



Revolutionizing Disease Free Layings Counting: Unleashing the Power of Machine Learning and AI

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Received: May, 2023; Revised: May, 2023 Accepted: June, 2023

Introduction

Chawki, a vital step in sericulture, entails rearing silkworms from eggs until their second molting stage. During this phase, the distribution of chawki to farmers is a crucial responsibility for chawki rearers. However, in some cases, chawki rearers may supply farmers with an excess of Disease free layings (DFLs), exceeding the farmers' capacity. This tactic is employed by distributors to encourage repeat purchases. Unfortunately, if farmers realize the surplus DFLs after a few days, a shortage of mulberry leaves occurs as most of them have been consumed. This situation forces the farmer to choose between discarding half of the

silkworms or incurring additional costs to purchase more mulberry leaves, resulting in significant financial loss. To address this issue, integrating machine learning algorithms has emerged as a promising solution. By utilizing artificial intelligence, farmers can accurately count the number of DFLs during procurement, optimizing their rearing space and available mulberry leaves. This breakthrough advancement empowers sericulture farmers to overcome challenges related to inaccurate counting, leading to improved efficiency, reduced losses, and increased profitability.

Harnessing Machine Learning in Counting Disease free layings

- **Dataset Preparation:** Curate and preprocess a collection of silkworm egg images for training and evaluation.
- **Model Selection:** Choose an appropriate machine learning model, such as a CNN or a pre-trained model, for egg detection and classification.
- **Model Training:** Train the selected model using deep learning techniques on the silkworm egg dataset.
- **Performance Evaluation:** Assess the trained model's accuracy, precision, recall, and F1-score for counting and classifying silkworm eggs.
- **System Integration:** Integrate the trained model into the chawki distribution system for automatic counting and classification.
- **Validation and Testing:** Validate and test the system using separate sets of silkworm egg images to ensure accuracy and reliability.
- **Statistical Analysis:** Conduct statistical analysis to compare the machine learning-based counting system with manual counting methods.
- **Computational Resources:** Utilize suitable computational resources for efficient dataset processing and model training.

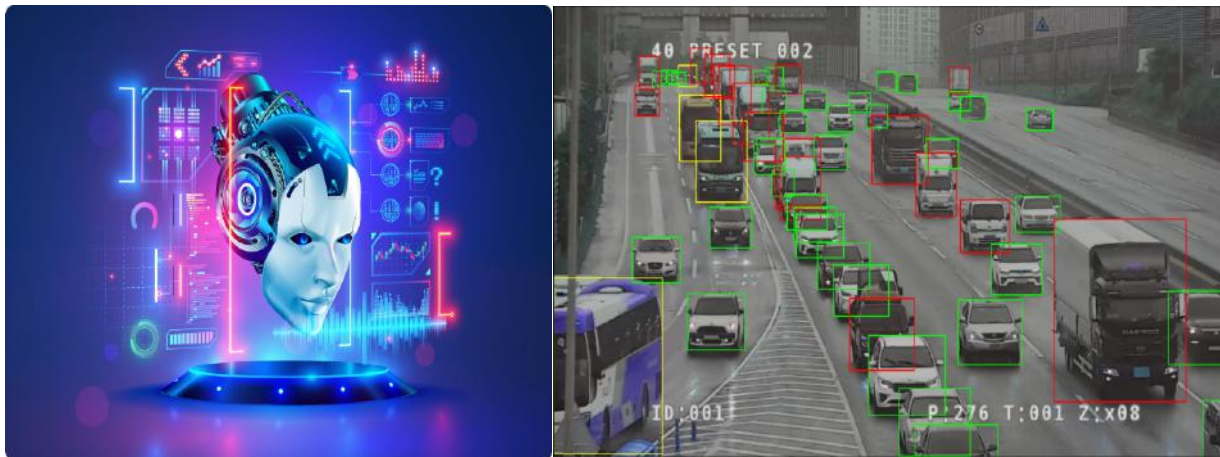


Fig1: Materials and Methods

Similar to the approach used for vehicle counting, we can utilize a similar method to accurately count Disease free layings (dflls). This technology-driven approach streamlines the counting process, ensuring precise

quantification of dflls and eliminating potential errors. By leveraging the success of this method in vehicle counting, we can revolutionize the counting of dflls in sericulture.

Related works on counting

The authors researched automating the counting and classification of silkworm eggs using deep learning. Their method outperforms previous image processing techniques by accurately segmenting and categorizing individual eggs as hatched or unhatched. They address limitations of earlier approaches,

achieving improved accuracy through uniform illumination and utilizing a standard key marker for image transformation. The deep learning model was trained on a large dataset, resulting in an impressive accuracy of over 97% and high repeatability in experimental results.



Fig2: Hatched worms and chawki worms

Researchers implemented Deep Learning, specifically using a pretrained YOLOv3 model, to create a vehicle counting system that doesn't require tracking vehicle movements. The system accurately counts cars, motorcycles, buses, and trucks in real-time video footage with a high accuracy of 97.72%. This approach enhances system performance and reduces deployment time, providing a simple yet effective solution for classifying and counting vehicles crossing the street.

Investigators proposed a precise vehicle counting framework using object detection,

tracking, and trajectory processing. They created datasets for vehicle detection and verification. Deep learning was employed for accurate object detection. A matching algorithm facilitated multi-object tracking, while trajectories were obtained. A trajectory counting algorithm accurately counted vehicles based on categories and movement routes, achieving over 90% accuracy. The framework operated at a speed of 20.7 frames per second. This precise vehicle counting system has potential applications in intelligent traffic control and dynamic signal timing.

Challenges

- Inaccurate counting and estimation of DFLs during chawki distribution.
- Overstocking of silkworms due to incorrect DFLs quantity provided to farmers.
- Inadequate availability of mulberry leaves for the rearing silkworms.
- Financial losses incurred by farmers due to excess silkworms or additional mulberry leaf purchases.
- Limited awareness and adoption of machine learning algorithms in the sericulture industry.
- Integration challenges in implementing machine learning systems for DFLs counting.
- Lack of standardized processes and guidelines for utilizing machine learning in chawki distribution.
- Variability in silkworm rearing capacity among different farmers leading to uneven distribution of DFLs.

Importance

- Enhanced accuracy and precision in counting dfl's
- Improved efficiency and time-saving
- Minimized errors and inconsistencies
- Optimized resource allocation and utilization
- Streamlined and automated counting process
- Real-time monitoring and data analysis

- Potential for predictive analytics and forecasting
- Facilitates data-driven decision-making

- Enables scalability and adaptability to varying volumes
- Reduces financial losses and enhances profitability

Conclusion

In conclusion, the integration of machine learning and artificial intelligence in DFL counting revolutionizes the sericulture industry. By accurately counting the number of DFLs during procurement, farmers can optimize their rearing space and effectively manage mulberry leaf consumption. This technology-driven approach eliminates the risks associated with inaccurate counting, resulting in enhanced efficiency and reduced financial losses for

farmers. By embracing this ground breaking advancement, sericulture farmers can unlock a pathway to increased profitability and sustainable growth in their operations. The future of DFL counting lies in the power of machine learning and AI, offering immense potential for transforming sericulture practices and ensuring the success of farmers in this vital industry.

References

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