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The Effect of Distance, Viewing Angle, and Static Time in Drone Image Detection Technology for Industrial Warehouse Inventory Scanning System

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Abstract

The rapid growth of automation and Industry 4.0 has increased the demand for efficient inventory management systems in industrial environments. Manual inventory inspection is time-consuming, labor-intensive, and prone to human error, particularly in large warehouses and high-storage facilities. The objective of this study is to investigate the effect of distance, viewing angle, and static time in drone image detection technology for industrial warehouse inventory scanning systems. A low-cost quadcopter platform (DJI Tello) was employed, equipped with a camera system and controlled using Python-based programming. Image processing and barcode detection were performed using OpenCV and YOLO integrated with *Pyzbar*, enabling real-time identification and decoding of inventory labels. Experimental evaluations were conducted to analyze the effects of distance, viewing angle, and time-based static positioning on detection accuracy. Repeated experimental procedures showed results that demonstrated that the drone was able to reliably detect and decode barcodes within an optimal range of 30–50 cm, with 30 cm being the most consistent. The optimally detectable viewing angle is within 10 degrees of elevation, with 0 being the most consistent. The optimal time to be exposed to the barcode exceeds 1 second, with 2 seconds showing consistently adequate detectability. The findings confirm that UAV-based image detection systems offer a practical, cost-effective, and scalable solution for automated inventory monitoring. This study emphasizes the possibility of integrating drone technology with computer vision to enhance efficiency, accuracy, and safety in industrial inventory management applications.

1. Introduction

Efficient inventory management is a critical requirement in industrial warehouses, particularly in facilities with high storage density and vertically arranged racks. Conventional inventory inspection methods rely heavily on manual visual checks and handheld barcode scanners, which are time-consuming, labor-intensive, and prone to human error. These limitations become more significant in large-scale warehouses, where accessing elevated storage locations introduces additional safety risks and operational inefficiencies [1].

The advancement of unmanned aerial vehicles (UAVs) and image processing technologies has enabled new approaches for automated inventory monitoring. Camera-equipped UAVs can navigate confined indoor environments and capture visual data from locations that are difficult to reach using conventional methods. When integrated with image detection algorithms, UAVs can perform non-contact inventory scanning by detecting and decoding barcodes directly from stored items, reducing the need for physical handling and manual intervention [2, 3].

Computer vision techniques such as OpenCV and deep learning–based object detection models, including YOLO, have been widely adopted for real-time visual recognition tasks due to their accuracy and computational efficiency [4, 5]. In inventory-related applications, barcode detection using image processing enables rapid identification of stored items from captured images. However, operational parameters such as camera-to-object distance, viewing angle, lighting conditions, and image quality [6, 7] strongly influence detection performance.

Low-cost UAV platforms such as the DJI Tello provide an economically viable solution for experimental and small-scale industrial applications. Despite their affordability and ease of deployment, such platforms are constrained by limited camera resolution, restricted onboard processing capability, and sensitivity to motion and environmental disturbances [8]. These limitations can adversely affect barcode detection accuracy, particularly under non-optimal lighting and oblique viewing angles. [9, 10]

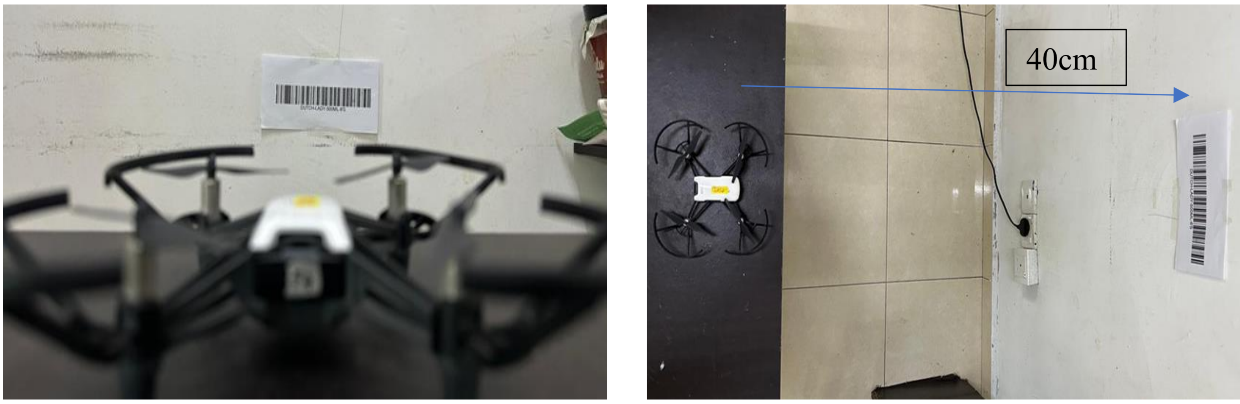
The problem addressed in this study is the lack of experimental validation for the distance, viewing angle, and static time of using low-cost UAVs for reliable barcode-based inventory scanning under varying operational conditions. Therefore, the objective of this research is to investigate the effect of distance, viewing angle, and static time in drone image detection technology for industrial warehouse inventory scanning systems. Experimental investigations are conducted to analyze barcode detection accuracy under different distances, viewing angles, lighting conditions, and static positioning using OpenCV and YOLO-based techniques. The findings of this study aim to establish practical operating limits and demonstrate the potential of low-cost UAV-assisted computer vision systems for automated inventory management in industrial environments.

2. Methodology

This study employed an experimental methodology to evaluate the performance of a UAV-based inventory scanning system using image detection techniques. A DJI Tello quadcopter was utilized as an aerial platform, with image acquisition carried out through its onboard camera system. Barcode detection and recognition were implemented using two approaches: a conventional OpenCV-based image processing pipeline and a YOLOv5 deep learning object detection model, enabling a direct performance comparison. The software used for this project, OpenCV and YOLOv5, was chosen because they are the most frequently utilized tools for image detection technology in industry. The experimental framework was designed to assess detection accuracy and consistency under varying camera-to-barcode distances, viewing angles, and time-based static positioning. All tests were conducted in a controlled indoor environment to minimize disturbances and ensure repeatability. Detection outcomes were recorded and analyzed to evaluate system feasibility, algorithm robustness, and operational limitations.

2.1 Experimental Design

The experimental program was structured to evaluate the performance of a UAV-based inventory scanning system through image detection under controlled indoor conditions. In the distance test, the UAV was positioned at predefined distances from the barcode target, spanning from proximity to the maximum detectable range, and held stationary while multiple image frames were captured to assess detection success, decoding consistency, and performance degradation with increasing distance (as shown in Fig. 1). The viewing angle test involved adjusting the UAV camera to incremental angles relative to the barcode surface, with the drone maintained in a static position at each angle to evaluate algorithm robustness under perspective distortion and oblique orientations (as shown in Fig. 2). In the time-based static positioning test, the UAV hovered at a fixed position for predetermined durations while capturing image data, enabling analysis of how hover stability and dwell time influence barcode recognition accuracy (as shown in Fig. 3). All experimental tests were performed using both conventional OpenCV-based image processing and a YOLOv5 deep learning detection model, allowing a comparative assessment of detection accuracy, consistency, and responsiveness across identical conditions. This comprehensive approach provided insight into the operational limits and practical feasibility of low-cost UAV-integrated barcode detection systems under realistic constraints.

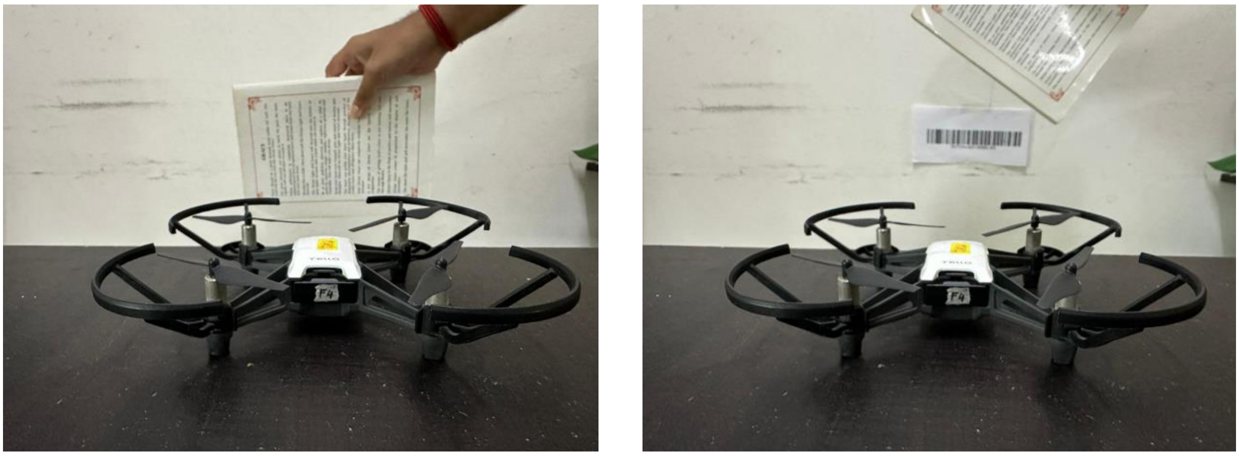


(a) **(b)**

Fig. 1 *Distance-based detection testing from (a) 30-50 cm with a constant angle; and (b) 40 cm with a constant angle*

(a) **(b)**

Fig. 2 *Viewing angle test with (a) angle set at 20 degrees elevation; and (b) constant distance of 30 cm*



(a) **(b)**

Fig. 3 *Time-based static positioning test with (a) no exposure to the barcode; and (b) the barcode exposed for a limited time*

2.2 Parameters and Controls

All experiments were conducted under controlled indoor conditions to minimize external disturbances and ensure repeatability. The UAV was operated at a fixed altitude, and the onboard camera settings were kept constant throughout all tests. The primary experimental variables were camera-to-barcode distance, viewing angle, and time-based static positioning. For each test condition, barcode detection was performed using both

OpenCV-based image processing and a YOLOv5 deep learning model and repeated 10 times to enable direct performance comparison. Detection outcomes were recorded and analyzed for consistency and accuracy. The complete experimental design parameters are summarized in Table 1.

Table 1 *Complete experiment design parameters*

Test category	Test Condition		
	Condition 1	Condition 2	Condition 3
Distance test (Camera-to-barcode distance)	30 cm	40 cm	50 cm
Viewing angle test (Camera viewing angle)	0°	10°	20°
Static positioning test (Exposure duration)	1 s	2 s	3 s

This methodology integrates controlled UAV experiments with algorithm-level performance evaluation to assess the feasibility of automated inventory scanning using image detection. By systematically analyzing distance, viewing angle, and static positioning time and comparing OpenCV-based and YOLOv5-based detection approaches, the study ensures reliable performance assessment under realistic operating conditions.

3. Results and Discussion

The experimental findings were obtained from the UAV-based inventory scanning tests, evaluating barcode detection performance under varying camera-to-barcode distances, viewing angles, and time-based static positioning. Detection outcomes were recorded for both OpenCV-based image processing and YOLOv5 deep learning models to allow comparative analysis. The results are presented and discussed to highlight the influence of operational parameters on detection accuracy, robustness, and consistency, giving insight into the feasibility and practical limitations of low-cost UAV-integrated image detection systems.

3.1 Distance Test Results

Fig. 4 shows the bar chart representing the success rate of OpenCV and YOLOv5 in detecting the barcode from different distances of 30–50 cm. The chart shows that at a distance of 30 cm, OpenCV successfully detects the barcode in all 10 repetitions, while YOLOv5 only detects it 8 out of 10 times. YOLOv5 detects multiple objects at once, so it doesn't focus solely on the barcode. At 40 cm of distance, OpenCV and YOLOv5 can scan the barcode 8 out of 10 times. Lastly, at 50 cm, OpenCV's performance deteriorates to 4 out of 10 times, while YOLOv5 can still detect the barcode 6 out of 10 times. Although YOLOv5 did not fully detect the initial distance of 30 cm, it still detected the barcode's rectangular shape from a distance due to programming, while OpenCV could not distinguish the barcode.

The findings of this study are consistent with and build upon prior research on UAV-assisted warehouse inventory systems and barcode recognition under constrained imaging conditions. Previous studies have emphasized the potential of UAVs to improve efficiency and automation in warehouse inventory management, while emphasizing the necessity of reliable perception and sensing capabilities for practical implementation [2]. In this study, the strong dependence of barcode detection accuracy on distance aligns with the findings reported in [6], where increasing camera-to-barcode distance was shown to reduce image resolution and decoding reliability. The degradation in OpenCV performance beyond 40–50 cm can be attributed to its reliance on clear edges and contours, which become less distinguishable as pixel density decreases. In contrast, YOLOv5 demonstrated comparatively better robustness at longer distances, consistent with deep learning-based detection approaches that rely on learned visual features rather than purely geometric characteristics [5, 10].

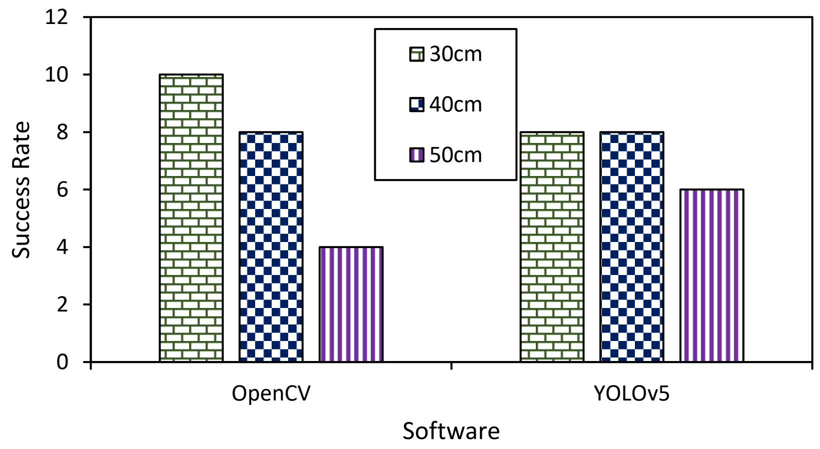


Fig. 4 *Comparison of detectability between OpenCV and YOLOv5 for distance*

3.2 Viewing Angle Test Results

Fig. 5 shows the success rate for both software, OpenCV and YOLOv5, to detect the barcode from an angle of 0 to 20 degrees. The horizontal distance between the drone and the barcode is set at a constant 30 cm. The success rate for 0-degree sides to OpenCV is 10 out of 10, whereas YOLOv5 achieves 8 out of 10. This data is shared with the distance result above since the setting is the same. When the angle is elevated to 10 degrees, both OpenCV and YOLOv5 can detect the barcode with the same success rate of 6 out of 10 repetitions. At 20 degrees, the rate of success drops significantly. For OpenCV, the success rate is only 1 out of 10 test runs, whereas YOLOv5 can detect 2 times. The reason is that the barcode is misaligned, the drone's camera quality is poor, and pixels distort, making the barcode unclear.

The viewing-angle results further support existing literature on the sensitivity of barcode recognition systems to perspective distortion. Zhang et al. [7] reported a significant decline in detection accuracy as viewing angle increases, which closely matches the sharp reduction in success rates observed beyond 10° in this experiment. As the barcode moves away from the camera's central field of view, perspective distortion and uneven pixel distribution reduce image clarity, affecting both OpenCV and YOLOv5 performance. These effects are further amplified by the limitations of low-cost UAV cameras, such as the DJI Tello, which have restricted resolution and image quality compared to industrial-grade sensors [8]. Such hardware constraints make precise alignment between the UAV and barcode particularly important for reliable detection.

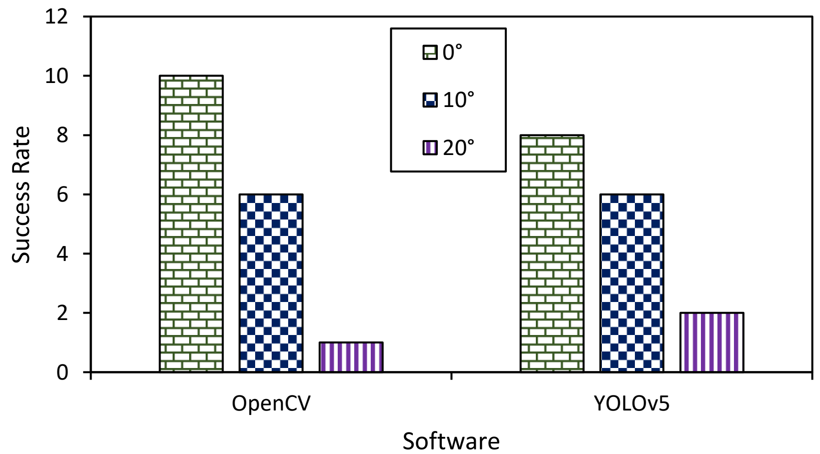


Fig. 5 *Comparison of detectability between OpenCV and YOLOv5 for viewing angle*

3.3 Time-Based Static Positioning Results

Fig. 6 shows the success rate for OpenCV and YOLOv5 in detecting the barcode when exposed to it for a limited period of time. The horizontal distance between the drone and the barcode is constantly set to 30 cm across all experiments. When the barcode is exposed for 1 second, it is detected 4 times by OpenCV and 2 times by YOLOv5. This discrepancy occurs because OpenCV can detect the barcode more quickly by forming a rectangle around it, while YOLOv5 can identify the rectangle but cannot read the barcode itself. When the barcode is exposed for 2 seconds, the rate of success increases drastically, with 8 times out of 10 for OpenCV and 6 times for YOLOv5. OpenCV is able to detect better when the distance is near, even when being exposed for just 2 seconds. When the barcode is exposed for 3 seconds, OpenCV is able to detect it every single time, whereas YOLOv5 fails twice. The static exposure time results highlight the importance of temporal stability in UAV-based image detection, an aspect that is often briefly addressed in earlier studies. OpenCV exhibited faster initial detection due to its lightweight, rule-based processing approach [4], allowing it to identify barcode contours even during short exposure periods. YOLOv5, however, required longer exposure times to reliably detect and decode the barcode, reflecting the additional computational and feature-extraction requirements of deep learning models [5]. The significant improvement in detection accuracy at exposure times of 2–3 s is consistent with established principles in robotic vision, where sufficient dwell time helps reduce motion blur and improves feature extraction reliability [9]. Overall, the experimental findings reinforce existing research that controlled UAV positioning and imaging conditions are critical for effective warehouse inventory automation [1], while also contributing experimentally validated insights tailored specifically to low-cost UAV-based barcode inventory scanning systems.

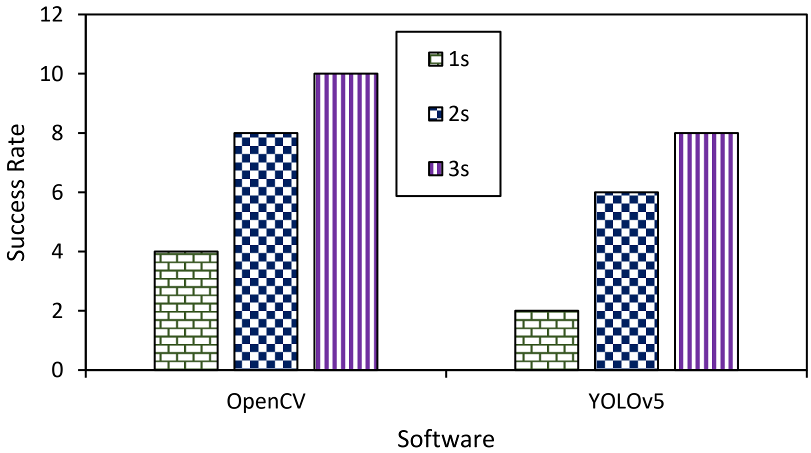


Fig. 6 *Comparison of detectability between OpenCV and YOLOv5 for time-based static positioning*

3.4 Optimization Parameter

Based on the experimental results, OpenCV and YOLOv5 demonstrate distinct performance characteristics under varying operational conditions. OpenCV consistently outperforms YOLOv5 at closer distances and under stable viewing conditions, achieving a perfect detection rate at 30 cm, a 0° viewing angle, and exposure times of 3 s. This is mainly due to its direct geometric and contour-based detection, which allows faster and more focused barcode recognition when the barcode is clearly visible and centrally aligned. In contrast, YOLOv5 shows better robustness at increased distances and moderate degradation conditions, such as at 50 cm, where it maintains a higher detection rate than OpenCV by leveraging learned features that can still recognize the barcode's rectangular structure even when pixel clarity reduces. However, YOLOv5's multi-object detection capability results in lower accuracy at very close ranges and short exposure times, as the model does not exclusively prioritize barcode detection. For viewing angles, both methods experience a significant decline beyond 10°, with YOLOv5 marginally outperforming OpenCV at higher angles due to its feature-based learning approach. Considering all parameters, the optimal operating conditions for reliable barcode-based inventory scanning using a low-cost UAV are a horizontal distance of 30–40 cm, a viewing angle of 0–10°, and a static exposure time of at least 2–3 s. Under these conditions, OpenCV provides the highest detection accuracy, while YOLOv5 serves as a more robust alternative when distance or image quality constraints are present.

4. Conclusion

This study experimentally evaluated the effectiveness of a low-cost UAV-based barcode inventory scanning system by analyzing the influence of distance, viewing angle, and static exposure time on detection accuracy using OpenCV and YOLOv5. The objective of this study is to investigate the effect of distance, viewing angle, and static time in drone image detection technology for industrial warehouse inventory scanning systems. The results demonstrate that barcode detection performance is highly sensitive to UAV positioning and image acquisition conditions. At shorter distances, particularly 30–40 cm, and low viewing angles of 0–10°, both OpenCV and YOLOv5 achieved higher success rates, confirming that proximity and near-perpendicular alignment between the drone and barcode are critical for reliable detection. OpenCV consistently performed better under optimal and stable conditions due to its fast, contour-based detection approach, while YOLOv5 showed comparatively better robustness at longer distances and under moderate degradation by leveraging learned visual features.

The static time experiments further revealed that sufficient exposure duration is essential for successful barcode recognition. Detection accuracy improved significantly when the barcode was exposed for at least 2 s. Near-perfect performance was achieved at 3 s, indicating that brief hovering is necessary to compensate for camera limitations and motion-induced blur in low-cost UAV platforms. Overall, the findings validate that a low-cost drone equipped with image detection algorithms can be effectively used for industrial warehouse inventory scanning when operated within well-defined parameters. The optimal configuration identified in this study, a 30–40 cm distance, a 0–10° viewing angle, and a minimum static time of 2–3 s, provides a practical guideline for implementing cost-efficient UAV-based inventory systems and serves as a foundation for future improvements involving better cameras, lighting control, and real-time detection optimization.

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Conflict of Interest

There is no conflict of interest regarding the publication of the paper.

Author Contribution

The authors confirm contributions to the paper as follows: ***study conception and design:*** *Thaanes Kumara Piran, Ahmad Hamdan Ariffin, Yashlen Pichyalagan;* ***data collection:*** *Thaanes Kumara Piran;* ***analysis and interpretation of results:*** *Thaanes Kumara Piran;* ***draft manuscript preparation:*** *Thaanes Kumara Piran, Ahmad Hamdan Ariffin, Yashlen Pichyalagan. All authors reviewed the results and approved the final version of the manuscript.*

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