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YOLO-AppleScab: A Deep Learning Approach for Efficient and Accurate Apple Scab Detection in Varied Lighting Conditions Using CARAFE-enhanced YOLOv7

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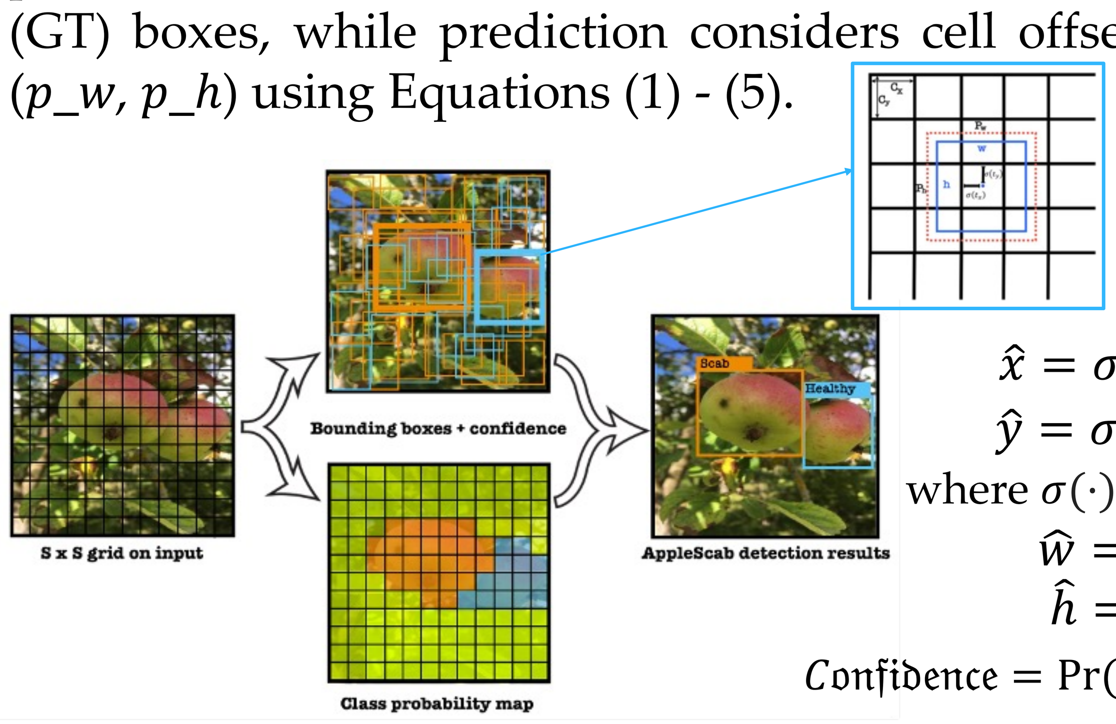
BACKGROUND: Plant and fruit diseases have a significant negative impact on agricultural economies due to reduced crop quality and yields. To mitigate losses and foster economic growth, the development of accurate, automated detection techniques is essential. Researchers are investigating novel methods to detect and address plant and fruit diseases, driven by factors such as climate change, globalization, and evolving agricultural practices. The integration of technology like remote sensing, genomics, monitoring systems, and artificial intelligence (AI) [1-2] is playing a pivotal role in improving disease detection and treatment processes. Additionally, AI-driven robotics are being utilized for disease detection and treatment, involving two core steps: computer vision-based fruit detection and robot-guided treatment.

AIMS: To improve apple fruit disease detection, including scab disease, using the YOLO-AppleScab model with ℂ𝔸ℝ𝔸𝔽𝔼 architecture in YOLOv7 for enhanced accuracy, evaluating performance with metrics like F1 score and exploring AI's potential impact on agricultural practices.

MATERIALS AND METHODS

YOLO model detection, R-Bboxes, and $\mathcal{Loss}$ Function

The YOLO framework divides images into an S x S grid, with each cell performing object detection and generating B bounding boxes with confidence scores indicating object presence. Using class probability maps from these scores, it accurately recognizes and classifies objects, enabling efficient, real-time detection. Each grid cell predicts x, y, w, h, $\mathcal{Confidence}$, and C class probabilities, totaling 5 values. $\mathcal{Confidence}$ gauges object presence and calculates Intersection over Union (IoU) with ground truth (GT) boxes, while prediction considers cell offset (c_x,c_y) and box prior (p_w, p_h) using Equations (1) - (5).



$$\hat{x} = \sigma(t_x) + c_x \quad (1)$$

$$\hat{y} = \sigma(t_y) + c_y \quad (2)$$

where $\sigma(\cdot)$ is sigmoid function,

$$\hat{w} = p_w e^{t_w} \quad (3)$$

$$\hat{h} = p_h e^{t_h} \quad (4)$$

$$\mathcal{Confidence} = \Pr(Object) \times IoU(GT, pred), \quad (5)$$

Figure 1: YOLO model detection with prediction of Bbox

Images Acquisition

Image dataset was collected in orchards, using smartphones (12MP, 13MP, 48MP) and a digital compact camera (10MP), capturing apples at various stages of development and damage. Images were taken from different viewpoints, times of day, and lighting conditions. The dataset, named AppleScabLDs, was curated by manually reviewing and sorting images of healthy and diseased (apple scab disease) apples. Subsets were created with and without scab symptoms, excluding images with visual noise. This meticulous selection process ensured noise wouldn't affect disease detection. The model's performance was evaluated using proper metrics and reported results. The dataset consisted of 297 images: 237 in the training set (200 healthy apples, 37 with scabs) and 60 in the test set (55 healthy apples, 5 with scabs). Samples from the dataset in various environments are shown in Figure 2.

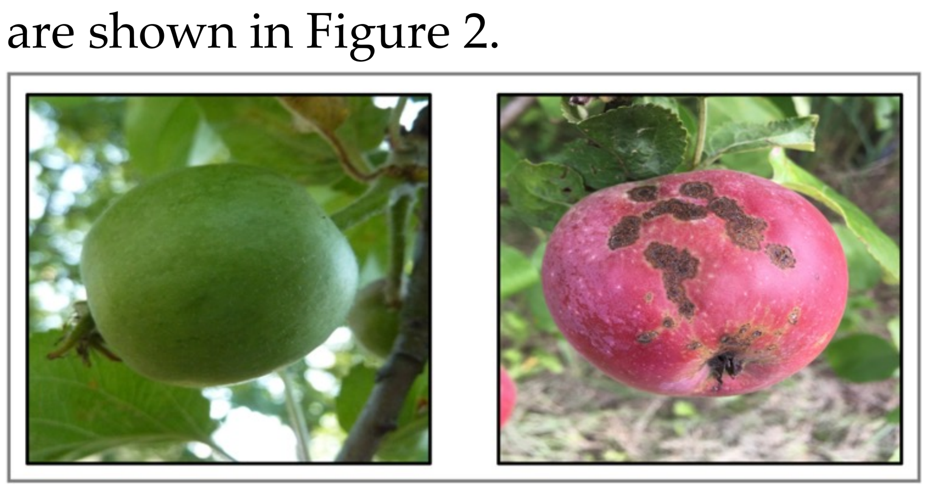


Figure 2: Apple fruit samples from dataset AppleScabLDs: healthy apple fruit (**left**), and infected apple by scab disease (**right**).

RESULTS

Visual cues are captured by deep neural networks in Figure 3, where YOLOv7's upsample and CARAFE generate 32 feature maps each, highlighting this ability. CARAFE's maps are richer, enhancing feature representation. Efficiency under varying illuminations was examined, with strong (48 apples) and soft light (56 apples) groups analyzed. Under strong light, healthy identification reached 90%, scab disease detection was 96.43%, and false detections were 5% for healthy and 0% for scab. Under soft light, healthy identification was 75.86%, scab disease detection reached 85.18%, with false detections of 6% for healthy and 7.41% for scab.

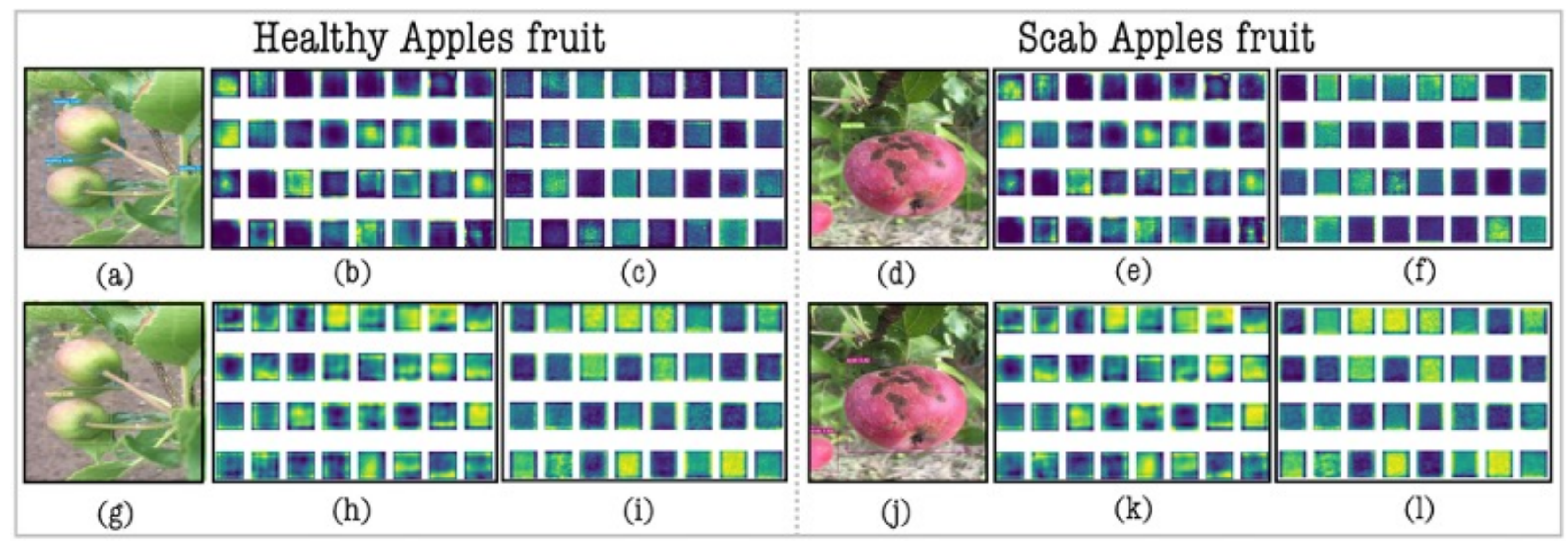


Figure 3: Feature maps activation in Upsample and ℂ𝔸ℝ𝔸𝔽𝔼 layers. (a, d) YOLOv7 prediction; (b, e) Stage 53 Upsample feature maps, (c, f) Stage 65 Upsample feature maps, (d, g) YOLO-AppleScab prediction; (h, k) Stage 53 ℂ𝔸ℝ𝔸𝔽𝔼 feature maps; (i, l) Stage 65 ℂ𝔸ℝ𝔸𝔽𝔼 feature maps.

Table 1: The detection performance of the proposed model

Illumination	Class	GT	Correctly Identified		Falsely Identified		Missed	
			Amount	Rate	Amount	Rate	Amount	Rate
Strong Light	Healthy	20	18	90%	1	5%	1	5%
	Scab	28	27	96.43%	1	0%	0	3.57%
Soft Light	Healthy	29	22	75.86%	2	6.87%	5	17.24%
	Scab	27	23	85.18%	2	7.41%	2	7.4%

Table 1 assesses model effectiveness by class, while $mAP_{0.5}$ and $mAP_{0.5-0.95}$ provide overall accuracy. Table 4 compares YOLO-AppleScab's performance against other methods. Table 5 highlights YOLO-AppleScab's excellence with 89.30% precision, 64% $mAP_{0.5-0.95}$, and 0.1752 seconds per image detection time, suitable for real-time robot-assisted disease detection in fruits.

Table 2: Classification metrics. Comparison with different SOTA of YOLOv3, YOLOv4, YOLOv7 and the proposed method for the two studied classes (healthy and scab) that apple represents. The input image size is 416x416.

Model	Healthy					Scab				
	Precision (%)	Recall (%)	F1 (%)	$mAP_{0.5}$ (%)	$mAP_{0.5-0.95}$ (%)	Precision (%)	Recall (%)	F1 (%)	$mAP_{0.5}$ (%)	$mAP_{0.5-0.95}$ (%)
Yolov3	88.38	56.64	69.04	68.60	41.60	68.20	91.80	78.23	92.10	69.80
yolov4	89.90	67.30	76.98	79.40	53.90	89.40	95.90	92.54	92.70	70,30
Yolov7	85.40	74.50	79.58	80.10	51,60	91.80	90.90	91.35	93.40	72.70
Yolo-Applescab	100	74.50	85.39	83.30	54.80	89.50	95.90	92.58	94.70	73.20

Table 3: Classification Metrics, Comparison with Different SOTA. of YOLOv3, YOLOv4, YOLOv7 and Faster R-CNN are used for benchmarking. The input image size is 416x416. The $mAP_{0.5-0.95}$ are expressed in percentages. Two classes (healthy and scab) represent the apple condition.

Model	Healthy	Scab
	$mAP_{0.5-0.95}$ (%)	$mAP_{0.5-0.95}$ (%)
YOLOv3	41.60	69.80
YOLOv4	53.90	70.30
YOLOv7	51.60	72.70
Faster R-CNN	47.03	59.79
YOLO-AppleScab	54.80	73.20

Table 4: A comparison of the different state-of-the-art detection methods.

Models	Precision (%)	Recall (%)	F1 score (%)	$mAP_{0.5}$ (%)	$mAP_{0.5-0.95}$ (%)	CPU Time (ms)
YOLOv3 [25]	76	74.10	75.04	80.40	55.70	175.1
YOLOv4 [23]	89.70	81.60	85.46	86.10	62.10	180.2
YOLOv7 [26]	88.60	82.70	85.55	86.80	62.20	153
Faster R-CNN [27]	77.80	68.30	72.74	77.85	53.41	194
YOLO-AppleScab	94.80	85.20	89.75	89.30	64	175.2

CONCLUSION

YOLO-AppleScab leverages YOLOv7 for healthy and scab-infected apple classification, countering overlap and lighting issues with ℂ𝔸ℝ𝔸𝔽𝔼 architecture. Experiments confirm its efficiency, boosting the F1 score by 4.2% while excelling under diverse lighting. With a strong light advantage of 90% accurate healthy apple identification (over 14% more than soft light) and 96.43% for scab-infected apples (over 11% higher), the method outperforms competitors, suggesting broad applications.

References

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