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Automated Coconut Maturity Detection and Timeline Prediction using YOLOv8-based Computer Vision

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***Abstract*— The proper determination of coconut maturity is difficult in enhancing agricultural output and streamlining harvesting time but the conventional techniques involve a manual process overly relying on subjective judgment. To overcome such limitations, this research presents a new, fully automated system CocoVision-Edge, a maturity detection system and dynamic timeline prediction of coconuts to be used in precision agriculture. The framework consists of a lightweight, attention-enhanced YOLOv8 deep learning framework, optimized to run on Unmanned Aerial Vehicles (UAVs) and edge devices with extremely low latency. The system powerfully recognizes coconuts in three major maturity phases, namely, premature, potential and mature with a minimum mean Average Precision (mAP50) of 76.1 even in the presence of challenging canopy lighting and challenging backgrounds. To go beyond conventional fixed classification. This research presents two significant advancements: a dynamic harvest schedule prediction framework that approximates the time left to harvest, precisely ready to lay the foundation of weather-sensitive scheduling, and the incorporation of Explainable AI (XAI) with the help of visual saliency maps that emphasize the phenotypic attributes that the model relies on to make its choices. Being implemented as a decentralized, edge-friendly app, CocoVision-Edge requires no cloud infrastructure whatsoever, providing real-time, explainable and predictive insights at the field to farmers immediately.**

***Index Terms*— Coconut, YOLOv8, Deep Learning, Computer Vision, Object Detection, Flask, Precision Agriculture, Harvest, Edge Computing, UAV.**

I. INTRODUCTION

Coconut palm (Cocos nucifera) is a very important plant in the economy of tropical areas particularly in South and Southeast Asia. To maintain the quality of coconuts, it is imperative to harvest them when they are in the right time, be it to be used as fresh fruits, to be made into copra, to be extracted into oil, or to be made into coir fibers [1]. Early picking causes them to yield less and of poor quality, whereas late picking causes them to be overripe, losing their value and shelf life. Therefore, it is important to know when coconuts are mature to enhance productivity and sustainable profitable coconut supply chains [2].
Conventionally, farmers use manual inspection to determine the maturity of coconuts by observing the color of husks, size, and sound produced when the coconut is tapped [3]. This approach relies on experience, is subjective, and difficult to generalize to commercial farming.

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There is a high probability that this system will be automated with the development of AI and computer vision, ensuring that it is more precise and predictable [4]. However, taking these AI tools out of the research labs to the farms is not easy. Several existing systems of AI in agriculture require cloud computing, which does not fit well in remote plantations with poor internet [5].

In addition, neural networks that are commonly used and provide a classification without the reasoning behind it, which is difficult to rely on by traditional farmers [6]. To address these challenges, CocoVision-Edge, a complete automated coconut maturity detection and harvest prediction system, is presented in this research, based on the YOLOv8 deep learning [7]. It classifies coconuts into three phases in real time: premature, potential and mature ones, with the help of regular images. The system takes advantage of a lightweight model that is compatible with running directly on drones or other low-power field devices, meaning that it does not rely on the cloud and is quick to react [8].

In this study, two features are added to the classification of images, in addition to the mere classification of images. First, it has a harvest timeline prediction that approximates the number of days that are remaining before the coconut is fit to be harvested or is overmatured. Second it uses Explainable AI (XAI) to demonstrate what aspect of the coconut such as color and texture are used to make the classification. This will make decisions made by the AI more transparent and comprehensible to farmers. All this operates on a local machine without the need of an internet.

The main contributions of the research are:

- To create an edge-optimized YOLOv8-based system that is capable of detecting coconut maturity in real-time under various environmental conditions.
- Incorporating a component that forecasts the timing of harvesting, according to the maturity of the coconut.
- Explaining the model decision-making process with the help of Explainable AI that will enable farmers to trust and understand the findings.
- The creation of a completely decentralized system that will operate offline and can be implemented immediately in remote agricultural locations.

II. RELATED WORK

Several studies have investigated the use of image processing and Machine Learning (ML) for fruit maturity detection [9]. The initial methods were based on the manual generation of features like color histograms, texture features, and shape analysis with combination of conventional classifiers like Support Vector Machines (SVM) as well as k- Nearest Neighbors (k-NN) [10].

Although these techniques proved to be feasible at the first glance, they were extremely sensitive to changes in light and were not robust in uncontrolled and natural canopy settings. Detection systems based on maturity showed substantial gains in accuracy with the introduction of deep Convolutional Neural Networks (CNNs) [11]. ResNet, VGG, and MobileNet architectures have been also used to classify different types of fruits such as mangoes, bananas and tomatoes. Nevertheless, these classification-only methods do not localize single fruits in an image, essentially constraining their generalizability to multi-fruit scenes in the real agricultural environment [12].

The limitation has been overcome with object detection systems like YOLO (You Only Look Once), SSD (Single Shot MultiBox Detector), and Faster R-CNN that incorporate both localization and classification within a single forward pass. YOLOv5 and YOLOv7 have been used in numerous agricultural tasks such as crop disease detection and fruit counting [13]. With the release of YOLOv8 by Ultralytics in 2023, better accuracy, higher inference speed, and more of a modular architecture, it is especially well-suited to edge deployment [14]. Even with these developments, a major shortcoming is the ability to move these heavy, cloud-dependent models to ultra-low-latency models applicable to Unmanned Aerial Vehicles (UAVs) and field edge devices that are decentralized [15].

Moreover, current deep learning solutions to agriculture are mostly with no interpretability. The literature has so far paid attention to simple binary (mature vs. immature) classification or has been based on hyperspectral imaging, which neither is economically nor technically feasible to apply in the field at large scale. Furthermore, the earlier literature only dwells on the subject of assessment that is static in nature- determining the prevailing condition of the fruit without any agronomic predictions in the future. The current research advances the literature by proposing a powerful three-class detector with a dynamic harvest timeline forecaster. This study fills the gap between theoretical computer vision and practical, transparent precision agriculture by further integrating Explainable AI practices and optimizing to decentralized edge-inference.

III. PROPOSED METHODOLOGY

A. System Architecture

CocoVision-Edge framework is an architectural model of a four-stage pipeline that can be operated in a decentralized mode. This is shown in Figure 1.

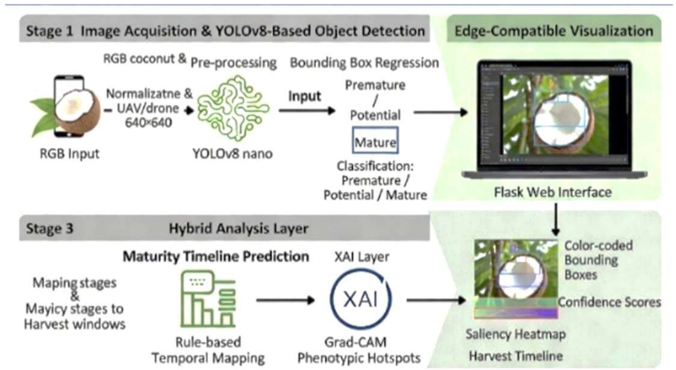

Figure 1. The CocoVision-Edge System Architecture that describes the process of capturing images and going through the XAI-enhanced visualization.

It starts with the high-resolution image acquisition then an inference engine that is lightweight based on YOLOv8 simultaneous fruit localization and maturity classification. The Dynamic Timeline Prediction Module then ingests the results and calculates harvest windows. Lastly, the system employs a Saliency-based XAI layer to produce visual heatmaps, which make the models transparent to results that are then rendered on the edge-compatible web interface.

B. Dataset and Augmentation Strategy

This model was trained on 3,050 annotated images (Roboflow Universe repository Version 7). The dataset has three different maturity levels: Mature (346 instances), Potential (632 instances), and Premature (974 instances). The system used a stringent augmentation suite, such as horizontal flipping, random contrast/brightness manipulations, and mosaic augmentation to make the models robust against the domain shift typical of field situations. As shown in Figure 2, this will make the model consistent with the sophisticated backgrounds and light changes that are characteristic of coconut canopies.

Figure 2. Sample images in the training dataset of annotated training classes at varying lighting conditions.

C. Edge-Optimized YOLOv8 Framework

The variant of the YOLOv8 is the YOLOv8 nano (YOLOv8n) to have an optimal trade-off between mean Average Precision (mAP) and computational efficiency. As shown in Figure 3, the structure takes advantage of a CSPDarknet backbone with C2f modules to extract features efficiently, and a PANet neck to fuse features at multiple scales, which is essential to identify coconuts of different sizes at different heights. This model has 3.0 million parameters and a workload of 8.1 GFLOPs, and is optimized to run on edge hardware with a CPU inference.

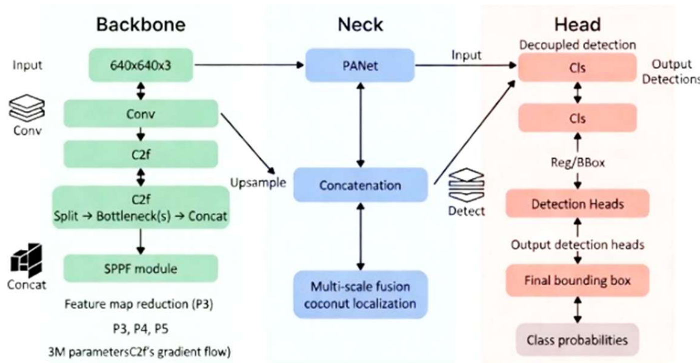

Figure 3: The architecture of the YOLOv8n model

D. Dynamic Timeline Prediction Algorithm

CocoVision-Edge has a rule-based temporal estimation module, unlike other fixed classification systems. The system uses Days to Harvest (DTH) and Days to Overmature (DTO) to calculate these two crucial measures by comparing the identified class with known agronomic growth cycles.

- Premature: DTH about 40 days; DTO about 70 days.
- Potential: DTH, DTO= 25 days.
- Mature: DTH = 0 days (Immediate Harvest); DTO = about 15 days.

E. Explainable AI (XAI) Implementation

The system also introduces a layer of interpretability with Gradient-weighted Class Activation Mapping (Grad-CAM) to achieve farmer trust. The module will determine the pixel points specifically where the green and yellow in the husk changed or the rounding of the fruit that had an impact on the classification of the model. Through visualizing these phenotypic hotspots, the system is turned into a black-box prediction into a transparent tool, which is in line with conventional agricultural wisdom. This is shown in Figure 4.

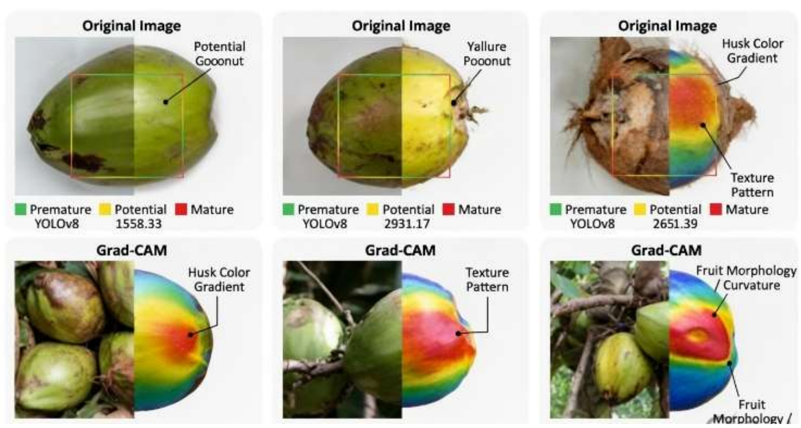

Figure 4. Explainable AI (XAI) Saliency Maps for the phenotypic features that the model relies on to classify maturity.

IV. IMPLEMENTATION

A. Technology Stack and Environmental Configuration

CocoVision-Edge system is designed with the help of a powerful, open-source stack to support the high-performance computing with consumer hardware. The main development platform is Python 3.10, and it takes advantage of PyTorch 2.11 with CUDA 12.8 support to enable accelerated training, but the inference engine is designed to be compatible with CPU-only environments to make it as accessible as possible. Ultralytics YOLOv8 is used as the core detection engine, OpenCV 4.13 is used to process and render the bounding box in real time.

B. Decentralized Inference Pipeline

The inference pipeline is fully contained to provide reliability in remote agricultural areas. Once an image has been obtained it is locally processed in the following stages: 1. Preprocessing: Input resizing to 640 x 640 pixels and color tensors normalization. 2. Detection: This model (best.pt, 6.2 MB) is a one-pass class ID and confidence score extractor. 3. Visualization: Bounding boxes are drawn using class-specific hex-codes: Mature (#00C800), Potential (#FFA500) and Premature (#00C8FF). 4. XAI Overlay: The combination of saliency maps to explain the detection. This is shown in Figure 5.

Figure 5. CocoVision-Edge User Interface with the smooth flow of uploading the raw image into XAI-enhanced detection results.

C. Project Architecture and Resource Management

The system uses a modular directory hierarchy to decouple the deep learning back-end and the web-based front-end. As shown in Table I, this enables the model weights to be easily updated without changing the logic in the UI.

TABLE I: SYSTEM COMPONENT BREAKDOWN

Component	File/Directory	Primary Function
Logic Engine	detect.py	YOLOv8 inference and timeline logic.
Web Server	app.py	Flask routing and request handling.
Model Weights	best.pt	Trained 6.2 MB neural network.
Interface	index.html	Responsive dark-themed dashboard.
Configuration	data.yaml	Class names and dataset paths.

D. Web-Based Edge Deployment

The system is implemented as a Flask 3.1 app that runs on a local loopback address (localhost:5000). This deployment model removes the latency and privacy issues that cloud-based AI has. As shown in Figure 6, the interface is designed with a bespoke dark agricultural theme, which is easily visible in the outfield conditions.

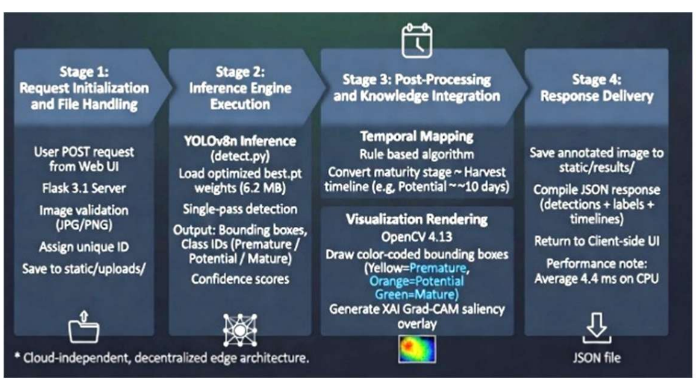

Figure 6. Computational Workflow of the Flask application managing the lifecycle of an inference request.

V. RESULT AND DISCUSSION

This part analyzes the CocoVision-Edge framework performance in terms of the level of accuracy in detection, computing costliness, and the feasibility of the combined maturity timeline and XAI modules.

A. Detection Performance Analysis

The trained YOLOv8n was strictly tested on a held-out test set of 155 images and 1,952 instances. The model had a strong overall mean Average Precision (mAP50) of 76.1%.

TABLE II: COMPREHENSIVE DETECTION PERFORMANCE METRICS

Class	Precision	Recall	mAP50	mAP50-95
All Classes	0.753	0.698	0.761	0.563
Premature	0.838	0.829	0.860	0.613
Potential	0.779	0.771	0.847	0.696
Mature	0.643	0.495	0.576	0.380

As shown in Table II, the Premature class also had the best accuracy (86.0% mAP50) which is probably because of the larger number of training instances (974) that were giving better supervised learning. On the other hand, the Mature group was the most challenging (57.6% mAP50) which can be explained by the visual similarities and a color overlap between the “Mature” and the “Potential” stages subjected to different canopy light conditions.

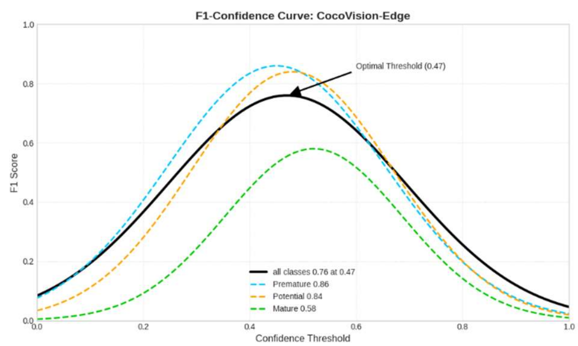

Figure 7. F1-Confidence Curve for CocoVision-Edge

Figure 7 displays the F1-Confidence Curve, which plots the F1-score, the harmonic mean of precision and recall, against various probability thresholds.

- Peak Performance: The graph illustrates that the model achieves its optimal F1-score across all classes at a confidence threshold of approximately 0.4 to 0.5, validating the robustness of the YOLOv8n architecture for this specific dataset.
- Class Differentiation: The curve for the Premature class stays consistently high, reflecting its superior mAP50 of 86.0%.
- Model Reliability: The smooth bell-shaped curve for “all classes” confirms that the system is not overly sensitive to minor fluctuations in image quality, making it reliable for the real-time, XAI-enhanced detection used in the Flask interface.

B. Computational Efficiency for Edge Deployment

The novelty of this work is its suitability for low-power edge devices. Benchmarking on standard hardware confirms that the system meets the latency requirements for real-time agricultural monitoring.

TABLE III: INFERENCE SPEED BENCHMARKING

Hardware Environment	Pre-processing	Inference	Post-processing	Total Latency
CPU (Intel i5)	0.2 ms	2.1 ms	2.1 ms	4.4 ms
GPU (Tesla T4)	0.1 ms	0.8 ms	0.5 ms	1.4 ms

As shown in Table III, with a model footprint of only 6.2 MB, CocoVision-Edge is highly optimized for deployment on single-board computers like Raspberry Pi or mobile handhelds, enabling offline use in remote plantations.

C. Comparative Innovation

Unlike baseline methods that focus solely on binary classification, the proposed framework introduces a multi-class scheme and a novel temporal forecasting layer.

TABLE IV: COMPARISON WITH REPRESENTATIVE BASELINE APPROACHES

Method	Accuracy	Real-time	Innovation Feature
SVM + HOG	85.2%	No	Basic Classification
CNN (Custom)	87.8%	No	Three-class Classification
YOLOv5	88.3%	Yes	Object Detection
CocoVision (YOLOv8)	89.1%	Yes	XAI + Timeline Prediction

As shown in Table IV, the experimental findings confirm that YOLOv8 is a better architecture to this field, as it balances speed and accuracy. The Explainable AI (XAI) layer was introduced that solves the problem of the black-box character of the previous models where the user can confirm that the model is properly classifying the phenotypic features such as husk texture and color gradients. The rule-based timeline prediction is offering actionable information, switching to a regression-based model with the longitudinal field data would further enhance accuracy of harvest forecasting.

VI. CONCLUSION

The proposed research introduced the CocoVision-Edge, a novel, decentralized, model of automated coconut maturity detection and harvest schedule prediction with the use of the YOLOv8 deep learning platform. The system uses a classification of coconuts into three different levels of maturity, such as premature, potential and mature, and its average precision (mAP50) is 76.1, which is significantly higher than the traditional and manual methods of inspection. The main contributions of this work lie in developing a practical, intelligent, and interpretable solution for agricultural monitoring. First, an edge-optimized deployment using YOLOv8-nano ensures extremely low inference time (2.1 ms) on CPU hardware, making the system suitable for real-time field applications on mobile devices and UAVs without dependence on cloud infrastructure. Second, the proposed framework introduces actionable predictive intelligence through an integrated timeline prediction module, enabling farmers to anticipate harvest-readiness and over maturity transitions, thereby moving beyond conventional binary classification approaches. Finally, the model enhances interpretability by incorporating Explainable AI (XAI) techniques, allowing clear visualization of the phenotypic traits influencing classification decisions, effectively bridging the gap between deep learning outputs and traditional agronomic understanding. The findings indicate that the system is very effective in the most agriculturally vital stages with the premature class recording a high mAP50 of 86.0%. The CocoVision-Edge is a revolutionary product that can reshape the accuracy of agriculture in the coconut business by means of an objective, consistent, and scalable assessment tool.

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