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Development and evaluation of a machine vision system for coconut harvesting and collection

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Abstract

This study aimed to develop and analyze a machine vision system for real-time coconut detection to enhance robotic harvesting and collection. Images of healthy and defective coconuts, both green and brown, were captured from Coimbatore and Tirupur districts in Tamil Nadu. These images were processed using a Faster R-CNN model integrated with necessary hardware and software. The system successfully identified the class and grade of coconuts, demonstrating potential applications in robotic harvesting and grading. The model achieved 88% precision and 85% accuracy. Limitations and proposed solutions for the system's operation are discussed with recommendations for operation-specific measures to improve future robotic developments.

Key words: Coconut farming, logistics, machine vision, robotics, model

Introduction

Coconut (*Cocos nucifera*), domesticated during the Neolithic age, is a vital crop in tropical regions, prevalent in over eighty countries (Setiado *et al.,* 2021). In India, coconut cultivation is a significant agricultural activity, with Tamil Nadu being a prominent producer (Table 1). Despite its commercial viability, coconut farming faces challenges such as labor shortages and high wages for skilled labourers (Manoharan and Megalingam, 2019). Traditional manual harvesting methods are hazardous and inefficient, necessitating the adoption of mechanized solutions.

Recent advancements in agricultural robotics have shown promise in addressing these challenges. Machine vision, a proven technology in crop detection and pest management (Habib *et al.,* 2020; Kim *et al.,* 2020; Kuznetsova *et al.*, 2020; Maray *et al.,* 2022; Montoya-Cavero *et al.,* 2022), offers the potential for enhancing robotic systems for coconut harvesting and collection. However, existing research primarily focused on model development for specific crops rather than multi-crop detection models (Xiao *et al.,* 2023).

This study aims to develop and evaluate a machine vision system for real-time coconut detection, with applications in robotic harvesting and grading. We focus on capturing and processing images from Coimbatore and Tirupur districts to create a robust model using the Faster R-CNN architecture. The system's performance, limitations, and potential improvements are discussed to provide a foundation for future advancements in robotic coconut harvesting.

Materials and methods

The research focused on the Coimbatore and Tirupur districts situated in the Tamil Nadu state. Since, coconut differes from other crops in harvest process, as after harvest cutting, the bunches falls of to the ground whereas other crops may have followed collection system. In coconut collection was done usually after the entire field's harvest cut completed. To address the ergonomic challenges faced by coconut laborers (Mohankumar *et al.*, 2013), a new system was designed for coconut collection and grading. This proposed system incorporates an advanced machine vision technology to enable robotic machinery for efficient harvesting,

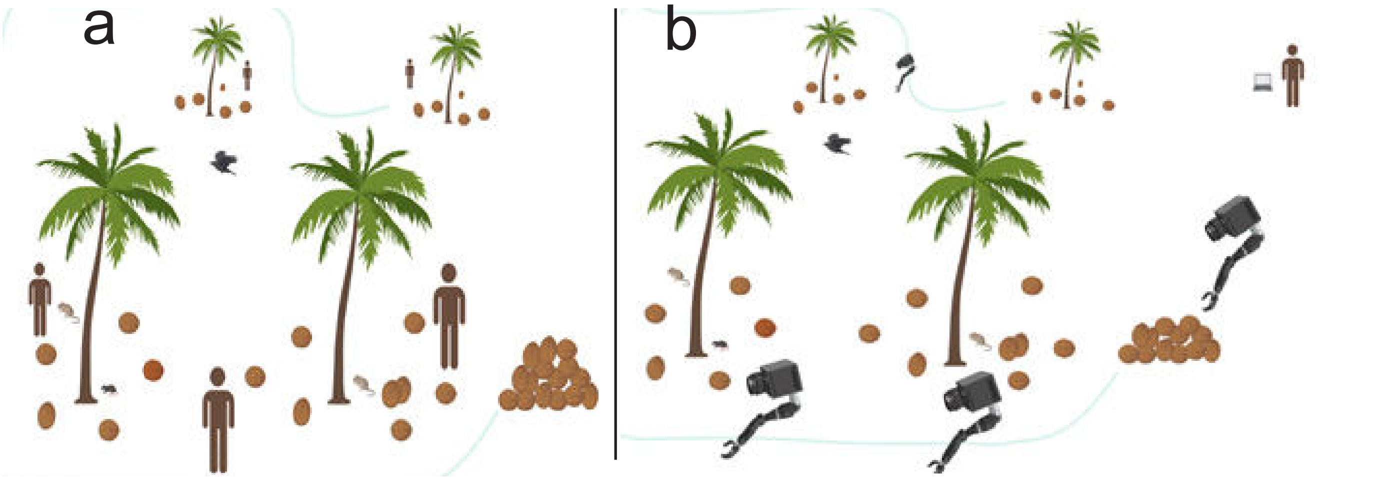

Fig. 1. Coconut harvesting and collection - (a) Existing practice (a) and (b) Proposed concept

Fig. 2. Proposed concept of stationery coconut grading system

collection, and simultaneous grading (Fig. 1) or, alternatively, stationary grading robots (Fig. 2). The proposed system necessitates a machine vision component, which was developed through key stages: Training dataset creation, testing as well as image collection done in the Jupyter environment on Anaconda with Python.

Image collection: A 48-megapixel smartphone camera (8 GB RAM and 128 GB storage) was employed to capture images for this study. A total of 1250 images were systematically gathered from the agricultural fields of farmers in Coimbatore and Tirupur districts. These collected images were then meticulously classified into three distinct categories: green, brown, and defective. Sample images are shown in Fig. 3.

Several key steps were followed in the study. Image datasets were categorized into green & brown, nondefective and defective images in a hierarchical structure for data collection. The collected data was then prepared as a training dataset through three stages: I then annotated, where the images were labeled with relevant categories, pre-processed, where the data was cleaned and standardized for consistency, and augmented, where the dataset diversity was increased by applying transformations such as rotation and flipping. This was followed by model development, which involved model design, model validation on unseen data, and model implementation for practical applications. A feedback loop was finally established, so that the model could feed back to earlier stages for continuous refinement and improvement.

Training: The training dataset underwent a series of processes,

Fig. 4. Annotation of different classes of coconuts

including annotation, pre-processing, augmentation, and model deployment. These were done in Python language with R-CNN architecture. During annotation, the collected images were categorized into three classes: green, brown, and defective. This involves marking the RoI (Region of Interest) which is referred to as the bounding box as shown in Fig.4.

The annotated images underwent several pre-processing steps, which included resizing to a standard dimension of 640x640, orientation adjustment, cropping, tiling, and isolation of specific RoI.

After the initial pre-processing stage, three distinct augmentation approaches were employed to create three distinct models. Typically, augmentation techniques encompass operations such as flipping (horizontal/vertical), cropping (5% zoom), rotating (-15° to +15°), shearing, cutting out, mosaicing, introducing noise, and colour (varying -25% to 25% exposure, hue, and saturation). The bounding box (after annotation, the marked portion of coconut in the image) RoI was also subjected to these augmentation techniques. However, for this study, augmentation was applied in three specific manners: no augmentation, selective augmentation (flip, rotate, noise, shear), and complete augmentation (all augmentation of image and bounding box).

Model validation: The performance of the developed models was initially assessed for feasibility using a set of 100 previously collected test images. Subsequently, the model underwent testing in five different fields. The identification performance was quantified in terms of true positives, true negatives, false positives, and false negatives. Precision, recall, and accuracy were then calculated for each model using the following equations (1,2 & 3) (referred from Dhivyanth *et al.,* 2022).

$$\text{Precision} = \frac{TP}{TP+FP} \quad (1)$$

$$\text{Recall} = \frac{TP}{TP+FN} \quad (2)$$

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (3)$$

Fig. 3. Some collected images of different classes of coconuts

Factors influencing the coconut machine vision system: The development of the machine vision system at the field level was documented and reported, taking into account various influencing factors. Solutions to address identified constraints were also discussed.

Results and discussion

Developed models 1 and 2 successfully identified the different classes of coconuts. Defective, green and brown coconuts were classified by the models. Whereas, the model developed from trial 3 failed to detect the coconuts and cannot classify the classes of coconuts. The performance of the developed models was assessed and found to be consistent with the reported values in Table 2. Trial 2 (selective augmentation) had the highest accuracy and precision. Classified coconuts on various classes of coconut identified from the developed model (from trial 2) are illustrated in Fig. 5. The limiting factors found on the machine vision of the coconut were the angle of view, light, noise and colour. They are explained in the discussion section.

Table 2. Confusion matrix

Trial	True positive	False negative	True negative	False positive	Precision	Recall	Accuracy
1	6/10	3/10	9/10	4/10	60%	0.67	68%
2	8/10	2/10	9/10	1/10	88%	0.80	85%
3	2/10	6/10	2/10	9/10	18%	0.25	21%

Confidence level: <85%

The study shows the feasibility of the deployment of machine learning for coconut identification and classification. This was also represented by previous studies earlier for coconut (Manjunath *et al.* (2016); Titus *et al.,* 2017) and a similar crop areca nut (Anitha *et al.,* 2022). From the confusion matrix, trial 2 was found to be precise and accurate. Followed by trial 1 and very least was trial 3. This infers that selective augmentation performs best for training the datasets. As it is commonly known that, augmenting by variation in hue-like factors affects the accuracy of the results, trial 3 failed to give reasonable outcomes. But no augmentation had satisfactory results but could not perform highest. Trial 2 which is superior has similar results to a mango detection algorithm which had 89% (Amna *et al.,* 2023). From the previous studies (Maharana *et al.*, 2022; Shin *et al.*, 2020), augmentation was considered an important step in the machine learning process and this study implies the importance of augmentation selection.

Various limitations observed during the experimented detection process are discussed as follows. Considerations for the angle of view are crucial when framing a shot, impacting the overall composition and perspective of the image. This can be understood from the images shown in Fig. 6. But the case doesn't affect much the harvest detection as compared to the collection or grading process. The effective solution for this was having more than one camera for identification, testing more than one time at different views, video processing with a rotational view, etc.

The quality and quantity of available light significantly influence the visual outcome, emphasizing the need for strategic lighting choices to enhance the performance. The effect of light influences much more harvest detection contrasting the collection detection (Fig.7) since the camera might focus bottom to top or side-wards prone to direct sunlight while harvesting whereas the camera focuses top to bottom or tilted top to bottom for collection systems not directly exposed to sunlight. Commercial availability of light sources and their constraints (Ren *et al.,* 2022) must be considered for nullifying these limits. In contrast, the grading machine vision system remains less challenged by light effects since the collected coconut can be mobilized and processed in optimum light-filled areas.

Managing and minimizing noise, unwanted visual distortions, or graininess, is essential for achieving a clean and professional appearance in photographs. Coconut harvest maturity detection was subjected to occlusion by the leaflets, petiole, cushion, or other tree parts. The same effect was experienced by Dhivyanth *et al.* (2022). Coconut identification for collection (Fig. 8) was affected by noise such as soil cover, shaded-leaf overlaps, etc., and needs in-depth training to achieve the best performance. Dataset acquired under different environmental conditions (Chen *et al.,* 2022) discussed similar constraints on fruit. Occluded and dense scenarios increase the difficulty in association with recall rate (Li *et al.,* 2022b).

Coconut harvest and utilization were based on colour (Javel *et al.,* 2018; Subramanian and Sankar, 2021). Careful attention to colour balance and saturation is vital, as it plays a pivotal role in conveying the actual by ensuring an accurate representation of the subject matter (Koirala *et al.,* 2019). Different varieties of coconut have colour variations in exocarp like green, orange,

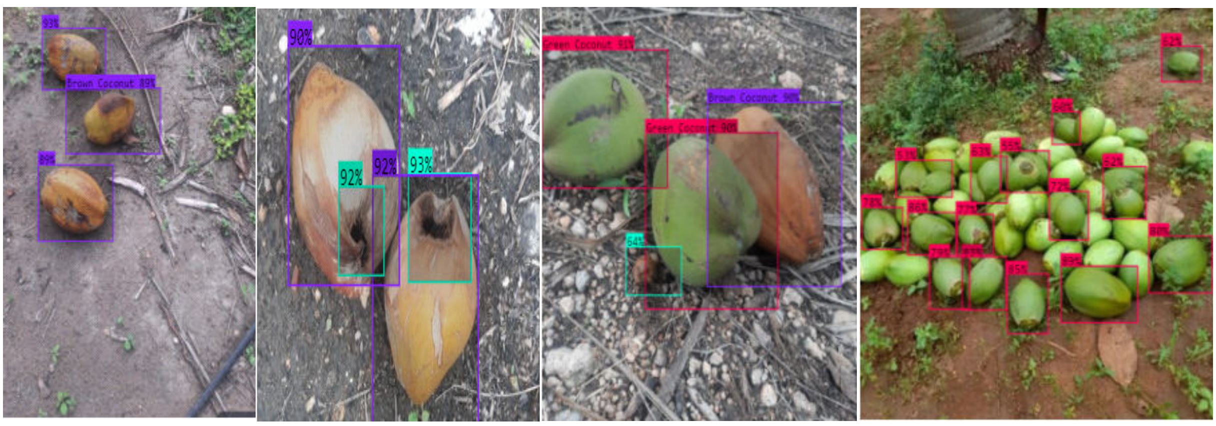

Fig. 5. Identification of various classes of coconut using the developed model

Fig. 6. Effect of angle of view in coconut machine vision classification

Fig. 7. Noise due to light on coconut detection through machine vision

Fig. 8. Image sets representing noise on coconut detection

yellow, etc. (Beveridge *et al.,* 2022).

Several advantages of coconut crops over fruit crops exist and are discussed as follows. Coconut maturity is common to the entire bunch while looking into the harvest maturity detection subjected to occlusion of various noises, whereas the collection system acquiring the image from the ground is subjected to different occlusions which are prone to affect the detection accuracy and precision. This also conveys that harvest detection has less probability to false positives but the collection operation's detection might have false positives (Fig. 6).

The results provide a solid foundation for the use of machine vision in efficient coconut harvesting and collection systems. When the proposed coconut collection and grading system is developed and integrated with machine vision technology, it is expected to offer the following benefits: elimination of human work through autonomous operations, saving time, labor, and energy by combining collection and grading processes, and providing farmers with the ability to make informed pricing decisions based on grade classified coconuts. In addition, it offers a practical solution to the problem of labor shortages in the agricultural sector. Machine vision based grading is anticipated to be a key innovation in agriculture, and coconut grading is expected to lead this advancement as noted in previous studies (Natarajan and Ponnusamy, 2022; Li *et al.*, 2022a).

The study revealed that the machine vision model shows to have 88% precision and 85% accuracy. Of the three augmentation methods used during dataset training, selective augmentation performed the best among the three. In addition, the study also identified several limiting factors of the machine vision system for coconuts, including angle of view, noise occlusion, color variations, and lighting conditions. According to these findings, it was concluded that operation-specific machine vision systems for harvesting, collection, and grading would outperform a centralized detection system. This study also provides useful insights and thoughts for constructing a reliable machine vision system for coconut operations.

References

Anitha, A.C., R. Dhanesha, C.L. Shrinivasa Naika, A.N. Krishna, P.S. Kumar, and P.P. Sharma, 2022. Arecanut bunch segmentation using deep learning techniques. *Int. J. Circuits, Sys. Signal Process.*, 16: 1064-1073.

Amna, M.W.A., L.I. Guiqiang, and M.F. Muhammad, 2023. Machine vision-based automatic fruit quality detection and grading. *Front. Agric. Sci. Engg., https://doi.org/10.15302/J-FASE-2023532*

Beveridge, F.C., S. Kalaipandian, C. Yang, and S.W. Adkins, 2022. Fruit biology of coconut (*Cocos nucifera* L*.). Plants*, 11(23): 3293.

Chen, J., H. Liu, Y. Zhang, D. Zhang, H. Ouyang, and X.A. Chen, 2022. Multiscale lightweight and efficient model based on yolov7: applied to citrus orchard. *Plants*, 11: 3260.

Dhivyanth, L.G., P. Soni, R. Pareek, Machavaram, M. Nadimi and J. Paliwal, 2022. Detection of coconut clusters based on occlusion condition using attention-guided faster R-CNN for robotic harvesting. *Foods*, 11(23): 3903.

Habib, M.T., A. Majumder, A.Z.M. Jakaria, M. Akter, M.S. Uddin and F. Ahmed, 2020. Machine vision based papaya disease recognition. *J. King Saud Univ.-Comput. Info. Sci*., 32(3): 300-309.

Javel, I.M., A.A. Bandala, R.C. Salvador, R.A.R. Bedruz, E.P. Dadios, and R.R.P. Vicerra, 2018. Coconut Fruit Maturity Classification using Fuzzy Logic, IEEE, *10th Int. Conf. on Humanoid, Nanotech., Inf. Tech., Commun. Control, Environ. Manage. (HNICEM).* Baguio City, Philippines.

Kannan, B., K.P. Ragunath, R. Kumaraperumal, R. Jagadeeswaran and R. Krishnan, 2017. Mapping of coconut growing areas in Tamil Nadu, India using remote sensing and GIS. *J. App. Nat. Sci.,* 9(2): 771-773.

Kim, W.S., D.H. Lee, and Y.J., Kim, 2020. Machine vision-based automatic disease symptom detection of onion downy mildew. *Comp. Elec. Agric.,* 168: 105099.

Koirala, A., K.B. Walsh, Z. Wang and C. McCarthy, 2019. Deep learning-Method overview and review of use for fruit detection and yield estimation. *Comp. Elec. Agric.*, 162: 219-234.

Kuznetsova, A., T. Maleva and V. Soloviev, 2020. Using YOLOv3 algorithm with pre-and post-processing for apple detection in fruit-harvesting robot. *Agron.*, 10(7): 1016.

Li, X., R.M. Guillermic, M. Nadimi, J. Paliwal and F. Koksel, 2022a. Physical and microstructural quality of extruded snacks made from blends of barley and green lentil flours. *Cereal Chem.,* 99(5): 1112-1123.

Li, Y., Q. Feng, T. Li, F. Xie, C. Liu and Z. Xiong, 2022b. Advance of Target visual information acquisition technology for fresh fruit robotic harvesting: A review. *Agron.*, 12: 1336.

Maharana, K., S. Mondal and B. Nemade, 2022. A review: Data pre-processing and data augmentation techniques. *Global Transitions Proc.*, 3(1): 91-99.

Manjunath, V.N., S. Aradhya, S. Siddesha and S.K. Niranjan, 2016. Segmentation of coconut crop bunch from tree images. *Second Int. Conf. on CCIP*. Mysuru, India.

Manoharan, S.K. and R.K. Megalingam, 2019. Coconut tree structure analysis - Background work for an unmanned coconut harvesting robot design. In: Info., *Communi. Computing Tech.. Commun. Comput. Info. Sci.,* Minz S., S. Karmakar, L. Kharb (eds), Springer, Singapore, 835: 207-222.

Maray, M., A.A. Albraikan, S.S. Alotaibi, R. Alabdan, M. Al Duhayyim, and W.K. Al-Azzawi, 2022. Artificial intelligence-enabled coconut tree disease detection and classification model for smart agriculture, *Comp. Elec. Engg.*, 104: 108399.

Mohankumar, A.P., D.A. Krishnan and K. Kathirvel, 2013. Development of ergo refined coconut tree climbing device. *Afr. J. Agric. Res.,* 8(44): 5530-5537.

Montoya-Cavero, L.E., R.D. Torres, A. Gómez-Espinosa and J.A.E. Cabello, 2022. Vision systems for harvesting robots: Produce detection and localization. *Comp. electron. Agric.*, 192: 106562.

Natarajan, S. and V. Ponnusamy, 2022. Agri-food products quality assessment methods. *Comp. Vision Machine Learning Agric.*, (2): 121-136.

Ren, Z., F. Fang, N. Yan and Y. Wu, 2022. State of the art in defect detection based on machine vision. *Int. J. Prec. Eng. Manufacturing-Green Tech*., 9(2): 661-691.

Setiado, H., M.A. Sinaga, D.S. Hanafiah and R.I. Damanik, 2021. Identification of morphological characters and kinship of coconut genotypes (*Cocos nucifera* L.) in Aceh Tamiang District, Aceh, *IOP Conf. Series: Earth Environ. Sci.*, 782(4): 042057

Subramanian, P. and T.S. Sankar, 2021. Detection of maturity stages of coconuts in complex background using Faster R-CNN model. *Biosys. Eng*., 202(6): 119-132.

Shin, J., Y.K. Chang, B. Heung, T. Nguyen-Quang, G.W. Price, and A. Al-Mallahi, 2020. Effect of directional augmentation using supervised machine learning technologies: A case study of strawberry powdery mildew detection. *Biosys. Eng*., 194: 49-60.

Titus, A.B., T. Narayanan and G.P. Das, 2017. Vision system for coconut farm cable robot. In 2017 IEEE *Int. Conf. Smart Tech. Manage. Comp, Commun., Controls, Energy Mater. (ICSTM),* IEEE. 443-450 pp.

Xiao, F., H. Wang, Y. Xu, and R. Zhang, 2023. Fruit detection and recognition based on deep learning for automatic harvesting: An Overview and Review. *Agron.,* 13(6): 1625.

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