TOBACCO COATED SEED RECOGNITION AND CLASSIFICATION METHOD BASED ON IMPROVED YOLOv10N
/
基于改进 YOLOv10n 的烟草包衣种子识别分类方法

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DOI: https://doi.org/10.35633/inmateh-79-96

Keywords: *tobacco seeds; coated seeds; YOLOv10; object detection; lightweight network*

ABSTRACT
Efficient classification of tobacco coated seeds is critical for seed quality assurance in the tobacco industry, yet the nearly identical appearance of coated seeds renders manual sorting labor-intensive and unreliable. Existing automated solutions either lack the precision required for distinguishing sub-millimeter size differences or are too computationally demanding for deployment on edge devices in seed processing facilities. To bridge this gap, this study proposes a lightweight classification model, EMC-YOLO, based on an improved YOLOv10n. This model optimizes YOLOv10n in three aspects: first, replacing the original backbone network with EfficientViT, balancing low computational requirements and global feature extraction capabilities; second, introducing an improved multi-scale spatial pyramid attention (MSPA) into the neck network, utilizing parallel dilated convolution to optimize feature fusion; third, employing the CARAFE operator for upsampling to enhance the edge restoration effect of small targets. Experiments show that the precision, recall, and mAP@0.5 of EMC-YOLO reach 95.12%, 91.20%, and 93.01%, respectively, representing improvements of 2.12, 1.20, and 1.01 percentage points over the original model. Simultaneously, the model reduces the number of parameters by 71%, computational load by 75%, and weight volume by 68.1%. This model achieves high-performance detection with low resource consumption, providing a technical reference for automated seed quality inspection. Validation on a designed seed detection platform under simulated production conditions yielded a coating qualification rate of 95.50%, meeting the 95% industrial benchmark, and confirming the practical feasibility of the proposed method for automated quality inspection in tobacco seed processing lines.

摘要
烟草包衣种子的精准分级对保障种子质量至关重要，然而包衣种子外观高度相似，人工分选劳动密集且易出错。现有自动化方案或精度不足以区分亚毫米级尺寸差异，或计算量过大难以部署于种子加工场景中的资源受限边缘设备。为此，本研究提出一种基于改进 YOLOv10n 的轻量级分类模型 EMC-YOLO。该模型通过三方面优化 YOLOv10n：第一，使用 EfficientViT 替换原主干网络，兼顾低计算量与全局特征提取能力；第二，在颈部网络引入改进的多尺度空间金字塔注意力（MSPA），利用并行空洞卷积优化特征融合；第三，采用 CARAFE 算子进行上采样，提升小目标的边缘恢复效果。实验显示，EMC-YOLO 的精确率、召回率及 mAP@0.5 分别达到 95.12%、91.20%和 93.01%，较原模型提升了 2.12、1.20 和 1.01 个百分点。同时，模型参数量减少 71%，计算量降低 75%，权重体积缩小 68.1%。该模型能在低资源消耗下实现高性能检测，为种子自动化质量检测提供了技术参考。在设计的种子检测平台上进行模拟生产条件下的验证，包衣合格率达 95.50%，超过 95%的行业基准，验证了所提方法在烟草种子自动化质量检测中的实际可行性。

INTRODUCTION
As a major economic crop in China, flue-cured tobacco leads global production in both scale and yield (*Han, 2025*). Seed coating improves seed quality and yield, driving growth in the tobacco industry (*Javed et al., 2022*). However, coated seeds share nearly identical shapes, sizes, and colors, making visual classification difficult (*Zinsmeister et al., 2020*). Manual sorting is slow, labor-intensive, and error-prone, creating a significant bottleneck in seed processing workflows. Given that China produces over 2 million tons of flue-cured tobacco annually, even a modest improvement in seed sorting efficiency can yield substantial economic benefits across

the industry. Thus, there is an urgent demand for efficient, automated sorting and quality control technologies deployable in tobacco seed processing lines.

Traditional image processing uses phenotypic features like size and shape (*Ozaktan et al., 2024*), but 2D visual data cannot capture internal properties, resulting in low accuracy. Other methods, such as chemical analysis or electronic noses (*Fu Jie, 2024*), require complex conditions and damage the samples. For small seeds, these traditional approaches often fail to extract enough features to distinguish subtle differences (*Reena S. et al., 2025*).

Deep learning has transformed image recognition by automatically capturing complex features through neural networks (*Yinglong Li, 2022*). This technology enables precise recognition in agriculture (*Feng Y. et al., 2023*) and handles large datasets effectively (*Wang D. et al., 2022*). Recent studies have optimized networks for small-target detection in agricultural contexts. For example, *Ye et al. (2022),* integrated additional micro-scale detection heads into YOLOv5 for densely-planted Chinese fir seedling identification, improving detection recall for small, overlapping targets but increasing model complexity. *Li J. et al., (2022),* developed Pineapple-Aerial-YOLO with a dedicated small-scale target enhancement framework, achieving improved localization at the expense of higher computational overhead. *Wu et al., (2023),* modified the YOLOv4 architecture with Res2block and depthwise separable convolutions for weed detection, reducing the parameter count of the originally heavy backbone while maintaining competitive detection accuracy.

Despite these advances, recognizing coated tobacco seeds remains challenging. Their sub-millimeter size variations and nearly identical surface morphology demand high detection precision, which typically requires deeper architectures with substantial parameter counts. Conversely, lightweight models designed for edge deployment in seed processing facilities often sacrifice fine-grained discrimination capability (*Li C. et al., 2021; Hamid et al., 2022*). To bridge this gap between detection accuracy and model efficiency, EMC-YOLO, an improved YOLOv10n model, is proposed. It replaces the backbone with EfficientViT, substantially reducing parameters while preserving global feature extraction; introduces a C2f_MSFA mechanism with parallel dilated convolution for adaptive multi-scale feature fusion; and employs CARAFE upsampling for content-aware edge recovery—thereby achieving high detection accuracy with substantially reduced computational requirements. This work contributes to the application of machine-vision-based detection methods in agricultural seed quality inspection, an increasingly important direction in agricultural engineering.

MATERIALS AND METHODS

Establishment of the dataset

Dataset

The dataset of coated tobacco seeds used in this study was independently collected and constructed. The seeds were provided and coated by the Sanming Branch of the Fujian Tobacco Agricultural Science Research Institute, while image acquisition was conducted in the laboratory of Fujian Agriculture and Forestry University. The acquisition equipment consisted of a Hikvision 20-megapixel MV-SC200 industrial camera and a 25-megapixel MVL-KF1224M industrial lens. The images were captured at a resolution of 5472 × 3648 pixels and saved in JPG format. To minimize background interference, black light-absorbing velvet was laid on the workbench. The coated seeds were scattered across the shooting area to simulate their natural distribution after output from a coating machine, ensuring each seed could be effectively captured. The image acquisition setup, consisting of the industrial camera, lens, black velvet-covered sample stage, and LED light source, is shown in Fig. 1

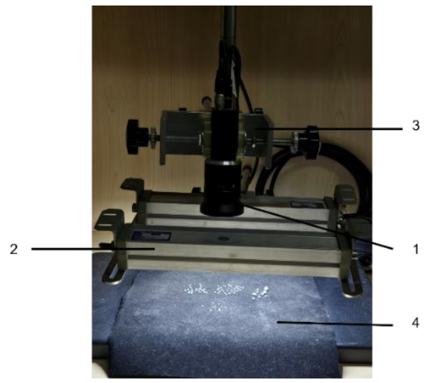


Fig. 1 – Image acquisition setup for coated tobacco seeds
1. industrial camera; 2. LED light source; 3. bracket; 4. black light-absorbing velvet

All collected images were manually annotated using the AnyLabeling tool. By drawing bounding boxes to precisely locate every coated seed, a dataset suitable for object detection tasks was constructed. Each seed instance is accompanied by bounding box annotation information to support deep learning model training. According to the national standard for tobacco seeds (GB/T 21138-2019, 2019), the coated seeds were categorized into four classes: qualified seeds (1.6mm–1.8mm), undersized seeds (< 1.6mm), oversized seeds (> 1.8mm), and damaged seeds (insufficient coating coverage with the seed clearly exposed). Considering that a single test batch contains 100 coated seeds, the number of seeds per image was controlled to under 200. All images were taken under indoor lighting supplemented by LED tubes, and a total of 320 original images were manually annotated using boxes tangent to the seed outlines. The types of coated tobacco seed samples are shown in Figure 2.

a.Qualified seeds b.Small seeds c.Oversized seeds d.Damaged seeds

Fig. 2 – Type of coated seeds collected

Data augmentation

To enhance model generalization and environmental adaptability, a multi-dimensional data augmentation scheme was implemented. This approach effectively expands the parameter search space and simulates real-world factory conditions, such as lighting fluctuations, occlusion, and varied target postures. Specifically, the system integrates photometric and geometric transformations, including random rotation, horizontal flipping, brightness adjustments, and random cropping, each with a probability of 0.5.

The dataset was divided into training, validation, and test sets at an 8:1:1 ratio, comprising 1024, 128, and 128 images, respectively. By fusing these augmentation strategies, the spatial and visual diversity of the training data was significantly improved, effectively reducing overfitting and ensuring robust performance across diverse industrial scenarios.

Improvement of the tobacco coating seed detection model of YOLOv10n

To accurately detect small and densely distributed coated tobacco seeds, this study proposes an improved model, EMC-YOLO, based on the YOLOv10n architecture (*Wang et al., 2024*). While maintaining a lightweight design, the model optimizes feature extraction, fusion, and upsampling as shown in Figure 3.

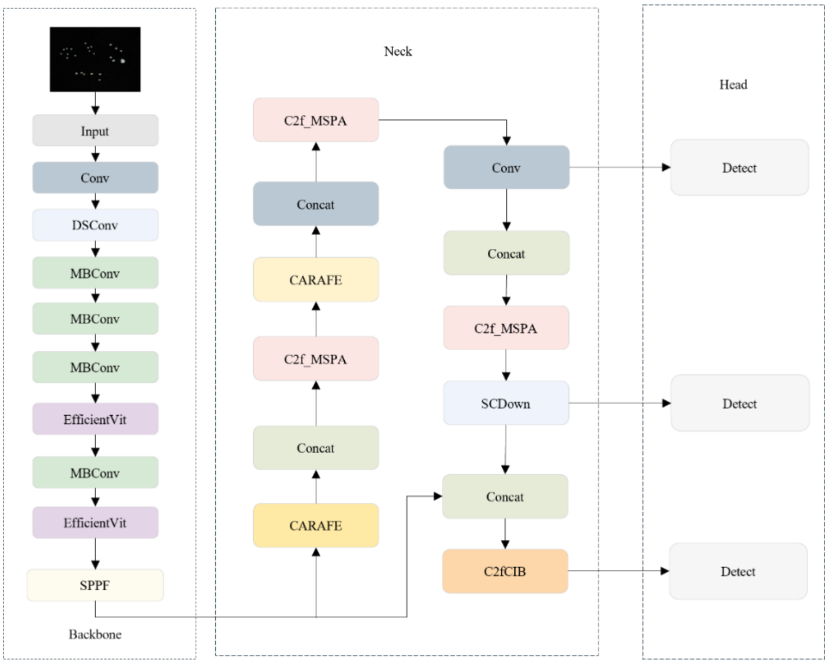


Fig. 3 – The network structure of EMC-YOLO

First, the original backbone is replaced with EfficientViT to enhance global modeling and fine-grained feature capture through grouped attention mechanisms while reducing parameters. Second, a Multi-Scale Spatial Attention (MSFA) module is introduced in the neck, utilizing multi-branch dilated convolutions and channel weighting for dynamic feature selection to better distinguish varying seed sizes. Finally, the CARAFE module replaces traditional upsampling to strengthen edge recovery and small-target detection through content-aware feature reorganization.

Efficient ViT backbone network

Due to the small diameter and subtle surface features of tobacco coated seeds, traditional backbones often lose discriminative textures during deep downsampling. To enhance feature extraction for tiny targets, this study introduces EfficientViT (*Liu X. et al., 2023*) to replace the original backbone, as shown in Fig. 4.

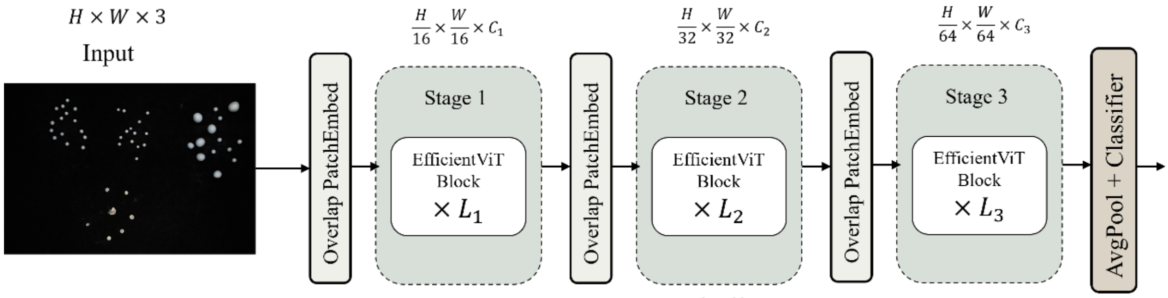


Fig. 4 – The network structure of EfficientViT

The advantage of EfficientViT lies in its core unit, the EfficientViT Block. As illustrated in Fig. 5, this unit features a unique FFN-CGA-FFN sandwich structure. Its operational mechanism utilizes the Cascaded Group Attention (CGA), which splits feature channels and transmits them layer-wise to create specialized attention heads. These heads focus on diverse features such as seed contours, coating integrity, and surface cracks. This hierarchical approach enables the model to accurately extract key semantics from complex reflections or background interference while minimizing computational redundancy.

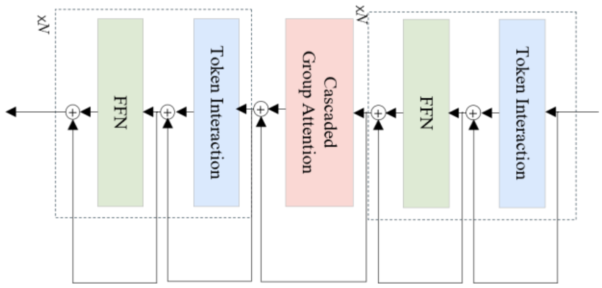


Fig. 5 – The structure of EfficientViT Block

Multi-scale spatial attention mechanism module

To address the continuous scale variation in the grain size of different varieties and batches of tobacco coated seeds, this study, inspired by the Multi-scale Spatial Pyramid Attention (MSPA) (*Yang Yu et al., 2024*), designed a Multi-scale Spatial Attention module (MSFA), whose detailed structure is shown in Fig. 6.

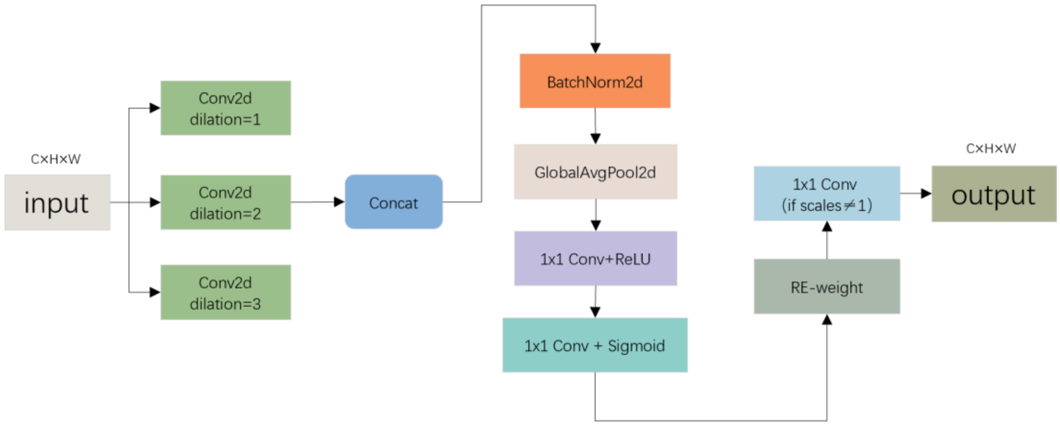


Fig. 6 – The network structure of MSFA

The original C2f module in YOLOv10 relies on fixed receptive fields *(Wang A. et al., 2024)*, which is sensitive to scale changes and lacks adaptive weighting, thus limiting the network to local information. To compensate, MSFA utilizes parallel dilated convolution branches to construct diverse receptive fields. Unlike the original MSPA, this study recalibrated the dilation rates and optimized spatial feature aggregation to suit the dense distribution of seeds. Through a dynamic feature selection mechanism, the module adaptively assigns higher weights to corresponding scale branches based on target size, simultaneously capturing local details and global context.

To further improve feature fusion, MSFA is integrated into the C2f structure to form the C2f_MSFA module (Fig. 7). This integration effectively addresses the limitations of the original C2f in processing scale-sensitive targets and enhances capture sensitivity during the feature fusion stage.

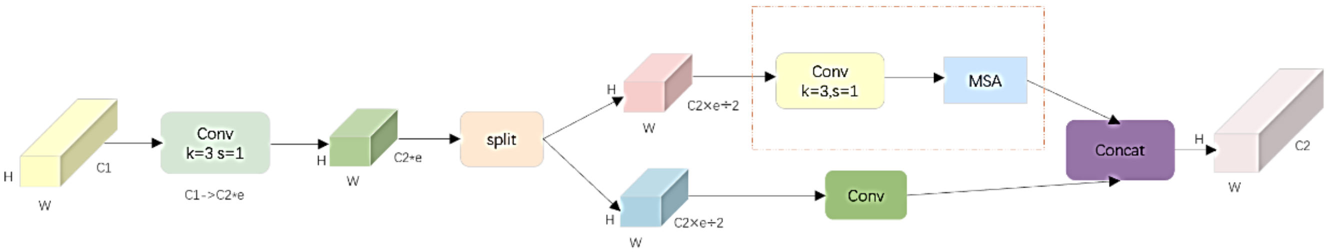


Fig. 7 – The network structure of C2f_MSFA

Sampling operator on CARAFE

In the upsampling stage, the original bilinear interpolation in YOLOv10 often ignores global semantic information (*Wang D. et al., 2022*), leading to blurring and artifacts at seed edges. Consequently, this study adopts the CARAFE content-aware upsampling module (*Wang J. et al., 2019*), with its structure shown in Fig. 8.

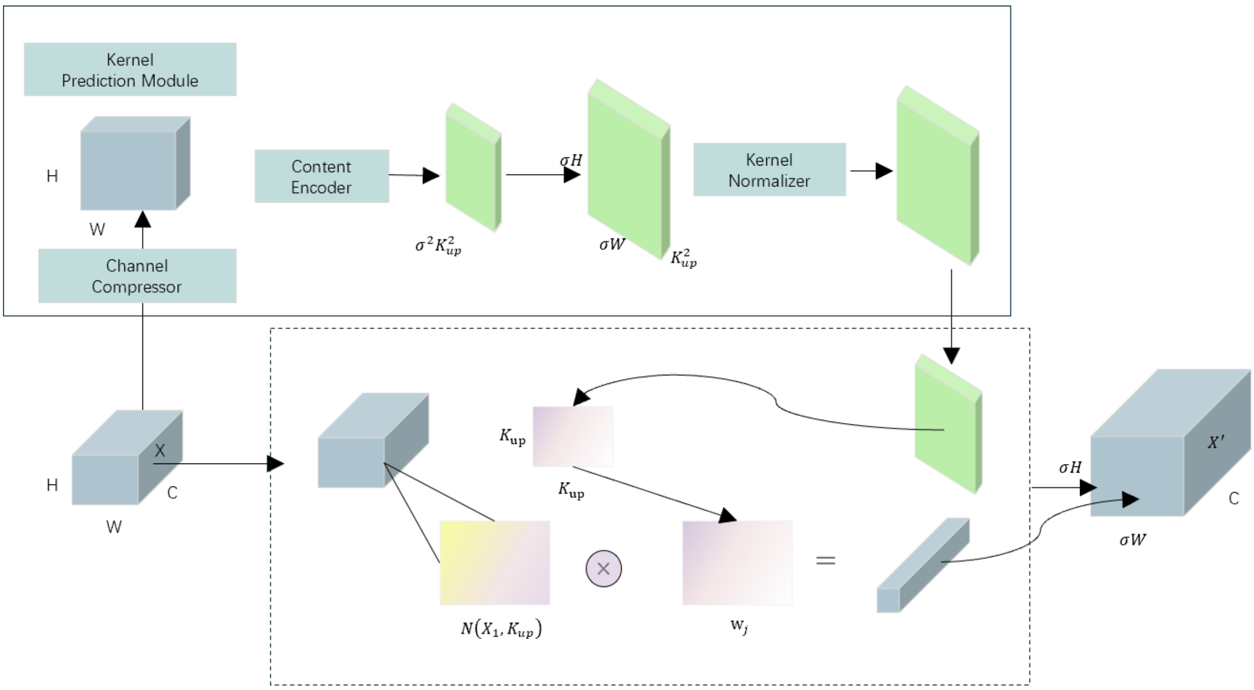


Fig. 8 – The network structure of CARAFE

Unlike traditional operators, CARAFE possesses content-aware capabilities. Its kernel prediction module dynamically generates exclusive kernels for each pixel by analyzing the local context between the seed and its surroundings. Subsequently, the reassembly module uses these adaptive kernels for dynamic feature aggregation. This mechanism allows the model to perceive boundary transitions and perform intelligent enhancement rather than mechanical pixel filling. Experimental results show that CARAFE effectively compensates for traditional interpolation deficiencies, significantly improving the recovery fidelity of tiny target edges and ensuring more precise localization.

RESULTS

Experimental results and analysis

Experimental indicators

To evaluate the performance of the tobacco seed classification model, core metrics such as Precision, Recall, and Mean Average Precision (mAP@0.5) are adopted. Specifically, mAP@0.5 reflects the model's detection stability when the Intersection over Union (IoU) threshold is set to 0.5. Regarding computational efficiency, resource consumption is quantified through the number of Parameters (Params) and Floating Point Operations (FLOPs). To better verify the effectiveness and robustness of the model, this study primarily selects mAP50 as the key evaluation metric.

Comparative experiment

To verify the effectiveness of the proposed EMC-YOLO model, it was compared with several lightweight object detection models, including NanoDet, YOLOv5n, YOLOv8n, and YOLOv10n. The results are summarized in Table 1.

Table1

Contrast test

Model	P/%	R/%	mAP@0.5/%	GFLOPs	Weights/MB
NanoDet	0.85	0.5	0.90	8.3	4.2
YOLOv5n	0.92	0.91	0.91	7.1	5.3
YOLO8n	0.93	0.91	0.92	8.1	6.3
YOLOv10n	0.93	0.90	0.92	63.4	33.5
EMC-YOLO	0.95	0.91	0.93	16.0	10.7

As seen in Table 1, EMC-YOLO outperforms the other lightweight models across all key accuracy metrics. Compared to NanoDet, YOLOv5n, YOLOv8n, and YOLOv10n, it achieves:

- +10.0%, +3.0%, +2.0%, and +2.0% improvement in Precision
- +41.0%, +0.0%, +0.0%, and +1.0% improvement in Recall
- +3.0%, +2.0%, +1.0%, and +1.0% improvement in mAP@0.5

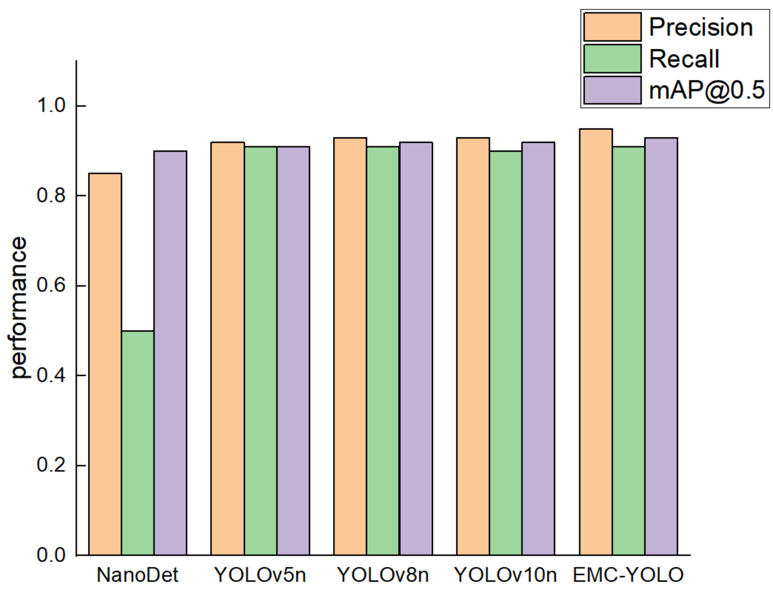


Fig. 9 – Comparison of detection performance of different models

As shown in Fig. 9, EMC-YOLO achieves the highest precision of 0.95 and the highest mAP@0.5 of 0.93 among the five models, which are 2 and 1 percentage points higher than those of YOLOv8n and YOLOv10n, respectively. The recall of EMC-YOLO is 0.91, similar to that of the other lightweight models.

EMC-YOLO achieves an optimal balance between performance and resource efficiency, reducing GFLOPs by 75% and weight size by 68.1% compared to YOLOv10n. These improvements enhance deployment flexibility and operational stability, making the model highly suitable for automated intelligent sorting of coated tobacco seeds.

Visualization of test results

To assess real-world robustness, a visual comparison between YOLOv10n and EMC-YOLO was conducted (Figure 10). The results show that EMC-YOLO provides superior localization with bounding boxes more accurately fitting seed boundaries. Notably, in small-size discrimination, EMC-YOLO correctly distinguished "undersized" from "qualified" seeds, whereas YOLOv10n missed 2 undersized and 4 qualified instances. Furthermore, EMC-YOLO eliminated the misclassification of 5 normal seeds as "oversized" and successfully detected damaged seeds missed by the baseline model. In dense regions, EMC-YOLO maintained high precision without the overlapping or missed detections observed in YOLOv10n. These results confirm that EMC-YOLO is significantly more robust for fine-grained classification, offering improved localization, fewer false positives, and higher recall under complex sorting conditions.

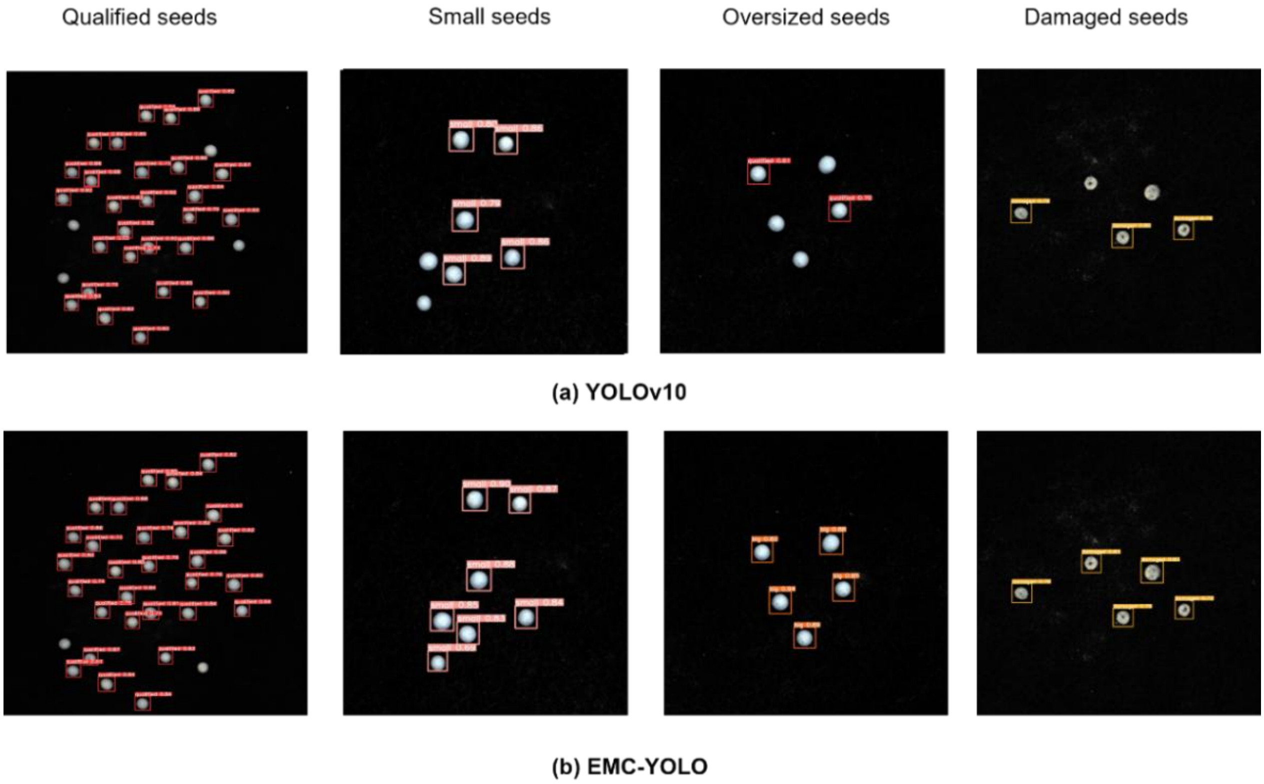


Fig. 10 – Comparison of different algorithm detect results

Ablation experiment

To evaluate the individual contribution of each improvement module, ablation experiments were conducted using YOLOv10n as the baseline. Modules tested include the EfficientViT, C2f_MSFA, and CARAFE mechanisms. All models were trained under identical conditions, and performance was evaluated using Precision (P), mAP@0.5, GFLOPs, and Parameters. The results are presented in Table 2.

The results show that:

- EfficientViT significantly reduced parameters from 16.5M to 4.9M and FLOPs by 75%, providing an efficient lightweight foundation for the model.
- C2f_MSFA improved mAP@0.5 to 0.91, effectively capturing fine-grained seed features through multi-scale modeling and dynamic weight allocation.
- CARAFE enhanced small-target localization and boundary detail recovery, further stabilizing detection performance.
- The final EMC-YOLO model, integrating all three modules, achieved a precision of 95% and mAP@0.5 of 0.93. Compared to the baseline, it achieved a 1% accuracy gain while reducing parameters by 71%, ensuring superior stability for industrial seed screening.

Table2

Ablation experiment

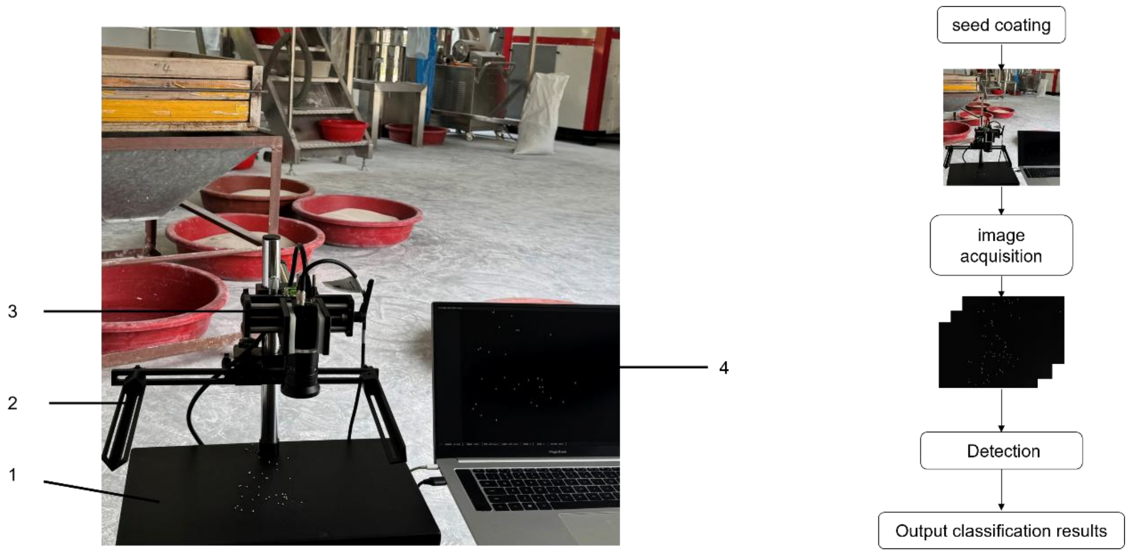
Number	EfficientViT	C2f_MSFA	CARAFE	P/%	R/%	mAP/%	Parameters/M	FLOPs/G	Model size/MB
1	×	×	×	0.93	0.90	0.92	16455016	63.4	33.5
2	√	×	×	0.88	0.58	0.68	4943528	8.9	10.9
3	×	√	×	0.91	0.88	0.91	2911751	9.1	6.2
4	×	×	√	0.90	0.86	0.90	2836080	8.5	6.1
5	×	√	√	0.91	0.88	0.91	3051855	9.3	6.5
6	√	×	√	0.95	0.90	0.92	4445608	14.9	9.9
7	√	√	×	0.94	0.91	0.92	4661380	15.8	10.4
8	√	√	√	0.95	0.91	0.93	4801484	16.0	10.7

Notes: "x" indicates not using this module; "√" indicates the adoption of this module; P is the precision rate; R is the recall rate; mAP is the average precision mean.

Practical application and validation

Design of the seed detection platform

To validate the practical applicability of the proposed EMC-YOLO model in a production-relevant environment, a tobacco coated seed detection platform was constructed in a factory setting, as shown in Fig. 11a. The platform mainly consists of an industrial camera, a camera stand, and a computer. The industrial camera is fixed above the sample stage by the camera stand to capture high-resolution images of the coated seeds, and the captured images are transmitted to the computer for real-time detection and classification using the EMC-YOLO model.



(a) (b)

Fig.11 – Detection platform and workflow

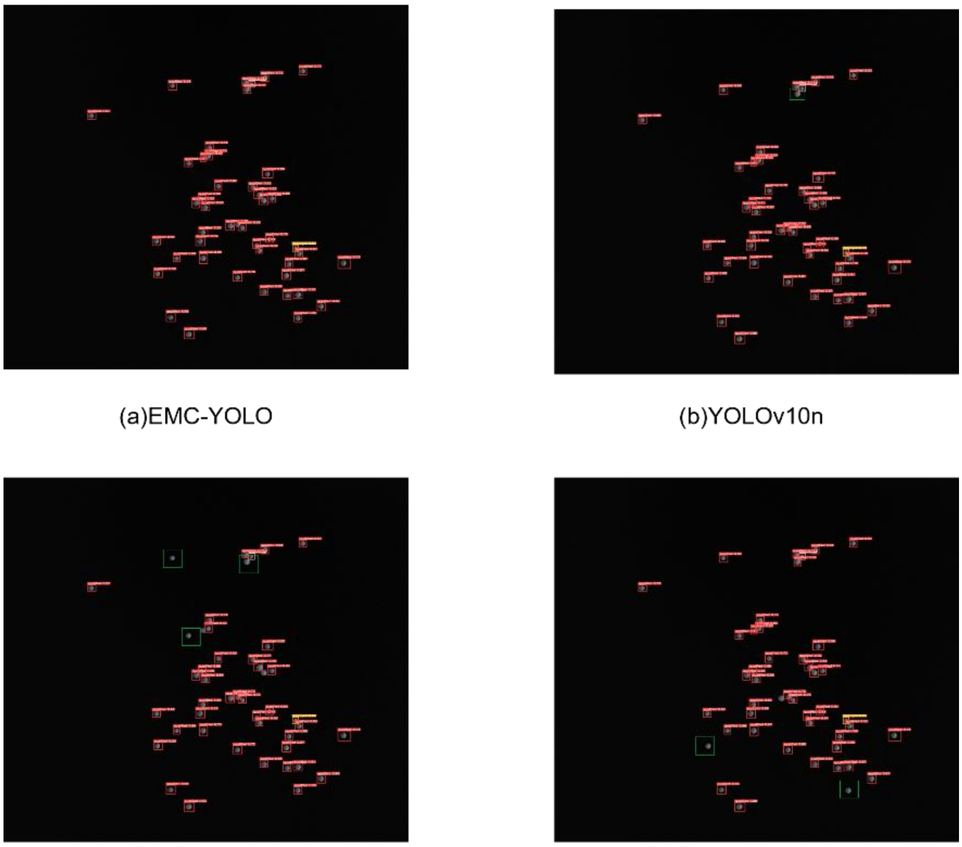
a) detection platform: 1. camera bracket; 2. industrial camera; 3. outlet of coating machine; 4. Computer
b) workflow

Platform workflow

After the coating process is completed, the coated seeds are placed on the sample stage, and the industrial camera is triggered to capture images. The acquired high-resolution images are transmitted to the computer through a data interface, where the EMC-YOLO model performs real-time multi-class detection and classification, outputting the count and proportion of seeds in each category. The workflow of the detection process is shown in Fig. 11b. The platform serves as a quality inspection aid for the coating machine, enabling operators to quantitatively assess the performance of the coating process without requiring a physical seed sorting mechanism.

Coating quality validation experiment

To further verify the performance of the proposed model in the experimental device, EMC-YOLO was compared with YOLOv10n, YOLOv8n, and YOLOv5n in terms of detection results. YOLOv5n exhibited more missed detections; although YOLOv10n and YOLOv8n performed well in certain aspects, their detection accuracy was inferior to that of EMC-YOLO. This result further confirms the feasibility and practicability of the EMC-YOLO model in practical applications. The detection comparison is shown in Fig. 12.



(a)EMC-YOLO (b)YOLOv10n

(c)YOLOv8n (d)YOLOv5n

Fig. 12 – Comparison tests of device end models

To evaluate the coating quality of seeds produced by the coating machine, a batch validation experiment was conducted. A total of 200 tobacco coated seeds were directly collected from the coating machine output. The seeds were placed on the sample stage in four batches of approximately 50 seeds each, and each batch was independently imaged and classified by the EMC-YOLO model. The coating qualification rate was calculated as the ratio of qualified seeds (1.6–1.8 mm) to the total number of seeds tested. The classification results of the four batches are summarized in Table 3.

Table3

Coating quality validation

Batch	Total number	Number of qualified seeds	Particle size compliance/%
1	50	48	96.0
2	50	46	92.0
3	50	48	96.0
4	50	49	98.0

As shown in Table 3, a total of 200 tobacco coated seeds were tested in four batches. Among them, 191 seeds were determined to be qualified, with an overall coating qualification rate of 95.50%, reaching the 95% threshold specified by GB/T 21138-2019. The test results also indicated that this model could effectively distinguish between qualified and unqualified seeds. Overall, the designed platform meets the requirements of practical applications and provides a reliable solution for the automatic quality inspection of tobacco coated seeds during the coating process.

CONCLUSIONS

By optimizing the YOLOv10n architecture, this study developed the EMC-YOLO model for the intelligent recognition and classification of coated tobacco seeds. The main conclusions are as follows:

1. The EMC-YOLO model integrates EfficientViT, C2f_MSFA, and CARAFE to deal with the small target size and subtle size differences of coated tobacco seeds. The precision, recall, and mAP@0.5 reached 95.12%, 91.20%, and 93.01%, which are 2.12, 1.20, and 1.01 percentage points higher than those of YOLOv10n. The accuracy for undersized seeds improved by 15%. With only 4.8M parameters and a 10.7 MB weight size, the model is suitable for deployment on edge devices.

2. The three modules worked together to improve the model. EfficientViT reduced the computational cost while keeping the global features. C2f_MSFA improved multi-scale feature fusion through dynamic weighting. CARAFE recovered the edges of small targets. These changes reduced missed detections and false detections under complex conditions, such as reflective surfaces and dense seed distributions.

3. A detection platform was built in a factory to test the model. Compared with YOLOv10n, YOLOv8n, and YOLOv5n, EMC-YOLO showed fewer missed detections and higher accuracy. In the validation experiment, 200 coated seeds were tested in four batches, and 191 seeds were classified as qualified. The coating qualification rate was 95.50%, which meets the national standard. The platform can be used as a quality inspection tool for the coating machine. Future work will focus on deploying the platform in actual seed processing lines and extending it to more coated seed varieties. These efforts are expected to promote the wider application of machine-vision-based detection methods in agricultural seed processing.

ACKNOWLEDGEMENT

This study is supported by Science and Technology Project of Sanming Tobacco Company, Fujian Tobacco Company (2025YY004), Construction Project of Fujian Provincial Key Laboratory of Agricultural Information Perception Technology (KJG22052A), and Key Technical Innovation and Industrialization Project of Fujian Province (2024XQ010)

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