

## TOBACCO-VISORTS: AN INTELLIGENT VISION-BASED SORTING FRAMEWORK FOR AUTOMATED TOBACCO LEAF CLASSIFICATION USING YOLOV8 AND STARFISH OPTIMIZATION

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### Abstract

Accurate tobacco leaf grading is critical for product quality and commercial value in the tobacco industry, yet traditional manual and semi-automated sorting methods suffer from inconsistency, subjectivity, and low efficiency. This paper presents Tobacco-VISORTS, an intelligent vision-based sorting framework that integrates advanced image enhancement, deep learning detection, metaheuristic optimization, and simulated airflow-driven actuation for automated tobacco leaf classification. The system employs Contrast Limited Adaptive Histogram Equalization (CLAHE) to enhance local contrast and preserve fine textural and color features under varying illumination conditions. YOLOv8 serves as the core detection and segmentation model, leveraging its C2f modules, PAN-FPN neck structure, and CIOU loss for precise real-time grading based on shape, texture, and color attributes. To eliminate manual hyperparameter tuning, the Starfish Optimization Algorithm (SFO) automatically optimizes critical parameters including learning rate, IoU threshold, and confidence score using a multi-objective fitness criterion. A Python-controlled virtual air-jet actuator simulates non-contact sorting with a theoretical response delay of 0.257 seconds. Experimental results on a benchmark tobacco dataset demonstrate that Tobacco-VISORTS achieves superior performance with an F1-score of 0.93, mAP@50 of 0.91, and AUC exceeding 0.93 across all grades, significantly outperforming conventional PLC-based systems and unoptimized deep learning models. The framework offers a scalable, real-time solution for intelligent tobacco processing.

### Introduction

Classification and sorting of tobacco products are essential procedures in the global tobacco industry, ensuring product quality, consistency, and processing efficiency, as accurate classification according to visual characteristics including color, appearance, shape, and defects is vital because these attributes directly influence the commercial value and end-use of tobacco products (Zhang *et al.* 2024, Zhao *et al.* 2025). Conventional techniques rely on manual experience or semi-automated systems, but these approaches suffer from inherent inconsistency, time consumption, and subjectivity. While computer vision and deep learning have recently enabled intelligent automation and real-time data-driven decision-making, achieving or even exceeding human-level visual inspection (Ying *et al.* 2024, Chen *et al.* 2025, Hasan *et al.* 2025), existing tobacco leaf sorting methods remain limited in their applicability and precision under real-world industrial conditions (Yang *et al.* 2024, Zhou *et al.* 2025). Manual sorting is labor-intensive and slow, whereas traditional automatic systems often become unpredictable and ineffective when faced with variations in lighting, leaf texture, and physical deformation (Teng *et al.* 2024, Yang *et al.* 2024, Zhang *et al.* 2025). These constraints underscore the urgent need for a smarter, more adaptive, and real-time tobacco sorting system that integrates advanced deep learning, image processing, and programmable actuation. Therefore, this study proposes Tobacco-VISORTS, an

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intelligent vision-based sorting framework with three specific objectives. The first objective is to develop a robust image enhancement and deep learning detection module that employs CLAHE for local contrast improvement and YOLOv8 for simultaneous segmentation and grading of tobacco leaves based on shape, texture, and color features. The second objective is to optimize hyperparameters automatically using the Starfish Optimization Algorithm (SFO) with a multi-objective fitness criterion, thereby eliminating inefficient manual tuning and maximizing classification accuracy and recall. The third objective is to simulate an integrated non-contact sorting mechanism driven by a Python-controlled air-jet actuator, enabling real-time, high-throughput sorting with full traceability and industrial applicability. By achieving these objectives, Tobacco-VISORTS aims to overcome the limitations of existing methods and provide an efficient, scalable, and intelligent solution for automated tobacco leaf grading.

### Materials and Methods

The development of agricultural process automation technology in recent years has focused more on the use of machine vision and deep learning technologies in crop recognition and sorting, including tobacco leaves (Luo *et al.* 2025, Wang *et al.* 2025). Nevertheless, the current approaches still lack in real-time flexibility, deployability and integration of end-to-end framework (Bhujade *et al.* 2025, Dharanya *et al.* 2025, Nguleni *et al.* 2025). This indicates that there is a need to create a universal intelligent system like the Tobacco-VISORTS.

As shown in Table 1, in recent years, the classification accuracy of computer vision and deep learning models has improved, but most of the models still lack real-time hardware integration and rely on manual hyperparameter tuning. To overcome these limitations, this study proposes Tobacco-VISORTS, which is an intelligent framework integrating CLAHE, YOLOv8, SFO, and a Python-based airflow injection driving mechanism for tobacco leaf grading. The proposed architecture is shown in Fig. 1a.

**Table 1. Problem formulation summary of existing tobacco sorting techniques with their respective advantages and disadvantages.**

| No. | Technique                                                                      | Advantage                                                                                  | Disadvantage                                                                               |
|-----|--------------------------------------------------------------------------------|--------------------------------------------------------------------------------------------|--------------------------------------------------------------------------------------------|
| 1   | Tobacco Leaf Loosening Detection (Wang <i>et al.</i> 2025)                     | Improves feeding consistency and reduces clumping for better sorting accuracy              | Focused only on physical dispersion, not classification or grading                         |
| 2   | YSFER-Tobacco Model for NTRM Detection (Shen <i>et al.</i> 2025)               | Accurately detects non-tobacco-related materials, enhancing safety and purity              | Limited to NTRM filtering, not leaf quality grading                                        |
| 3   | CMENet – Cross-Modal Enhancement Network (He <i>et al.</i> 2023)               | Combines RGB and spectral data for improved grading accuracy                               | Requires complex multi-sensor setup and higher computational cost                          |
| 4   | Improved Bilinear CNN with Attention (Lu <i>et al.</i> 2023)                   | Effectively handles fine-grained classification of diverse tobacco leaf types              | May be computationally intensive and harder to deploy in real-time industrial environments |
| 5   | Hyperspectral Superpixel-Based Sorting (Li <i>et al.</i> 2023)                 | Detects small impurities like stems with high precision                                    | Expensive hyperspectral hardware and potential latency for real-time operations            |
| 6   | Multi-Scale-X-ResNet for Shredded Leaf Classification (Niu <i>et al.</i> 2022) | Robust multiscale feature extraction ensures high accuracy across visually complex samples | Tailored for shredded leaves only, limiting generalization to whole-leaf grading tasks     |

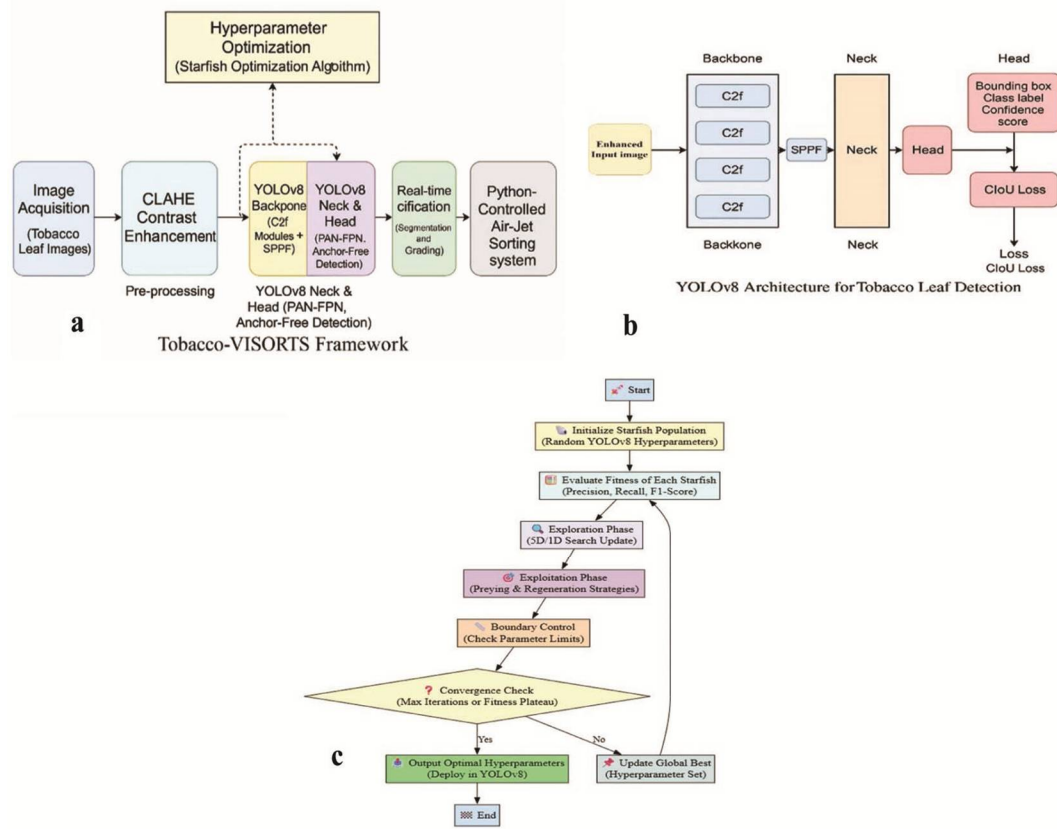


Fig. 1. (a): Proposed conceptual architecture of Tobacco-VISORTS, (b): Structure of YOLOv8 backbone network and (c): Flowchart of the proposed methodology.

In the Tobacco-VISORTS algorithm, image preprocessing is used to enhance image quality before classification. CLAHE is employed to enhance local contrast and highlight the details of tobacco leaves. It operates on small regions called tiles, performing equalization processing on each tile separately, and then recombining them using bilinear interpolation. This can improve the brightness and darkness without excessively amplifying noise. To prevent an increase in noise in uniform areas, CLAHE will clip the histogram at the threshold. Let the histogram bin count of gray level  $i$  be  $H(i)$ , and  $T$  be the clipping threshold. The clipped histogram is given by formula (1),

$$H_c(i) = \min(H(i), T) \quad (1)$$

In this,  $H_c(i)$  evenly distributes the redundant pixels among all the pixel bins to avoid saturation. This retains the fine textures and color variations on the tobacco leaf surface, thereby enhancing the classification and defect detection capabilities of the YOLOv8 module.

YOLOv8 is a core model for real-time detection, segmentation and grading of tobacco leaves based on shape deformation, color change and texture. Its backbone network inherits the efficient structure of YOLOv5 and introduces an improved C2f module (Lopez-Jimenez *et al.* 2025, Rasheed and Zarkoosh 2025), which integrates the idea of ELAN from YOLOv7 on the basis of the early C3 design. This improves the gradient flow and feature reuse, helping to distinguish the

subtle visual differences between different tobacco leaf varieties. Each C2f module consists of a convolutional module and multiple Darknet bottleneck modules connected through the Split-Concat operation. The backbone network of YOLOv8 (Fig. 1b) uses four C2f modules. Each convolutional module contains two-dimensional convolution, batch normalization and SiLU activation function.

SiLU enables faster convergence and better extraction of non-linear features, as shown in equations (2) and (3),

$$f(X) = X * \text{sigmoid}(X) \quad (2)$$

$$\text{sigmoid}(X) = \frac{1}{1+e^{-X}} \quad (3)$$

SiLU is a non-monotonic continuous activation function with a global minimum of about -0.28 and captures complex feature patterns better than ReLU and tanh. The main network consists of five 3×3 convolutional modules, followed by a SPPF module. This module contains two convolutional layers and three max pooling layers, which are used for multi-scale feature fusion and spatial preservation under different input sizes (Kumar *et al.* 2022). YOLOv8 also includes a neck structure based on PAN-FPN, which consists of two up sampling layers, four C2f modules, and several connection operations, used to represent tobacco leaves of different sizes and orientations (Chen *et al.* 2023). Each prediction result contains bounding box coordinates, class labels, and confidence scores, and bounding box regression applies the CIoU loss as shown in formula (4).

$$\mathcal{L}_{CIoU} = 1 - IoU + \frac{\rho^2(b, b^{gt})}{c^2} + \alpha v \quad (4)$$

Where  $\rho$  is the Euclidean distance between the center of the predicted box and center of the true box,  $c$  is the length of the diagonal of the smallest enclosing box,  $v$  is the aspect ratio consistency term, and  $\alpha$  is the trade-off parameter. This enhances the localization precision and increases the general strength of Tobacco-VISORTS.

Hyperparameter tuning plays a vital role in enhancing performance of deep learning classifiers. Parameters like learning rate, IoU threshold and confidence determine to a great extent whether the classification is correct or incorrect in tobacco leaf detection. Hand tuning can be typically inefficient and can result in inaccurate performance. In order to address this issue, Tobacco-VISORTS applies SFO algorithm in order to tune hyperparameters automatically. SFO is a nature-inspired meta-heuristic algorithm, which is modeled on the motion and foraging of starfish, which balances global exploration and local exploitation. It is used in conjunction with YOLOv8 to enhance accuracy of classification and robustness of the system (Zhu *et al.* 2016).

This work aims at applying SFO to hyperparameter optimization of YOLOv8. It employs a tailored multi-objective fitness criterion of tobacco defect classification where precision and recall are all equal. The fitness of the  $i$ th candidate solution is  $g$ . In this case,  $\alpha$ ,  $\beta$ , and  $\gamma$  are weighting factors with  $\alpha + \beta + \gamma = 1$ . Such a measure allows SFO to trade off accuracy and detection strength. Since the learning rates, the values of the IoU, and confidence threshold and other hyperparameters were to be searched in an iterative manner, as indicated in Fig. 1c, strict control of boundaries was applied to keep all the configurations within the feasible range, to avoid unstable training and hasten the process of converting to a reliable global optimum.

The Toyota-VISORTS framework was designed to simulate an industrial tobacco grading line with a pure Python-based software pneumatic jet drive module. Despite the fact that no physical hardware was used, the industrial setting was recreated in this simulation, and the conveyor belt was traveling at 0.70 m/s, the distance between the camera and the nozzle was 0.18 cm, and the theoretical travel time of the virtual jetting was found to be 0.257s. Following the classification with YOLOv8, a fixed pulse duration of 100ms and a simulated pressure of 3.0 bar were used to

trigger the corresponding virtual jetting. Drive instructions and metadata were captured to have full traceability. The modular Python implementation supports real-time control and can be deployed on embedded systems such as Raspberry Pi or Arduino.

## Results and Discussion

This section evaluates the performance of the Tobacco-VISORTS framework in real-time detection, classification, and sorting of tobacco under different experimental conditions (Table 2). The performance indicators include precision, recall, F1 score, classification accuracy, and throughput, and are compared with the PLC-based system and the unoptimized deep learning model. The results confirm the advantages of CLAHE preprocessing, YOLOv8 detection, and the optimization method based on SFO, as well as the real-time processing capability of the airflow sorting module. Fig. 2a shows the input image and the preprocessed image, and Fig. 2b shows the segmentation and classification results of YOLOv8.

**Table 2. Implementation variables and hyperparameter configurations used in the Tobacco-VISORTS framework.**

| Sl. No. | Variable                                          | Value            |
|---------|---------------------------------------------------|------------------|
| 1       | Population Size (N)                               | 30               |
| 2       | Maximum Iterations (Tmax)                         | 100              |
| 3       | Learning Rate (LR)                                | [0.0001 – 0.01]  |
| 4       | IoU Threshold                                     | [0.3 – 0.7]      |
| 5       | Confidence Threshold                              | [0.25 – 0.9]     |
| 6       | Batch Size                                        | [16 – 64]        |
| 7       | Number of Epochs                                  | 100              |
| 8       | Input Image Size                                  | 640 × 640 pixels |
| 9       | Fitness Weights ( $\alpha$ , $\beta$ , $\gamma$ ) | (0.3, 0.3, 0.4)  |
| 10      | Momentum                                          | [0.85 – 0.95]    |

The tobacco leaf disease segmentation dataset consists of 3500 high-resolution image-mask pairs from two subsets - the RGB images have a resolution of 800×800 and include corresponding pixel-level disease masks. The consistent structure, clear annotations, and one-to-one correspondence between the images and masks make it suitable for training and testing deep learning models for tobacco leaf disease detection (Chzili 2025).

Figs 2d, 3 and 4a illustrate the robust classification performance of the framework across grades A, B, and C. The confusion matrix shows high accuracy, with only minor misclassifications between adjacent grades, while the ROC analysis confirms strong discriminatory ability, with all grades achieving an AUC of 0.93 or higher.

Comparative analysis with baseline models, including YOLOv8, YOLOv5-Seg, Mask R-CNN, and U-Net, confirms the superiority of the proposed framework. The overall performance of Tobacco-VISORTS was the best, with F1 of around 0.93, and mAP of 0.91 at 50 and a highest AUC of 0.97, as indicated in Figs 3a, b and c. CLAHE, together with SFO, also enhanced both the detection accuracy and minimized false positives.

Fig. 4b depicts the Tobacco-VISORTS interface that uses an airflow-jet drive system to obtain real-time classification and sorting of tobacco leaves. The interface shows the scanned tobacco leaves, estimated grades, name of the image and the classification, and links the output to a sorting

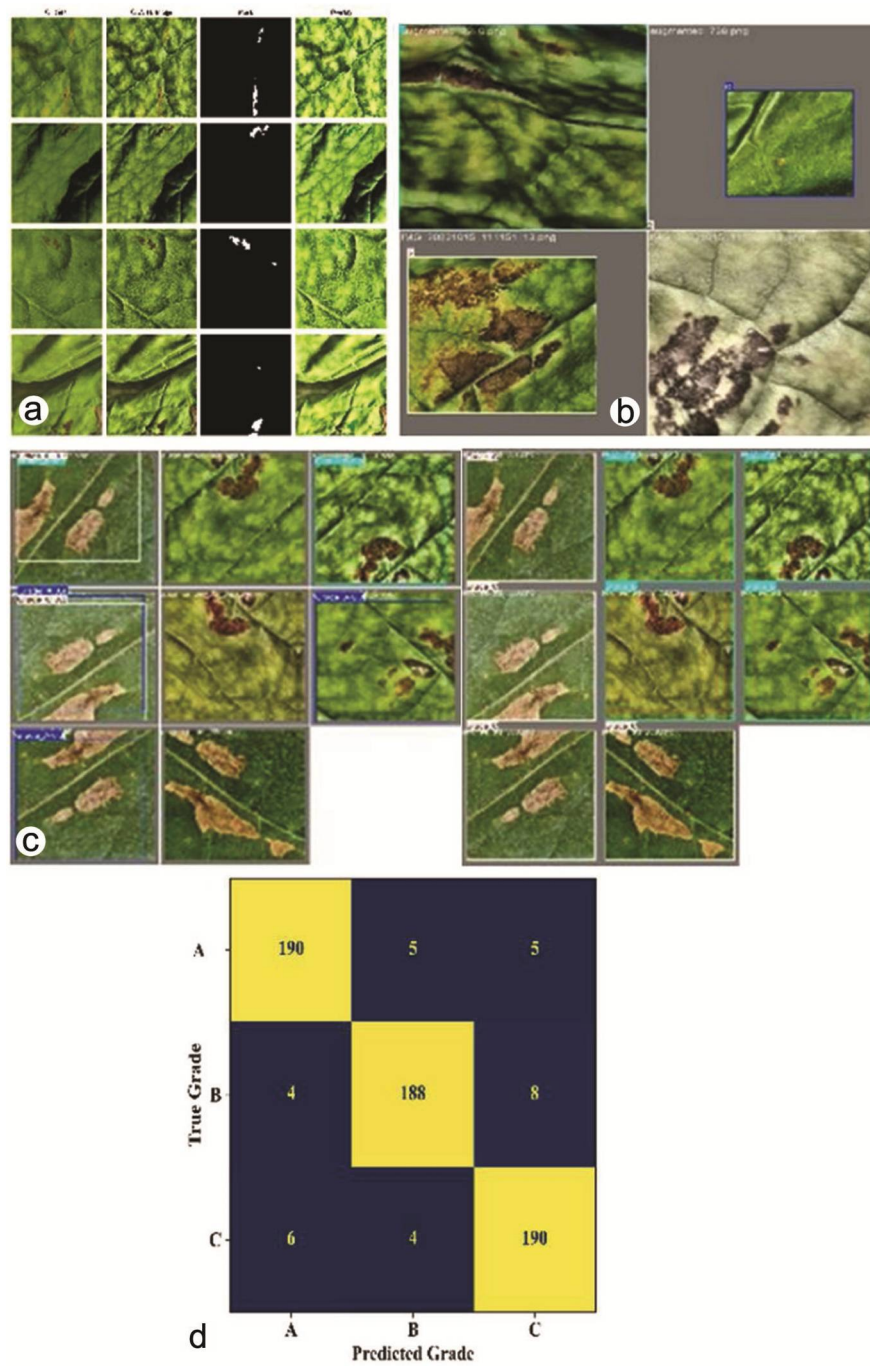


Fig. 2 (a): Input image and CLAHE pre-processed output, (b): YOLOv8 training batch with annotations, (c): YOLOv8 validation batch predictions and ground truth labels and (d): Confusion matrix for tobacco leaf grading across different quality classes.

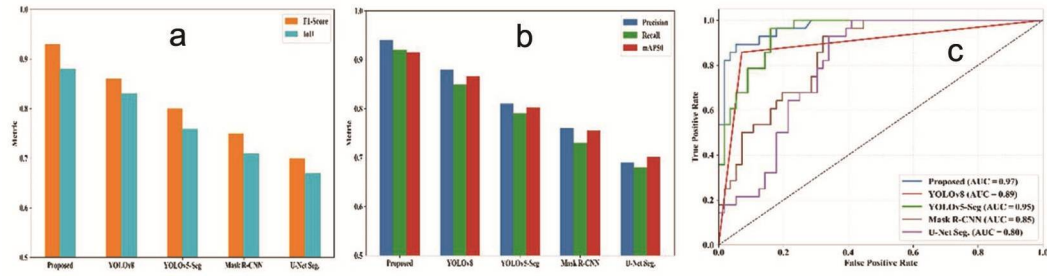


Fig. 3 (a): Validation curves for F1-score and IoU, (b): Performance measures including precision, recall, and mAP, and (c): ROC validation curves for the tobacco leaf classifier across different grades.

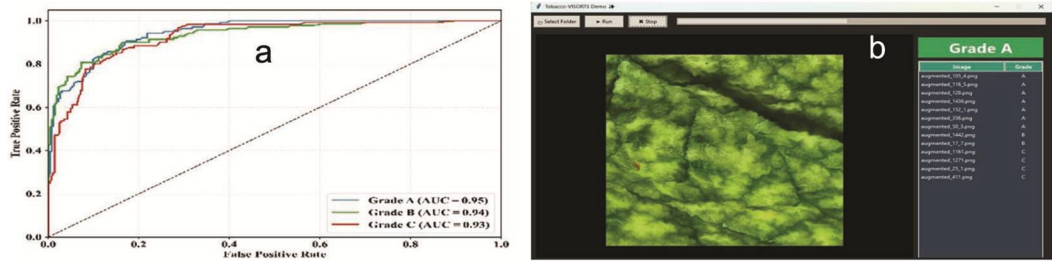


Fig. 4. (a): ROC validation curves for the sorting process and (b): Grading analysis of tobacco leaves across quality classes.

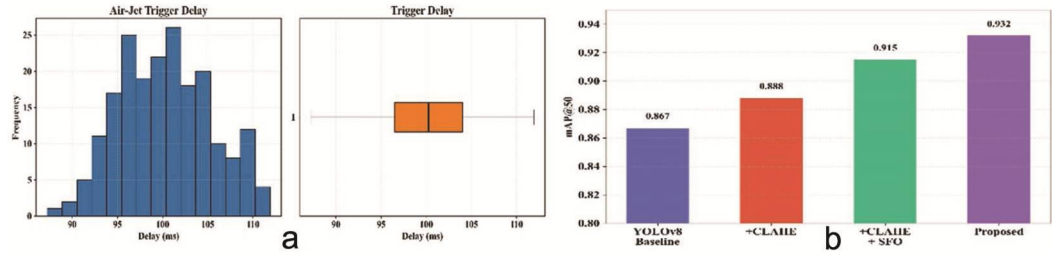


Fig. 5 (a): Sorting analysis showing real-time air-jet actuation delay and throughput and (b): Ablation study comparing YOLOv8 baseline with CLAHE and SFO enhancements.

machine which is operated by Python, allowing the automatic sorting of the tobacco leaves into respective quality grade boxes. This software design will be used to provide a more flexible alternative to the conventional PLC system, as it allows making accurate, fast, and non-contact sorting.

In real time driving, Fig. 5a demonstrates a stabilized delay of airflow using a median close to 100 milliseconds and low variance off the requirements of low-latency sorting in industrial high-speed scenarios. The ablation experiment in Fig. 5b also affirms the overall impact of the proposed module, in which CLAHE improvement and SFO modification have allowed the YOLOv8 baseline to achieve a mAP@50 of 0.867 up to 0.932 in the entire framework. Overall, the suggested Tobacco-VISORTS model is a combination of sophisticated image processing, classification, and control technologies, offering an efficient, scalable, and real-time intelligent tobacco grading solution. This system has been proven to be superior to traditional methods in accuracy, speed and consistency in experimental results. Future directions include more adaptive

light correction, cloud monitoring, and expansion of the system to the visual sorting of different crops. To sum up, Tobacco-VISORTS offers an efficient and versatile solution to attain complete automation and high accuracy in the processing of tobacco and minimize human error and enhance industry standards.

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