

“ML Based Smart Silkworm Egg Count System For Sericulture”

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ABSTRACT--Sericulture is an important agricultural activity in India and is mainly carried out in rural areas. In this field, silkworm eggs are supplied to farmers in the form of Disease-Free Laying (DFL) sheets. Normally, the counting of eggs and checking whether the eggs are hatched or not is done manually in grainage centers. This process requires a lot of time and depends on human, which can always cause the mistakes, especially when the number of eggs is large. In this project, a Machine Learning based system was developed to count silkworm eggs and also to check whether the eggs are hatched or not. Images of DFL sheets were collected during the project work and used as input to the system then the Basic image processing steps were an applied mainly to improve the visibility, although in some images the improvement was not very clear. A Convolutional Neural Network (CNN) model was then used for egg classification, using the image data that was collected during testing. During testing, it was noticed that the system worked better when the images were the clear and a properly captured. For low-light images, the output was not always the same and small differences were noticed during testing. In most tests, the accuracy stayed around 90% to 93%. This was taken as acceptable for this project work, since the main aim was to reduce a manual effort rather than achieve perfect results.

Keywords: Sericulture, Silkworm Eggs, Machine Learning, Image Processing, CNN, Egg Counting, Hatchability Detection, Smart Agriculture.

I. INTRODUCTION

Sericulture is a traditional agro-based activity in India and is mainly practiced in rural areas. It plays a significant role in supporting the livelihood of many farming families. The production of silk depends a lot on the quality of silkworm eggs that are supplied to farmers. These eggs are usually provided on Disease-Free Laying (DFL) sheets. If the egg count or hatchability is not correct, it may affect cocoon production and the final silk output.

In many grainage centers, egg counting is still done manually by workers by looking at the DFL sheets. This process takes time and needs constant attention. During practical observation, it was seen that errors can occur because of eye strain and repeated work. Also, when the eggs are placed very close to each other then,

counting them correctly becomes difficult in some cases. These errors may affect planning and reduce overall production efficiency. Due to these limitations, automation is needed in this process. Machine Learning and image processing techniques were considered as a possible approach for automatic egg counting in this project. The CNN models work well for image-based tasks and were used in this project to detect small objects like silkworm eggs. The main focus was to apply these techniques in a simple and practical manner for sericulture use.

II. LITERATURE SURVEY

Traditional Manual and Image-Based Egg Counting Method In sericulture, silkworm eggs are traditionally counted manually by workers in grainage centers. This process requires considerable time and effort, particularly when thousands of eggs are present on a single Disease-Free Laying (DFL) sheet. Since the eggs are very small and often closely grouped, accurately counting them by hand is difficult. Workers may become tired and less focused after a long time, which can lead to mistakes in the final count.

Kawade et al. [15] found that manually counting silkworm eggs for a long time can cause eye strain and reduce workers' attention. As a result, the accuracy of the egg count may decrease, which could affect how seed quality is assessed and how production is planned in sericulture.

To overcome the problems with manual counting, researchers have studied different image processing methods to automatically find and count silkworm eggs. Methods like an Silkworm eggs may be automatically detected and counted using picture thresholding and morphological Silkworm eggs have been separated from the image's backdrop using In Due in part to the time-consuming nature of this process, earlier efforts by a number of researchers focused on counting silkworm eggs with basic image processing techniques. Common methods such as image thresholding and morphological operations were performed to isolate egg regions from the background in the image previously [4]. These methods made manual counting easier. However, their performance in all conditions was not consistent.

In most cases, egg detection accuracy was impacted by uneven lighting conditions, low image quality as well as overlapping eggs

on DFL sheets. Due to these reasons, the outcomes derived from the techniques such as machine learning were not always consistent across diverse

methods found it difficult to generate reliable results under the different image conditions.

A. Machine Learning and Deep Learning Approaches

Machine Learning and Deep Learning Approaches

Researchers started employing datadriven models to increase the precision of silkworm egg detection as machine learning techniques advanced. Li et al. [3] classified silkworm eggs using neural network techniques and got improved results, because it relied on carefully prepared photos and manual feature selection. Convolutional Neural Networks (CNNs), in particular, gained popularity later on due to ability to automatically extract significant characteristics from photos. CNN based egg counting system created by Patil and Deshmukh [8] demonstrated enhanced efficiency despite variations in egg size and color. Wang et al.'s related study described a method for counting and recognizing eggs using digital images.

Research has shown that models using Convolutional Neural Networks (CNNs) are better at recognizing complex visual patterns. However, their accuracy is still affected by certain factors. For example, problems like eggs that are the close together and low lighting can reduce how well these models work.

Wang et al. [9] demonstrated the strength of CNNs in handling complex visual patterns during silkworm egg detection.

B. Hatchability Analysis and Smart Sericulture

Systems Beyond egg counting, hatchability analysis determining whether eggs have successfully hatched is main factor in evaluating seed quality, ensuring effective sericulture practices. Although image processing and machine learning have introduced new possibilities for automation and precision in agriculture, only a few solutions address both egg counting and hatchability analysis together. Most current approaches remain limited to monitoring tasks, which leaves a clear gap in research.

Complementary studies by Bhuvaneshwari et al. [13] and Vairam et al. [14] confirmed significantly improve production efficiency and consistency in sericulture. Building on these developments, the proposed ML-based Smart Silkworm Egg Counting System is intended to provide simple, accurate, practical solution for real-world sericultural applications

III. PROPOSED SYSTEM

The proposed system aims to develop an the automated method for detecting and counting silkworm eggs from images of Disease-Free Laying (DFL) sheets applying machine learning techniques. Its main goal is to reduce dependence on manual counting while improving accuracy and efficiency in sericulture. Traditionally, workers count silkworm eggs by hand, a process that is both time-consuming and labor-intensive. Since thousands of eggs may be present on a single DFL sheet then manual counting often results in fatigue and errors. Traditionally, silkworm eggs are counted manually by workers, a process that is both time-consuming and labor-intensive. With thousands of eggs often present on a single DFL sheet, which help in manual counting can easily lead to fatigue and errors. To

the overcome these challenges, we proposed system employs image processing and machine learning to an automatically detect and count eggs, it will help in reducing human effort and improving reliability.

The system begins with an image acquisition, where the high-resolution cameras or scanning devices are used to capture the images of DFL sheets and also these images are then passed through a the preprocessing stage that enhances their quality by applying operations such as resizing, noise removal, and contrast adjustment. Preprocessing makes the egg regions more the distinct and easier to detect.

Following segmentation, the egg regions are the separated from the background, which helps to reduce noise and the makes detection more accurate. Segmentation techniques allow individual egg areas to be identified within the image so they can be analyzed separately.

After detection, the system counts the eggs then generates the final output, which includes both the total number of the eggs and the classification results. This automated process reduces help to the manual effort, improves accuracy and delivers results more quickly than traditional methods. In the practice, the system provides valuable support for sericulture farmers and researchers, helping to ensure more the effective management of silkworm egg production.

IV. OBJECTIVES

The main aim of this project is to develops a simple automated system that count silkworm eggs and identify whether they are hatched or unhatched using Machine Learning and image processing.

- To reduce the manual work involved in egg counting and improve accuracy while working with Disease-Free Laying (DFL) sheets used in grainage centers.

- The project is to mainly focuses on solving practical problems that were observed during manual egg counting, such as time consumption and counting errors.

- During this projects works , manual counting method was replaced a with a computational approach so that the process could become faster and less tiring.

- To classify silkworm eggs into the hatched and unhatched categories are using a CNN model based on the available image data.

- While working with the training data, differences in color and texture between eggs were noticed and later used during classification.

- Basic image is preprocessing steps like noise removal and contrast adjustment were applied improve image clarity, though the effect varied for different images.

- DFL sheet images were collected and labeled training and testing purposes.

- The performance of the system was checked using accuracy and processing time, and the results were also compared with manual counting.

Finally, the system gives simple outputs like total egg count and hatchability percentage, and it helps in reducing errors and dependence on skilled labor.

V. SYSTEM ARCHITECTURE

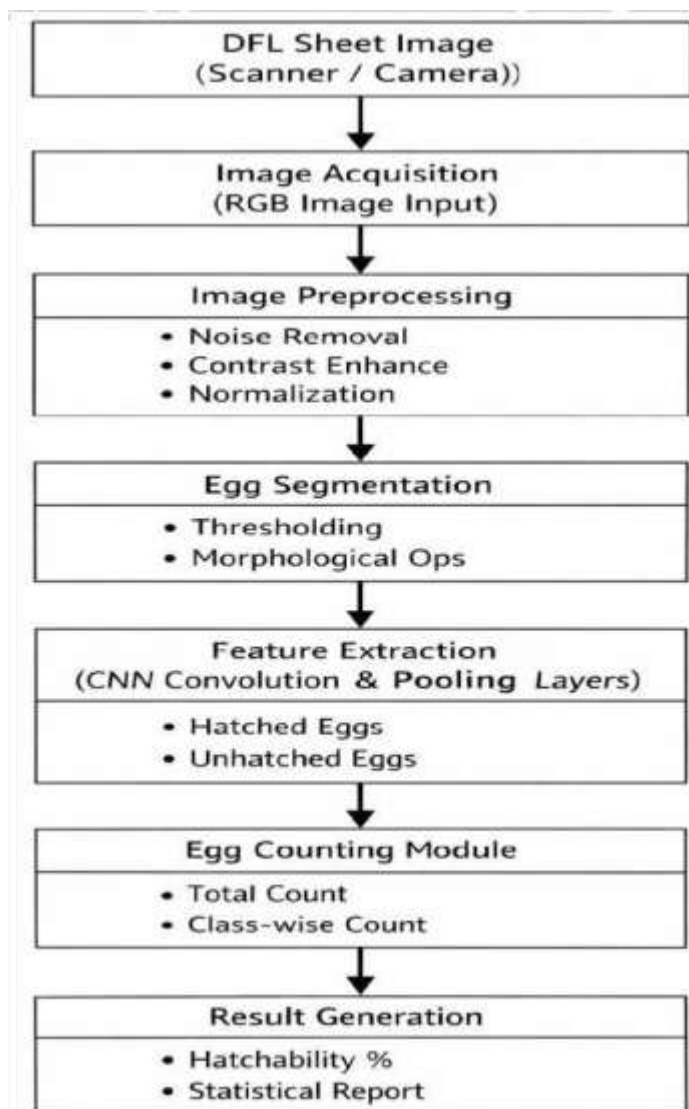
The architecture of the proposed system describes sequence operations performed for egg detection and counting.

The process begins with image acquisition images of DFL sheets are captured using a digital camera or scanner. Captured images are passed through the preprocessing operations as the resizing, noise removal, contrast enhancement.

After preprocessing, image segmentation is performed to identify egg regions within the image. Segmented regions are processed using a Convolutional Neural Network to extract features and classify eggs.

Finally, the system counts the detected eggs and provides the total egg count along with the hatchability percentage.

This system is developed to make silkworm egg counting and hatchability checking easier and less time-consuming. In many sericulture centers, this work is still carried out manually. Counting eggs by hand takes a lot of time and can be very tiring, especially when there are many eggs on a single DFL sheet. To reduce this effort, images of Disease-Free Laying (DFL) sheets are taken using a normal camera or a scanner. These images are then checked and slightly improved so that the eggs are clearly visible. Unwanted noise in the images is removed and small changes are made to improve clarity wherever required.



The proposed system follows a structured workflow for detecting and counting silkworm eggs from DFL sheet images. The process begins with capturing an egg sheet image using a scanner or camera. The captured

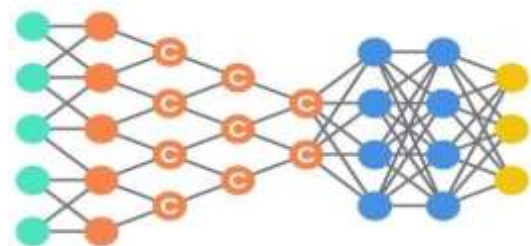
image then undergoes preprocessing steps such as noise removal, contrast enhancement, and normalization to improve image quality. After preprocessing, egg segmentation is performed using thresholding and morphological operations to identify egg regions. Segmented regions are then processed using a Convolutional Neural Network (CNN) to extract important features and classify eggs as hatched or unhatched. Finally, the egg counting module calculates the total egg count and generates the hatchability percentage with a statistical report.

VI. METHODOLOGY

This project aims to simplify the system to automate the process of counting silkworm eggs on Disease-Free Laying (DFL) sheets. In traditional sericulture practices, egg counting is usually done manually, which requires significant time and effort from workers. The task becomes even more difficult when the DFL sheets contain a large number of eggs, making the counting process slow and tiring. Because of this, worker fatigue can sometimes lead to mistakes or inaccurate counts. To address these challenges, the first stage of the proposed automated system focuses on capturing clear images of the DFL sheets using imaging devices. In our experiment, images of the DFL sheets are captured using a mobile phone camera, and in some cases, the images were taken under normal room lighting so that the silkworm eggs were clearly visible. After collecting the images, we applied several pre-processing steps to improve their quality. At this stage, noise in the images was reduced and basic adjustments were made to highlight the eggs more clearly.

Once the images were preprocessed, the egg regions were separated from the background using image processing methods such as thresholding and segmentation. This allowed the system to focus only on the areas containing eggs instead of the entire image.

The detected egg regions were then given as input to a Convolutional Neural Network (CNN) to extract important features from the images. CNN models are commonly used for image analysis because they can automatically learn visual patterns such as edges, shapes, and textures. These learned features help the system classify the eggs and improve the counting process.



Deep Convolutional Network

VII. MATHEMATICAL MODEL

The convolution operation used in the CNN model can be expressed as:

$$F(i,j) = \sum \sum I(i+m, j+n) \times K(m,n)$$

Where

I represents the input image

K represents the convolution kernel

F represents the resulting feature map

camera or a scanner. The images are taken under normal lighting conditions so that the eggs are clearly visible. After capturing the images, basic preprocessing operations are performed. Noise present in the image is reduced and adjustments are made to improve the visibility of the eggs.

After preprocessing, the egg regions are separated from the background using simple image processing techniques such as thresholding and segmentation. This step allows the system to focus only on the egg regions present in the image.

Once the egg regions are detected, a Convolutional Neural Network (CNN) model is used to extract important features from the images. CNN models are widely used in image recognition tasks because they can automatically learn patterns such as shapes, textures, and edges from image data. The extracted features are then used to classify the eggs and assist in counting them accurately.

The architecture of the deep convolutional neural network used in this study is shown in Fig. 3. The classification probability is calculated using the softmax function. The performance of the model is evaluated using classification accuracy, which is calculated as:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

Here, TP, TN, FP, and FN represent the different outcomes of the classification results.

VIII. DATASET DESCRIPTION

In this work, the dataset consists of images of silkworm egg sheets collected from or local sericulture farmers and nearby grainage centers. These images were collected or during visits to sericulture farms where silkworm eggs are produced and maintained on Disease-Free Laying (DFL) sheets. Each DFL sheet contains a large number of silkworm eggs placed close to each other.

Parameter	Value
Total Images	1200
Training Images	900
Testing Images	300
Image Resolution	512 × 512
Classes	Hatched Eggs, Unhatched Eggs

For creating the dataset, photographs of the DFL sheets were taken using a high-resolution digital camera under normal lighting conditions. Care was taken to make sure that the egg regions were clearly visible in the images so that the individual eggs could be identified during the analysis process. In order to

increase the variation in the dataset, multiple images were captured from different positions and lighting conditions.



Fig. 1. Sample images of silkworm egg sheets are collected from sericulture farms for dataset creation.

After collecting the all images, they were manually checked and only the clear images with properly visible egg regions were selected. The selected images were then resized to a fixed resolution of 512 × 512 pixels so that the input size remains the same during the training and testing of the machine learning model.

IX. EXPECTED RESULTS

The proposed automated system for silkworm egg detection and counting is the expected to provide reliable results by combining image processing techniques with machine learning methods. The main aim of this system is to reduce the manual effort involved in counting silkworm eggs, which is generally a time-consuming task and may sometimes lead to human errors.

The system is the expected to detect silkworm eggs with an accuracy of more than 90%. In the addition to egg detection, the model is also designed to classify the eggs into two categories: hatched eggs and unhatched eggs. This classification helps in evaluating the viability of the eggs, which is important for maintaining quality standards the in sericulture practices.

Another expected advantage of this system is the reduction in processing time. In the traditional methods, manual counting of eggs may take several hours, especially when the number of eggs on the sheet is large. By using the the automated approach, the same task can be completed in a much shorter time, thereby improving overall all efficiency.

The system is also calculates important parameters such as the total number of eggs and the, number of hatched eggs, and the hatching ratio. Since these values are generated automatically, so the chances of manual calculation errors are reduced using this system. The final results are displayed through simple and user-friendly interface so that farmers, researchers, and agricultural professionals can easily understand the output.

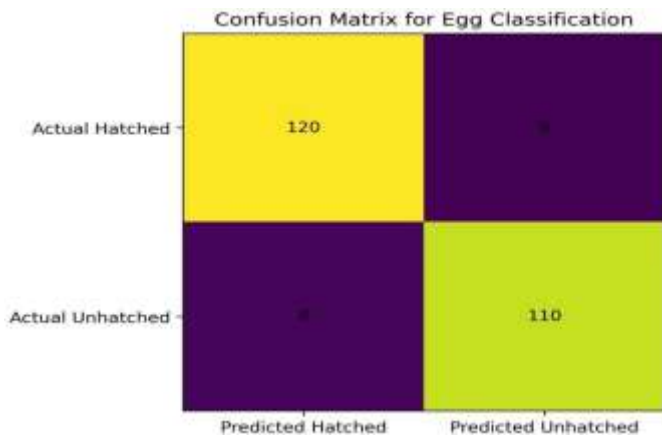
X. CONFUSION MATRIX TABLE

Actual / Predicted	Hatched Eggs	Unhatched Eggs
Hatched Eggs	120	6
Unhatched Eggs	8	110

The confusion matrix is represented the performance of the proposed CNN-based model used for classifying silkworm eggs. From the test the dataset, 120 hatched eggs were correctly identified by the model, while 6 hatched eggs were wrongly classified as unhatched eggs. In the same way, 110 unhatched eggs were correctly detected, whereas 8 eggs were incorrectly classified.

These results indicate that the proposed model performs well in distinguishing between hatched and unhatched eggs. The number of misclassified samples are is comparatively low, and they which shows that the CNN model is able to learn the important features of the eggs effectively. Overall, the results obtained from the confusion matrix demonstrate that the system achieves the good classification accuracy.

Confusion Matrix Graph



XI. DISCUSSION

This is my experimental results obtained from the proposed system show that machine learning techniques can be effectively used for silkworm egg detection and counting. The Convolutional Neural Network (CNN) model used in this work achieved higher accuracy when compared with traditional machine learning methods such as Support Vector Machine (SVM) and Random Forest classifiers. This improvement is mainly because CNN models are capable of learning complex visual features directly from image data.

From the confusion matrix analysis, it can be observed that most of the egg samples were classified correctly, with a only the small number of misclassifications. This indicates that the model is able too distinguish between hatched and unhatched eggs rwith good the accuracy, even when the eggs are located very close to each other on the DFL a sheets.

Another atadvantage of the proposed system is the reduction in the time required for egg counting. In a traditional mmethods,

manual counting takes a long time and requires continuous observation by workers. The automated system reduces this effort and helps in improving the overall efficiency of the process. By reducing manual inspection, worker fatigue can also be minimized.

However, some factors may still affect the system performance. Variiae tions the inn lightings conditions, poor the image quality, and overlapping eggs may e reduce the detection accuracy in certain are the situations. In the future, these is sues are the can the b be addressed is by using a larger than the dataset and more advanced the deep learning architectures to further improve the performance of the system.

XII. MOTIVATION AND PROBLEM STATEMENT

Sericulture is an important t agricultural activity practiced in many rural areas for silk production. For a many farming families, it serves as a major source of income. The quality and quantity of silks produced largely depend on the proper handling and monitoring of silkworm eggs on Disease-Free Laying (DFL) sheets.

In many grainage centers, the process of egg counting and inspection is still performed manually. This a process is time-consuming and completely dependent on human effort. When the number of the eggs on the sheets is very large, manual counting becomes difficult and errors may occur when the. Errors in manual egg counting can affect the overall efficiency and the reliability of the production process. Because , it becomes important find better and more reliable method for egg counting.

To reduce, this ,this project focuses on the developing an automated system for counting silkworm eggs. The main objective of the system is reduce manual effort and improve the accuracy of egg counting by using ML techniques. By introducing automation into tprocess, the system can provide more consistent results and help to farmers and agricultural workers make bettera decisions.

XIII. FUTURE WORK

Although the proposed Smart Silkworm Egg Counting System produces encouraging results, and there is stillt room for improvement. In future work, the system can be extended to support real-time egg counting using live video streams. This will allow faster monitoring of egg sheets, especially in large grainage centers where many sheets need to be analyzed.

Advanced deep learning models such as YOLO , Faster R-CNN can also be explored to improve detection performance, particularly when the eggs are very close to each other or overlapping. Another a possible improvement is integrating the system with mobile or web-based applications. And This would allows users to monitor the results remotely and store the data into the to cloud for future analysiis.

Collecting more images under different lighting and environmental conditions can make the model is to more reliable. larger dataset helps ,the system learn better a perform more accurately in real-world situations.

XIV. CONCLUSION

In this project, a Smart Silkworm Egg Counting System based on machine learning was developed to detect and count silkworm eggs on Disease-Free Laying (DFL) sheets. In many grainage centers,

egg counting is still done manually, which causes a lot of time and may lead to errors when the number of eggs is too large.

To solve this problem, our proposed system uses a Convolutional Neural Network (CNN) model to identify and classify the eggs. By analyzing visual features such as brightness and texture, this proposed system can classify between hatched and unhatched eggs.

The automated system this provides faster results compared to manual counting and also reduces human efforts. This system helps in minimize counting errors and improves the efficiency of silkworm seed production. Overall, the system can support better monitoring and management in sericulture activities.

XV. REFERENCES

- [1] Agriculture in India, "Smart Farming in Sericulture – Automated Monitoring Systems," 2023. [Online]. Available: <https://www.agricultureinindia.net/sericulture/smartfarming-in-sericulture/>
- [2] Silk Mark India, "Digital Tools Transforming the Indian Silk Industry," *India Silk Reports*, 2022. [Online]. Available: <https://www.silkmarkindia.com/digital-toolssilk-industry>
- [3] S. Li, Y. Zhang, and X. Wang, "Silkworm egg classification and counting using neural networks," in *Proceedings of the ACM Conference*, 2019. doi: 10.1145/3310986.3310988.
- [4] J. Chen et al., "An image processing algorithm for silkworm egg counting," in *Advances in Intelligent Systems and Computing*. Springer, 2017, pp. 321–330. [Online]. Available: https://link.springer.com/chapter/10.1007/978-3319-53556-2_32
- [5] A. Kumar and R. Singh, "A survey on egg counting and monitoring using image processing and IoT," *International Journal of Trend in Scientific Research and Development (IJTSRD)*, 2018. [Online]. Available: <https://www.ijtsrd.com/papers/ijtsrd13000.pdf>
- [6] Y. Liu et al., "Silkworm detection at larval stage using Mask R-CNN," *Smart Agriculture*, vol. 4, no. 2, 2022. [Online]. Available: <https://www.smartag.net.cn/EN/10.12133/j.smartag.SA202201012>
- [7] M. Zhang et al., "Deep learning for egg morphology recognition and cocoon sorting," *Sensors*, vol. 23, no. 2, 2023. [Online]. Available: <https://www.mdpi.com/14248220/23/2/868>
- [8] R. Patil and S. Deshmukh, "Automated silkworm egg counting system using deep learning," in *IEEE Xplore*, 2021. [Online]. Available: <https://ieeexplore.ieee.org/document/9562804>
- [9] L. Wang et al., "Deep learning-based object detection and classification of silkworm eggs," *Machine Vision and Applications*. Springer, 2021. [Online]. Available: <https://link.springer.com/article/10.1007/s00542-02105826-5>
- [10] K. Sharma et al., "Image-based egg counting and hatchability estimation for sericulture using machine learning," 2021. [Online]. Available: <https://www.researchgate.net/publication/352379534>
- [11] H. Shi, X. Chen, M. Zhu, L. Li, J. Wu, and J. Zhang, "A deep learning-based method for silkworm egg counting," *Precision Agriculture*, 2025.
- [12] H. V. Pavitra and C. G. Raghavendra, "An overview on detection, counting and categorization of silkworm eggs using image analysis approaches," *Global Transitions Proceedings*, vol. 3, no. 1, pp. 45–52, 2022. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S2666285X22000188>
- [13] T. Bhuvaneshwari et al., "Smart sericulture systems based on Internet of Things (IoT) and image processing," *Advances in Research*, vol. 26, no. 5, pp. 137–147, 2022. [Online]. Available: <https://www.journalair.com/index.php/AIR/article/view/1473>
- [14] N. Vairam et al., "IoT-based yield monitoring of mulberry silkworms using image processing technique," *Journal of Scientific Research and Reports*, vol. 31, no. 5, pp. 29–37, 2022. [Online]. Available: <https://journaljsrr.com/index.php/JSRR/article/view/3002>
- [15] R. Kawade, T. Dhamale, and D. Dhake, "Image processing based silkworm egg counting methods," *IOSR Journal of Engineering (IOSR-JEN)*, vol. 9, no. 4, pp. 56–60, 2019. [Online]. Available: <https://www.iosrjen.org/Papers/Conf.19014-2019/Volume4/12.%2056-60.pdf>