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COMPARATIVE ANALYSIS OF ANCHOR-BASED AND ANCHOR-FREE YOLO MODELS FOR MOBILE-BASED TROPICAL FRUIT DISEASE DETECTION

MURNI SYAFIQAH BALQIS MOHD SUKOR[1],
A. R. SYAFEEZA[1,*], ASAR KHAN[1], SHAHID RAHMAN[2]

[1]Faculty of Electronics and Computer Technology and Engineering,
Universiti Teknikal Malaysia Melaka, Malaysia
[2]Department of Computer Science, University of Buner, Pakistan
*Corresponding Author: syafeeza@utem.edu.my

Abstract

Fruit diseases pose a major challenge to crop yield and quality, particularly in tropical fruits such as bananas, mangoes, and guavas. These fruits are dietary staples and contribute significantly to Malaysia's agricultural GDP, rural livelihoods, and export income. Traditional manual detection methods are time-consuming and error-prone, highlighting the need for automated and mobile-compatible solutions. This study presents a comparative analysis of anchor-based (YOLOv7-tiny) and anchor-free (YOLOv8n and YOLOv10n) object detection models for detecting fruit diseases. A custom dataset comprising 19 disease and disease-free classes was compiled and augmented. All models were trained with consistent hyperparameters and evaluated using mAP@50, precision, recall, and F1-score metrics. YOLOv8n achieved the highest mAP@50 of 0.945, followed closely by YOLOv10n at 0.936, while YOLOv7 tiny demonstrated consistently lower performance across all evaluated metrics. The results demonstrate the superior performance and adaptability of anchor-free models, making them better suited for real-time, resource-constrained environments such as mobile agricultural applications. This study provides insights for deploying lightweight deep learning models in tropical fruit disease detection, contributing to precision farming, and supporting Malaysia's food security and economic sustainability.

Keywords: Fruit disease detection, Object detection, YOLOv7-tiny, YOLOv8n, YOLOv10n.

1. Introduction

Fruits are naturally low in calories and fat while supplying essential nutrients including vitamin C, potassium, and dietary fiber [1], making them a vital component of a healthy diet. Beyond their nutritional benefits, fruits play a pivotal role in global agriculture, contributing to local consumption, international trade, economic stability, and food security. In 2022, global production reached approximately 59 million metric tons for mangoes, mangosteens, and guavas, while banana production exceeded 135 million metric tons worldwide [2]. With a 2022 production output of 26.3 million metric tons, India is a strong producer, especially of mangoes [3]. These production figures underscore the economic significance of fruit cultivation for farmers and the broader agricultural sector.

However, these fruits are exposed to various diseases that are significant challenges to agricultural productivity. The most common disease that affects bananas, mangoes, and guavas is anthracnose disease, caused by Colletotrichum species that can lead to yield losses up to 100% [4]. This disease affects commercially farmed fruit cultivars due to the absence of resistant varieties. Other than anthracnose, other diseases also affect these fruits that need to be taken care of at an early stage. By detecting the diseases early, farmers can separate the diseased fruits from the healthy, so the disease stops affecting more fruits.

Conventional fruit disease identification relies heavily on manual inspection by farmers or agricultural experts. Such approaches are time-consuming, labor-intensive, and prone to subjective judgment and human error [5, 6]. Considering these issues, computer vision-based object detection models have surfaced as promising medium for early and precise disease identification. Such models do facilitate the automation of disease recognition processes, hence improving both operational efficiency and diagnostic precision in fruit disease detection. A study on mango fruit disease detection reveals that a computer vision system utilizing convolutional neural networks (CNNs) achieved a classification accuracy of 98% significantly enhancing in the quality assessment [7]. Among object detection frameworks, the You Only Look Once (YOLO) family has emerged as a leading solution due to its real-time detection capability and end-to-end learning architecture, making it suitable for time-critical agricultural applications.

Despite extensive use of YOLO models in agricultural imaging, most existing studies focus on accuracy improvements within a single YOLO variant, with limited investigation into the comparative effectiveness of anchor-based versus anchor-free detection paradigms, particularly under mobile and resource-constrained deployment scenarios. Moreover, there is a lack of systematic benchmarking using balanced multi-fruit datasets under consistent training configurations**,** which makes it difficult to draw reliable conclusions regarding model suitability for real-world agricultural use.

This study addresses the identified research gap by investigating whether anchor-free YOLO models provide superior detection accuracy and deployment suitability compared to anchor-based YOLO models for mobile-based tropical fruit disease detection. To this end, a comparative evaluation is conducted involving one anchor-based model (YOLOv7-tiny) and two anchor-free models (YOLOv8n and YOLOv10n), using a custom-prepared, balanced dataset comprising banana, mango, and guava disease images. Model performance is assessed using standard object detection metrics, including mean Average Precision (mAP@50), precision, recall, F1-score, and inference latency, with particular emphasis on real-time applicability. The focus on lightweight YOLO variants is motivated by practical agricultural constraints such as limited computational resources, unstable network connectivity, and the need for reliable on-device inference in rural farming environments. Accordingly, the findings aim to guide researchers and developers in selecting detection models that balance accuracy and computational efficiency for precision agriculture applications, particularly in tropical regions with comparable operational conditions.

This study contributes (i) a comprehensive comparative evaluation of anchor-based vs. anchor-free YOLO models for tropical fruit disease detection, (ii) deployment insights for mobile-compatible systems, and (iii) a custom, balanced dataset for disease classification in bananas, mangoes, and guavas, enabling future development of lightweight agricultural diagnostic tools.

2. Literature Review

The integration of deep learning techniques in agriculture has expanded significantly in recent years, particularly for applications related to crop monitoring, pest detection, and plant disease diagnosis. Among various object detection frameworks, the You Only Look Once (YOLO) family has gained considerable attention due to its real-time detection capability, unified architecture, and suitability for deployment in time-sensitive agricultural environments [8]. Continuous architectural improvements across successive YOLO versions have enhanced detection accuracy while maintaining computational efficiency, reinforcing their suitability for precision farming applications.

2.1. YOLO-based object detection in agricultural applications

YOLO-based models have been widely adopted for agricultural object detection tasks, including fruit disease identification, pest monitoring, and crop and weed detection. Recent studies demonstrate that enhanced YOLO architectures can achieve robust performance across diverse crop types. For example, MAR-YOLOv9, an improved variant of YOLOv9, was evaluated on multiple agricultural datasets involving maize, wheat, rapeseed flowers, and rice panicles, achieving an improvement of up to 39.18% in mAP@50 compared to several mainstream object detectors, and outperforming the base YOLOv9 model by 1.28% [9].

Similarly, YOLOv8 variants have shown promising performance in pest and disease detection tasks. In the detection of fall armyworms, YOLOv8n achieved the highest mAP@50 compared to larger YOLOv8 variants, highlighting the effectiveness of lightweight architectures for agricultural monitoring [10]. Comparable results were reported in crop and weed detection tasks, where YOLOv8-based models achieved a mAP@50 of approximately 89.7%, demonstrating their robustness in complex outdoor environments [11].

To further address deployment constraints, several studies have focused on optimizing YOLO models for lightweight and real-time operation. Apple-YOLO, a modified YOLOv5-based architecture incorporating depth wise separable convolution, achieved an mAP@50 of 96.04% with an inference speed of 34 FPS and a compact model size of 5.33 MB, illustrating the feasibility of deploying high-accuracy disease detection systems on mobile or edge platforms [12].

2.2. Challenges in fruit disease detection

Despite these advancements, accurate fruit disease detection remains a challenging task due to several inherent factors. Disease symptoms often exhibit high inter-class similarity and intra-class variability, which can lead to misclassification, particularly when lesions vary in size, shape, colour, and texture [13]. These challenges are further amplified in natural farming environments where background clutter, occlusion, and illumination variations are common [14].

Another major limitation highlighted in existing studies is the scarcity and limited diversity of annotated datasets. Many works rely on self-constructed datasets with relatively small sample sizes, which restricts model generalization across different crops, disease types, and environmental conditions [13, 15, 16]. Furthermore, annotation strategies vary across studies. While whole-object annotation is commonly used, micro-annotation techniques that focus on fine-grained disease symptoms have been shown to improve detection sensitivity, albeit at the cost of increased annotation effort [17].

2.3. Anchor-based versus anchor-free YOLO paradigms

Earlier YOLO implementations in agriculture are based on anchor-based detection mechanisms, such as those employed in YOLOv5 and YOLOv7. Although effective, anchor-based models require predefined anchor boxes and multi-scale detection heads, which can increase computational complexity and may introduce redundancy when detecting small or irregular disease regions [18]. Simplification of these architectures can reduce computational load but may lead to a decline in detection accuracy [18].

More recent YOLO variants have transitioned towards anchor-free detection paradigms. Anchor-free models eliminate the need for predefined anchor boxes and instead rely on adaptive sample selection strategies, allowing better flexibility in handling scale variation and complex object morphology. This design shift has been reported to improve localization accuracy and reduce false positives in visually complex scenarios [19]. However, in agricultural applications, anchor-free YOLO models are often evaluated independently, without direct comparison to anchor-based counterparts under identical experimental conditions.

2.4. Research gap and motivation

From the reviewed literature, several gaps can be identified. First, there is a lack of systematic benchmarking between anchor-based and anchor-free YOLO models for fruit disease detection using the same dataset and training configuration. Second, most existing studies focus on single-crop datasets, limiting their applicability to real-world agricultural settings where multiple fruit types coexist. Third, deployment-related factors such as inference speed, model size, and suitability for mobile or edge devices are often underreported, despite their importance for practical agricultural adoption.

The existing studies summarized in Table 1 confirm the effectiveness of YOLO-based models for agricultural disease detection; however, limitations remain in terms of comparative evaluation, dataset diversity, and deployment-oriented analysis. In particular, the relative advantages of anchor-free YOLO models over anchor-based variants in mobile-based, multi-fruit disease detection scenarios remain insufficiently explored. This study seeks to address these limitations by providing a structured comparative analysis of YOLOv7-tiny, YOLOv8n, and YOLOv10n using a balanced tropical fruit disease dataset, thereby offering practical insights for the design of lightweight agricultural diagnostic systems.

Table 1. Meta-analysis of YOLO-based fruit and crop disease detection studies.

Ref.	YOLO Variant	Application / Crop	Detection Paradigm	Dataset Characteristics	Performance Metrics	Reported Limitations
[8]	Multiple YOLO variants	General agriculture (survey)	Anchor-based & Anchor-free	Review of multiple datasets	Accuracy, mAP	Lacks experimental benchmarking; mainly descriptive
[9]	MAR-YOLOv9	Maize, wheat, rapeseed, rice	Anchor-free	Multi-dataset agricultural images	mAP@50	Evaluated across datasets but not focused on disease symptoms
[10]	YOLOv8n, YOLOv8m, YOLOv8l	Fall armyworm detection	Anchor-free	Field images, pest-focused	mAP@50	Focused on pest detection, not fruit diseases
[11]	YOLOv8	Crop and weed detection	Anchor-free	Outdoor field images	mAP@50	Not evaluated for disease localization
[12]	Modified YOLOv5 (Apple-YOLO)	Apple leaf diseases	Anchor-based	Controlled leaf images	mAP@50, FPS	Single-crop dataset; limited background variation
[13]	YOLO-based CNN models	Papaya fruit diseases	Anchor-based	Self-constructed dataset	Accuracy	Struggles with visually similar symptoms
[14]	YOLO-Leaf	Apple leaf diseases	Anchor-based	Natural environment images	Precision, Recall	Limited robustness to background clutter
[15]	Enhanced YOLOv7	Lychee diseases	Anchor-based	Edge-computing dataset	mAP, FPS	High computational demand
[16]	LSD-YOLOv8n	Lemon surface diseases	Anchor-free	Surface-level disease images	Accuracy, mAP	Limited to single fruit type
[17]	YOLO with micro-annotation	Common bean diseases	Anchor-based	Fine-grained symptom annotation	Accuracy	Annotation process is labor-intensive
[18]	Simplified YOLOv5	Real crop monitoring	Anchor-based	Real-field images	Accuracy, FPS	Reduced accuracy after model simplification

3. Method

3.1. Data preparation and annotation

The image dataset used in this study comprises RGB images of bananas, mangoes, and guavas collected from publicly available open-source agricultural datasets. The use of open-access datasets for plant disease detection is consistent with prior YOLO-based agricultural studies and supports reproducibility and benchmarking 19, 20].

The images represent natural fruit conditions, including variations in background, illumination, fruit orientation, and disease manifestation, reflecting realistic field scenarios relevant to mobile-based agricultural applications [20]. A total of 5,700 original images were curated and categorised into 19 classes, including both diseased and disease-free conditions across the three fruit types. Each class was intentionally balanced to contain 300 images, following established practices for mitigating class imbalance in supervised learning [21].

All images were resized to a uniform resolution of 640 × 640 pixels, consistent with YOLO input requirements [22, 23]. Annotation was performed using bounding box labelling, where disease-affected regions were manually marked based on visible symptoms. Bounding box annotation remains the dominant approach for object detection-based disease localisation in agricultural applications [19, 20]. The annotation process was conducted using the Roboflow platform to ensure consistency, accuracy, and compatibility with YOLO training pipelines.

To enhance dataset diversity and improve model generalisation, data augmentation techniques were applied, including horizontal and vertical flipping, 90° rotations, saturation adjustment, exposure variation, and random noise injection. Such augmentation strategies are widely adopted to improve robustness under varying environmental conditions in agricultural imaging [20, 22].

After augmentation, the dataset increased to 13,680 images. The dataset was split into training (80%), validation (10%), and testing (10%) subsets, corresponding to 10,944 and 1368 images for each validation and testing. This split ratio is commonly adopted to balance training efficiency and unbiased evaluation while reducing overfitting risk [24].

3.2. Model selection and architectural rationale

Three YOLO-based object detection models were selected for this study: YOLOv7-tiny, YOLOv8n, and YOLOv10n. The selection was guided by two primary criteria:

(i) suitability for lightweight and mobile deployment; and

(ii) representation of both anchor-based and anchor-free detection paradigms.

YOLOv7-tiny represents an anchor-based architecture, employing predefined anchor boxes and multi-scale detection heads. Anchor-based YOLO models have been widely adopted in agricultural applications due to their maturity and reliable localisation performance [22, 23]. However, such models require anchor tuning and may introduce redundancy when detecting small or irregular disease regions [23].

In contrast, YOLOv8n and YOLOv10n adopt anchor-free detection mechanisms, eliminating predefined anchor boxes and directly predicting object centres and bounding boxes. Anchor-free detection has been shown to improve adaptability to scale variation and complex object morphology, which are common characteristics of fruit disease symptoms [19, 20]. YOLOv10n further refines detection efficiency through architectural optimisation, targeting improved localisation accuracy and reduced inference latency.

YOLOv9 was not included in this study to maintain a clear focus on lightweight models optimised for mobile deployment. Existing YOLOv9-based studies primarily emphasise large-scale benchmarking rather than on-device inference feasibility, which is less aligned with the objectives of this work [19].

3.3. Training strategy and hyperparameter configuration

All models were trained using transfer learning, where pretrained weights were used for initialisation. Transfer learning is a well-established strategy in YOLO-based agricultural detection tasks, enabling faster convergence and improved feature extraction when domain-specific datasets are limited in size [22, 23].

To ensure a fair comparison, identical hyperparameters were applied across all models. Training was conducted for 50 epochs, which was found to provide stable convergence without excessive overfitting, consistent with prior YOLO-based agricultural studies [20, 21]. The batch size was set to 16, balancing training stability and GPU memory constraints, while the learning rate was fixed at 0.01, a commonly adopted value in YOLO training pipelines [22, 23].

The image input size during training was set to 640 pixels, allowing improved spatial resolution for small disease symptoms while maintaining computational feasibility. No layers were frozen during training, enabling full adaptation of the network parameters to the target dataset.

Overfitting prevention was addressed through data augmentation and validation monitoring, both of which are widely recommended in agricultural object detection studies [21, 22]. Explicit early stopping was not applied, as validation performance remained stable throughout training. Training and evaluation were performed using Visual Studio Code version 1.109.5 on Windows 11, leveraging an NVIDIA GeForce RTX 4050 laptop GPU which is commonly used in recent YOLO-based agricultural studies due to its accessibility and adequate computational capability [21, 24].

3.4. Performance evaluation metrics

Model performance was evaluated using standard object detection metrics, including mean Average Precision at an Intersection over Union threshold of 0.5 (mAP@50), precision, recall, F1-score, and inference latency. These metrics are widely employed in YOLO-based agricultural object detection studies to assess both detection accuracy and practical deployment suitability [19-21]. Precision, recall, and F1-score are defined as:

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (1)$$

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

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

where TP, FP, and FN denote true positives, false positives, and false negatives, respectively. Inference latency was included as a critical metric to evaluate real-time feasibility, particularly for mobile-based agricultural applications where computational resources are limited [22, 23]. Table 2 shows the specifications of the three YOLO models.

Table 2 shows the repository links required to obtain the pretrained models used in this study. All experiments were conducted on a workstation equipped with an Intel i5-13450HX processor, 16GB RAM, and an NVIDIA GeForce RTX 4050 Laptop GPU. The models were trained using Python in a Windows-based environment via Visual Studio Code, with separate environments configured for each YOLO version to ensure dependency isolation. The Ultralytics YOLO framework ensured effective model creation and optimization during the deployment and training phases.

Table 2. Specifications of YOLOv7-tiny, YOLOv8n, and YOLOv10n.

Model	Parameters	Repository	Ref.
YOLOv7-tiny	6.2M	https://github.com/WongKinYiu/yolov7.git	[22]
YOLOv8n	3.2M	https://github.com/ultralytics/ultralytics	[23]
YOLOv10n	2.3M	https://github.com/THU-MIG/yolov10.git	[24]

4. Results and Discussion

4.1. Quantitative performance evaluation

All three models, namely YOLOv7-tiny, YOLOv8n, and YOLOv10n, were trained and evaluated under identical experimental settings to ensure a fair comparison. Performance was assessed using mean Average Precision at an Intersection over Union threshold of 0.5, precision, recall, F1 score, and inference latency. These metrics are widely adopted in YOLO based agricultural object detection studies to evaluate both detection accuracy and practical deployment suitability [19-21, 25]. Table 3 summarises the quantitative results obtained on the test dataset.

Table 3. Results of YOLOv7-tiny, YOLOv8n, and YOLOv10n.

Metric	YOLOv7-tiny	YOLOv8n	YOLOv10n
mAP@50	0.799	0.945	0.936
Precision (P)	0.762	0.926	0.923
Recall (R)	0.783	0.906	0.906
F1-score	0.772	0.916	0.914
Inference latency (ms)	4.6	5.1	5.8

Figures 1-3 illustrate the training and validation performance of YOLOv7-tiny, YOLOv8n, and YOLOv10n, respectively. YOLOv7-tiny exhibits slower convergence and higher loss fluctuations, whereas YOLOv8n and YOLOv10n demonstrate faster convergence and more stable validation behaviour, indicating improved optimisation and generalisation capability.

YOLOv8n achieved the highest detection accuracy, with an mAP@50 of 0.945, followed closely by YOLOv10n at 0.936, while YOLOv7-tiny exhibited substantially lower performance. The improvement observed in anchor-free models indicates superior localisation and classification capability, particularly for visually complex and small disease symptoms.

Precision and recall values further confirm this trend. YOLOv8n and YOLOv10n both achieved precision values exceeding 0.92, significantly reducing false-positive detections compared to YOLOv7-tiny. Similarly, recall values of 0.906 for both anchor-free models demonstrate improved sensitivity in detecting diseased regions.

Although YOLOv7-tiny exhibited the lowest inference latency, its inferior detection accuracy limits its suitability for reliable disease diagnosis. In contrast, YOLOv8n offers a more favourable balance between accuracy and inference speed, making it particularly suitable for mobile-based deployment.

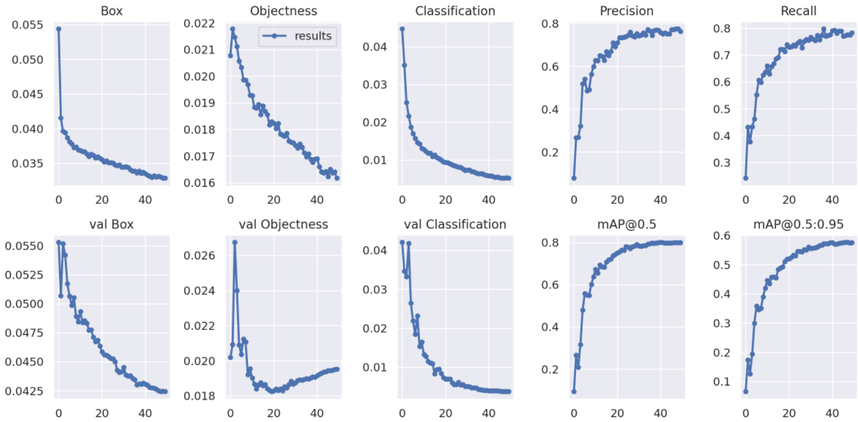

Fig. 1. YOLOv7-tiny results.

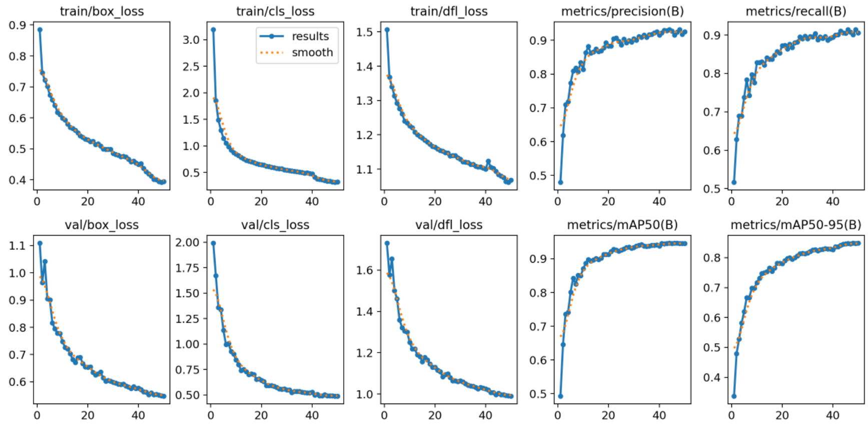

Fig. 2. YOLOv8n results.

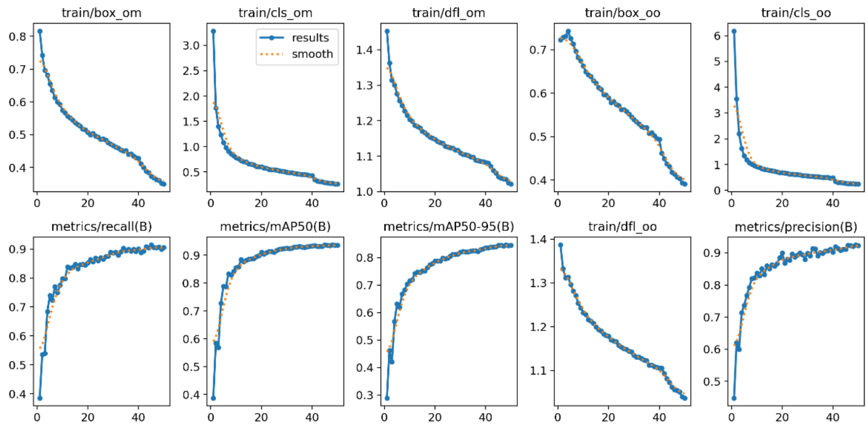

Fig. 3. YOLOv10n results.

4.2. Statistical significance analysis

To validate whether the observed performance differences are statistically meaningful, a one-way Analysis of Variance (ANOVA) test was conducted on the final mAP@0.5 values collected from five independent runs with different seeds, which all three models were run with 1 to 5 seeds respectively to the first to the fifth runs and the findings are shown in Table 4. This approach was applied to evaluate differences in mAP at 0.5 and F1 score as recommended in comparative deep learning studies [25].

A significant effect of model choice is indicated on mAP@0.5 ($F(2, 12) = 84.99$, $p < 0.001$), showing that at least one model's (YOLOv7-tiny) mean mAP differs significantly from the others.

To find the particular pairwise differences, a Tukey's Honestly Significant Difference (HSD) post-hoc test was subsequently performed. Due to the ANOVA findings, YOLOv8n and YOLOv10n performed much better than YOLOv7-tiny with $p < 0.05$. In contrast, there was no statistically significant difference between YOLOv8n and YOLOv10n which both with $p > 0.05$, suggesting that the two anchor-free models had comparable detection capability.

These findings verify that YOLOv8n and YOLOv10n's performance improvements are associated to the architectural enhancements rather than random variance. However, although YOLOv8n and YOLOv10n do not have notable difference, the deployment factors like computational efficiency and inference latency may serve as determining factors between the two models for real-world fruit disease detection applications.

Table 4. Final mAP values across multiple runs (seeds) for YOLOv7-tiny, YOLOv8n, and YOLOv10n.

Model	Run 1	Run 2	Run 3	Run 4	Run 5
YOLOv7-tiny	0.717	0.806	0.753	0.810	0.770
YOLOv8n	0.925	0.936	0.937	0.931	0.931
YOLOv10n	0.938	0.929	0.934	0.932	0.932

4.3. Misclassification analysis using confusion matrices

The confusion matrix analysis reveals that YOLOv7-tiny exhibits the highest misclassification rates, particularly when distinguishing anthracnose disease across bananas, guavas, and mangoes, as well as phytophthora disease in guavas, as illustrated in Figs. 4-7. These misclassifications are primarily attributed to the visual similarity of disease symptoms, including overlapping lesion patterns and colour variations. In addition, YOLOv7-tiny produces a higher number of false positives in background regions, indicating reduced robustness in complex visual environments.

In contrast, YOLOv8n demonstrates improved feature discrimination and higher recall, resulting in fewer misclassifications across visually similar disease classes. YOLOv10n further enhances this capability, achieving the lowest false positive and false negative rates and exhibiting the strongest diagonal dominance in the confusion matrices. This indicates superior class separation and localisation accuracy for anchor-free detection models.

Fig. 4. Anthracnose disease of bananas.

Fig. 5. Anthracnose disease of guavas.

Fig. 6. Anthracnose disease of mangoes.

Fig. 7. Phytophthora disease of guavas.

Table 5 indicates that YOLOv7 tiny exhibits misclassification rates approaching 30 percent for visually similar disease classes. In comparison, YOLOv8n demonstrates a consistent reduction in misclassification rates, with average values near 20 percent, reflecting improved feature extraction and higher recall. YOLOv10n further refines this performance, maintaining misclassification rates below 18 percent across all evaluated classes. These results confirm that anchor free detection models achieve superior disease differentiation and improved robustness when compared to anchor-based architectures.

Table 5. Comparison per class (key misclassifications).

True Class	YOLOv7-tiny	YOLOv8n	YOLOv10n
Banana Anthracnose	30.8%	21.5%	15.3%
Guava Rust Puccinia	31.9%	23.2%	17.6%
Mango Bacterial Canker	29.3%	20.8%	13.7%
Background (False Positives)	25.1%	17.9%	11.5%

Table 6 summarises the overall performance characteristics of the evaluated models. YOLOv10n achieves the strongest classification performance in terms of precision and misclassification reduction, whereas YOLOv8n provides a more favourable balance between detection accuracy, model size, and inference efficiency. In contrast, YOLOv7-tiny demonstrates consistently lower performance across all evaluated metrics, reflecting the limitations of anchor-based detection in visually complex disease scenarios.

Table 6. Performance observations.

Model	Accuracy	False Positives	False Negatives	Disease Differentiation
YOLOv7-tiny	Lowest	High	High	Weakest
YOLOv8n	Medium	Medium	Medium	Medium
YOLOv10n	Highest	Lowest	Lowest	Best

4.4. Accuracy efficiency trade-off for mobile-based deployment

While YOLOv10n marginally improved precision compared to YOLOv8n, it also incurred higher inference latency. This trade off highlights an important consideration for real world deployment. In mobile and edge based agricultural systems, slight reductions in detection accuracy may be acceptable if they result in faster response times and lower computational demand [19, 21, 25].

YOLOv8n emerges as the most balanced model, offering high detection accuracy with moderate inference latency. Its lightweight architecture and stable performance make it particularly suitable for real-time disease detection on mobile devices operating under constrained computational resources. This observation is consistent with prior studies emphasising the practicality of lightweight anchor-free YOLO variants for on device agricultural monitoring [19, 21, 25].

4.5. Discussion summary

Overall, the results demonstrate that anchor-free YOLO models significantly outperform the anchor based YOLOv7-tiny model in tropical fruit disease detection tasks. The removal of predefined anchor boxes enables anchor-free models to adapt more effectively to irregular and small disease regions, which are common in agricultural imagery [19, 25].

Between the two anchor-free models, YOLOv8n provides the most practical balance between accuracy, inference speed, and deployment feasibility, while

YOLOv10n offers marginal accuracy gains at the cost of increased inference latency. These findings directly address the research question posed in this study and support the selection of YOLOv8n as a suitable model for mobile-based precision agriculture applications.

5. Conclusions

This study presented a systematic comparative evaluation of anchor based and anchor free YOLO models for tropical fruit disease detection, with a specific focus on mobile-based agricultural deployment. The primary objective was to determine whether anchor free detection paradigms offer measurable advantages over anchor-based models when applied to visually complex fruit disease scenarios under constrained computational conditions.

The experimental results demonstrate that anchor free models, namely YOLOv8n and YOLOv10n, consistently outperform the anchor based YOLOv7 tiny model across all evaluated performance metrics, including mean Average Precision at an Intersection over Union threshold of 0.5, precision, recall, and F1 score. Statistical significance analysis confirms that the observed performance improvements of anchor free models over YOLOv7 tiny are not attributable to random variation, thereby validating the effectiveness of anchor free architectures for fruit disease localisation and classification. These findings directly address the research question posed in this study and confirm the suitability of anchor free YOLO models for agricultural disease detection tasks.

Between the two anchor free variants, YOLOv8n provides the most balanced trade-off between detection accuracy and inference efficiency. While YOLOv10n achieves marginally higher precision and lower misclassification rates, it incurs increased inference latency. Given the practical constraints of mobile and edge based agricultural systems, YOLOv8n emerges as the most suitable model for real time fruit disease detection, offering reliable performance while maintaining computational efficiency.

Confusion matrix analysis further supports these conclusions by revealing that anchor free models achieve superior class separation and reduced false positive and false negative rates, particularly for visually similar disease symptoms such as anthracnose across different fruit types. In contrast, YOLOv7 tiny exhibits higher misclassification rates and reduced robustness under complex visual conditions, limiting its applicability for reliable disease diagnosis in real world environments.

Despite these promising results, this study is subject to several limitations. The dataset is restricted to three tropical fruit types and relies solely on RGB visual features, without incorporating multispectral or temporal information. Additionally, although inference latency was evaluated, on device testing on real mobile hardware was not conducted. These limitations present opportunities for further investigation.

Future work will focus on extending the proposed framework to additional fruit types and disease categories, as well as incorporating lightweight model optimisation techniques such as pruning, quantisation, and knowledge distillation to further improve deployment efficiency. Evaluating the models on actual mobile and edge devices under real field conditions will also be prioritised. Furthermore, integrating multimodal data sources, such as thermal or hyperspectral imagery, may enhance disease discrimination for visually ambiguous symptoms.

Overall, this study provides empirical evidence that anchor free YOLO models, particularly YOLOv8n, offer a robust and practical solution for mobile based tropical fruit disease detection. The findings contribute to the advancement of precision agriculture by supporting informed model selection for real world agricultural monitoring systems.

Nomenclatures

F1-score	Harmonic mean of precision and recall
IoU	Intersection over Union
mAP@50	Mean average precision calculated at an intersection over union threshold of 0.50
Precision	Ratio of true positives to predicted positives
Recall	Ratio of true positives to actual positives

Abbreviations

AI	Artificial Intelligence
YOLO	You Only Look Once

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References

1. Mat Zin, S.H.H.B.; Rosnan, S.B.; and Mohd Shafee, C.T.M.N. (2023). A study on the fruits and vegetables consumption patterns among adults in Malaysia. *International Journal of Academic Research in Business and Social Sciences*, 12(11), 1550-1568.
2. Food and Agriculture Organization of the United Nations. (2020). *Major tropical fruits market review*. FAO.
3. Food and Agriculture Organization of the United Nations. (2023). *Major tropical fruits market review*. FAO.
4. Dofuor, A.K. et al. (2023). Mango anthracnose disease: The current situation and direction for future research. *Frontiers in Microbiology*, 14, 1168203.
5. Ramya, A.; and Rajeshwari, K. (2025). Detecting diseased pomegranates using Vgg16-based deep learning approach. *International Journal of Research Publication and Reviews*, 6(3), 5291-5294.
6. Sandhi, A.; Kumar, R.; Kumar, D.; and Bhardwaj, R. (2024). A comprehensive hybrid model for apple fruit disease detection using multi-architecture feature extraction. Research Square.

7. Nithya, R.; Santhi, B.; Manikandan, R.; Rahimi, M.; and Gandomi, A.H. (2022). Computer vision system for mango fruit defect detection using deep convolutional neural network. *Foods*, 11(21), 3483.
8. Alif, M.A.R.; and Hussain, M. (2024). YOLOv1 to YOLOv10: A comprehensive review of YOLO variants and their application in the agricultural domain. arXiv, 1-31.
9. Lu, D.; and Wang, Y. (2024). MAR-YOLOv9: A multi-dataset object detection method for agricultural fields based on YOLOv9. *PLOS ONE*, 19(10), e0307643.
10. Mhala, P.; Gupta, A.; and Sharma, S. (2024). YOLOv8 based detection of fall armyworm in field crops. *Proceedings of the* 2024 *IEEE* 5th *India Council International Subsections Conference* (*INDISCON* 2024), Chandigarh, India, 1-6.
11. Thakur, A.; Sonu; and Kumar, R. (2024). Object detection approach for crop and weed identification based on deep learning. *Proceedings of the* 2024 *IEEE International Students' Conference on Electrical*, *Electronics and Computer Science* (*SCEECS* 2024), Bhopal, India, 1-6.
12. Li, J.; Zhu, X.; Jia, R.; Liu, B.; and Yu, C. (2022). Apple-YOLO: A novel mobile terminal detector based on YOLOv5 for early apple leaf diseases. *Proceedings of the* 2022 *IEEE* 46th *Annual Computers*, *Software*, *and Applications Conference* (*COMPSAC*), Los Alamitos, CA, USA, 352-361.
13. De Moraes, J.L.; De Oliveira Neto, J.; Badue, C.; Oliveira-Santos, T.; and De Souza, A.F. (2023). YOLO-Papaya: A papaya fruit disease detector and classifier using CNNs and convolutional block attention modules. *Electronics*, 12(10), 2202.
14. Li, T.; Zhang, L.; and Lin, J. (2024). Precision agriculture with YOLO-Leaf: Advanced methods for detecting apple leaf diseases. *Frontiers in Plant Science*, 15, 1452502.
15. Xiao, J.; Kang, G.; Wang, L.; Lin, Y.; Zeng, F.; Zheng, J.; Zhang, R.; and Yue, X. (2023). Real-time lightweight detection of lychee diseases with enhanced YOLOv7 and edge computing. *Agronomy*, 13(12), 2866.
16. Wang, S.; Li, Q.; Yang, T.; Li, Z.; Bai, D.; Tang, C.; and Pu, H. (2024). LSD-YOLO: Enhanced YOLOv8n algorithm for efficient detection of lemon surface diseases. *Plants*, 13(15), 2069.
17. Gomez, D. et al. (2024). Advancing common bean (Phaseolus vulgaris L.) disease detection with YOLO driven deep learning to enhance agricultural AI. *Scientific Reports*, 14(1), 15596.
18. Nnadozie, E.C.; Casaseca-de-la-Higuera, P.; Iloanusi, O.; Ani, O.; and Alberola-López, C. (2024). Simplifying YOLOv5 for deployment in a real crop monitoring setting. *Multimedia Tools and Applications*, 83(17), 50197-50223.
19. Zhang, S.; Chi, C.; Yao, Y.; Lei, Z.; and Li, S.Z. (2020). Bridging the gap between anchor-based and anchor-free detection via adaptive training sample selection. *Proceedings of the* 2020 *IEEE/CVF Conference on Computer Vision and Pattern Recognition* (*CVPR*), Seattle, WA, USA, 9756-9765.
20. Joseph, V.R.; and Vakayil, A. (2022). SPlit: An optimal method for data splitting. *Technometrics*, 64(2), 166-176.

21. Yadav, S.; and Bhole, G.P. (2020). Handling imbalanced dataset classification in machine learning. *Proceedings of the* 2020 *IEEE Pune Section International Conference* (*PuneCon*), Pune, India, 38-43.
22. WongKinYiu. (n.d.). YOLOv7. Retrieved April 16, 2026, from https://github.com/WongKinYiu/yolov7.git.
23. Ultralytics. (n.d.). Ultralytics. Retrieved April 16, 2026, from https://github.com/ultralytics/ultralytics.
24. jameslahm. (n.d.). YOLOv10. Retrieved April 16, 2026, from https://github.com/THU-MIG/yolov10.git.
25. Terven, J.; Córdova-Esparza, D.-M.; and Romero-González, J.-A. (2023). A comprehensive review of YOLO architectures in computer vision: From YOLOv1 to YOLOv8 and YOLO-NAS. *Machine Learning and Knowledge Extraction*, 5(4), 1680-1716.