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Cocoon quality assessment and silk yield estimation YOLOv8 and EfficientNet-B0

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ABSTRACT

Silk production depends heavily on accurate cocoon grading, yet manual inspection is slow, inconsistent, and varies between operators. This creates problems in quality control and affects the final yield of raw silk. To address this, we present an automated system that uses computer vision to detect, separate, and grade silk cocoons without human involvement. The system combines a you only look once version 8 (YOLOv8) model for segmenting individual cocoons from tray images and an EfficientNet-B0 classifier for identifying defects across six categories, including one qualified class and five defect types. After detection and grading, the pipeline also estimates the percentage of good cocoons and predicts silk yield based on standard industry measures. The model was trained on 3,068 cocoon samples and achieved 96.1% mean average precision (mAP) for segmentation and 97% accuracy for classification. The system can count cocoons, assess quality distribution, and provide batch-level yield estimates. This automated approach improves reliability, reduces manual effort, and offers consistent grading suitable for both farm-level and industrial environments. With low operating cost and simple deployment, the system supports modern, scalable, and data-driven sericulture.

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1. INTRODUCTION

The world silk market is a very profitable part of the economy, and in 2024 the value of the silk market will reach 11.85 billion USD, with a predicted upgrade to 26.28 billion USD by 2033, arising to an astonishing annual growth rate of 9.25% [1]. The latter underlines the rising level of demand on the high-quality silk products across the world, the ability to assess the quality of cocoons efficiently and accurately becomes more important than ever before regarding the sustainability in the industry and corresponding to the requests of the market.

The traditional method of cocoon quality assessment is based on a manual examination of an experienced technician, which is oriented on visual aspects of the surface and structural integrity. This approach is not scalable and consistent because it is time-consuming, and there are no standardized procedures. Manual evaluation provides an accuracy of 70-80% with a significant difference between operators especially when it comes to borderline quality samples [2]-[4]. Such restrictions form bottlenecks of production and difficulties in ensuring quality control [5].

Detection technologies have been advancing drastically, where the you only look once (YOLO) framework [6] proposed integrated and real-time capabilities of object detecting that changed the field. YOLOv4 [7], YOLOv5 [8], YOLOv6 [9], and YOLOv7 [10] and follow-on versions have further enhanced speed and accuracy to the extent that the ability to detect objects in real-time has become useful in industrial settings. Such progress has been put in concurrence with the efficient neural network structures like EfficientNet [11], [12] which have implemented new benchmarks in model scaling in convolutional neural networks (CNN), striking an improved balance between computation effectiveness and performance.

Recent research has demonstrated that automated cocoon quality assessment using fine-grained deep learning models—incorporating attention mechanisms, bilinear feature learning, and multiscale fusion—can achieve accurate and consistent cocoon sorting in sericulture applications [13], [14]. Moreover, end-to-end automated cocoon processing systems based on multi-stage machine learning pipelines for Bombyx mori have shown practical feasibility for improving silk quality and production efficiency, while also revealing deployment challenges in industrial settings [15].

The related specialized detection and classification tasks concerning cocoon assessment have been resolved in a number of ways. Implemented circular knitting fabric defects classification with Applied MobileNetV2 [16] and showed the efficiency of lightweight architectures in the area of textile quality control [17]. Developed special lightweight CNN to classify the quality of silkworm cocoons due to the limitations of work in industrial conditions because of the complexity of computations that are required. Such methods that stress efficiency are necessary to implement in practice when speed of processing and use of resources are important aspects [18], [19].

Cocoon quality assessment extends beyond visual inspection to include physical and chemical attributes that directly affect silk yield and consistency. Prior studies have addressed critical quality control challenges such as dead cocoon identification using CNN [20], cocoon gender classification through hybrid image processing and machine learning frameworks [21]. Advanced non-destructive inspection approaches, including X-ray–based internal structure analysis, have further demonstrated the potential to capture quality characteristics not observable through conventional optical methods [22], [23]. More recently, research has shifted toward real-time industrial applicability, improves YOLOv5 with ConvNeXt and ECANet attention for mAP@0.5 of 96.46% on mixed silkworm images for sericulture quality monitoring [24].

Modern advances in computer vision have enabled fully automated cocoon classification systems, including dual-camera deep vision frameworks that demonstrate the feasibility of integrated industrial inspection pipelines [25]. Broader surveys in precision agriculture further highlight the effectiveness of deep learning–based visual analytics across tasks such as plant disease detection, underscoring their relevance to agricultural quality assessment [26]. High-precision object detection models, including faster region-based convolutional neural network (Faster R-CNN), have established robust region-proposal mechanisms for accurate feature localization in complex scenes [27]. Parallel progress in image segmentation architectures, exemplified by hybrid convolution–ViT models such as GH-UNet, illustrates the adaptability of deep learning across domains [28], [29]. These developments build upon foundational breakthroughs in large-scale visual recognition, notably the ImageNet-driven success of AlexNet and subsequent multi-scale and attention-based deep architectures that continue to advance large-scale image understanding [30].

Research on efficient defective cocoon recognition has made important contributions to automated quality control systems. Advanced studies have focused on vision-based methods for intelligent picking systems, developing analytical models that can be implemented in cocoon testing processes [31]. Machine learning applications are proving useful in improving crops and ensuring sustainable production in the agricultural setting [32], and the generation of extensive datasets has been invaluable in training powerful machine learning models. ImageNet [33] has become an essential tool in the development of computer vision research, since it involves hierarchical multi-scale image databases where efficient model training and evaluation are possible.

Recent advancements in computer vision have substantially improved object detection accuracy. Methods based on focal loss [34] are effective in handling crowded visual scenes, while deep learning models [35] learn complex features from large datasets, enabling robust detection performance. Recent studies highlight the increasing use of these techniques in precision agriculture [36], and their successful application in domains such as medical face mask detection [37] demonstrates their adaptability to agricultural quality assessment tasks.

Existing works primarily address cocoon classification using limited datasets (800-2800 cocoons) and lack instance-level segmentation. Meanwhile the previous work has not integrated yield estimates in a given framework. The proposed framework overcomes these limitations by combining YOLOv8-based cocoon segmentation with EfficientNet-B0 multi-class defect classification on a dataset of 3,068 tray-level images, enabling accurate grading and batch-level silk yield prediction within a lightweight and deployable system.

2. METHOD

2.1. Data collection

We collected raw images of 3,460 cocoons with smartphones (Realme 9i 5G and Samsung M11 with 50 MP cameras). The photos were taken of bivoltine and cross-breed cocoons mounted on trays covered with black sheets to produce uniformity of backgrounds. Images were of good quality and clear due to standardized light set up. Actual quality variations were represented by cocoon samples that were collected in active silk farms and processing centers. Individual photography was also performed at the same distance (30-40 cm) and angles. We created data set of 3068 individual cocoons images with the entire quality range including premium specimens and all classes of defects including difficult to classify borderline cases. The distribution across categories is shown in Table 1.

Table 1. Distribution of cocoon types across bivoltine and cross-breed varieties

Type	Category	Bivoltine	Cross-breed	Total
Qualified	Good	485	288	773
	Double	342	126	468
	Crushed	427	254	681
Defective	Decayed	286	188	474
	Pierced	122	85	207
	Yellow spotted	328	137	465
Total		**1990**	**1078**	**3068**

The dataset includes various quality categories of bivoltine cocoons as shown in Figure 1, which illustrates sample images for each type: Figure 1(a) qualified category holds good cocoons of detailed white/cream colour, structural integrity of the cocoons, and no visible defects. The defective category is divided into the following categories: Figure 1(b) double cocoons with two pupae in the same cocoon body (as a rule, the quality of silk is infringed considerably); Figure 1(c) crushed bodies with visible physical damage with the crop deformation; Figure 1(d) decayed cocoons with dark pigmentation, which indicates the biological degeneration; Figure 1(e) pierced cocoons with holes of emerged moths or any external damage; and Figure 1(f) yellow spotted cocoons with the stinking that had rather negative influence on final silk quality.

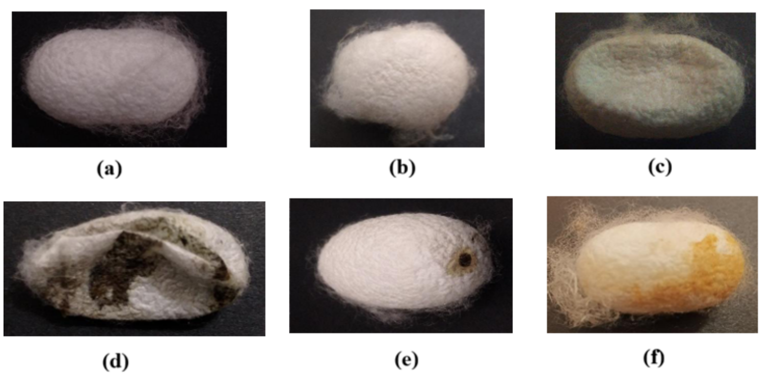


Figure 1. Visual examples of silk cocoon quality categories used in this study: (a) qualified cocoon, (b) double cocoon, (c) crushed cocoon, (d) decayed cocoon, (e) pierced cocoon, and (f) yellow-spotted cocoon

2.2. Data preprocessing

The standardization of cocoons through image preprocessing was done to bring the cocoons to a 640×640 pixels lighted, blurred, and angled corrected image. There was an optimized brightness that came with BGR to RGB conversion. Roboflow allowed detection training with an accurate labeling of bounding boxes. The methods of dataset augmentation were rotation, flipping, brightness, and resizing. More techniques capable of high specialization such as mosaic (stitching four photos) and mixup (melding photos) promoted diversity. The dataset split: 70% training, 20% validation, and 10% testing. All the images were clear to the eye with details related with the quality assessment.

2.3. Cocoon segmentation using you only look once version 8

We adopt the YOLOv8s model [38] for cocoon instance segmentation because it offers a practical balance between detection accuracy and computational cost, making it well suited for deployment on commonly available industrial GPU systems. Since the core architecture of YOLOv8 has been extensively described in prior work [38], this study concentrates on how the model was configured and optimized specifically for cocoon segmentation. To ensure reliable performance under real sericulture conditions, the training data included both bivoltine and cross-breed cocoons, covering a wide range of variations in size, shape, color, and surface defects.

Several input resolutions (416×416, 512×512, and 640×640) were evaluated during preliminary experiments. Among these, 640×640 consistently produced clearer cocoon boundaries and more accurate instance separation, while remaining within acceptable GPU memory limits. Based on validation trends, the model was trained for 50 epochs, which proved sufficient for stable convergence. Extending the training duration beyond this point did not improve performance and, in some cases, resulted in mild overfitting. Hyperparameters were refined through systematic validation experiments, where batch sizes of 16, 8, and 4 were tested; a batch size of 8 was selected as it provided stable convergence under available memory constraints. Training was performed using stochastic gradient descent with Nesterov momentum set to 0.937 and an initial learning rate of 0.01, gradually reduced using a cosine annealing schedule to promote smooth optimization. Automatic mixed precision (AMP) was enabled to reduce memory usage and accelerate training without affecting accuracy. To further improve generalization, data augmentation strategies such as mosaic augmentation, mixup blending, random rotations, and scaling were applied. Early stopping with a patience of 50 epochs was used to prevent overfitting. The overall YOLOv8-based segmentation pipeline adopted in this work is illustrated in Figure 2.

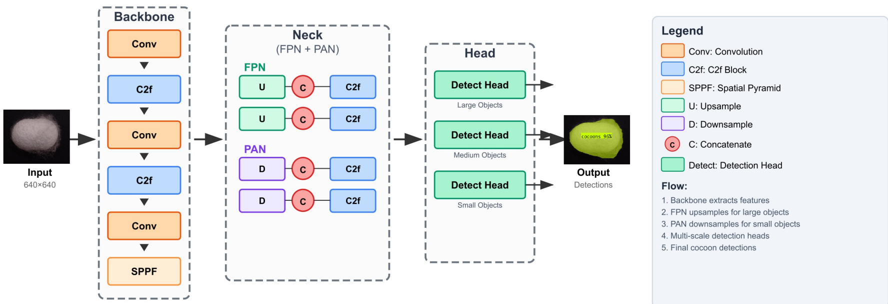


Figure 2. YOLOv8 segmentation architecture showing the backbone for feature extraction, the neck for multi-scale feature fusion, and the head for cocoon detection and segmentation

2.4. Cocoon defect classification using EfficientNet-B0

We employ EfficientNet-B0 [39] as the cocoon defect classification backbone due to its favorable accuracy–efficiency trade-off and suitability for real-time industrial applications. As the architectural details of EfficientNet have been extensively documented in prior work [39], this study focuses on its task-specific adaptation for cocoon quality classification rather than reiterating generic network design aspects. The segmented cocoon regions obtained from the YOLOv8 stage are resized to 224×224 RGB images and normalized using ImageNet statistics before being fed into the pre-trained EfficientNet-B0 backbone with a customized classification head.

Model training was performed for a maximum of 30 epochs, with early stopping triggered based on validation loss stagnation to prevent overfitting. This epoch limit was selected empirically, as extending training beyond this point did not result in additional performance gains. Optimization was carried out using the Adam optimizer with parameters $\beta_1 = 0.9$ and $\beta_2 = 0.999$, and an initial learning rate of 3×10^{-4}, which was adaptively reduced using the ReduceLROnPlateau scheduler. A batch size of 32 was chosen to ensure stable gradient updates, with gradient accumulation applied when necessary. Regularization was achieved using a dropout rate of 0.3 prior to the final classification layer. To mitigate class imbalance among cocoon defect categories, weighted random sampling was employed during training. Data augmentation strategies, including horizontal flipping, photometric jittering (up to 20%), and random rotations (up to 10°), were applied to enhance generalization. The EfficientNet-B0 classification architecture used in this study is illustrated in Figure 3.

Figure 3. EfficientNet-B0 architecture with MBConv blocks and SE attention mechanisms for cocoon quality classification

2.5. Proposed YOLOv8–EfficientNet-B0 based cocoon quality and yield estimation

The proposed Algorithm 1 offers a comprehensive procedure to evaluate the quality of the cocoon and predict the yield of silk based just on the photos of the trays taken under the conditions of the real farm. It starts with the training of a YOLOv8-based segmentation network on annotated images of trays to precisely localize individual cocoons and an EfficientNet-B0-based classifier on cocoon samples cropped to distinguish between those ready to be presented to the market ("qualified") and those with defects. When deploying, the trained detector outputs cocoon-regions in every image, which are subsequently padded, cut and scored with the classifier to be labeled as either high or low quality. The system then estimates a round number of the riveted cocoons, using projected numbers, and using constants based both on the average weight of a cocoon and the rate at which the cocoon is extricated to arrive at the estimated silk output. The pipeline produces annotated images and structured per-tray reports as well as global summaries of performance measured in segmentation, classification and yield estimation accuracy.

Algorithm 1: YOLOv8–EfficientNet-B0 based cocoon quality and yield estimation

Input: $\mathcal{D}_{tray}$: tray images; $\mathcal{D}_{crop}$: cocoon crops; $\mathcal{I}_{test}$: farmer tray images
Output: Per-tray CSV, annotated images, global metrics
Function `TrainYOLO` ($\mathcal{D}_{tray}, E_y, I_y, B_y, device$)
  Init YOLOv8-segmentation with pretrained weights
  Train E_y epochs at resolution I_y, batch B_y; validate via mAP
  Save best weights `YOLO_W`
Function `TrainCLF` ($\mathcal{D}_{crop}, E_c, I_c, B_c, device$)
  Init EfficientNet-B0 with pretrained backbone; apply augmentation and balancing
  Train E_c epochs at resolution I_c, batch B_c; evaluate via AUC/Acc
  Save best weights `CLF_W`
Function `ExtractCrops` (I, *YOLO_W*, PAD, TH_{CONF})
  Run YOLOv8 inference on I with confidence TH_{CONF}
  For each box b: clamp bounds, pad by PAD, extract RGB crop
  Append $(crop, b)$ to $\mathcal{C}$
  return $\mathcal{C}$
Function `ClassifyCrops` ($\mathcal{C}$, *CLF_W*, TH_{PROB})
  For each $(crop, b) \in \mathcal{C}$: compute p for "qualified"
  Label = 1 if $p \geq TH_{\text{PROB}}$ else 0; append $(b, label, p)$ to L
  return L
Function `EstimateYield` ($L, AVG\_COC\_WT, SILK\_F$)
  $q \leftarrow$ count labels $= 1$; $d \leftarrow$ total $-q$
  $est\_wt \leftarrow q \cdot AVG\_COC\_WT$; $est\_silk \leftarrow est\_wt \cdot SILK\_F$
  return $(total, q, d, est\_silk)$
Function *MainPipeline*($\mathcal{D}_{tray}, \mathcal{D}_{crop}, \mathcal{I}_{test}, \Theta_{train}, \Theta_{infer}, device$)
  `YOLO_W` $\leftarrow$ `TrainYOLO` ($\mathcal{D}_{tray}, \Theta_{train}$)
  `CLF_W` $\leftarrow$ `TrainCLF` ($\mathcal{D}_{crop}, \Theta_{train}$)
  for $I \in \mathcal{I}_{test}$ **do**
    $\mathcal{C} \leftarrow$ `ExtractCrops` (I, *YOLO_W*, Θ_{infer})
    $L \leftarrow$ `ClassifyCrops` ($\mathcal{C}$, *CLF_W*, Θ_{infer})
    stats $\leftarrow$ `EstimateYield` (L, Θ_{infer})
    Annotate & save image; append CSV row
  Compute global segmentation, classification, and yield metrics
  return summary

The silk yield estimation module has complete production forecasting according to the analysis of cocoon quality distribution and total weight of a batch. Industry-standard renditta values, illustrated in the system architecture in Figure 4, and will depend on the conversion ratios, obtained empirically, of cocoon weight (dry weight) to recoverable silk weight in the different quality grades. The estimation of the yield has (1):

$$\text{Renditta} = \frac{\text{weight of batch} \times \text{qualified cocoon percentage}}{100 \times \text{raw silk produced}} \tag{1}$$

where effective renditta will be the weight of cocoon needed to provide 1 kilogram of raw silk and include quality dependent processing losses. The renditta value also indicates that efficiency of silk production proportionately follows the existence of the percentage of qualified cocoons. When the higher percentage of qualified cocoons is achieved, the renditta will be reduced and it implicates that lesser amount of kilograms of cocoons are needed to attain one kilogram of raw silk. calculation was expressed as (2):

$$\text{Silk yield (kg)} = \frac{\text{total cocoon weight (kg)}}{\text{effective renditta}} \tag{2}$$

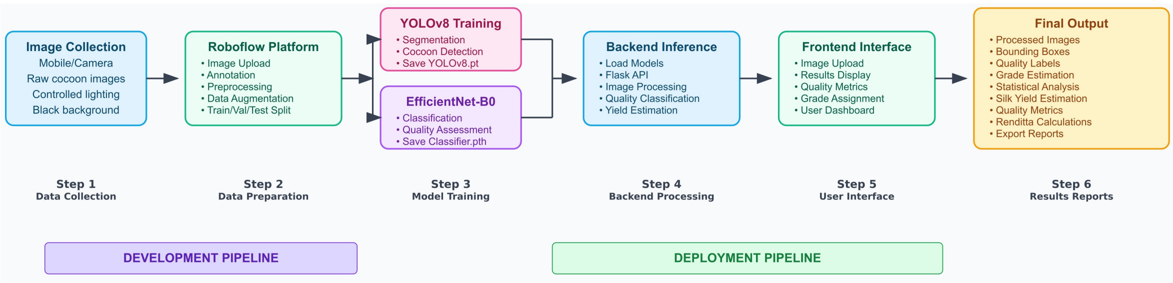


Figure 4. System architecture diagram showing the integrated YOLOv8 and EfficientNet-B0 pipeline for cocoon quality assessment

This model represents that of an automated grading system under which grading classification by quality is based on qualified percentages of cocoon as grade A (premium) above 85%, grade B (standard) of 70-84%, grade C (commercial) of 50-69%, grade and -below quality (substandard) of less than 50%.

3. RESULTS AND DISCUSSION

Our quality of cocoon assessment was analytically evaluated by deeply testing a wide range of both performance scales measures of segmentation and classification. Strict validations were applied in testing and ensured reliability and reproducibility.

3.1. Evaluation metrics and model performance

3.1.1. Segmentation evaluation

The measured performance of segmentation was benchmarked using standard computer vision metrics that were optimized towards object detection tasks and further to delineation of boundaries. The important metrics of evaluation as shown in (3):

$$\text{IoU} = \frac{|P \cap G|}{|P \cup G|} \tag{3}$$

The intersection over the Union (IoU) is used to calculate the precision of the space overlap; here, the set of regions predicted (P) is an input and the ground truth annotations (G) are one as shown in (4):

$$\text{mAP} = \frac{1}{N}\sum_{i=1}^{N} \text{AP}_i \tag{4}$$

The mean average precision (mAP) measures the overall detection quality, where AP_i represents the average precision for class i as shown in (5):

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{5}$$

Precision is calculated to determinate the accuracy of the detection, the variables here are TP indicating the true positives and FP which is the false positives as shown in (6):

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{6}$$

Recall measures detection completeness, where FN represents false negatives as shown in (7):

$$F1 = \frac{2 \times \text{precision} \times \text{recall}}{\text{precision} + \text{recall}} \tag{7}$$

F1-score provides a balanced performance assessment by combining precision and recall.

The YOLOv8 segmentation model performed excellently in the detection and boundary of cocoon as demonstrated by the performance curve in Figures 5–7. The system performed astonishingly 96.1% mAP@0.5, which means extremely precise recognition of cocoon with few false detections. The precision measure of 98.3% indicates very low false positive quantities; the recall quantity of 94.9% affirms that it detects all the cocoons in the batch images. The balanced F1-score of 96.6% means an ideal balance related to both the precision and the recall.

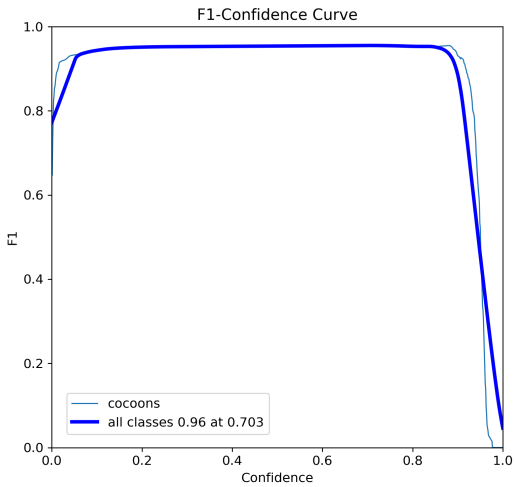


Figure 5. F1-score curve of the YOLOv8 segmentation model showing the balance between precision and recall across confidence thresholds

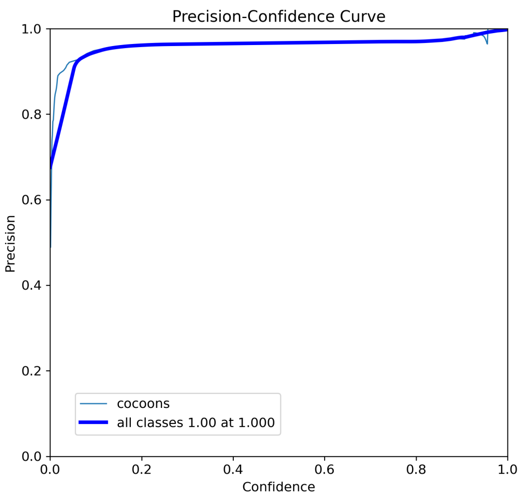


Figure 6. Precision curve of the YOLOv8 segmentation model illustrating detection accuracy at different confidence levels

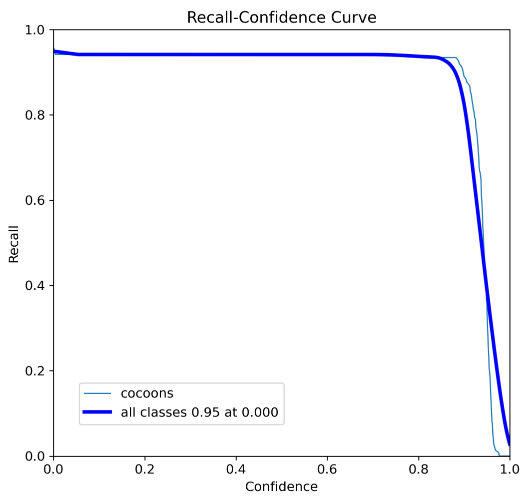


Figure 7. Recall curve of the YOLOv8 segmentation model indicating the model's ability to detect cocoons across confidence thresholds

The model attains a high level of performance in various intensities of scenarios to perform well in instances of dense cocoon formation and diverse lightning conditions, as depicted in the segmentation results (Figure 8). The system effectively differentiates between individual cocoons in dense arrangements and appropriately defines the cocoons in order to perform the next quality evaluation.

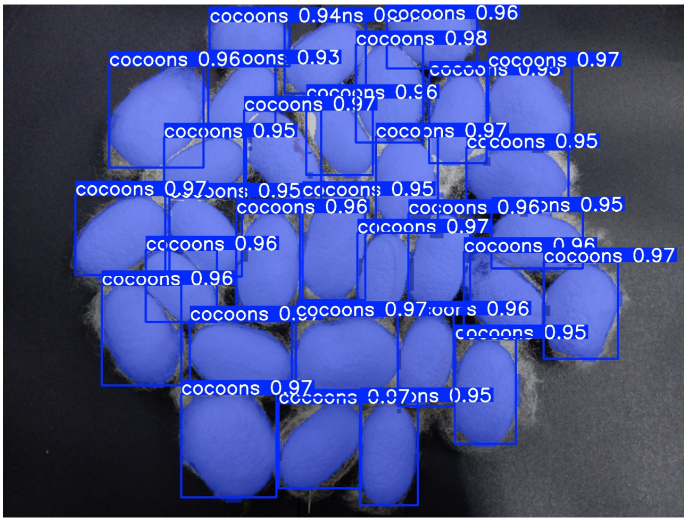


Figure 8. Qualitative segmentation results of the YOLOv8 model demonstrating accurate cocoon localization and boundary separation under varying density and lighting conditions

3.1.2. Ablation study on YOLOv8 variants and augmentation

To validate the design choices, an ablation study was conducted comparing three YOLOv8 segmentation variants—YOLOv8n, YOLOv8s, and YOLOv8m—trained for 50 epochs under identical settings. As shown in Table 2, YOLOv8s provides the best balance between accuracy and efficiency, achieving an mAP@0.5 of 0.961 with moderate training time. Although YOLOv8n trained faster, its detection accuracy was slightly lower, while YOLOv8m required significantly longer training without clear performance improvement. Additional experiments evaluating Mosaic and MixUp augmentation further improved segmentation performance, increasing mAP@0.5 from 0.958 to 0.963 while slightly enhancing precision and recall.

Table 2. Ablation analysis of YOLOv8 variants and augmentation strategies (50 epochs)

Experiment	Model	mAP@0.5	Precision	Recall	Training time (s)
exp_n	YOLOv8n-seg	0.960	0.987	0.952	1774.5
exp_s	YOLOv8s-seg	0.961	0.980	0.953	1969.43
exp_m	YOLOv8m-seg	0.958	0.981	0.954	3024.93
exp_no_aug	YOLOv8s (no augmentation)	0.958	0.980	0.953	1784.55
exp_full_aug	YOLOv8s (Mosaic+MixUp)	**0.963**	**0.981**	**0.955**	1997.23

3.1.3. Classification evaluation

The performance of the classification models was assessed by conserving some conventional metrics on grading of cocoon quality. Total correct classifications are quantified as overall accuracy as in all the classes there are counts of correct classification; calculations of precision, recall, and F1-scores of the classes follow the same procedure as segmentation calculation.

The precision–recall curve ((Figure 9) shows strong defect detection performance, with the operating point close to the upper-left region, while the ROC analysis achieves an ideal AUC of 1.00, indicating perfect class separability. The confusion matrix ((Figure 10) confirms reliable classification, correctly identifying 71 defective and 79 qualified cocoons, with a low false negative rate of 6.6% and zero false positives. Overall, the EfficientNet-B0 model attains an accuracy of 97.0% and demonstrates balanced performance across quality categories, as reported in Table 3.

The defective cocoon classification was specific with 100% precision and 93% recall whereas qualified cocoon assessment had 94% precision and 100% recall. Macro and weighted average were on the same level getting 97% which implied consistency among categories. In real-time deployment validation, current system functionality is demonstrated. Dissection of a few sample batches showed that there were a total of 31 cocoons, 23 of which qualified specimens (74.19%) and 8 that were defective (25.81%), as illustrated in Figure 11.

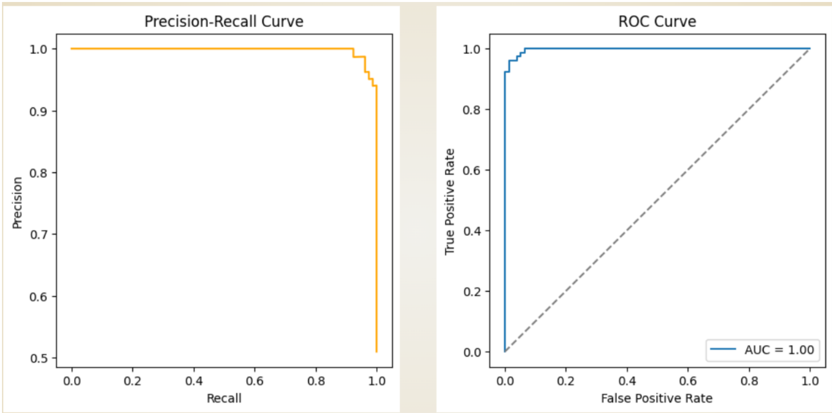


Figure 9. Precision–recall curve and ROC curve of the EfficientNet-B0 classification model, illustrating strong class separability and balanced performance

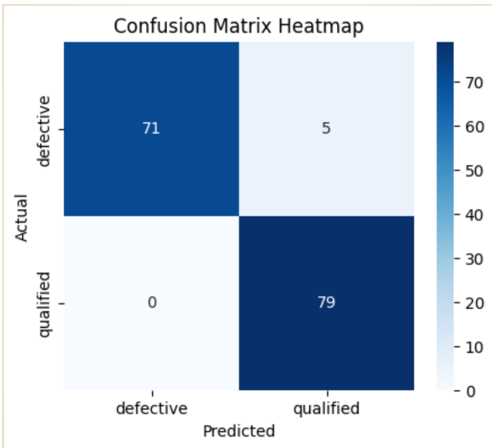


Figure 10. Confusion matrix for classification model

Table 3. Classification performance metrics for quality grades

Class	Precision	Recall	F1-score	Support
Defective	1.00	0.93	0.97	76
Qualified	0.94	1.00	0.97	79
Accuracy		**0.97**		
Macro Avg	**0.97**	**0.97**	**0.97**	**155**
Weighted Avg	**0.97**	**0.97**	**0.97**	**155**

Statistical significance versus baselines: Table 4 presents a comparative evaluation of the proposed YOLOv8–EfficientNet-B0 framework against representative baseline methods reported in prior cocoon detection and classification studies. The proposed approach exhibits consistently strong and well-balanced performance across all evaluation metrics, achieving 96.1% mAP@0.5, 97.0% classification accuracy, and a 96.6% F1-score, while maintaining high precision (98.3%) and recall (94.9%). Compared with existing YOLO-based detectors, anchor-based architectures, and lightweight convolutional neural network models, the proposed two-stage framework outperforms or remains competitively aligned across heterogeneous datasets and experimental settings.

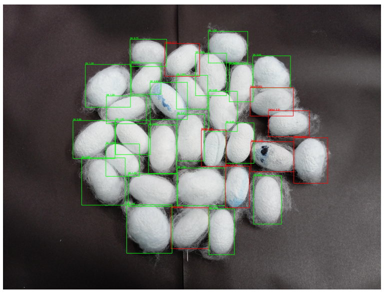


Figure 11. EfficientNet-B0 classification results illustrating predicted cocoon quality categories

Table 4. Statistical comparison with baseline methods

Method	Dataset size (cocoons)	mAP@0.5 (%)	Accuracy (%)	F1-score (%)	Precision (%)	Recall (%)
Proposed YOLOv8–EfficientNet-B0	3068	96.1	**97.0**	**96.6**	**98.3**	**94.9**
CD-YOLO [40]	2800	**97.5**	95.6	94.0	97.5	94.3
YOLOX [40]	2800	94.2	93.3	93.0	94.2	93.8
RetinaNet [40]	2800	92.0	90.2	91.0	92.0	91.5
SSD [40]	2800	89.5	83.3	84.0	89.5	85.0
BGA-YOLOX-s [41]	1609	94.8	–	–	–	–
CBL-YOLOv3 [42]	800	92.5	–	91.0	–	–
K-YOLOX [43]	–	94.2	–	92.5	–	–

3.1.4. Silk grade output and yield estimation

Under the integrated system, production metrics is very detailed as analysis pipelines compute detailed forecast on the basis of defect distributions and industry proven renditta values on silk yields predictions. Figure 12 illustrates the application interface that demonstrates functions with an analysis of 100 kg cocoon batch. Analyzing the system, 90% of cocoons (90 kg) passed the qualification test and 10% (10 kg) were defective. With a renditta of 6.55, the system estimated the production of silk of 15.27 kg, a 15.27% conversion rate and grade A (premium) quality rating. The overview of the production summarizes the essential parameters such as the batch weight, the percentage of qualification, renditta coefficient, the anticipated silk output by kilograms of raw material, and so forth, and thus, the resulting facts may determine resource planning and process tactics.

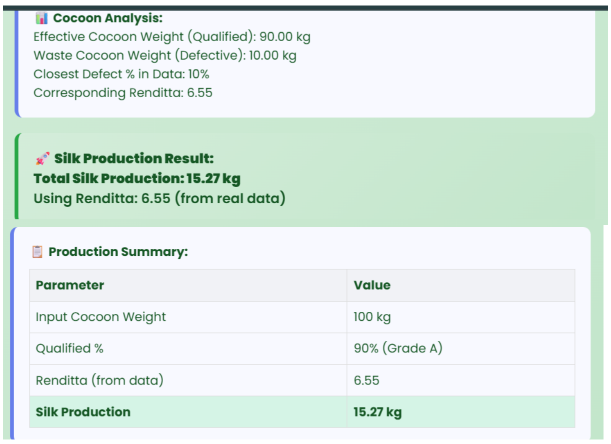
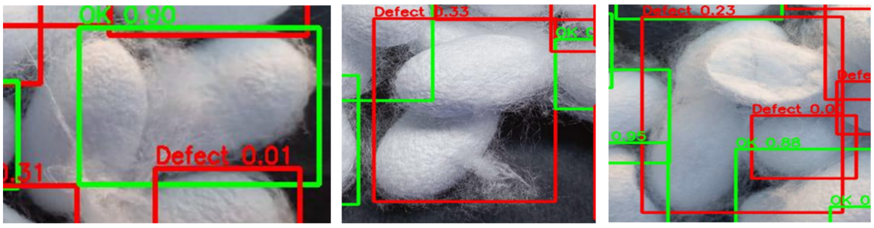


Figure 12. Silk yield estimation interface showing batch-level quality distribution and predicted raw silk output

3.2. Error analysis

Despite its overall strong performance, the model has some limitations in specific real-world situations, as shown in Figure 13. Figure 13(a) in densely packed trays, overlapping cocoons might be combined into a single instance, leading to both under-segmentation and counting errors. Figure 13(b) changes in lighting, like shadows or low light, can change how cocoons look, causing healthy samples to be incorrectly classified as defective. Figure 13(c) when overlapping occurs in poor lighting, the model might treat multiple cocoons as one, incorrectly labeling the entire cluster. These results indicate that performance may decline in the presence of occlusion, lighting variation, and visually complex patterns.



(a) (b) (c)

Figure 13. Representative failure cases of the proposed cocoon analysis system: (a) overlapping cocoons merged as one instance, (b) lighting-induced misclassification, and (c) combined overlap and lighting effects

4. CONCLUSION

The primary contribution of this study is the development of a large in-house dataset comprising 3,068 annotated bivoltine cocoon images, coupled with a customized segmentation–classification architecture that enhances quality control and reduces operational costs. The web-based deployment of the proposed system enables scalable and accessible quality assessment for both small-scale farms and industrial silk reeling units, establishing a practical automation baseline for sericulture. The proposed YOLOv8–EfficientNet-B0 two-stage pipeline achieves a segmentation performance of 96.1% mAP@0.5, 98.3% precision, 94.9% recall, F1-score of 96.6% and a classification accuracy of 97.0%. In addition, the integrated system enables batch-level silk yield estimation using industry-standard renditta values, demonstrating a practical conversion example of 100 kg cocoons producing an estimated 15.27 kg of raw silk. Future work will focus on extending the framework to larger multi-breed datasets with overlapping of cocoons and enabling real-time factory-level deployment.

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This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C	: **C**onceptualization	I	: **I**nvestigation	Vi	: **Vi**sualization
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CONFLICT OF INTEREST STATEMENT

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

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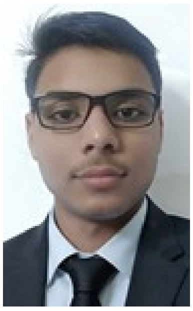

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