Automated Shallot Classification on Conveyor Belts Using Watershed Transform and Otsu Thresholding

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Received: 9 September 2025 | Revised: 13 October 2025, 5 November 2025, and 28 November 2025 | Accepted: 29 November 2025

ABSTRACT

Manual classification of shallots often lacks precision, especially when bulbs overlap or have irregular shapes on conveyor systems. This study presents an automated computer vision approach combining Otsu thresholding and the watershed transform to detect and measure shallot diameters. Data were collected from video recordings under varying conveyor speeds and camera distances. The processing pipeline—consisting of preprocessing, segmentation, and feature extraction achieved a segmentation accuracy of 99.57% and a diameter estimation Mean Absolute Percentage Error (MAPE) as low as 2.84%. These results demonstrate a significant improvement in separating overlapping objects and measuring irregular shapes. This system contributes to the literature on post-harvest classification automation and shows strong potential for implementation in industrial shallot processing lines to enhance efficiency, ensure consistent quality, and significantly reduce reliance on manual labor. However, the system's performance may vary under extreme lighting conditions, indicating opportunities for further improvement.

Keywords-shallot; Otsu thresholding; watershed transform; computer vision; agricultural automation

I. INTRODUCTION

Automation in post-harvest processing is essential for improving efficiency and ensuring consistent quality classification. Shallots (Allium cepa var. aggregatum) represent a key agricultural commodity in Indonesia, particularly in Enrekang Regency, where accurate size-based grading directly influences market value [1, 2]. Manual classification remains highly inconsistent, especially when bulbs overlap or form double-bulbed structures on conveyor belts [3]. These industrial challenges highlight the need for an automated vision-based system capable of reliable segmentation and diameter measurement [4].

Several computer vision techniques have been explored for agricultural classification. Prior studies applied watershed segmentation for shallot size estimation [5, 6] but suffered from over-segmentation due to limited preprocessing. Deep learning models, such as Mask R-CNN [7], offer high accuracy but demand substantial computational resources and large annotated datasets, making them impractical for real-time deployment in resource-constrained environments. Classical methods, such as HSV thresholding [8], Otsu thresholding [9], and various hybrid techniques [10-12], have demonstrated potential but still struggle with overlapping objects and variable lighting conditions. These limitations emphasize a persisting gap: classical methods are efficient but lack robustness for clustered objects, while deep learning techniques are powerful yet often unsuitable for real-time processing on conveyor systems.

Otsu thresholding is widely used for initial foreground-background separation due to its simplicity and ability to select optimal grayscale thresholds automatically [16, 17]. Although effective for isolated objects, its performance decreases when shallots touch or overlap, as pixel intensities merge into a single region. The watershed transforms, conversely, excels at separating adjacent objects by analyzing intensity gradients and topographic structure [18-20]. However, a watershed alone is prone to over-segmentation in noisy images. Combining both methods, Otsu for thresholding and watershed for boundary refinement, forms a complementary hybrid capable of addressing the limitations of each individual technique.

Computer vision has played an important role in agricultural automation, from sorting and grading to disease detection and yield estimation [21-24]. In conveyor-based environments, real-time segmentation and measurement require lightweight yet robust algorithms capable of handling motion blur, perspective distortion, and variable illumination. A hybrid Otsu Watershed framework provides a feasible balance between computational efficiency and segmentation accuracy, making it suitable for industrial post-harvest systems. Table I summarizes representative studies involving Otsu thresholding, watershed segmentation, and hybrid models. Most prior studies either lack robustness in overlapping-object scenarios or rely on computationally expensive deep learning frameworks.

TABLE I. COMPARATIVE SUMMARY OF RELATED STUDIES

Reference/Year	Method	Object	Key limitation	Result/Accuracy	Gap addressed
[13]/2024	Otsu + CNN	Mango fruit	Works only under uniform light	95.2%	No real-time processing
[14]/2024	Watershed	Shallot	Over segmentation	MAPE 3.51%	No hybrid thresholding
[15]/2022	Watershed + CNN	Corn seed	Computationally heavy	High accuracy	Not conveyor-based
This study	Otsu + Watershed	Shallot	–	99.57% accuracy	Real-time conveyor segmentation

The present study addresses these gaps by integrating Otsu thresholding and watershed transformation into a streamlined segmentation pipeline designed specifically for real-time shallot classification on conveyor belts. The contributions of this study are threefold: (1) introducing a hybrid Otsu Watershed segmentation method optimized for overlapping and double bulbed shallots, (2) evaluating its performance under multiple industrial conditions involving variable conveyor speeds and camera distances, and (3) demonstrating a practical, low-cost computer vision system suitable for real-time agricultural classification workflows.

II. METHODOLOGY

This study employs a computer vision-based approach consisting of preprocessing, image segmentation using Otsu thresholding and watershed transform, and feature extraction to detect and measure shallot diameters. The system was evaluated using video data captured under various conveyor speeds and camera distances to simulate industrial conditions.

A. Research Object

The main object of this research is the shallot, which is commonly evaluated based on its physical diameter to determine market quality. Manual quality determination methods are often inconsistent and prone to subjective bias, leading to unreliable classification results. These issues become even more apparent when shallot is placed on a conveyor belt during the sorting process. On such platforms, it is common for shallots to appear either in close proximity to one another or in double-bulbed formations, making precise size differentiation difficult. This visual proximity results in classification ambiguity, as overlapping shallots may be incorrectly interpreted as a single unit or mismeasured altogether. This study aims to address these challenges by developing a computer vision-based system that can distinguish individual shallots more accurately, particularly when they appear clustered or overlapped during processing on a conveyor belt.

B. Research Design and Type of Data

This research adopts a system development approach based on image processing and computer vision. Figure 1 illustrates the research workflow implemented in this study.

The data used in this research are categorized into two types: primary and secondary. The primary data consist of video recordings of shallots moving along a conveyor belt under controlled lighting and speed conditions. Each shallot's actual diameter was also measured using an electronic digital caliper prior to recording, providing the ground truth for validation. Secondary data include supporting literature and comparative studies on image segmentation and object detection, which help in shaping the algorithm design and system architecture.

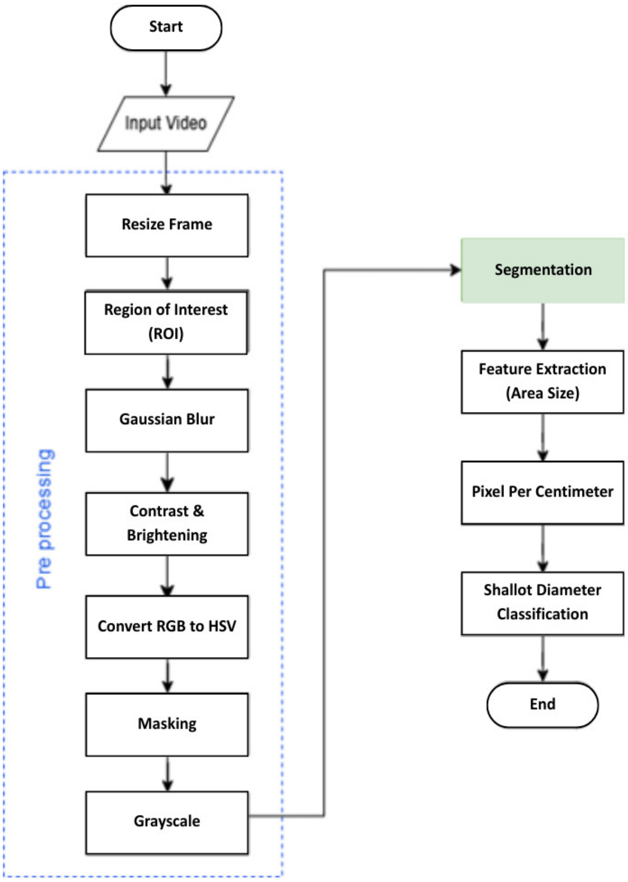


Fig. 1. Research workflow implemented in this study.

C. Data Sources

The shallot used in this study is of the Allium cepa var. aggregatum variety and was sourced from farmers in Enrekang Regency. These samples were selected due to their relevance to regional agricultural practices and their varying shapes and sizes, which are ideal for testing segmentation robustness. Video recordings were conducted in the Artificial Intelligence and Multimedia Processing (AIMP) Laboratory, Department of Informatics Engineering, Faculty of Engineering, Hasanuddin University, Gowa. This facility provides controlled conditions necessary for high-resolution image acquisition. A Logitech Brio Ultra HD webcam was used for capturing the videos, mounted in a top-down orientation within an enclosed box to minimize external light interference. The use of a white conveyor belt surface enhanced object-background contrast, while the camera was placed at distances of 10 cm and 15 cm to evaluate perspective influence. Belt speeds were varied at 0.15 m/s, 0.18 m/s, and 0.27 m/s to simulate real-world processing conditions. The resulting video recording is saved in .MP4 format with 30 Frames Per Second (FPS) and a resolution of 1920 × 1080 pixels. The shallot data collection on the conveyor is shown in Figure 2.

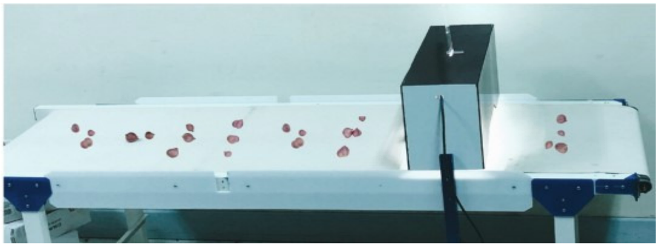


Fig. 2. Illustration of shallot data collection on a conveyor machine.

During the data collection phase, multiple experimental scenarios were designed and conducted to evaluate the system's performance under varying operational conditions. Specifically, the scenarios involved systematically adjusting the speed of the belt conveyor and the distance between the camera and the surface of the onion samples. These parameters were chosen due to their significant impact on image clarity, object detection accuracy, and size estimation precision in a real-time processing environment. The conveyor speed affects the motion blur and image acquisition timing, while the camera distance influences the resolution and field of view, which are critical for precise segmentation and measurement. The specific combinations of belt conveyor speeds and camera-object distances used in these experimental setups are presented in Table II.

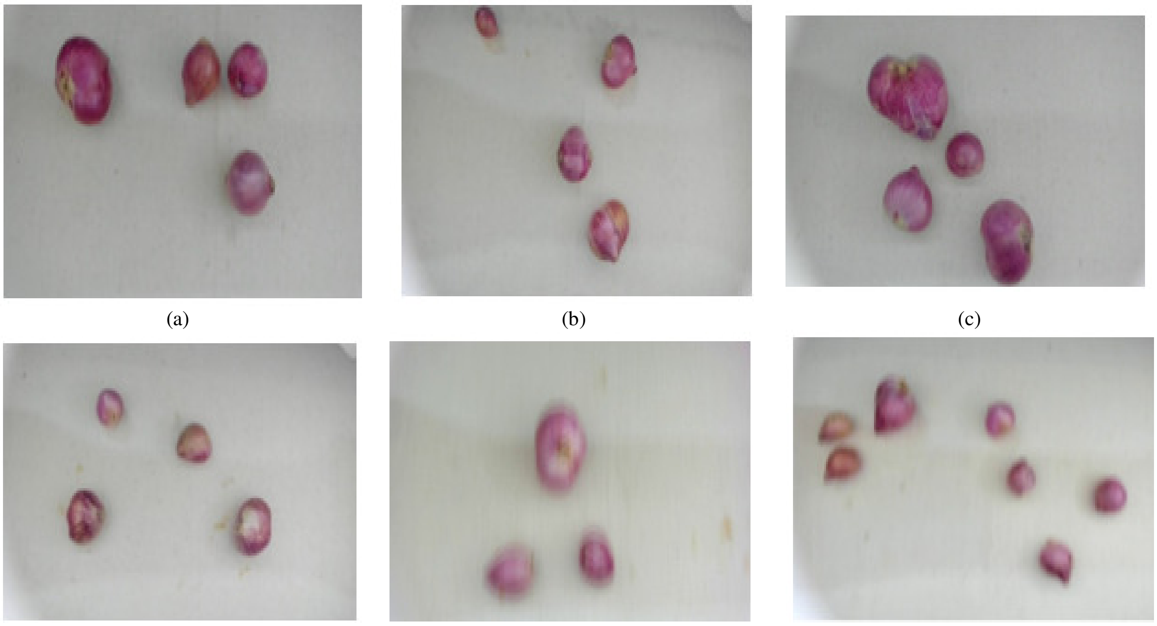
TABLE II. TEST DATA COLLECTION SCENARIOS

Scenario	Conveyor speed	Camera distance
Scenario 1	0.15 m/s	10 cm
Scenario 2	0.15 m/s	15 cm
Scenario 3	0.18 m/s	10 cm
Scenario 4	0.18 m/s	15 cm
Scenario 5	0.27 m/s	10 cm
Scenario 6	0.27 m/s	15 cm

By combining different values of conveyor speeds and camera distances, the study aimed to simulate a range of realistic industrial conditions and assess the robustness and adaptability of the proposed image processing system. The conveyor speed was selected based on the minimum and maximum operational limits of the conveyor system used in the AIMP Laboratory, Hasanuddin University. Figure 3 depicts an example of a shallot frame in each conveyor speed and camera distance scenario based on Table II.

D. Data Collection

The data collection process followed a structured workflow. First, each shallot bulb was manually measured using a digital caliper to obtain an accurate diameter. The shallots were then placed randomly on the moving conveyor belt, and videos were recorded at a resolution of 1920×1080 pixels with 30 FPS. The lighting intensity was maintained at 132 lux to ensure image clarity.



(a) (b) (c)

(d) (e) (f)

Fig. 3. Frame results of conveyor speed and camera distance: (a) 0.15 m/s and 10 cm, (b) 0.15 m/s and 15 cm, (c) 0.18 m/s and 10 cm, (d) 0.18 m/s and 15 cm, (e) 0.27 m/s and 10 cm, (f) 0.27 m/s and 15 cm.

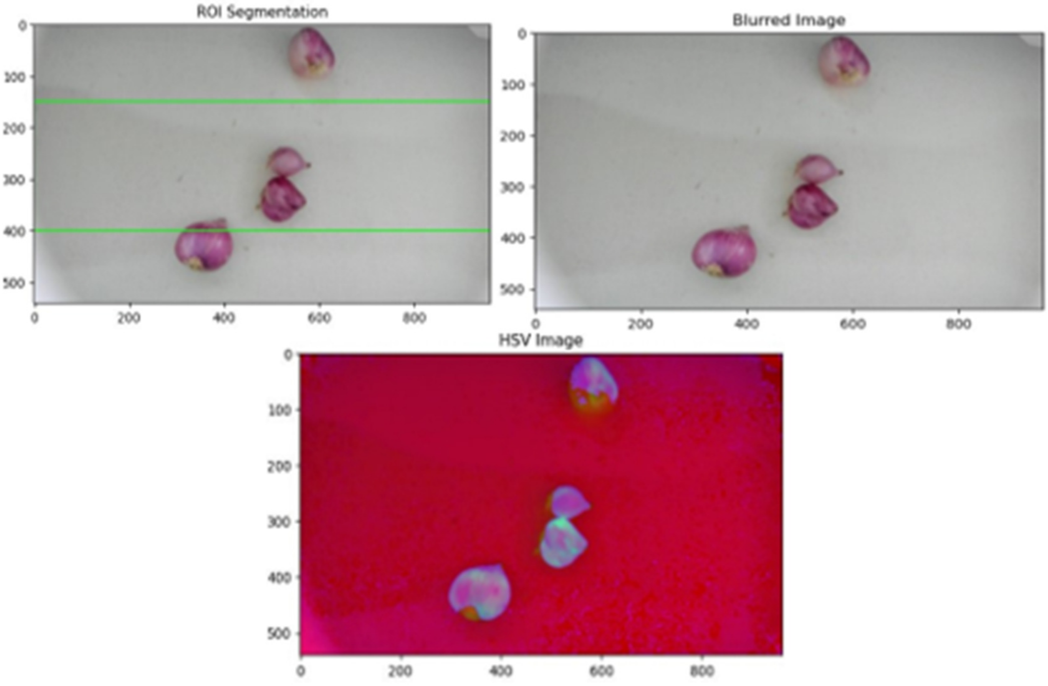


Fig. 4. Results of: ROI, blurring, and HSV conversion.

Each video captured different scenarios based on combinations of conveyor belt speeds and camera distances. The system's software pipeline began by resizing each video frame to 960×540 pixels to reduce computational load. Region of Interest (ROI) cropping was applied to eliminate irrelevant areas, followed by Gaussian blur for noise reduction, brightness and contrast adjustment, and color space conversion from RGB to HSV. Masking was used to isolate objects based on color thresholds. The image was then converted to grayscale, and segmentation was performed using Otsu thresholding and watershed transform, followed by morphological operations, distance transformation, and connected component analysis. Figure 4 presents an example of the implementation of ROI, blurred image, and RGB to HSV color conversion.

E. Data Analysis Techniques

To analyze the performance of the system, three key evaluation metrics were employed: Root Mean Squared Error (RMSE), MAPE, and segmentation accuracy. RMSE was used to measure the deviation between the estimated diameter and the actual measurement, offering insights into the system's precision. MAPE calculated the percentage of error relative to the ground truth, allowing for evaluation across different object sizes. Segmentation accuracy was determined by comparing the number of correctly segmented shallots to the total count of shallots in the frame, expressed as a percentage. These metrics were applied across different test conditions, including variations in conveyor speed and camera distance, to determine the system's robustness. By triangulating these measurements, the study ensured an assessment of the system's capability to classify and measure shallots accurately in real-time operational settings. The RMSE and MAPE were calculated by:

$$\text{RMSE} = \sqrt{\frac{1}{m}\sum_{i=1}^{m}(X_i - Y_i)^2} \quad (1)$$

where m is the amount of data, Xi is the predictive value, and Yi is the actual value.

$$\text{MAPE} = \frac{1}{m}\sum_{i=1}^{m}\left|\frac{Y_i - X_i}{Y_i}\right| \quad (2)$$

$$\text{Accuracy} = \frac{\text{Correctly Segmented Shallots}}{\text{Total Shallots}} \times 100\% \quad (3)$$

III. RESULT

Key evaluation metrics, such as segmentation accuracy, MAPE, and RMSE, were analyzed to assess the reliability of the method in real-time industrial conditions.

A. Otsu Thresholding Result

Otsu thresholding served as the initial segmentation step by separating shallots from the background in grayscale images. Under favorable conditions (10 cm camera distance, 0.15 m/s belt speed), the method produced clear binary masks with a segmentation accuracy of 99.14%. However, accuracy decreased when the camera distance increased to 15 cm (97.42%) or when conveyor speed increased, dropping to 89.27% (10 cm) and 87.55% (15 cm) at 0.27 m/s. These results highlight the sensitivity of Otsu thresholding to motion blur, reduced sharpness, and overlapping objects, which often cause merged boundaries.

B. Relation to Research Problem

The segmentation results obtained through Otsu thresholding, while effective under controlled conditions, demonstrate limitations in real-world scenarios, particularly when dealing with overlapping or closely positioned shallots. This finding reinforces the core issue identified at the outset of the study: that manual or single-method segmentation is insufficient for accurately classifying clustered bulbs. Although Otsu thresholding performs reliably for isolated objects, its inability to resolve double-bulbed or adjacent samples leads to reduced accuracy in both classification and diameter measurement. In the context of agricultural industry applications, such segmentation inaccuracies can compromise the reliability of automated grading systems, which depend on precise object delineation to ensure consistency and quality control. Therefore, the integration of the watershed transform becomes essential not merely as a technical refinement but as a necessary enhancement to meet the demands of industrial-scale automation. These results underscore the broader relevance of accurate segmentation as a primary requirement for effective post-harvest processing, justifying the adoption of multi-step segmentation pipelines in practical implementations.

C. Watershed Transform Result

Building on the binary masks generated by Otsu thresholding, the watershed transforms effectively refined object boundaries using distance maps and morphological preprocessing. At 10 cm and 0.15 m/s, segmentation accuracy improved to 99.57%, while even under high-speed conditions (0.27 m/s, 15 cm), accuracy remained higher (93.56%) than Otsu alone. This demonstrates the capability of the hybrid method to resolve overlaps and delineate adjacent objects more consistently.

Watershed segmentation successfully separated double-bulbed and closely positioned shallots by identifying local intensity maxima and generating clear boundary markers. Accuracy improvements, such as 98.62% at 0.18 m/s and 10 cm (compared to Otsu's 97.87%), further validate the method's strength in handling irregular shapes and borderline connected objects in dynamic environments.

D. Implication of Watershed Transform Result

The findings from the watershed transform directly address the segmentation challenges posed in the research question. By accurately separating touching shallots, the system overcomes the visual ambiguity encountered during manual classification and single-method segmentation. This supports the main objective of the study: to develop a reliable detection system for clustered or double-bulbed shallots. The enhanced accuracy achieved through the watershed algorithm not only validates its integration into the classification workflow but also demonstrates its potential for deployment in automated post-harvest systems. The ability to consistently segment objects under varying operational conditions affirms the system's robustness in addressing the limitations of traditional methods.

E. Computer Vision Result

The computer vision system in this study utilized a series of image processing modules to extract meaningful information from video frames. After successful segmentation, the system measured the diameter of each detected shallot using a pixel-to-centimeter conversion factor derived from calibration data. These measurements were then used to categorize each bulb into one of four size classes: jumbo, large, medium, and small. At a belt speed of 0.15 m/s and camera distance of 10 cm, the system achieved an RMSE of 0.19 cm and an MAPE of just 2.84%. This indicates high precision in real-world classification scenarios, particularly when operational variables are well controlled. The computer vision system successfully automated a process that is typically performed manually and often inconsistently. Figures 6 and 7 present graphs of the average RMSE and MAPE at each conveyor speed and camera distance.

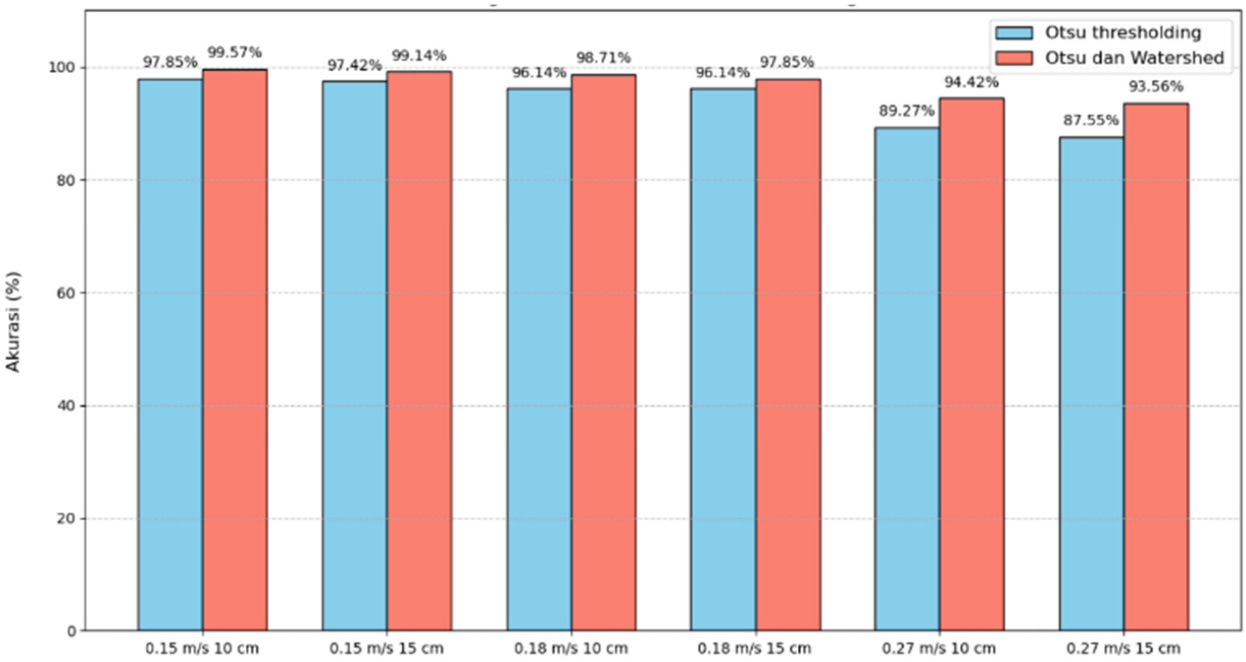


Fig. 5. Comparison of segmentation results using Otsu thresholding and the watershed transform combined with Otsu thresholding.

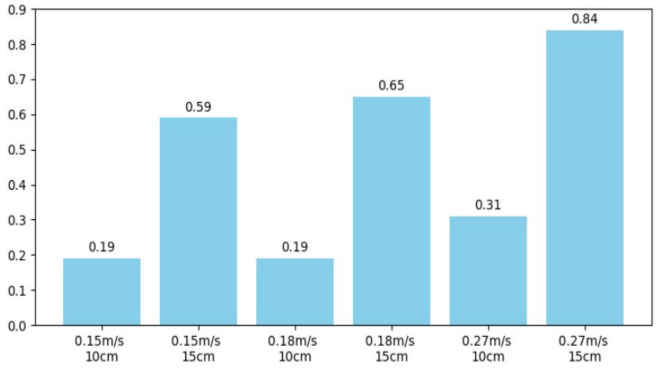


Fig. 6. Average RMSE for varying conveyor speeds and camera distances.

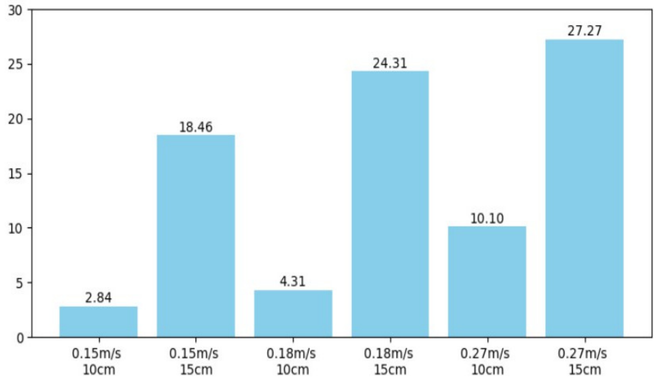


Fig. 7. Average MAPE for varying conveyor speeds and camera distances.

Overall, these findings demonstrate that the proposed system maintains stable performance under varying operational parameters. The integration of Otsu thresholding and watershed transform effectively minimizes segmentation errors, even under slight motion blur or illumination changes. The robustness of this approach confirms its reliability for continuous, high-throughput sorting environments.

F. Interpretation of Computer Vision Results

Measurement accuracy decreased at higher speeds and greater camera distances due to motion blur and reduced visual clarity, with MAPE reaching 27.27% and RMSE 0.31 cm at 0.27 m/s and 15 cm. Despite this, most MAPE values remained below 10% under moderate conditions, indicating acceptable performance. The results emphasize the impact of physical setup on accuracy, while demonstrating the system's resilience across variable operational environments.

The successful implementation of a pixel-to-centimeter measurement model in a dynamic conveyor setting directly addresses the research aim of measuring shallot diameter automatically and accurately. The system's ability to function effectively across varying operational scenarios supports its applicability in real-world environments. Furthermore, the use of computer vision minimizes human intervention and reduces classification subjectivity. These results confirm that the integration of Otsu thresholding, watershed transform, and calibrated measurement techniques provides a solution to the initial problem, thereby meeting both the detection and classification objectives of the study. A summary of the research findings in relation to the original objectives is displayed in Table III.

TABLE III. SUMMARY OF RESEARCH OBJECTIVES AND CORRESPONDING FINDINGS

Research objective	Findings
Develop a system capable of detecting shallots with double shallots and overlapping shallots using Otsu thresholding and the watershed transform.	The combined method of Otsu thresholding and the watershed transform achieved high segmentation accuracy, reaching 99.57% at 0.15 m/s and 10 cm camera distance, outperforming Otsu thresholding alone (99.14%) under the same conditions.
Evaluate the system's performance in measuring the diameter of *shallots* using image segmentation and pixel-to-centimeter ratio, especially under double bulb and overlapping conditions.	The system achieved low RMSE (0.19 cm) and low MAPE (as low as 2.84%) at optimal settings. Performance decreased at higher conveyor speeds and longer camera distances, with MAPE increasing to 27.27% at 0.27 m/s and 15 cm camera distance.

IV. DISCUSSION

A. Comparison with Previous Studies

The hybrid integration of Otsu thresholding and the watershed transform demonstrates clear improvements over earlier segmentation techniques commonly used in agricultural product classification. Prior studies relying on basic thresholding or color filtering often struggled with overlapping or clustered objects, whereas the two-stage segmentation pipeline in this research was able to resolve these complexities more consistently. With segmentation accuracy reaching 99.57% under optimal conditions, the proposed approach surpasses several previous implementations, offering a more robust and quantifiable solution supported by RMSE and MAPE metrics. These results position the method as a substantial contribution to post-harvest computer vision applications.

B. Significance of the Findings

The findings have both theoretical and practical significance. Theoretically, the study provides a replicable framework demonstrating how classical and region-based segmentation can be combined effectively in dynamic environments. Practically, the system offers a feasible automation pathway for small- and medium-scale agricultural operations, improving classification consistency, reducing dependence on manual labor, and supporting productivity in regions where shallots constitute an economically significant crop. The method's efficiency and low computational cost further enhance its applicability.

C. Implications for Computer Vision and Image Processing

The study illustrates the ability of classical segmentation techniques to adapt to real-world conveyor scenarios characterized by movement, orientation variation, and image noise. The consistent performance across different conveyor speeds and camera distances highlights the robustness of the approach. The diameter estimation model using pixel-to-centimeter conversion aligns with broader precision-agriculture trends, reinforcing the relevance of lightweight and real-time computer vision methods for commodity-scale classification tasks.

D. Relevance to Local Agricultural Development

The system presents benefits for local agricultural stakeholders, enabling more efficient and standardized post-harvest workflows. Automated grading improves market competitiveness and reduces human error, particularly in rural areas where skilled labor for manual sorting is limited. Since the system requires only moderate hardware specifications and simple imaging equipment, it is well-suited for community-based or cooperative agricultural operations.

E. Limitation of the Research

Although effective, the system exhibits reduced accuracy at high conveyor speeds and longer camera distances due to motion blur and diminished image clarity. Its reliance on controlled lighting and a uniform background may also limit generalizability to more complex environments. Additionally, performance depends on precise calibration, which must be repeated whenever camera or hardware adjustments occur. These limitations indicate the need for environment-specific tuning before large-scale deployment.

V. CONCLUSION

This study demonstrates that combining Otsu thresholding with the watershed transform significantly enhances the segmentation accuracy of shallots under dynamic, real-time conveyor conditions. The proposed hybrid method outperforms Otsu thresholding used in isolation and remains robust across variations in conveyor speeds and camera distances, achieving a segmentation accuracy of up to 99.57% and diameter measurement precision with a Root Mean Squared Error (RMSE) as low as 0.19 cm. These findings confirm the suitability of classical hybrid segmentation techniques for post-harvest processing environments where overlapping or irregularly shaped objects frequently occur.

Beyond its technical contribution, the system provides a practical and cost-effective solution for automating shallot classification, offering a scalable and reproducible model that can be adapted to other agricultural commodities. Its consistent performance across multiple scenarios highlights its potential for improving quality control processes in agricultural supply chains, particularly in regions where manual sorting remains labor-intensive and prone to inconsistency.

Despite its strengths, the system's performance is sensitive to extreme lighting variations and significant changes in camera positioning, suggesting opportunities for further refinement. Future research should investigate adaptive illumination strategies, enhanced calibration procedures, and the integration of machine learning or deep learning models to improve versatility in more diverse operational environments. Expanding the system to other crop types or linking it with IoT-based agricultural platforms also represents a promising direction for advancing real-time agricultural automation.

ACKNOWLEDGMENT

The research is funded by Hasanuddin University Grant (AIMP Thematic Research Group) under Contract No.00518/UN4.22/PT.01.03/2025. The authors extend their sincere appreciation to the Thematic Research Group for the continuous assistance and facilitation provided throughout the project. Their support, including administrative help to create a conducive research environment, played an essential role in ensuring the successful completion of this study. The authors gratefully acknowledge the institutional resources and contributions provided by Hasanuddin University.

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