Real-Time Cocoon Quality Classification via CAE- Enhanced YOLOv8 Detection Framework

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Abstract -Automated cocoon grading system gives better results in regards to silk production as it produces more predictable results, w ith many times faster than manual methods while still attaining a close to a stable silk quality. Manual grading by hand is very labor intensive since it is based on human eye inspection, with inconsistent outcomes. The research paper proposes an automated system for grading cocoon using a combined image acquisition control based system with data augmentation based on convolution auto encoder (CAE) technology and YOLOv8 framework for cocoon classification. With CAE augmentation, we generated 689 samples for the original collection of 305 cocoon images. We trained their study and manufactured YOLOv8 based on their results preprocessing parameters. The system achieved 98% classification accuracy and 97.5% mAP, showing its effectiveness in classifying cocoon quality. Your pipeline offers a scalable real, time automated cocoon inspection system.

Keywords: Autoencoder, Cloud computing, Cocoon grading, Data augmentation, Deep learning, Image preprocessing, Real, time classification, YOLOv8

1. INTRODUCTION

Cocoon grading plays a crucial role in sericulture, impacting silk production, reeling efficiency, and the economic worth of ten cocoons. Traditionally, this grading is done by hand by experienced workers who look at factors like texture, color, consistency, and any flaws New tech in computer vision and deep learning has made it possible to have automated systems that check things visually really well and consistently [3] But when it comes to real-world silk farming, how well these systems work really hinges on both how accurate the classifiers are and how solid the rest of the software setup is A deployable solution must integrate image acquisition, standardized pre-processing, and reliable model inference,while remaining compatible with downstream decision- making or control modules. In this paper, we're suggesting a complete software design for automated cocoon checking The system hooks up controlled image grabbing, standard pre-processing, and YOLOv8-based spotting and sorting to churn out dependable grading results The proposed pipeline's effectiveness has been confirmed through tests in a cloud setup, showing it's a solid base for future hook-ups with physical sorting or gear-driven systems in semi-automated reeling units Recent studies show that automated systems for grading cocoons are more reliable when they use consistent ways to capture and prepare images Multi-scale deep learning models have proven to be better at spotting issues in cocoons than older computer vision methods

Today's YOLO-based detection systems make it possible to inspect crops effectively by striking a good balance between precise identification and quick, real-time performance There aren't enough research papers out there that really dig into how well these model-focused methods stack up against the whole software pipeline approach when they're actually running Manual human cocoon grading often ends up with mixed outcomes since the judgments are based on individual views and workers' tiredness The automated solutions currently available do not meet the needs of real sericulture operations. This software system will assist small to medium silk-reeling companies in enhancing their grading precision This will let them handle their business more cheaply Manual cocoon grading takes its sweet time and can be pretty subjective, which means the quality isn't always consistent Automated systems are all about the model evaluation rather than creating practical workflows. This study aims to build a real-time software-controlled system that uses the YOLOv8 model to grade cocoon quality through controlled imaging methods. The main contributions of this work are:

(1) Development of a controlled cocoon imaging setup,

(2) CAE-based augmentation for small cocoon datasets

(3) YOLOv8-based real-time cocoon classification pipeline, and
(4) cloud-integrated inference workflow.

1.1 Organisation of the Paper

After that, the rest of the paper follows this structure. •
Section II: Literature survey, inference, motivation, and objectives
Section III: Materials and Methods
Section IV: Experimental Results
Section V: Conclusion and Future work

2. LITERATURE SURVEY

Automation in cocoon grading has started from manual techniques to vision, based techniques in order to address the subjective nature of traditional techniques, manual labor, and inconsistency. Cocoon quality has been manually defined in terms of physical and economic measures [1], and advanced image processing techniques empowered more independence and consistency to cocoon grading [6], [7]. ML, based vision systems increased the speed of classifications and showed the effectiveness of fully automated cocoon inspection in a sericulture scenario [2], [3]. In recent years, advances in the state of the art and breakthroughs in deep learning have translated into applicability of CNN, based architectures for cocoon quality assessment tasks, enabling visual end, to, end learning for the task. On the other hand, in the cocoon classification task attention and multi, scale features have increased the accuracy of cocoon classification and defect detection [4], [5]. Existing databases of limited and imbalanced data are still difficult, to, learn for the cocoon classification task. Effective data augmentation techniques [10], [11] and pre, processing strategies have made the cocoon classification task more model transfer learning capable and stabilized for the model to converge. Autoencoders and generative adversarial networks have been investigated to learn additional visual features in order to improve visual representation learning of visually restricted datasets [16], [18], [20], [21], but the unified system for cocoon classification task is still an unexplored area. For valid real, time implementation, YOLO, based systems sit at thebest accuracy and speed trade, off of agriculture inspection applications [12], [22]. The strength of the literature is applying the YOLOv8 model for optimal real, time implementation on resource limited environments [23]. Cloud, based systems for inspection were also discussed in terms of modular and scalable strategies for the overall inspection task inspired by the use of cloud [2], [9], but the end, to, end approach for automated cocoon grading is still in a state of art discussion. The review therefore validates that though the deep learning approaches and the real, time detection systems have enhanced the cocoon inspection by accuracy, there is still an urgent need for smooth software pipelines to incorporate the image acquisition, model training and inference on the deployment, ready level. These aspects have fed directly into the approach taken in this work.

3. MATERIALS AND METHODS

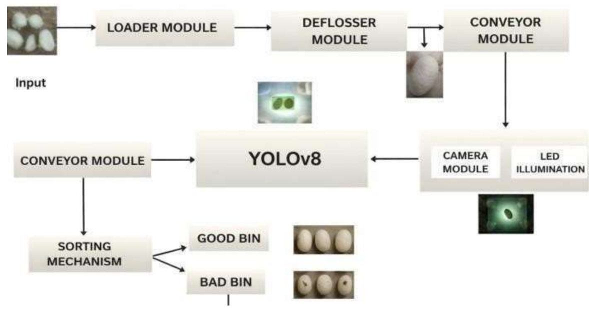

Fig.1. Overall workflow of proposed solution

In this system, the hardware simply moves the cocoons through loading, cleaning, and conveying, while the main intelligence lies in the software. As each cocoon passes under the inspection zone, a high-resolution camera with controlled LED lighting captures clear, shadow-free images. These images are enhanced using a Convolutional Autoencoder (CAE), which removes noise and improves important surface details like texture and shape. The refined images are then fed into YOLOv8, which performs real-time detection and classification in a single pass. Based on YOLOv8's prediction, the system quickly decides whether the cocoon is good or defective and sends the signal for automatic sorting.

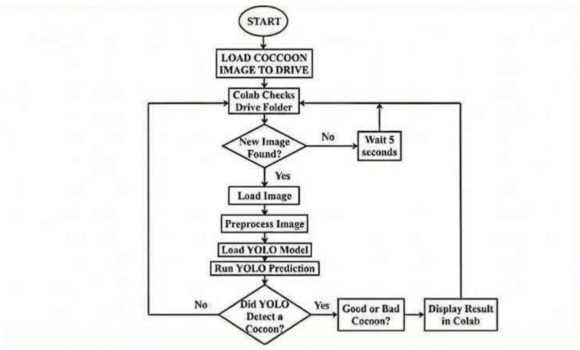

Fig.2. Automated YOLOv8 inference workflow for cocoon classification with cloud monitoring and decision-based result display.

The iterative nature of the training of the YOLOv8 model can be viewed in Fig. 2. The labeled cocoon dataset is loaded to train the model. The validation accuracy of the model is checked at the end of each training cycle. If the validation accuracy is satisfactory then the weights of the model are saved; else the hyperparameters are optimized and the model is trained again. This process is done until the validation accuracy of the trained model stabilizes and the weights are saved, signaling the end of the training stage of the model. Only the training set is augmented using CAE. This is so, because the class imbalance issue is to be addressed and diversity in the learned feature representations is to be increased while the validation and test set are left unaltered to evaluate the model's accuracy and generalization on unseen data respectively. The learned information from the training set is used to update the weights of the model to learn the peculiar features of the training images and at the same time validate the performance of the model to choose the most accurate model and revise the hyperparameters like class weight adaptation and learning rate. The trained and validated model is finally tested on only the test set to evaluate its accuracy and effectiveness [12], [23].

3.1 Materials

Depth images were captured with an Intel RealSense D435i depth camera, which captures images in resolutions up to 1280 720 pixels at 30 fps [24]. The LED illumination was diffused to make it as uniform as possible and a neutral matte background was used in order to reduce shadows and reflections. The camera, object distance was held at a fixed 29.3cm for consistency. Model development and inference was done in python, based deep learning frameworks, but image loading and synchronization were done on Google drive. There are 305 cocoons images (“Good” and “Bad” cocoons) labeled manually in the dataset, taken under controlled environment such as an even LED lighting, a consistent background, and an object, to, camera distance of 29.3cm. To allow the model to learn all possible features and be more capable of generalization, the entire dataset was augmented using a pre, trained Convolutional Autoencoder (CAE). The CAE is an architecture that compresses the input to form a low, dimensional latent space, then reconstructs the original image. This guarantees that the synthetic samples would remain geometrically consistent and texturally accurate while keeping the addition of realistic variations to the original image. Unlike various other generative architectures such as generative adversarial networks (GANs) that generate uninteresting artifacts, CAE based augmentation preserves the shape of a cocoon. The CAE was trained on 250 training images (1% of the entire dataset) for 100 epochs (24 hours) with a learning rate of 0.001, batch size of 32 and MSE as the loss function, resulting in an increased number of images to a total of 689. The dataset was then randomly split into training, validation and test sets with a ratio of 70:20:10. The table below summarizes the total number of images for each class before and after augmentation.

TABLE I. CLASS WISE DISTRIBUTION OF DATASET BEFORE AND AFTER AUGMENTATION

Category	GOOD CLASS	BAD CLASS
Before Augmentation	95	217
After Augmentation	206	498

3.2 YOLOv8 Training & Inference Workflow

The YOLOv8 model was trained using the AdamW optimizer, with a learning rate of 0.0001, batch size of 16, and a weight decay of 0.0005. The training was carried out for a total of 300 epochs. Since they wanted to preserve the natural cocoon morphology, Mosaic and MixUp augmentations were disabled. A mixed dataset of original and CAE, augmented images was used to train the YOLOv8 model, while the test set was held back for measuring the final model accuracy. The team relied on validation performance for model tuning and checkpoint selection. The inference loop was implemented on Google Colab. The trained model was used to automatically fetch newly arrived cocoon images from cloud storage and save the predictions. YOLOv8 depicts bounding, box location estimates, objectness scores, and class probabilities via a single forward propagation, as a way to treat object detection as a single, stage regression problem [12], [23]. To provide a single bounding box for each cocoon image and categorize each as either ‘Good’ or ‘Bad’, during inference each image was also subjected to non, maximum suppression to remove duplicates. With this single, shot detection framework, it is possible to achieve low, latency real, time inspection at the time of cocoon arrival to allow for automatic cocoon sorting in the silk reeling factories.

3.3 Data Preprocessing and Cloud Retrieval

Images from Google Drive were fetched using an automated retrieval script developed on Google Colab. All the images were given to the YOLOv8 model after being resized to the 128x128 pixel size. The authors did very little processing as they intended to preserve all the cocoon morphology and texture traits.

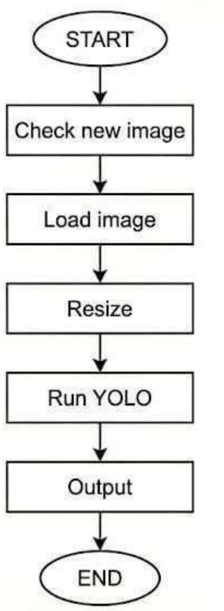

Fig. 3. End-to-end inference workflow for automated cocoon classification

The complete end, to, end inference process for automated cocoon grading using the YOLOv8 network is illustrated Figure 3. On receiving the cocoon image, the system will automatically load and resize the image according to the input size of a trained network. The raw image will be fed into the YOLOv8 model and then extract the object image and recognize the cocoon based on the learned visual features and then classify the cocoon based on its quality characteristics. The results from the inference stage is then displayed which contains the quality class of cocoon, Good or Bad, with the related confidence score.

3.4 Advantages of YOLOv8 for Cocoon Inspection

The first forward pass the system makes is to identify objects and determine the class of the object. This does have an advantage in that it can provide a faster real, time performance than two, stage detectors like Faster R, CNN. The anchor, free detection system allows for better detection of agricultural objects such as cocoons. The process gains by improving the accuracy in locating these objects. YOLOv8 performs well in detection while reducing the operational demands making it suitable for automation inspection systems.

4. EXPERIMENTAL RESULTS

Quality parameters are cocoon grading using visual features comprising surface texture and shape uniformity and visible imperfections and color uniformity and physical integrity. Manual cocoon grading incorporates these parameters as basis for evaluation. The independently testing of the cocoon grader was performed on the isolated test set outlined in Section III [24]. Using a test set that was never used in training or validation, this provided insight as to the ability of the classifier in identifying Good or Bad cocoons under a controlled imaging environment. The test set is indicative of how successfully the system would operate in a real world situation where generalizability and reliability is important. The training was more balanced with the CAE based augmentation to the underrepresented Bad cocoon class, which reduced class bias and resulted in more stable learning [17], [20], [21]. Table 1 of Section III documents the distribution profile of the dataset before and after augmentation. The augmentation almost doubles the number of samples, notably increasing the number of minority class samples, and adding intra, class diversity. Examples of the CAE, augmented images are shown in Figure 4. The augmentation preserves natural cocoon shape, surface texture, and orientation, but adds other finer details. The additional variation enables the model to learn a more reliable set of features, which is reflected in the high accuracy of the test set classifications. Tiny dataset models generally do not perform as well without such augmentation, especially on minority classes.

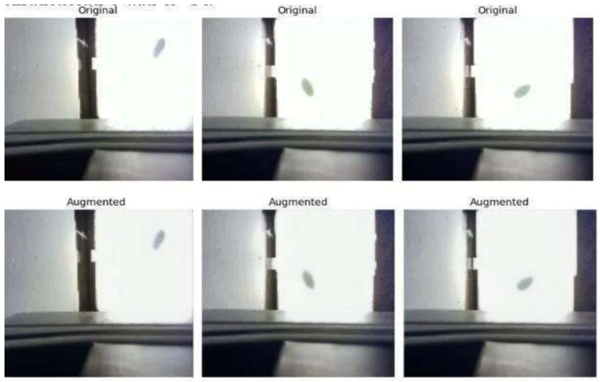

Fig.4. Original and CAE-generated cocoon images

In Figure 4, typical original cocoon images and their corresponding samples produced by convolutional autoencoder (CAE) are demonstrated. The CAE applies variations that are controlled and at the same time keeps the basic visual structure of the cocoon images, thus making sure the original data distribution is not disturbed. The YOLOv8 classifier performs better on images of cocoons that it has never seen before thanks to the samples produced in this way, which are used in the training process to broaden the variety of feature representations learned.

World-class, indeed, overall, and class various, describes the classifier outcome of the YOLOv8, with hyperparameters described in Section III. Table 2 elaborates the quantitative assessment.

TABLE II. PERFORMANCE METRICS OF YOLOV8 FOR COCOON CLASSIFICATION

Metric	Good Cocoons (%)	Bad Cocoons (%)	Overall (%)
Accuracy	99	97	98
Precision	98	96	97
Recall	97	95	96
F1-Score	97.5	95.5	96.5
mAP (0.5:0.95)	98.2	96.8	97.5

Thus, due to the high accuracy and F1, score, the system was able to classify with cocoons with very minimum false negatives and false positives. The reasons for the slight variations in the results for the Good and Bad cocoons were mainly due to the original class imbalance which was countered by the CAE based augmentation and the weight adjustments in training. The results for accuracy, precision, recall, F1, score and mAP which are comprehensive to each other are seen in table 2 for both the classes. Looking at the metrics, it is evident that the YOLOv8 model performs consistently in providing accurate decision about the cocoons even if the dataset faced an imbalance initially.

TABLE III. PERFORMANCE METRICS EQUATIONS AND DEFINITIONS

Metric	Equation	Definitions
Precision	$\mathbf{Precision} = \dfrac{\mathbf{TP}}{\mathbf{TP+FP}}$	The proportion of correctly predicted positive samples out of all samples predicted as positive.
Recall	$\mathbf{Recall} = \dfrac{\mathbf{TP}}{\mathbf{TP+FN}}$	The proportion of actual positive samples that were correctly identified by the model.
F1-Score	$\mathbf{F1\ score} = \dfrac{\mathbf{2TP}}{\mathbf{2TP+FP+FN}}$	The harmonic mean of precision and recall, providing a balanced measure of both.
Accuracy	$\mathbf{Accuracy} = \dfrac{\mathbf{TP+TN}}{\mathbf{TP+TN+FP}}$	The overall proportion of correctly classified

Where **TP** = True Positives, **FP** = False Positives, **FN** = False Negatives, and **TN** = True Negatives.

Figure 5. YOLOv8 output with a confidence score and a good bounding box

Figure 5 shows the detection and classification results of YOLOv8 on high quality cocoons. The bounding boxes indicate the position of the cocoon in the image, and the confidence scores show that the model is robust to accurately classify the cocoon in a well, controlled imager. The results above show the robust ability of the model to identify flaw free cocoons with characteristic shapes to progress to grading automation.

the clarity of the matrix illustrates the CAE based image

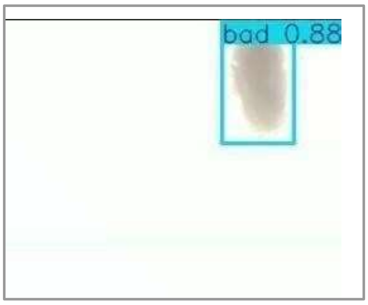

Fig.6.YOLOv8 results of showing bad bounding box along with confidence score

The detections and classifications obtained by applying YOLOv8 to the background, processed Bad, quality cocoon images are displayed in Figure 6. Overall, the model has demonstrated its potential to identify the defective cocoon set with a quite high level of precision and confidence despite this class being somewhat underpopulated in the dataset. When the bounding boxes given by the detections overlaid the defected cocoon image, they delineated the regions in which visual anomalies was found so as to be indicative of the cocoon's defectiveness, and this capacity to spot the visual cues that characterize defective cocoon proves it has learned the visual features of poor, quality cocoons.

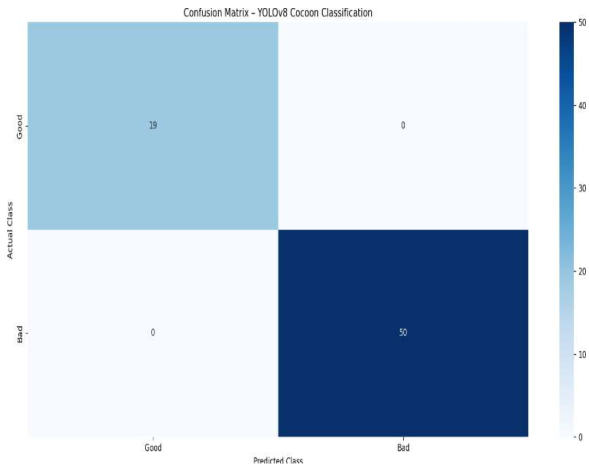

Fig. 7. YOLOv8 Confusion Matrix for test dataset

The test dataset confusion matrix (see Fig. 7) shows an intuitive overview of the classifiers ability to generalize to previously unseen examples. It highlights that most 'Good' cocooning samples were correctly classified with a negligible number of 'Good' cocooning examples being confounded into the 'Bad' class, and vice versa for the 'Bad' class, thus validating the learning ability of the designed CAE, based set augmentation so that the YOLOv8 model learns discriminative features for both classes even in the presence of limited training data. Although there were some minor misclassifications, they are attributable to the visually subtle textural/ surface defect cross, over between classes. Overall,

augmentation is sufficient for the object detector to learn

meaningful features for accurate classification by the YOLOv8 model despite the training data abundance constraints. Furthermore, the model enables vastly reliable, real, time inference which is made possible through well controlled imaging, minimal or no input data pre, processing, and CAE, based augmentation. High mAP values don't impair the model's ability to predict the position and class of the object, and the cloud storage enables continuous process monitoring along with instant inference in practice, thus providing a semi, automated method for reeling units operation. The fusion of these capabilities makes the system very viable for real, world deployment. Consequently, the model produces not only impressive class, based inference results and high confidence scores but also very few classification errors. This allows for minimization of human intervention during the sericulture process, reducing potential human errors, and possibly boosting throughput. More modifications can be easily made to the system in order to extend the detected categories or use it in larger scale production units.
The results demonstrate that YOLOv8 trained on CAE, augmented image set and via controlled acquisition can reliably auto, grade cocoons. Our quantitative metrics indicate that the system is robust to many of the complications associated with small data set size, class imbalance, and intra, class visual similarity. Misclassifications were few and often based on subtle differences in visual cues, and can be further reduced with more augmented samples, or 3D imaging from multiple angles. Our proposed system shows both high classification accuracy and spatial localization (determined from the metrics, visual results, and confusion matrix) and can therefore be used in practice, validating the pipeline from acquisition to cloud inference, thus validating the approach outlined in section III.

5. LIMITATIONS

However, despite the positive outcomes, the proposed framework also has some major shortcomings. The number of cocoon images in the dataset is only 305, which may not be representative of the actual diversity of the cocoon images and may affect the generalizability of the model. The performance of the model in more complex real-world scenarios is also yet to be determined since all the images were captured under controlled lighting and background conditions. Although the images are labeled carefully, there may be some subjectivity involved, and the actual natural diversity of the cocoon images may not be captured comprehensively by the CAE-based augmentation. The depth and texture features that may help in improving the accuracy of the classification are also not considered by the model.

6. CONCLUSION AND FUTURE WORK

The proposed work offers a software framework for a fully automated cocoon grading system using CAE-based augmentation, controlled image acquisition, and Yolov8 classification. The proposed system is robust, dependable, and scalable to the sericulture industry based on the quantitative validation of performance metrics.
The future work will be focused on increasing the dataset to include a wider range of cocoon morphologies and environmental conditions to improve the generalization capabilities of the model. In addition, advanced augmentation strategies, domain adaptation, and multi-modal sensor fusion, such as the use of depth information from RGB-D cameras, will be investigated. After these improvements, the system will be implemented in reeling units and integrated with automated sorting equipment. This will provide a critical validation of the system's performance, scalability, and usefulness in the full sericulture production chain.

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