text{mAP} = \frac{1}{N} \sum_{n=1}^N \int_0^1 P(R) dR, \quad (5)$$

where N is the number of classes, and $P(R)$ denotes precision as a function of recall.

2.5.2. Reel-Synchronous Frame Selection and Onion Counting

Figure 6 presents representative sequential frames illustrating the effect of upper conveyor position on onion visibility. The upper rubber-reel conveyor rotates toward the sorting unit such that the conveyor surface facing the camera moves downward, whereas the onions retained within each reel pitch are transported upward on the opposite side. Consequently, the ascending onion group and the descending reel surface repeatedly intersect within the camera view. In Figure 6a, an onion group appears in the lower portion of the collection unit and is sufficiently exposed for detection. As the group ascends, it is repeatedly occluded and re-exposed by the crossing reels (Figure 6b–d,f–h), passing approximately six reel crossings before leaving the camera view. These observations indicate that onion visibility changes cyclically with the conveyor phase. This periodic structural occlusion limits the applicability of conventional object-tracking algorithms and fixed-reference-line-based counting. Although a single occlusion event may be bridged using a tracking buffer, repeated interruptions at successive reel crossings shift the position and phase of the onion group during each occlusion interval. Machine vibration and conveyor motion contribute to this displacement. As a result, repeated occlusion may interrupt temporal association between consecutive detections. This can lead to track fragmentation or reassignment of object IDs, thereby increasing the risk of counting errors. To address this limitation, the conveyor class was used as a dynamic image-based reference for frame selection. Frames were captured only when the conveyor reached a predefined reference position, providing both relatively consistent onion visibility and a repeatable reference phase within the conveyor cycle (Figure 6e), rather than relying solely on a fixed ROI or single-class onion detection.

To minimize the effects of onion occlusion, a conveyor-position-based frame selection procedure was implemented using the detected conveyor bounding box as a dynamic image reference, because the apparent conveyor position varies with machine vibration, slight camera motion, and reel phase during field operation. A predefined ROI was established near the observation position where onion visibility was relatively high, corresponding to a single reel-pitch band between adjacent rubber reels. When multiple conveyor bounding boxes were detected in the same frame, the uppermost bounding box was designated as the reference based on the consistent top-to-bottom motion of the conveyor. Frames were selected only when the conveyor bounding box intersected the ROI after a predefined minimum frame interval had elapsed [30]. Because adjacent conveyor elements were spaced 254 mm apart, multiple conveyor bounding boxes did not intersect the ROI simultaneously. This procedure prevented redundant sampling from adjacent frames while ensuring positional consistency among the selected images. The ROI was defined in the resized inference frame (1280×1280 px) as a fixed horizontal band spanning $y = 725\text{--}735$ px, i.e., a reference line at $y = 730$ px (0.570 of the frame height) with a tolerance of ± 5 px. The minimum frame interval was 10 frames (approximately 0.08 s), which suppresses

re-triggering within a single reel crossing while remaining an order of magnitude shorter than the reel-passage interval.

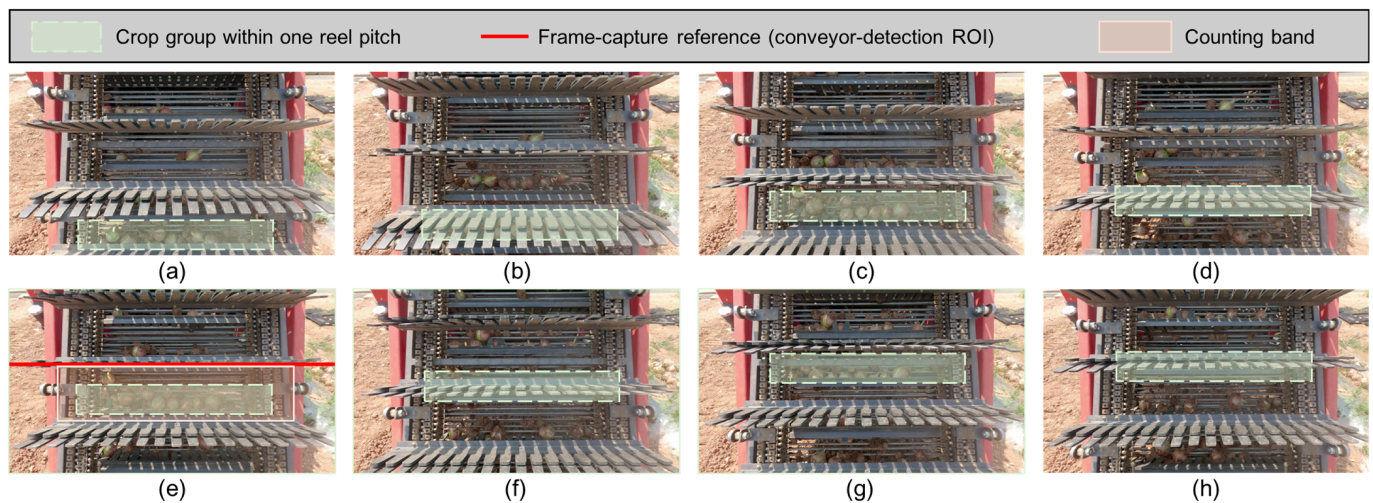


Figure 6. Representative sequential frames of an onion group passing through the dual-conveyor structure. The onion group within one reel pitch (green dashed box) alternates between visible and occluded states as it ascends, crossing six reels within the camera view (a–h). In (e), the detected conveyor reaches the frame-capture reference (red line), and the onions within the counting band (orange) are counted.

For onion counting, video sequences recorded during the field tests were processed using the trained YOLOv8n model together with the proposed frame selection procedure. The video sequences used for the counting experiment were completely independent of the images used for model training, validation, and testing, and the 45 field trials were evaluated. The selected frames were subjected to object detection, and the number of onion bounding boxes detected within the counting band was defined as the detected onion count.

The manual reference count for each trial was established by repeatedly reviewing the recorded video and manually counting the onions passing through the counting region. The analyzed duration of each trial was calculated as

$$T_i = N_{i,i} \Delta t_i \quad (6)$$

where T_i is the analyzed duration of trial i , $N_{i,i}$ is the number of selected frames, and Δt_i is the corresponding onion-count update interval. The travel distance was calculated as

$$L_i = v T_i \quad (7)$$

where L_i is the travel distance and v is the forward speed, which was maintained at 0.2 m/s. The count recovery ratio for each trial was calculated as

$$R_i = \frac{D_i}{A_i} \times 100 \quad (8)$$

where A_i and D_i are the manual reference count and detected onion count, respectively. A value greater than 100% indicates overcounting, whereas a value below 100% indicates undercounting.

No separate object-tracking algorithm was used. Because the upper conveyor advances unidirectionally with a constant reel pitch, each intersection of the conveyor bounding box with the ROI corresponds to the arrival of a new reel segment. The minimum frame

interval limited frame selection to one representative frame for each reel-passage event. Consequently, successive selected frames were intended to represent newly exposed reel segments, thereby reducing the risk of repeated counting without requiring inter-frame identity association.

Figure 7 illustrates the frame selection procedure. After the trained object detection model was loaded, video frames were processed sequentially, and the conveyor class was extracted from the detection results. The algorithm then determined whether the minimum frame interval had elapsed and whether the detected conveyor bounding box intersected the ROI. When both conditions were satisfied, the corresponding frame was saved and logged. This procedure was repeated until all frames had been processed.

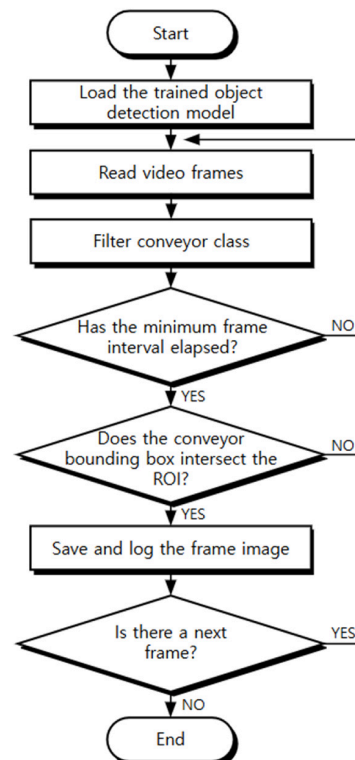


Figure 7. Flowchart illustrating the conveyor-position-based frame selection procedure using the detected conveyor bounding box and region of interest.

2.5.3. Ablation Design

To quantitatively evaluate the contribution of the conveyor-position-synchronized frame selection strategy, an ablation experiment was conducted using the same 45 field trials used for the onion-counting evaluation. Three counting strategies were compared: fixed-period sampling, YOLOv8n combined with ByteTrack, and the proposed reel-synchronous frame selection method. The same YOLOv8n detector, input image size of 1280 pixels, confidence threshold of 0.25, and counting band were applied to all three methods. For the fixed-period baseline, frames were sampled at a constant interval of 0.9 s regardless of the detected conveyor position. The 0.9-s interval was selected because it corresponds to the mean onion-count update interval (0.89 s) observed for the proposed method, thereby matching the temporal sampling frequency while removing the conveyor-position-based synchronization criterion. For the tracking-based comparison, ByteTrack was applied to onion detections in consecutive video frames using the default Ultralytics ByteTrack configuration without additional parameter tuning. Only the onion class was tracked, and each unique track ID was counted once when the center of its bounding box entered the counting band. Repeated reel-induced occlusion can interrupt onion trajectories and cause

track loss or ID reassignment, thereby reducing the reliability of tracking-based counting. In contrast, the proposed method determined counting events using the detected conveyor position without requiring persistent inter-frame object identities. The count recovery ratio was calculated using the same procedure as that used for the original onion-counting evaluation; the same definition was applied to all three methods, and possible overcounting was represented by values greater than 100% rather than being capped at 100%. Because naive summation of detections over consecutive frames results in repeated counting of the same bulbs, continuous-frame counting inherently requires identity management. The tracking-based baseline therefore represents the standard continuous-frame approach, whereas fixed-period sampling isolates the effect of removing the reel synchronization alone.

2.6. Adaptive Conveyor Speed Control

Figure 8 illustrates the conceptual control logic used to adjust conveyor speed according to detected onion count during collection. When a large number of onions are detected in the camera view, the conveyor should operate at a higher speed to promptly transfer the incoming onions and prevent accumulation. However, onion cultivation in South Korea is generally characterized by relatively uniform row and plant spacings. Under a constant forward speed, onions are therefore expected to enter the collection unit at a relatively consistent rate. Consequently, a low number of detected onions may indicate not only a low instantaneous inflow but also a temporary bottleneck beneath the collection unit caused by onions not being lifted smoothly with the soil. Under such conditions, excessively increasing the conveyor speed may allow only part of the delayed onion mass to be received, reducing collection stability and potentially increasing onion loss. Accordingly, the control strategy was designed to increase conveyor speed when the detected onion count was high and decrease it when the count was low.

The rotational speed of the collection conveyor was controlled using the number of onions detected by the object detection model. Onion counting was performed in Python by aggregating the detected onion bounding boxes, and the resulting count N served as the control input from which the target conveyor speed was determined.

The target rotational speed was defined to increase linearly with the detected onion count. To maintain conveyor operation under low-inflow conditions, a minimum rotational speed, $n_{\min}$, was specified. As the detected onion count increased, the target speed increased linearly until reaching the maximum rotational speed, $n_{\max}$. The saturation threshold $N_{\text{sat}} = 20$ was calibrated empirically during preliminary tests and was subsequently verified against the per-segment counts recorded during field operation. Counts of 20 or more occurred in approximately 2–20% of the reel segments depending on engine speed, with a maximum of 25, so the threshold corresponds closely to the upper envelope of the observed inflow rather than to a typical value. The proportional control band therefore governed most of the operating time. The maximum-speed command was engaged only during the intermittent dense arrivals that follow a temporary lifting delay, which is the condition in which the full conveying capacity is required. The threshold also remains well below the geometric holding capacity of the counting band (approximately 30–45 bulbs for the 1.24 m band width and typical bulb diameters), so it represents an operationally saturated inflow rather than a physical limit of the conveyor. At a given engine speed, the conveyor rotational speed is proportional to the pump discharge flow and hence to the displacement ratio. The commanded speed was therefore mapped linearly to the target displacement ratio, $\beta_{\text{target}} = n/n_{\max} \in [0.5, 1]$. The minimum rotational speed was set to $n_{\min} = 0.5 \cdot n_{\max}$, which is equivalent to limiting the pump to 50% of its maximum displacement. This lower bound keeps the conveyor moving under low-count conditions so that intermittently arriving onions are still transported without accumulation at the

transfer point. It also keeps the swash-plate actuation within a displacement range in which the pump response remains stable. The analysis in Section 3.4 confirms that the net saving remains positive throughout the commanded displacement range. The target rotational speed (n) was calculated as

$$n = n_{\min} + \left(\frac{n_{\max} - n_{\min}}{N_{\text{sat}}} \right) \times \min(N, N_{\text{sat}}), \quad (9)$$

where $n_{\min}$ is the minimum rotational speed maintained under low-count conditions, N is the current detected onion count, and N_{sat} is the saturation threshold above which the rotational speed remains constant.

Accordingly, when $N < N_{\text{sat}}$, the target rotational speed increases linearly with the detected onion count and reaches $n_{\max}$ when $N \geq N_{\text{sat}}$. To prevent abrupt speed changes caused by rapid variations in the detected onion count, a swash-plate limiter based on a first-order exponential response was applied. The temporal variation in the swash-plate angle (θ) was calculated as

$$\frac{d\theta}{dt} = \frac{\theta_{\text{target}} - \theta_{\text{current}}}{\tau}, \quad (10)$$

where θ_{target} is the target swash-plate angle determined by the controller, θ_{current} is the current swash-plate angle, and τ is the time constant.

Equation (10) represents a first-order lag model in which the swash-plate angle gradually converges to the target value rather than changing instantaneously. The rate of change is higher when the difference between the target and current angles is large and decreases as the current angle approaches the target value.

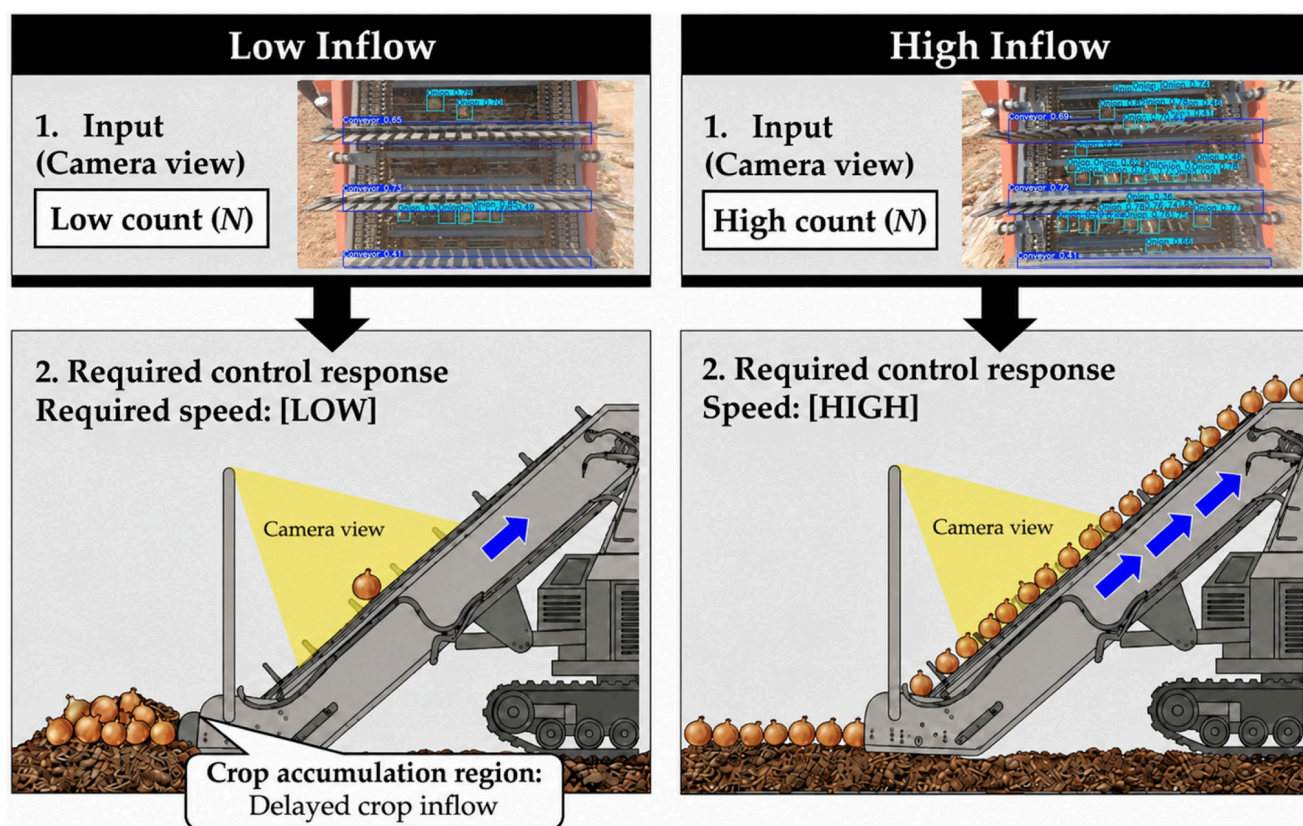


Figure 8. Conceptual control logic for conveyor speed under low- and high-inflow conditions. ChatGPT (GPT-5.5, OpenAI, San Francisco, CA, USA) was used solely for layout arrangement and visual refinement of this figure; all data, control logic, labels, and scientific content were developed and verified by the authors.

The target conveyor speed was calculated from the detected onion count using the linear control law in Equation (9), and the corresponding swash-plate angle was regulated through the limiter described by Equation (10). This strategy enabled the conveyor speed to respond to variations in onion inflow while suppressing excessive transient responses in the hydraulic drive. Because the speed command is generated directly from the reel-synchronous onion count and the resulting conveying state is neither measured nor fed back, the strategy constitutes vision-based feedforward control. It should be distinguished from feedback (closed-loop) control, in which a measured output is compared with its reference, and from adaptive control in the strict sense, in which controller parameters are adjusted online. In this paper, “adaptive” refers to inflow-adaptive speed regulation in this feedforward sense. This structure is consistent with the timing characteristics of the system. Each count update arrives once per reel passage. The interval was 0.80–0.97 s (mean 0.89 s) across the 45 field trials, the spread reflecting variation in crop feeding and conveying conditions during field operation. The count remains constant within each interval. The YOLOv8n inference time of 26.80 ms per image is negligible against this interval. The first-order swash-plate response ($\tau = 0.3$ s) reaches approximately 93% of its target within the shortest observed update interval (0.8 s) and 95% within $3\tau \approx 0.9$ s, so the commanded displacement is substantially established before the next update. In the present study the detector was executed on a workstation-class GPU (NVIDIA T4) and has not yet been deployed on an embedded platform. Because inference is required only once per reel passage, the 26.80 ms inference time occupies less than 5% of even the shortest count-update interval. This leaves a latency margin of more than 0.5 s for embedded execution (e.g., NVIDIA Jetson Orin-class modules), whose end-to-end verification remains for the implementation stage. The selected YOLOv8n model comprises approximately 3.0 million parameters and 32.8 GFLOPs at the 1280×1280 input used in this study, which is compatible with the memory of embedded modules of this class. The overall response is therefore governed by the discrete update interval rather than by detection latency or actuator dynamics, and no new error information becomes available within an interval on which a feedback loop could act.

2.7. Simulation Model

A simulation model was developed and evaluated using Simcenter AMESim (version 2021.2, Siemens Digital Industries Software, Munich, Germany) to analyze the hydraulic response of the collector under varying onion inflow conditions. AMESim has been widely used to analyze the hydraulic circuits and power requirements of agricultural machinery, and a similar approach has recently been applied to self-propelled garlic and onion collectors [31]. The model incorporated the drivetrain and mechanism specifications, vehicle and load conditions, hydraulic fluid properties, and pump efficiency parameters.

The simulation model was established and checked in a stepwise manner on the field-validated framework reported in [31]. First, the engine and fuel-consumption submodels were adopted from that study. There, a Willans-line-based engine model reproduced the measured fuel-consumption rate and engine power with R^2 values of 0.975 and 0.960 and mean absolute percentage error (MAPE) values of 1.79% and 2.20%, respectively, across 36 field operating conditions. Second, the overall transmission efficiency (η_t), defined as the ratio of the delivered hydraulic power to the Willans-line-based net engine power, was identified in [31] from dedicated stationary unit tests, yielding 0.715–0.726 across the tested engine speeds. A representative value of 0.72 was adopted. Because η_t was identified from a separate test campaign but under closely related operating conditions of the same machine, the agreement of the fuel-consumption predictions in Section 3.3 should be interpreted as a calibration consistency check rather than a fully independent

predictive validation. As model inputs, the engine speed and a constant equivalent load torque were prescribed; the torque was calibrated at each engine speed to reproduce the measured collection-circuit pressure, so the pressure agreement in Section 3.3 reflects this calibration rather than an independent prediction. The simulated flow rate, in contrast, is determined by the pump displacement, drivetrain ratios, and engine speed, essentially independently of both the load calibration and η_t . Its agreement with the measurements is therefore the quantity that provides validation information unaffected by the efficiency identification. The required hydraulic power and fuel consumption follow from the calibrated pressure and the predicted flow rate. The mass of the conveyed onions was not modeled explicitly. This constant-torque representation is justified by the narrow pressure variation observed in this study (42.6–43.6 bar; standard deviation (SD) ≤ 0.4 bar across engine speeds) and across four fields and crop conditions in [31]. This narrow range suggests that crop-load fluctuations had a limited influence on the circuit pressure under the tested conditions. Dynamic load variations arising from the onion mass, accumulation, and impacts are nevertheless not represented by the constant torque, and their effects are addressed as a limitation in Section 4. Finally, the variable-displacement configuration was implemented by replacing only the pump block, while retaining the model validated in [31], the hydraulic circuit, the calibrated load torque, and the Willans-line-based fuel estimation described above.

The object detection algorithm and the AMESim model were coupled using the time-series onion counts obtained from the selected video frames, so that both pump configurations were compared under identical field-derived inputs without introducing an additional stochastic inflow model. The count sequence and its update timing were applied as recorded and were assumed to be independent of the commanded conveyor speed (Section 4.4). The detected onion count was converted into the target conveyor rotational speed using the control equation described in Section 2.6 and subsequently into a swash-plate displacement command for the variable-displacement pump. Thus, the vision-derived onion count served as the input signal for evaluating the hydraulic response of the proposed conveyor speed control strategy. The first-order lag described in Section 2.6 ($\tau = 0.3$ s) was applied to the swash-plate command. Pump discharge flow rate was regulated according to the swash-plate signal, and the resulting engine output was determined by the hydraulic motor and rotational load conditions. The simulations were run with the standard AMESim variable-step integrator at default tolerances over 50 s, and outputs were exported at a 10 ms communication interval.

The hydraulic power of the hydraulic motor was calculated from the simulated pressure and flow rate:

$$P_{\text{hydraulic}} = \frac{p \times Q}{600}, \quad (11)$$

where $P_{\text{hydraulic}}$ is the hydraulic power (kW), p is the hydraulic pressure (bar), and Q is the hydraulic flow rate (L/min); the factor 600 converts the pressure–flow product from bar·L/min to kW ($1 \text{ bar} \cdot \text{L/min} = 10^5 \text{ Pa} \times 10^{-3} \text{ m}^3/60 \text{ s} = 1/600 \text{ kW}$).

Figure 9 shows the AMESim model developed to evaluate the hydraulic drive characteristics and fuel consumption of the conveyor system under fixed- and variable-displacement pump configurations. The model consisted of three modules: (1) a control and input module, (2) a conveyor-drive load module, and (3) a fuel estimation module. In the control and input module, the vision-derived onion count and engine speed were used to generate the pump control signal, while the pump speed controller and swash-plate dynamics represented the actuator response. The conveyor-drive load module simulated hydraulic power transmission and conveyor loading during operation. The fuel estimation module employed a field-calibrated Willans-line method to estimate fuel consumption from the specified no-load fuel consumption rate and the relationship between fuel con-

sumption and engine load. Using this model, the hydraulic flow rate, pressure, required hydraulic power, and fuel consumption were simulated and compared for the fixed- and variable-displacement pump configurations.

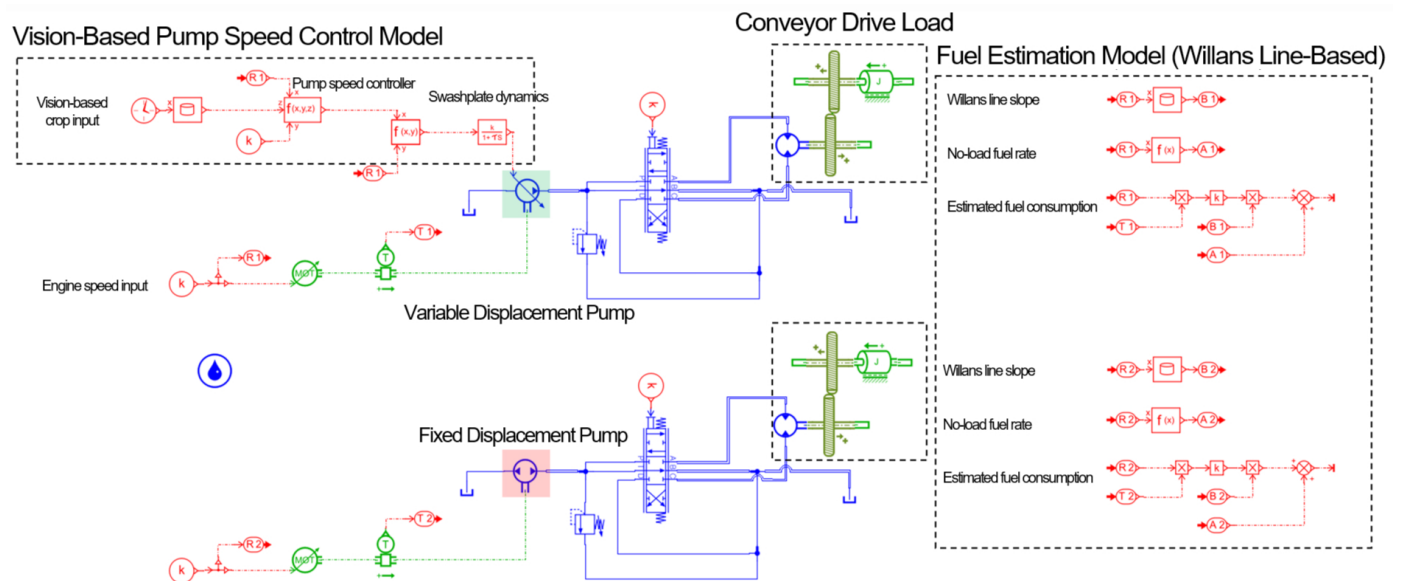


Figure 9. Hydraulic simulation model for conveyor drive control in the onion collector under variable-displacement (**top**) and fixed-displacement (**bottom**) pump configurations.

Table 6 summarizes the main parameters used in the AMESim model, including the drivetrain and vehicle/load conditions, hydraulic fluid properties, and pump settings and efficiencies. These parameters define the hydraulic transmission characteristics and operating conditions of the simulation.

Table 6. Parameters of the AMESim simulation model for the onion collector.

Category	Parameter	Value
Drivetrain/mechanism	Gear ratio (Hydraulic motor to conveyor rotation shaft)	5:11
	Vehicle mass (kg)	3170
Vehicle/load	Operator mass (two operators) (kg)	150
	Wheel radius (mm)	95.5
	Density ($\text{kg}\cdot\text{m}^{-3}$)	840
Hydraulic fluid	Bulk modulus (bar)	13,000
	Dynamic viscosity (cP)	32
	Overall transmission efficiency (–)	0.72
Pump & efficiencies	Variable-displacement pump setting (–)	Commanded displacement ratio β (0.5–1.0)

2.8. Efficiency Model and Sensitivity Analysis

As described in Section 2.7, the field-identified overall transmission efficiency $\eta_t = 0.72$ applies to the fixed-displacement configuration at full displacement ($\beta = 1$). Because the efficiency of a swash-plate pump decreases at partial displacement, applying this constant value to the variable-displacement configuration may overestimate the benefit. The present evaluation was defined at the specification level, namely a $14 \text{ cm}^3/\text{rev}$ swash-plate unit, rather than for a specific commercial product. Efficiency maps are generally not published

for small variable-displacement pumps of this class, and the scarcity of comprehensive part-displacement test data, noted as early as 1984 [32], still applies to units of this size. The influence of partial-displacement losses was therefore quantified using a classical loss-coefficient model of the Wilson–McCandlish–Dorey family [32,33], anchored at the field-identified operating point, following the recommendation in [32] that loss coefficients be determined at the intended operating condition.

In the reduced form retaining the dominant loss terms [34], the volumetric and mechanical efficiencies of the pump are expressed by Equations (12) and (13), in which both loss terms scale with the inverse of the displacement ratio, as in the original formulation [32]. The compressibility term was neglected because the pressure-to-bulk-modulus ratio is approximately 0.3% in this circuit. The pressure- and speed-dependent loss terms were lumped into single anchored coefficients because the circuit pressure remained nearly constant (42.6–43.6 bar) across all conditions. Because η_t is identified only as an overall efficiency, the partition of the total loss between the pump and the remaining drivetrain cannot be resolved from a single anchor point. This partition was therefore treated as a sensitivity parameter α , defined as the fraction of the total loss attributed to the pump, and swept over $\alpha \in \{0.35, 0.50, 0.65\}$, corresponding to standalone pump efficiencies of approximately 0.90–0.82. The coefficients C_s and K were determined such that the model reproduces $\eta_t = 0.72$ at $\beta = 1$ and $p = p_0$ for each α , with the pump loss divided equally between the volumetric and mechanical terms. This treatment is conservative, as measured torque losses at small displacements fall substantially below the $1/\beta$ scaling [32]. The resulting efficiency curves are shown in Figure 10.

$$\eta_v = 1 - C_s \frac{p/p_0}{\beta}, \quad (12)$$

$$\eta_m = \left[1 + \frac{K}{\beta(p/p_0)} \right]^{-1}, \quad (13)$$

where η_v and η_m are the volumetric and mechanical efficiencies of the pump, C_s and K are the anchored loss coefficients, β is the displacement ratio, and p_0 is the reference pressure at the anchor point.

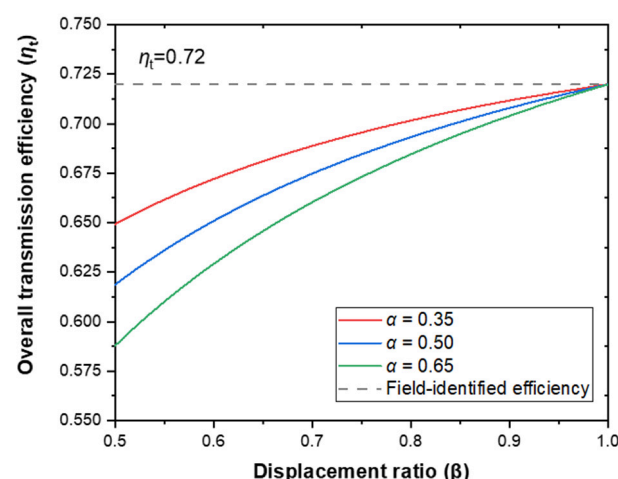


Figure 10. Anchored loss-model efficiency curves for pump loss fractions $\alpha = 0.35, 0.50$, and 0.65 over the commanded displacement range ($\beta = 0.5$ – 1.0), with the field-identified overall efficiency ($\eta_t = 0.72$, dashed line) adopted as the baseline scenario.

The resulting efficiency trajectory $\eta_t(\beta(t), p(t))$ was applied to the variable-displacement operation, and the net fuel consumption was re-evaluated through the identical Willans-

line-based chain. In this chain, the delivered hydraulic power in Equation (11) is divided by η_t to obtain the net engine power; the constant-efficiency case corresponds to the baseline scenario.

2.9. Statistical Analysis

To quantify the uncertainty in object-detection performance on the held-out test set, 95% confidence intervals (CIs) for precision, recall, and mAP@0.5 were estimated using nonparametric bootstrap resampling of the test images with replacement. A total of 1000 bootstrap iterations were performed, and the 2.5th and 97.5th percentiles of the bootstrap distributions were used as the lower and upper bounds of the 95% CIs. Because these CIs were obtained by resampling individual images, they quantify uncertainty within the evaluated image-level test subset only and should not be interpreted as comprehensive uncertainty regarding generalization across different fields, seasons, cultivars, or acquisition campaigns.

For the statistical analysis of the onion count recovery ratio, the individual field trial was defined as the independent experimental unit, with 15 trials at each engine speed ($n = 45$ in total). Individual selected frames, detections, and within-trial observations were not treated as independent replicates. Trial-level count recovery ratio was expressed as the mean $\pm$ standard deviation for each engine speed condition. Normality was assessed using the Shapiro–Wilk test, and homogeneity of variance was evaluated using Levene’s test. Because the assumptions of normality and homogeneity of variance were satisfied, the untransformed count recovery ratio data were analyzed using one-way analysis of variance (ANOVA) to evaluate the effect of engine speed. The magnitude of the engine-speed effect was quantified using eta-squared (η^2), and Tukey’s honestly significant difference (HSD) test was used for pairwise comparisons. Statistical significance was defined at $p < 0.05$.

In addition to the count recovery ratio, trial-level error metrics were calculated to quantify both the direction and magnitude of the counting error. The signed counting error for trial i was defined as

$$e_i = D_i - A_i \quad (14)$$

where a negative value indicates net undercounting and a positive value indicates net overcounting. The absolute relative error was calculated as

$$\text{ARE}_i = \frac{|D_i - A_i|}{A_i} \times 100 \quad (15)$$

Counting performance at each engine speed was further summarized using bias, mean absolute error (MAE), and root-mean-square error (RMSE):

$$\text{Bias} = \frac{1}{n} \sum_{i=1}^n (D_i - A_i) \quad (16)$$

$$\text{MAE} = \frac{1}{n} \sum_{i=1}^n |D_i - A_i| \quad (17)$$

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^n (D_i - A_i)^2} \quad (18)$$

where $n = 15$ for each engine-speed condition. The relationship between the manual reference count and detected count across all 45 trials was additionally evaluated by linear regression:

$$D_i = b_0 + b_1 A_i + \varepsilon_i \quad (19)$$

where b_0 and b_1 are the regression intercept and slope, respectively, and ε_i is the residual error.

For the ablation comparison, count recovery ratios were summarized descriptively as the mean $\pm$ standard deviation for the 15 trials at each engine speed and for all 45 trials combined. No inferential statistical claim was made for this comparison.

Hydraulic sensor measurements and simulation outputs were treated as time-series data rather than independent experimental replicates. Therefore, individual time-series samples were not subjected to inferential comparisons among engine speeds. These data were summarized descriptively using the mean, standard deviation, minimum, maximum, integrated energy values, and model-validation error metrics, as appropriate. Standard deviations for time-series and simulation outputs represent temporal variability within the analyzed trajectory rather than variability among independent replicates.

3. Results

3.1. Performance of the Object Recognition Model

Table 7 and Figure 11 compare the performance of the lightweight YOLO-based models evaluated in this study (YOLOv5n, YOLOv8n, YOLOv9t, YOLOv11n, YOLOv12n, and YOLOv26n). The comparison was conducted to confirm the suitability of the primary model under two predefined criteria, onion-class recall and processing speed, for the proposed collector system. Overall, all models achieved high detection performance for both the onion and conveyor classes, with only minor differences in accuracy.

Table 7. Detection performance of the evaluated object recognition models on the validation subset at the best validation epoch, and comparison with lightweight YOLO variants.

Model	Class	Precision	Recall	F1-Score	AP@0.5	mAP@0.5	mAP@0.5:0.95	Inference Time (ms/Image)	Framerate (fps)
YOLOv5n	Onion	0.947	0.841	0.891	0.940	0.967	0.524	26.67	37.49
	Conveyor	0.982	0.994	0.988	0.994				
YOLOv8n	Onion	0.920	0.891	0.905	0.942	0.959	0.536	26.80	37.31
	Conveyor	0.967	0.981	0.974	0.976				
YOLOv9t	Onion	0.955	0.873	0.912	0.960	0.970	0.538	31.61	31.64
	Conveyor	0.962	0.975	0.968	0.980				
YOLOv11n	Onion	0.946	0.851	0.896	0.944	0.966	0.533	27.19	36.78
	Conveyor	0.976	0.989	0.982	0.988				
YOLOv12n	Onion	0.949	0.851	0.897	0.947	0.970	0.522	63.21	15.82
	Conveyor	0.982	0.983	0.982	0.992				
YOLOv26n	Onion	0.937	0.861	0.897	0.939	0.967	0.536	63.51	15.75
	Conveyor	0.984	0.999	0.991	0.995				

More pronounced differences were observed in processing speed. YOLOv5n, YOLOv8n, and YOLOv11n achieved substantially higher frame rates than YOLOv12n and YOLOv26n, indicating greater computational efficiency for processing field images. Among these three candidates, YOLOv8n achieved the highest recall for the onion class (0.891). Because onion detection provides the basis for reel-synchronous onion counting in the proposed control framework, high recall is particularly important for minimizing missed detections during operation. Moreover, because the proposed frame selection procedure inherently suppresses duplicate counting, missed detections become the primary remaining source of counting error, further supporting the selection of a model with high recall. Although YOLOv9t achieved slightly higher precision, F1-score, and mAP@0.5 for onion detection, its lower frame rate made it less favorable when both detection perfor-

mance and processing speed were considered. Therefore, YOLOv8n was selected as the final object detection model based on its balanced detection performance and computational efficiency. Representative detection results obtained during field operation are shown in Figure 12, demonstrating reliable detection of both onion and conveyor objects under practical operating conditions.

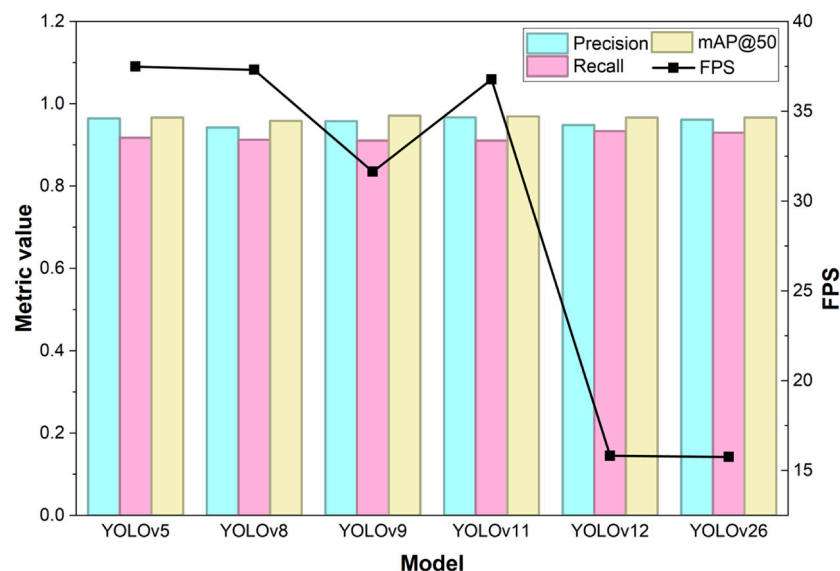


Figure 11. Performance comparison of the evaluated YOLO models at the best validation epoch. FPS is represented by the black line with square markers.



Figure 12. Representative object detection results overlaid on camera images of the collection unit during field operation.

Figure 13 presents the validation performance of the selected YOLOv8n model. Precision, recall, and mAP@0.5 increased rapidly during the early stages of training before stabilizing, indicating effective feature learning. Precision and mAP@0.5 remained consistently high throughout training, whereas recall exhibited relatively greater fluctuations.

Nevertheless, the overall trends demonstrate stable detection performance under the selected training conditions.

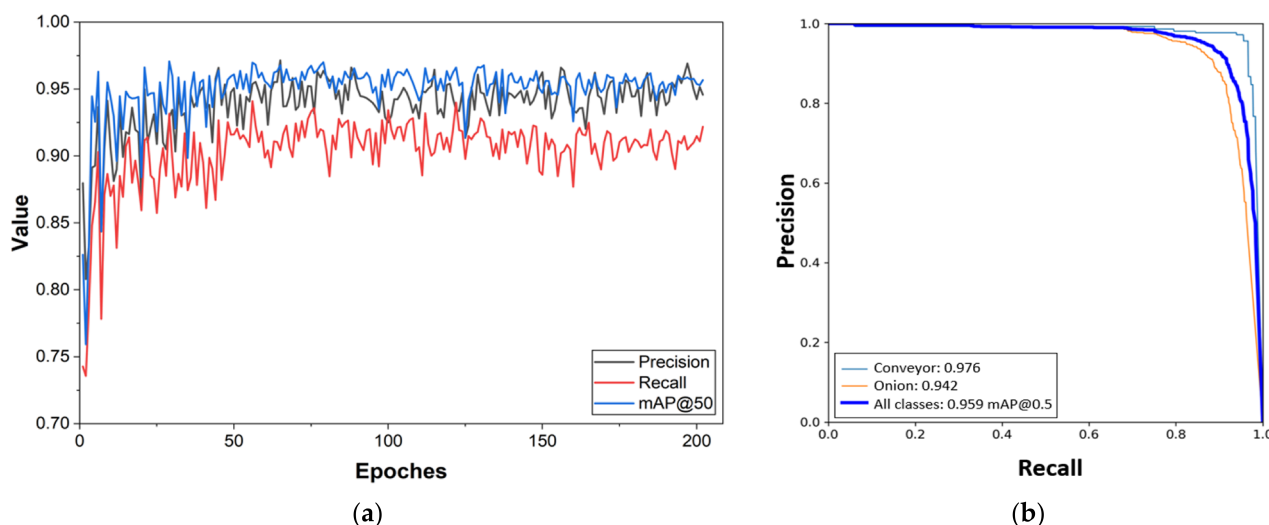


Figure 13. Validation performance of the YOLOv8n model: (a) Precision, recall, and mAP@0.5 over the training epochs evaluated on the validation set; (b) Precision–recall curves for the detected classes on the validation set, together with the overall performance.

The precision–recall curves in Figure 13 further demonstrate the model’s performance. The average precision (AP) values were 0.976 and 0.942 for the conveyor and onion classes, respectively, and the overall mAP@0.5 reached 0.959. These results indicate that the model reliably detected both onions and the conveyor under field operating conditions, demonstrating its suitability for reel-synchronous onion counting in the proposed collector system.

To further assess the influence of training-set size, a learning-curve analysis was performed using 25%, 50%, 75%, and 100% of the available training data. As shown in Figure 14, the corresponding mAP@0.5 values were 0.939, 0.959, 0.969, and 0.965, respectively. The improvement in mAP@0.5 progressively decreased as the training-set size increased, and the difference between the 75% and 100% training sets was only 0.004. These results indicate that the detection performance approached a plateau within the evaluated dataset range.

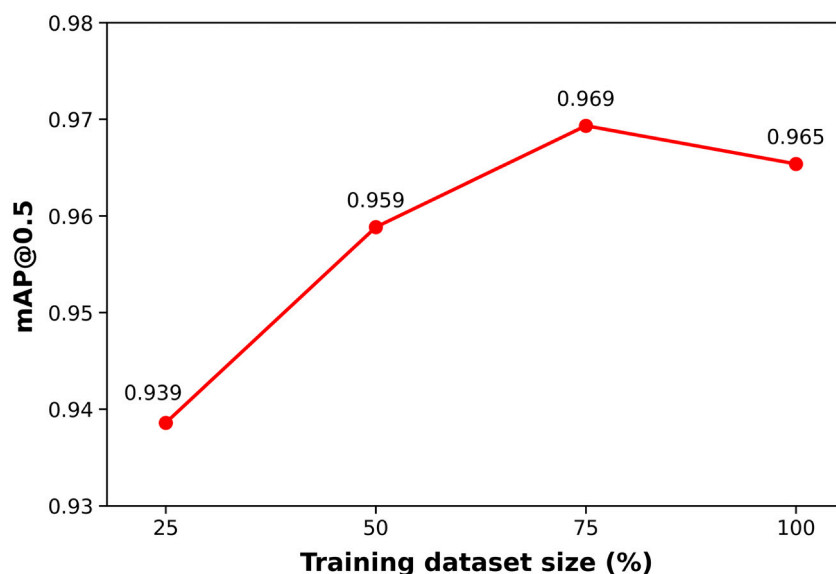


Figure 14. Effect of training dataset size on the mAP@0.5 of YOLOv8n.

The selected YOLOv8n model was evaluated on the independent test subset consisting of 31 field images extracted from three source videos that were not used for training or validation. As shown in Table 8, the model achieved a precision of 0.952 (95% CI: 0.918–0.970), a recall of 0.944 (95% CI: 0.911–0.974), and mAP@0.5 of 0.959 (95% CI: 0.931–0.981).

Table 8. Detection performance of the selected YOLOv8n model on the independent test subset.

Metric	Estimate	95% CI
Precision	0.952	0.918–0.970
Recall	0.944	0.911–0.974
mAP@0.5	0.959	0.931–0.981

3.2. Onion Count Recovery Ratio

Table 9 summarizes the counting performance and trial-level error metrics obtained from 15 trials at each engine speed. The mean count recovery ratio remained above 95% at all engine speeds, reaching $95.14 \pm 2.70\%$, $95.09 \pm 2.23\%$, and $95.42 \pm 2.92\%$ at 2000, 2300, and 2600 rpm, respectively. The assumptions of normality and homogeneity of variance were satisfied (Shapiro–Wilk test: $W = 0.9701$, $p = 0.2919$; Levene’s test: $F(2, 42) = 0.4457$, $p = 0.6434$). One-way ANOVA showed no significant effect of engine speed on the count recovery ratio ($F(2, 42) = 0.0689$, $p = 0.9336$, $\eta^2 = 0.0033$). Tukey’s HSD test also showed no significant pairwise differences between 2000 and 2300 rpm (adjusted $p = 0.9987$), 2000 and 2600 rpm (adjusted $p = 0.9535$), or 2300 and 2600 rpm (adjusted $p = 0.9373$).

Table 9. Onion-counting performance and trial-level error metrics at different engine speeds.

Engine Speed (rpm)	Total Manual Reference Count	Total Detected Count	Mean Count Recovery Ratio ^a (%) (Mean $\pm$ SD)	Bias (Onions/Trial)	MAE (Onions/Trial)	RMSE (Onions/Trial)	Mean Absolute Relative Error (%)
2000	1501	1437	95.14 ± 2.70	−4.27	4.27	4.49	4.86
2300	1433	1367	95.09 ± 2.23	−4.40	4.40	4.63	4.91
2600	1275	1222	95.42 ± 2.92	−3.53	3.53	3.99	4.58

^a Values are presented as mean $\pm$ standard deviation based on 15 independent field trials per engine-speed condition. One-way ANOVA showed no effect of engine speed on the count recovery ratio ($F(2, 42) = 0.0689$, $p = 0.9336$, $\eta^2 = 0.0033$).

The corresponding bias values were −4.27, −4.40, and −3.53 onions per trial, while the MAE values were 4.27, 4.40, and 3.53 onions per trial and the RMSE values were 4.49, 4.63, and 3.99 onions per trial, respectively. The mean absolute relative errors were 4.86%, 4.91%, and 4.58% at 2000, 2300, and 2600 rpm, respectively, with an overall value of 4.78%. Across all 45 trials, the overall bias was −4.07 onions per trial, indicating a slight net tendency toward undercounting. Detailed trial-level metadata and counting errors for all 45 trials are provided in Table S1, allowing readers to examine trial-to-trial variability and the magnitude and direction of the counting errors.

All trial-level net errors were non-positive. This indicates that net undercounting, rather than net overcounting, predominated at the trial level. However, because the error was evaluated using trial-level manual and detected totals, compensating for overcounting and undercounting within individual frames cannot be completely excluded. Missed detections were primarily associated with temporary onion occlusion by the upper conveyor, partial overlap between adjacent onions, and occasional soil adhesion to the onion surface.

Figure 15 compares the detected onion count with the manual reference count across all 45 trials. A strong linear association was observed, with the regression expressed as $Detected = 1.0403 \times Actual - 7.8332$ and $R^2 = 0.9962$. Most observations were located slightly below the 1:1 reference line, consistent with the negative trial-level bias. These

results demonstrate that the proposed frame-selection and object-detection procedure maintained consistent counting performance across the tested range of onion counts while exhibiting a small systematic tendency toward undercounting.

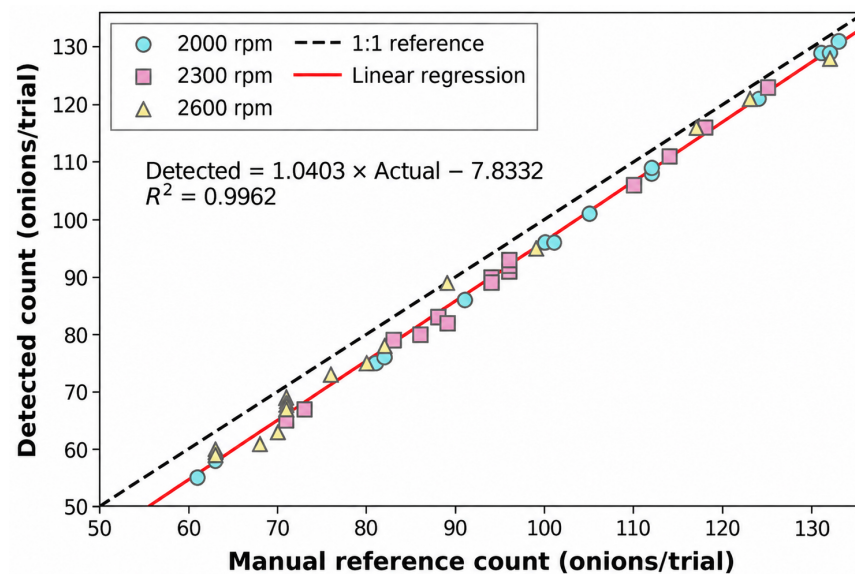


Figure 15. Comparison of manual reference and detected onion counts across 45 trials. Most observations lie slightly below the 1:1 reference line, reflecting the slight systematic undercounting observed in the trial-level error analysis.

An additional ablation comparison was conducted to quantitatively assess the contribution of conveyor-position synchronization to onion-counting performance. As shown in Table 10, fixed-period sampling achieved mean count recovery ratios of $90.4 \pm 2.8\%$, $88.6 \pm 3.1\%$, and $86.9 \pm 2.8\%$ at engine speeds of 2000, 2300, and 2600 rpm, respectively, resulting in an overall count recovery ratio of $88.6 \pm 3.2\%$. The YOLOv8n + ByteTrack method achieved corresponding count recovery ratios of $93.4 \pm 3.5\%$, $90.7 \pm 3.4\%$, and $90.0 \pm 2.7\%$, with an overall count recovery ratio of $91.4 \pm 3.5\%$. In comparison, the proposed reel-synchronous method achieved $95.1 \pm 2.7\%$, $95.1 \pm 2.2\%$, and $95.4 \pm 2.9\%$, respectively, with an overall count recovery ratio of $95.2 \pm 2.6\%$. Thus, the proposed method improved the overall count recovery ratio by 6.6 percentage points compared with fixed-period sampling and by 3.8 percentage points compared with the tracking-based method. Moreover, the count recovery ratio of the proposed method remained approximately constant across the tested engine speeds, whereas both baseline methods showed decreasing count recovery ratios with increasing engine speed. These results quantitatively support the contribution of conveyor-position-synchronized frame selection to robust onion counting under periodic reel-induced occlusion.

Table 10. Comparison of onion count recovery ratios among the three counting strategies at different engine speeds (fixed-period sampling, tracking-based, and proposed reel-synchronous selection).

Method	2000 rpm	2300 rpm	2600 rpm	Overall
Fixed-period sampling	$90.4 \pm 2.8\%$	$88.6 \pm 3.1\%$	$86.9 \pm 2.8\%$	$88.6 \pm 3.2\%$
YOLOv8n + ByteTrack	$93.4 \pm 3.5\%$	$90.7 \pm 3.4\%$	$90.0 \pm 2.7\%$	$91.4 \pm 3.5\%$
Proposed reel-synchronous	$95.1 \pm 2.7\%$	$95.1 \pm 2.2\%$	$95.4 \pm 2.9\%$	$95.2 \pm 2.6\%$

Values are presented as mean $\pm$ standard deviation ($n = 15$ trials for each engine-speed condition; $n = 45$ overall).

3.3. Calibration of Hydraulic Simulation Model Under Fixed-Displacement Pump Configuration

Table 11 compares the field-measured and simulated hydraulic performance of the fixed-displacement pump at engine speeds of 2000, 2300, and 2600 rpm. The measured mean flow rate, required power, and fuel consumption increased with engine speed, indicating that higher engine speeds increased both hydraulic flow supply and energy demand. In contrast, the measured pressure remained within a relatively narrow range, suggesting that it was governed primarily by the conveyor load and hydraulic resistance rather than engine speed. Consequently, the increase in required power was mainly attributable to the higher hydraulic flow rate.

Table 11. Comparison of field-measured and simulated hydraulic performance of the fixed-displacement pump at different engine speeds, together with the corresponding error metrics.

Variable	Engine Speed (rpm)	Measured (Mean $\pm$ SD)	Simulated	MAPE (%)	RMSE
Flow rate (L/min)	2000	19.69 $\pm$ 0.08	19.60	0.47	0.12
	2300	22.57 $\pm$ 0.12	22.54	0.13	0.13
	2600	25.39 $\pm$ 0.11	25.48	0.34	0.14
Pressure (bar)	2000	42.58 $\pm$ 0.30	42.69	0.24	0.32
	2300	42.99 $\pm$ 0.36	42.98	0.02	0.36
	2600	43.60 $\pm$ 0.36	43.32	0.64	0.46
Required power (kW)	2000	1.40 $\pm$ 0.01	1.39	0.23	0.01
	2300	1.62 $\pm$ 0.02	1.61	0.15	0.02
	2600	1.85 $\pm$ 0.02	1.84	0.30	0.02
Fuel consumption (kg/h)	2000	1.18 $\pm$ 0.01	1.17	0.52	0.01
	2300	1.32 $\pm$ 0.01	1.33	0.37	0.01
	2600	1.51 $\pm$ 0.01	1.52	0.70	0.02

Measured values are presented as the descriptive mean $\pm$ standard deviation of the recorded time-series data, whereas simulated values represent the corresponding deterministic model outputs. Time-series samples were not treated as independent experimental replicates, and no inferential statistical comparisons were performed.

The simulated flow rate closely followed the measured values at all engine speeds ($\text{MAPE} \leq 0.47\%$). Because the flow rate is determined by the pump displacement, drivetrain ratios, and engine speed, this agreement validates the flow path of the circuit model independently of both the load calibration and the identified transmission efficiency. The pressure agreement ($\text{MAPE} \leq 0.64\%$) confirms that the calibrated equivalent load torque reproduces the mean circuit pressure at each engine speed. The required hydraulic power ($\text{MAPE} \leq 0.30\%$) and fuel consumption ($\text{MAPE} \leq 0.70\%$) follow from these two quantities. Because η_t was identified from the same machine and closely related conditions, these latter error metrics characterize calibration consistency rather than independent predictive accuracy. Figure 16 compares the measured and simulated time series of the circuit flow rate and pressure, together with the residuals. The measured signals exhibited only minor temporal variability (coefficient of variation 0.41–0.54% for flow rate and 0.71–0.85% for pressure), and the residuals showed no systematic drift (means of -0.09 to $+0.09$ L/min and -0.11 to $+0.29$ bar). These results indicate that the constant-load, steady-state representation captures the mean operating condition of the fixed-displacement configuration under the tested field conditions. Transient load effects below this variability level were not resolved.

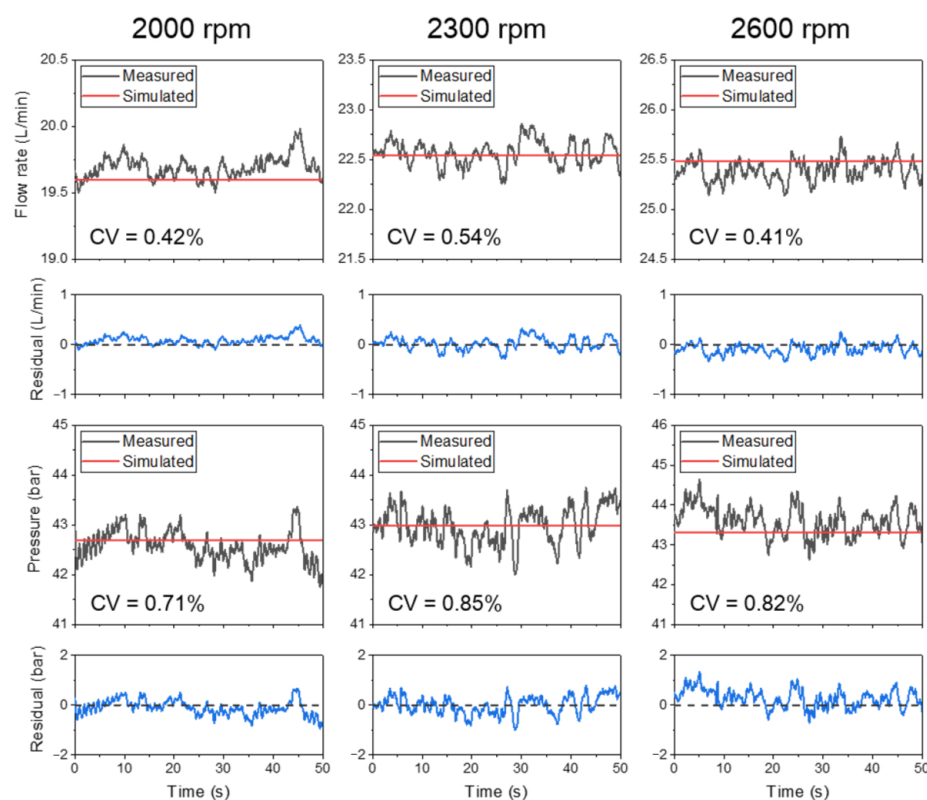


Figure 16. Measured and simulated (steady-state) time series of the collection-circuit flow rate and pressure at each engine speed, with residuals, defined as measured minus simulated values; The blue lines represent the residuals, and the dashed lines indicate zero residual. CV denotes the coefficient of variation in the measured signal.

3.4. Simulation-Based Comparison of Fixed-Displacement and Variable-Displacement Pump Configurations

Table 12 summarizes the simulated hydraulic performance and fuel consumption of the variable-displacement pump at engine speeds of 2000, 2300, and 2600 rpm. The average hydraulic power and corresponding fuel consumption increased with engine speed. In addition, the maximum, minimum, and standard deviation values indicate that the pump output was continuously adjusted in response to the simulated onion-count sequence. The fuel-consumption values correspond to the constant-efficiency baseline described in Section 2.8.

Table 12. Simulated hydraulic performance and fuel consumption of the variable-displacement pump at different engine speeds.

Engine Speed (rpm)	Statistic	Flow Rate (L/min)	Pressure (bar)	Required Power (kW)	Fuel Consumption (kg/h)
2000	Max./min.	19.60/9.80	42.97/41.98	1.39/0.69	1.17/0.94
	Mean $\pm$ SD	16.95 $\pm$ 2.28	42.47 $\pm$ 0.18	1.20 $\pm$ 0.16	1.10 $\pm$ 0.05
2300	Max./min.	22.54/11.27	43.16/42.06	1.61/0.79	1.33/1.05
	Mean $\pm$ SD	19.07 $\pm$ 3.50	42.68 $\pm$ 0.30	1.36 $\pm$ 0.26	1.24 $\pm$ 0.09
2600	Max./min.	25.48/12.74	43.49/42.14	1.84/0.89	1.52/1.18
	Mean $\pm$ SD	21.07 $\pm$ 3.99	42.87 $\pm$ 0.38	1.51 $\pm$ 0.30	1.40 $\pm$ 0.11

Mean $\pm$ standard deviation values describe temporal variation within each deterministic simulation trajectory and do not represent independent simulation replicates. No inferential statistical comparisons were performed among engine speeds.

Figure 17 compares the simulated hydraulic flow rate and pressure profiles under the fixed-displacement and variable-displacement pump configurations at different engine speeds. As shown in Figure 17a–c, the flow rate under the fixed-displacement configuration remained nearly constant over time because the pump operated at a constant displacement for a given engine speed. In contrast, the flow rate under the variable-displacement configuration varied continuously and was generally lower. This result indicates that the variable-displacement pump adjusted the hydraulic flow rate in response to the conveyor's operating demand, whereas the fixed-displacement pump supplied an almost constant flow regardless of temporal variations in demand. Moreover, the difference between the two configurations became more pronounced as engine speed increased, suggesting that the variable-displacement pump has greater potential to reduce unnecessary hydraulic flow under higher-speed operating conditions.

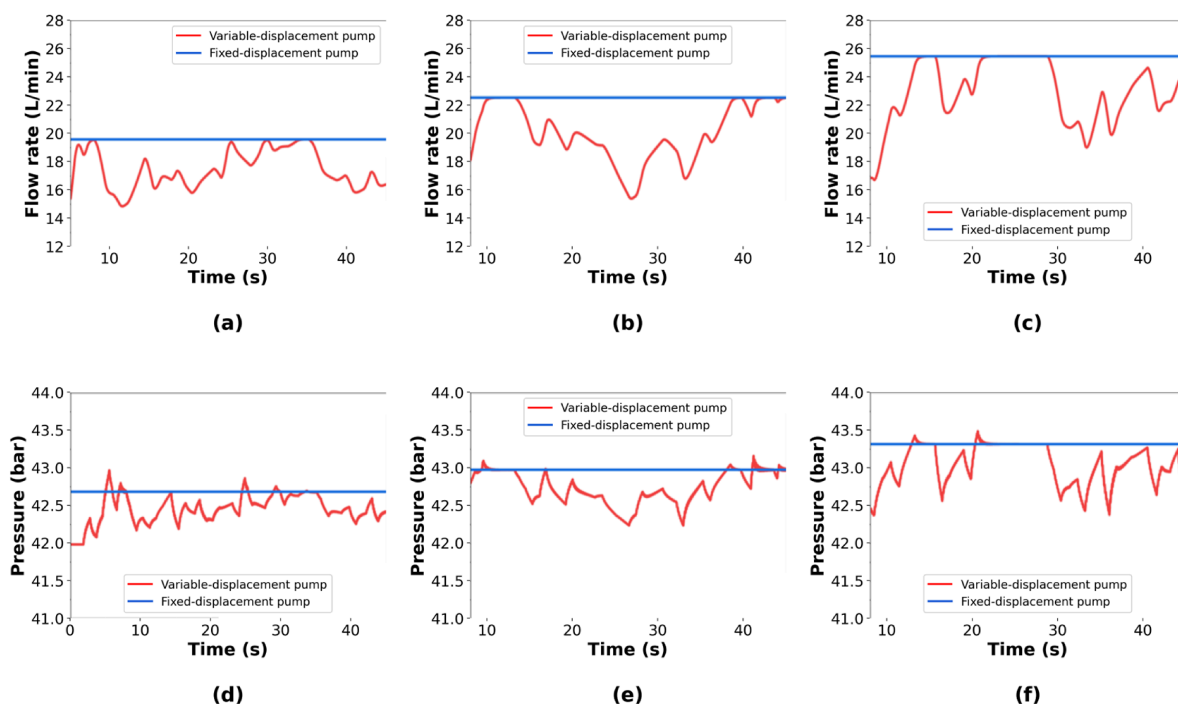


Figure 17. Simulated hydraulic flow rate and pressure profiles for the fixed- and variable-displacement pump configurations at different engine speeds: (a,d) 2000 rpm; (b,e) 2300 rpm; and (c,f) 2600 rpm.

Figure 17d–f present the corresponding simulated hydraulic pressure profiles. Under the fixed-displacement configuration, the pressure remained nearly constant throughout operation. In contrast, the variable-displacement configuration exhibited slight temporal pressure fluctuations as the pump displacement and hydraulic flow rate were adjusted in response to the conveyor's operating demand. However, these fluctuations remained small, within approximately 1.0–1.5 bar.

Figure 18 compares the required hydraulic power profiles of the conveyor drive system under the fixed- and variable-displacement pump configurations at the three engine speeds. The shaded area represents the cumulative hydraulic energy saved over time. The required power and the cumulative energy are determined by the circuit pressure and flow rate and are therefore independent of the transmission-efficiency assumption, although they inherit the constant-load representation of the conveyor circuit. Under the fixed-displacement configuration, the required power remained nearly constant because the pump displacement was not adjusted to accommodate temporal variations in conveyor demand. In contrast, the required hydraulic power under the variable-displacement config-

uration varied continuously in response to the target conveyor operating condition and was generally lower. Consequently, the shaded region between the two profiles represents the cumulative reduction in hydraulic energy demand achieved by the variable-displacement pump. A larger shaded area therefore indicates greater energy-saving potential relative to the fixed-displacement configuration.

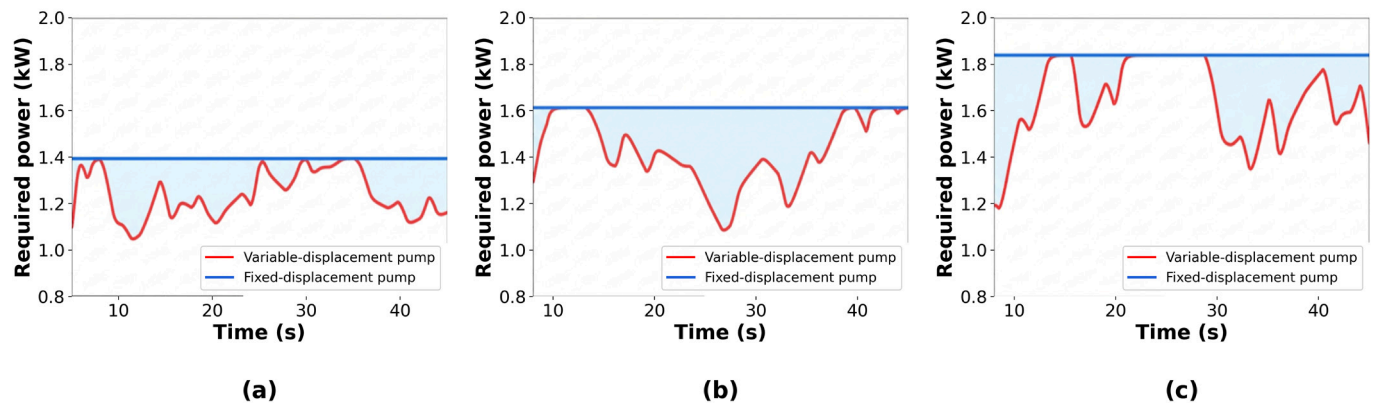


Figure 18. Comparison of simulated required-power profiles for the fixed- and variable-displacement pump configurations at engine speeds of (a) 2000 rpm, (b) 2300 rpm, and (c) 2600 rpm; The light blue shaded area represents the cumulative hydraulic energy saved by the variable-displacement pump.

Table 13 summarizes the cumulative hydraulic energy demand obtained by integrating the required-power profiles shown in Figure 18 over time. These results quantitatively confirm the differences represented by the shaded areas in Figure 18, demonstrating that the variable-displacement configuration reduced cumulative hydraulic energy demand by adjusting the pump displacement to match the conveyor operating requirements.

Table 13. Cumulative hydraulic energy demand and energy savings under the fixed- and variable-displacement pump configurations at different engine speeds.

Engine Speed (rpm)	Cumulative Hydraulic Energy (kJ)		Hydraulic Energy Saved (kJ)	Energy Reduction (%)
	Fixed-Displacement Pump	Variable-Displacement Pump		
2000	69.69	60.00	9.69	13.90
2300	80.69	67.88	12.81	15.88
2600	91.94	75.36	16.58	18.03

As listed in Table 14, the estimated average reduction decreased from 14.28–18.72% under the field-identified efficiency to 11.50–16.94% across the loss-partition scenarios ($\alpha = 0.35$ – 0.65), decreasing monotonically with α , but remaining positive and monotonic with engine speed in all loss-partition scenarios. The spread among the α scenarios was 1.4–1.8 percentage points at each engine speed, indicating that the estimate is more sensitive to the engine-speed condition than to the assumed loss partition.

The robustness of these estimates can be assessed against the duty-cycle-averaged break-even efficiency, defined as 0.72 multiplied by the cumulative hydraulic-energy ratio of the variable- to fixed-displacement configurations, below which the net saving vanishes. For the recorded field duty cycles, the break-even efficiency was 0.620, 0.606, and 0.590 at 2000, 2300, and 2600 rpm, whereas the effective mean efficiency of the variable-displacement operation remained 0.690–0.708 under all loss-partition scenarios, leaving margins of 7.7–10.0 percentage points. In addition, the predicted efficiency exceeded the instantaneous break-even condition ($\eta_t > 0.72\beta$ at the near-constant circuit pressure) throughout the

commanded displacement range, so the estimated saving cannot become negative under any duty cycle. A complementary sweep of the control-law parameters was performed by post-processing the simulated displacement commands. The estimated saving varied by less than ± 2 percentage points under variations in the swash-plate time constant (0.15–1.0 s), response delay (up to 0.5 s), and counting error ($\pm 5\%$). It remained positive under all examined settings of the saturation threshold and minimum-speed ratio. The saving is therefore governed primarily by the engine speed and the efficiency scenario rather than by the actuation dynamics or counting accuracy. The field-identified estimates should accordingly be interpreted as upper-bound values, and the loss-model estimates as conservative values.

Table 14. Estimated net fuel consumption (excluding no-load consumption) of the fixed- and variable-displacement pump configurations at different engine speeds.

Engine Speed (rpm)	Net Consumption of Fixed-Displacement Pump (kg/h)	Net Consumption of Variable-Displacement Pump ^a (kg/h)	Average Reduction (%)			
		Mean $\pm$ SD ^b	$\eta_t = 0.72$	$\alpha = 0.35$	$\alpha = 0.50$	$\alpha = 0.65$
2000	0.45	0.39 $\pm$ 0.05	14.28	12.88	12.21	11.50
2300	0.53	0.44 $\pm$ 0.09	16.36	14.76	13.99	13.16
2600	0.64	0.52 $\pm$ 0.11	18.72	16.94	16.07	15.14

^a Net consumption values refer to the field-identified constant-efficiency scenario ($\eta_t = 0.72$).

^b Mean $\pm$ standard deviation values describe temporal variation in the deterministic simulation outputs. These time-series values were summarized descriptively and were not treated as independent replicates for inferential testing.

4. Discussion

4.1. Counting Performance Under Periodic Reel-Induced Occlusion

Beyond the hydraulic evaluation, the counting results provide evidence for the effectiveness of the proposed occlusion-handling strategy. The trial-level analysis showed an overall bias of -4.07 onions per trial and a strong linear relationship between the manual reference and detected counts ($R^2 = 0.9962$). These results indicate that synchronization with reel-passage events reduced the risk of repeated counting under the periodic machine-induced occlusion, a failure mode consistent with the occlusion-related detection limitations identified in previous reviews [10–13]. In other words, reliable counting was achieved without the identity management required by tracking algorithms in this dual-conveyor structure. Because conveyor mechanisms with periodic visual obstruction are common in harvester-mounted vision applications, this event-synchronized sampling approach may also be applicable to other crop-handling machines with similar structural occlusion. Table 15 positions the present study against representative related studies.

Table 15. Comparison of the present study with representative related studies on crop-flow perception and machine-side control.

Study	Crop/Application	Method	Detection Performance	Counting/Inflow Performance	Processing Speed	Occlusion/ Counting Strategy	Machine-Control Integration
Boatswain Jacques et al. (2021) [35]	Shallot/harvester conveyor	Watershed-based machine vision	Precision 76.0%; Recall 72.7%; overall detection accuracy 59.2%	62.6% of onions correctly detected per frame	NR	Camera above conveyor; occlusion, overlap and lighting remained major error sources	No; yield monitoring
Zhang et al. (2024) [7]	Wheat/combine feed-quantity prediction	Improved YOLOv5s + plant weight estimation	mAP ₅₀ 78.1%; Precision 85.2%; Recall 70.9%	Mean feed-quantity relative error 4.19%	Detection 101.7 ms; complete prediction 1.34 s	Dense-object detection; no mechanical-phase synchronization	Prediction intended to support closed-loop harvesting control
Safre et al. (2025) [8]	Tart cherry/harvester conveyor counting	YOLOv8/YOLO11 + BoT-SORT	Best mAP ₅₀ 0.92	Count-harvested-weight relation: R ² = 0.62; RMSE = 10 kg	YOLOv8n 7.5 ms; YOLO11x 44 ms	BoT-SORT tracking; high-density/occlusion conditions remained challenging	No; yield mapping
Lai and Lang (2025) [17]	Sugarcane/harvester feeding and conveyor control	I-YOLOv8n-seg + depth + PLC	Precision 95.6%; Recall 90.2%; mAP ₅₀ 94.8%	Mean feeding-amount detection error: 5.69%	96.2 FPS; overall system response 2 s	Segmentation + depth sensing; no reel-phase synchronization	Yes; conveyor roller control, blockage reduced 17.76% → 4.32%
Shi et al. (2026) [9]	Grain/dynamic grain-flow counting	Improved YOLOv8n + dual-line counting	Precision 90.6%; Recall 91.4%; mAP 94.5% †	Counting accuracy 89.76%	NR	Dual-line counting + direction, shape and IoU-based filtering	No; grain-yield monitoring
This study	Onion/self-propelled dual-conveyor collector	YOLOv8n + conveyor-position-synchronized frame selection	Precision 95.2%; Recall 94.4%; mAP ₅₀ 95.9% ‡	Overall count recovery ratio 95.2 ± 2.6%	26.80 ms/image (~37.3 FPS)	Reel-synchronous event sampling using conveyor position; persistent IDs not required	Vision count used as control input in field-calibrated simulation; on-machine implementation not yet performed

NR, not reported. † IoU threshold not specified in the source. ‡ Independent field-only test subset (Table 8).

4.2. Energy-Saving Mechanism and Machine-Level Implications

The proposed control strategy reduced the simulated hydraulic power demand primarily by regulating the supplied flow rate according to the estimated onion count. The pressure remained nearly unchanged between the two pump configurations and far below the relief setting of the circuit. This is a consequence of the constant equivalent load torque and is consistent with the narrow pressure band measured in the field. The maximum flow rate remained comparable when higher conveyor speeds were required. These results indicate that unnecessary hydraulic supply was suppressed during low-demand periods without limiting the flow required for conveyor operation. This flow-dominant energy-saving mechanism is consistent with the load characteristics identified in a previous field study of the same collector [31]. In this study, the hydraulic working units were the primary contributors to total power demand at higher engine speeds and pump flow increased almost linearly with engine speed under nearly constant pressure. The present results extend those findings by demonstrating, within the field-calibrated simulation framework, that decoupling pump flow from engine speed through displacement control directly recovers the excess hydraulic supply previously identified as the primary source of inefficiency.

The fuel-saving effect should also be interpreted at the conveyor-subsystem level. The collector used in this study was a relatively small self-propelled machine equipped with a 25.4-kW engine, and the collection conveyor accounted for only a limited portion of the total engine output. Consequently, although the field-calibrated simulation indicated a clear reduction in the conveyor's net fuel consumption, the immediate fuel-cost benefit for the tested machine may be modest. Nevertheless, the proposed approach remains meaningful because agricultural collection and harvesting machines commonly employ conveyor transfer mechanisms and hydraulic drive systems. In absolute terms, the estimated net savings correspond to approximately 0.08–0.14 L/h, or 0.9–1.6 L/ha at the standard forward speed of 0.2 m/s and the 1.24 m working width. At the machine level, this represents approximately 1.8–2.7% of the total fuel consumption measured under comparable upland-onion field conditions [31]. This figure follows directly from the fuel-share structure of the platform: the collection conveyor accounts for only 13–14% of the total fuel use, within which the proposed control achieved a 14.3–18.7% reduction. The machine-level impact of the framework therefore scales with the fuel share of the controlled circuit and increases with engine speed as the flow-proportional hydraulic demand grows [31]. Accordingly, larger benefits can be expected on platforms in which conveying and handling circuits represent a greater share of the total load, such as integrated dig-and-collect harvesters or higher-throughput collection systems, and when the same flow-on-demand strategy is extended to the remaining hydraulic circuits. Potential secondary benefits, such as stabilization of the crop density delivered to the sorting conveyor and the associated manual sorting workload, remain to be experimentally evaluated.

The reported savings correspond to a general-purpose setting of the control law rather than an optimized one. Within the same framework, raising the saturation threshold from 20 to 25 increased the estimated saving by 6.5–7.3 percentage points, to 21.5–25.2% across the tested engine speeds. This occurs because the count-to-displacement gain decreases and a lower conveyor speed is commanded at every inflow level. The accompanying reduction in transport margin, together with its possible effects on accumulation and collection loss, is not represented in the constant-load model. Lowering the threshold to 15 reduced the savings by 5.5–7.2 percentage points (to 7.1–13.0%), and the minimum-speed ratio shifted the estimates similarly, by ± 2.6 –3.3 percentage points (11.7–22.0% over the ratio range of 0.4–0.6). In practical deployment, these two parameters could therefore be tuned to the pump efficiency characteristics, crop conditions, and expected inflow level of a given operation, suggesting room for site-specific optimization. However, external factors arising

from the crop and soil are difficult to control in agricultural fields. The present study therefore adopted the general-purpose setting, and the optimization itself remains for the field implementation stage.

4.3. Robustness of the Vision System Under Field Conditions

Robustness to field disturbances was addressed at three levels in the present framework: illumination variation through adaptive histogram equalization and exposure/saturation augmentation; machine vibration and camera motion through the conveyor-detection-based dynamic reference; and periodic structural occlusion through reel-synchronous sampling. The residual error sources observed in the 45 trials—soil adhesion, partial overlap between adjacent bulbs, and transient occlusion—all acted through missed detections, which motivated the recall-oriented model selection and is consistent with the net undercounting observed at the trial level. Because undercounting lowers the commanded conveyor speed, the failure mode of the control law under heavier soil coverage is conservative with respect to energy use, although it may reduce the transport margin. Nevertheless, detection accuracy may decline under greater illumination variability, severe onion overlap, stronger machine vibration, different onion varieties or bulb sizes, and heavier soil adhesion than encountered in the tested sessions. Conditions such as dust deposition on the lens, rain, and low-angle sunlight remain untested. Although the held-out test subset was independent at the source-video level, it contained only 31 images from three source videos. The present detection results should therefore be interpreted as performance under the evaluated field conditions rather than as a comprehensive assessment of generalization across sites, seasons, and cultivars. Targeted improvements for future work include expanding the dataset across illumination, soil-moisture, and cultivar conditions, adding illumination normalization or active lighting at the camera housing, protecting the lens against dust and spray, and checking the manual reference counts with multiple observers.

4.4. Scope of Validation and Limitations

The scope of validation in this study should be clearly distinguished. The field experiments verified the feasibility of vision-based onion counting under actual operating conditions and provided the hydraulic measurements for calibrating the fixed-displacement pump model, whereas the variable-displacement configuration was evaluated through simulation using field-derived onion-count data and the field-calibrated hydraulic model. The reported fuel savings should therefore be interpreted as estimated potential savings rather than as direct measurements from the control system implemented on the machine, and this study should accordingly be regarded as a preliminary feedforward simulation and feasibility study of the proposed framework. Such staged validation is commonly adopted during the early development of agricultural machinery control systems before full-scale hardware implementation and field verification.

Several limitations should be considered before practical implementation. First, no measured efficiency map was available for the variable-displacement pump, so its partial-displacement losses were represented by an anchored classical loss model whose loss partition between the pump and the remaining drivetrain could not be identified from a single operating point; this uncertainty was bounded by a sensitivity analysis rather than eliminated. Second, the conveyor load was represented as a constant equivalent torque calibrated at each engine speed. Dynamic load variations induced by the onion mass, accumulation, and impacts were not modeled, and their effects on the circuit pressure and the achievable saving require dedicated field measurements under varying crop loads and an extended load model, together with the on-machine implementation of the variable-

displacement pump control itself. Third, the field-derived count sequence was applied with its original timing, although the control itself alters the conveyor speed and hence the reel-passage interval and the count accumulated per reel. The magnitude and direction of this coupling and its potential effect on control performance cannot be determined from the present simulation alone. Its effect on the achievable saving and on inflow uniformity, which was not evaluated here, therefore requires assessment under on-machine operation. Future studies should therefore expand the field dataset, implement the pump displacement control on the machine, and validate the feedforward conveyor speed control under actual operating conditions, extending it, where required, with feedback of the measured conveyor speed. Such validation should cover its effects on collection efficiency, onion loss, bulb damage, dynamic conveyor load, and long-term fuel consumption.

5. Conclusions

In this study, a vision-based feedforward conveyor speed control framework for a self-propelled onion collector was developed and evaluated. The proposed system estimates the onion count per reel segment through forward-view image recognition and adjusts conveyor speed using a variable-displacement hydraulic pump. Because the collector's compact dual-conveyor structure causes periodic occlusion by the upper conveyor, a region-of-interest-based frame selection procedure was introduced to acquire images at consistent observation positions. By synchronizing frame acquisition with the reel-passage event, this procedure enabled accurate onion counting without inter-frame identity association, thereby reducing the risk of repeated counting in the occlusion-prone conveyor system. The YOLOv8n-based object recognition model achieved stable detection performance for both the onion and conveyor classes. On the independent field-only test subset, the selected YOLOv8n model achieved a precision of 0.952, a recall of 0.944, and an mAP@0.5 of 0.959. Mean count recovery ratios remained high across the tested engine speeds, reaching 95.14%, 95.09%, and 95.42% at 2000, 2300, and 2600 rpm, respectively. The ablation comparison showed overall count recovery ratios of 88.6% for fixed-period sampling and 91.4% for YOLOv8n + ByteTrack, compared with 95.2% for the proposed reel-synchronous method. These results quantitatively support the contribution of conveyor-position synchronization to robust onion counting under periodic reel-induced occlusion. Trial-level error analysis indicated only a slight systematic undercounting. These results demonstrate that the proposed vision-based method can provide reliable onion inflow information for vision-based feedforward conveyor speed control under field operating conditions. However, because the independent test subset comprised only 31 images from three field videos, the detection performance should be interpreted as validated under the current test-field conditions; additional multi-site evaluations across different cultivars and seasons are required to confirm broader generalization.

The AMESim-based hydraulic model, with the equivalent load torque calibrated to the measured circuit pressure, reproduced the measured flow rate independently of the identified transmission efficiency, and the pressure, required hydraulic power, and fuel consumption were consistent with the field measurements ($\text{MAPE} \leq 0.70\%$). Because the load torque was calibrated to the same measurements and the transmission efficiency was identified from a separate test campaign on the same machine, these error metrics characterize calibration consistency rather than independent predictive accuracy. Independent experimental validation of the variable-displacement configuration, including the dynamic conveyor load, remains a subject for future work. The relative fuel-saving estimates are structurally insensitive to the value of the common efficiency constant. The remaining uncertainty in the efficiency assumption was quantified through the sensitivity analysis in Section 2.8, which confines the estimates to 11.5–18.7% across all loss-partition scenarios.

Simulation-based evaluation using the calibrated model showed that the variable-displacement pump reduced unnecessary hydraulic output by adjusting pump displacement according to the estimated onion count. Compared with the fixed-displacement configuration, the variable-displacement pump reduced the conveyor's net fuel consumption, excluding no-load consumption, by average values of 14.28%, 16.36%, and 18.72% at 2000, 2300, and 2600 rpm, respectively. When partial-displacement efficiency losses were accounted for through the anchored loss model, the estimated savings ranged from 11.50% to 16.94% across the loss-partition scenarios, remaining positive in all cases. The feedforward conveyor speed control strategy also reduced cumulative hydraulic energy demand by matching pump displacement to the conveyor's operating requirements, thereby suppressing unnecessary hydraulic output under variable onion inflow conditions.

Overall, the results demonstrate that vision-based reel-synchronous onion counting can be effectively integrated with vision-based feedforward conveyor speed control in the collector. The proposed framework provides a practical basis for reducing hydraulic power demand and improving energy efficiency in bulb onion collection systems. The reported energy and fuel savings represent estimated potential benefits derived from a field-calibrated simulation framework. Their verification through on-machine implementation and field experiments remains the focus of future work. This includes effects on crop throughput, onion loss, bulb damage, dynamic conveyor load, and total-machine fuel consumption, none of which were experimentally evaluated under the proposed control in this study.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/agronomy16181788/s1>, Table S1: Trial-level metadata and counting errors for the onion-counting experiment.

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Conflicts of Interest: The authors declare no conflicts of interest.

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