Detecting Motion-Induced Blur Palm Tree for Oil Palm Automation in Online System Settings

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***Abstract*— Detecting palm trees efficiently is essential for automating tasks in oil palm plantations, including targeted spraying, harvesting, weed management, and yield estimation. However, challenges arise when capturing images in motion. This research focuses on using YOLO-based detectors to identify palm trees affected by motion-induced blur. Three models are trained with different datasets: one with only sharp palm tree images, another with a mix of sharp and blurred objects, and a third segregating the two categories. The models' performance is evaluated for accuracy and inference time, demonstrating the effectiveness of our approach in pinpointing motion-blurred palm trees. This study enhances the reliability of systems analyzing visual data in real-time.**

I. Introduction

The oil palm industry faces productivity challenges due to labor shortages, prompting the adoption of automation for tasks such as pesticide spraying and fruit harvesting. Detection of palm trees is crucial for automation, involving visual sensors on mobility platforms like UGVs and drones. However, uneven terrain and motion-induced blur from mobile sensors compromise image quality. Factors like vibrations, camera shake, and slow shutter speeds contribute to these distortions, impacting the performance of detection models trained on sharp images. Solving these challenges is essential for optimizing automation systems and improving efficiency in the oil palm industry

II. Methodology

Addressing blurry images often involves using deblurring algorithms, but these can be time-consuming and unsuitable for real-time online systems. In our study, we opt for a different approach by expanding training datasets. Three distinct datasets are employed: one with sharp palm tree images, another blending sharp and blurred objects, and a third isolating the two categories. These datasets, captured with a ZED2i camera on a mobility platform in a plantation (as depicted in Fig. 1), introduce variations in sensor movement speed and lighting conditions. Additionally, motion-blurring augmentation is explored to increase the number of blurry images. We use YOLO-based models, specifically YOLOv5s [2] by Ultralytics, known for their compact size and swift inference, enabling real-time detection in online systems. The evaluation of trained models includes assessing detection accuracy in both sharp and blurry scenarios, utilizing metrics proposed in [3].

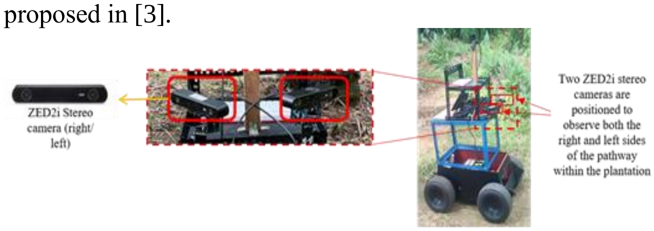

Figure 1. Data collection platform

III. Results and Discussion

The study presents training and testing datasets summary, including sharp and motion-induced blurry images. Six trained models are developed as summarized in Table 1. Evaluation of these models reveals that the optimal training configuration involves splitting the palm tree classes into sharp and blurry groups while unfreezing the backbone layers of the YOLOv5s architecture during training.

Table 1. Summary of the trained model

Model	**Description**
YOLOv5s_s_freeze YOLOv5s_s_unfreeze	One class output (palm tree). Trained using only sharp images.
YOLOv5s_c_freeze YOLOv5s_c_unfreeze	One class output (palm tree). Trained using a combination of sharp and blurry images.
YOLOv5s_sb_freeze YOLOv5s_sb_unfreeze	Two-classes output (sharp tree & blurry tree). Trained using sharp and blurry images respectively.

References

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