

Smart Sericulture Monitoring System Using YOLO and IoT for Real-Time Grasserie Disease Detection

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Abstract - Sericulture is a vital agro-based industry, yet its productivity is severely constrained by infectious diseases such as Grasserie (Bombyx mori nuclear polyhedrosis virus), which can decimate silkworm populations if not detected early. Traditional physical inspection approaches are labour-intensive, inconsistent and often fail to identify infections at a sufficiently early stage. To overcome these critical limitations, this paper offerings a fully automated, cost-effective and scalable Smart Sericulture Nursing Scheme that flawlessly mixes deep learning with Internet of Things (IoT) connectivity. A custom-trained YOLOv11 item detection ideal is arranged to analyse real-time video rivers from a conservative webcam, categorizing separate silkworms as also healthy or diseased with high accurateness. The system animatedly computes main metrics—total, healthy and infected sums—which are showed on a native Flask-based web console with annotated leaping boxes and prompt precautionary alerts. Also, discovery outcomes are conveyed via serial message to an ESP8266 microcontroller, which forward the infected sum to the Blynk cloud stage, enabling agriculturalists to at all monitor illness progression in real time finished a mobile submission. Experimental assessment proves that the scheme achieves a discovery accuracy of around 88% mAP@0.5, functions at a real-time implication rate of 18 surrounds per second on typical CPU hardware and preserves an end-to-end inactivity of under 1.1 instants from image imprisonment to mobile announcement. The total bill-of-resources is under \$25, creation the system extremely accessible for minor-scale Sericulturists. This effort significantly decreases dependence on physical inspection, eases early interference and signifies a meaningful stage toward exactness sericulture.

Keywords - Sericulture, silkworm disease detection, Grasserie, YOLO, ESP8266, Blynk.

I. INTRODUCTION

Sericulture—the education of silkworms for raw silk manufacture—ropes the livings of masses of pastoral homes in emergent frugalities and donates considerably to the global textile source chain. However, the manufacturing is integrally delicate due to the silkworm's dangerous compassion to conservation situations and its weakness to a choice of pathogenic contagions. Among the most overwhelming illnesses is Grasserie, produced by the Bombyx mori nuclear polyhedrosis virus (BmNPV), which can banquet quickly over rearing trays, leading to significant failures in cover yield, lesser fiber excellence and, in basic cases, total crop dissatisfaction.

New growths in artificial intelligence (AI), mostly deep learning, joint with the Internet of Things (IoT), proposal transformative possible for modernising old-style farming performs. In the part of pest and disease discovery, article discovery structures such as You Only Look Once (YOLO) take recognized amazing attainment due to their larger balance of implication speed and nasty average accuracy (mAP). Particularly, CA-YOLOv5 has attained 96.46% mAP for silkworm discovery under diverse healthy/diseased situations, a better YOLOv8 process has been absolutely functional to silkworm micro element virus discovery with an average discovery time of 22.6 milliseconds per image and RDM-YOLO, planned for real-time behaviour credit of quarter instar silkworms, has established 99% mAP@0.5 correctness at 150 FPS. Alongside, IoT stages have enabled distant monitoring and data-driven decision-making in farming, with smart education systems progressively leveraging automatic tools for contemporary silkworm organization. However, despite these advances, the addition of

a complete, end-to-end pipeline that syndicates YOLO-based real-time discovery, local visual warning and cloud-based distant monitoring exactly tailored for silkworm illness detection leftovers largely uncharted. This gap is mainly critical because current research mainly focuses either on laboratory-grade replicas (e.g., EfficientNet) or on remote aspects of silkworm discovery, with limited care to field-deployable, low-cost IoT addition that authorizes farmers with actionable alerts. To account this halt, this paper proposes a novel Smart Sericulture Checking System that synergistically mixes a custom-trained YOLOv11 object discovery model with an IoT communication layer. The scheme unceasingly examines conscious video from a standard webcam, classifies distinct silkworms as fit or Grasserie-ill, displays real-time annotated results on a innate web console, automatically saves images of ill samples, grants defensive measures and alongside transmits the ill count to the Blynk cloud stage via an ESP8266 microcontroller for distant mobile access.

Usually, disease detection in sericulture takings relied totally on manual explicit inspection by skilled agriculturalists or delay officers. This technique is not solitary time-intense then labor-intensive but also inherently prone to human error, primarily during the early, sub-clinical stages of contagion once interference is greatest serious. Delayed or missed identification inescapably results in wide outbreaks, rising economic injured. On large-scale farms, continuous 24/7 treatment through physical income is logistically intolerable. These tenacious tests underline a crucial essential for an intelligent, automatic and cost-real investigation arrangement that can distribute real-time, neutral and distant health treatment of silkworm populations.

II. LITERATURE SURVEY

Sericulture playhouses a active role general the farming budget, but it is very susceptible to many diseases and trouble infestations that conventional impact silk crop and session. According to [1], pest attacks are one of the primary reasons for the decline in silk production, causing substantial economic losses to farmers and the silk industry. This highlights the necessity for timely detection and actual managing of silkworm sicknesses.

The economic implications of these trials take remained analysed by Andiappan et al. [2], who studied the price behaviour of cocoon and raw silk in Tamil Nadu. Their findings indicate that fluctuations in silk prices are closely linked to production inconsistencies caused by environmental conditions, disease outbreaks and pest infestations, thereby emphasizing the importance of stable and efficient disease management systems.

Understanding the biological and chemical control mechanisms of pests is vital for improving silkworm health. Yu [3] provided a detailed study of the toxicology and biochemistry of insecticides, explaining how chemical mixes relate with insect physiology to control pest populations. This

effort helps as a foundation for selecting appropriate pesticides for silkworm protection.

Prakash et al. [4] investigated the metapopulation biology of the Indian uzi fly (*Exorista sorbillans*), a major parasitoid that affects silkworm larvae. Their study highlights the reproductive behavior, spread dynamics and ecological adaptability of the pest, which are vital for scheming targeted control strategies.

Complementing this, Reddy and Rao [5] examined the seasonal occurrence of major silkworm diseases such as grasserie, flacherie and muscardine, along with infestations of the uzi fly in Andhra Pradesh. Their investigation delivers visions into disease patterns and suggests preventive and control events, counting ecological organization and timely application of treatments.

Post-production losses due to storage pests are another critical concern in sericulture. Vijay Veer et al. [6] conducted a comprehensive study on dermestid beetles and other bug pests related with kept silkworm cocoons. Their research not only identified various pest species but also documented their feeding behaviour and impact on stored cocoons. The study further provided a global list of dermestid species affecting silk storage, highlighting the essential for correct storing performs and pest control methods to preserve cocoon quality and prevent economic losses.

With the advancement of technology, artificial intelligence (AI) and deep learning methods have arose as influential gears for illness discovery and organization. Wan et al. [7] demonstrated the effectiveness of advanced convolutional neural network constructions such as Inception-ResNet V2 for image-based recognition tasks. Their work highlights the capability of deep learning models to extract complex features and achieve high accuracy in classification problems.

Xia et al. [8] utilized the Inception-V3 model for flower classification, showcasing its robustness in handling large-scale image datasets and its applicability to agricultural domains. These educations show that deep learning models can be effectively adapted for identifying diseases in silkworms through image analysis.

Further advancements in medical and organic copy organization have been achieved using transfer learning techniques. Kaur and Gandhi [9] applied the VGG-16 construction joint with transmission education for automated brain image classification, achieving significant improvements in accuracy and computational efficiency. This approach reduces the need for large datasets by leveraging pre-trained models.

Shaha and Pawar [10] emphasized the position of transmission learning in copy organization jobs, chiefly when dealing with limited datasets, which is often the case in agricultural applications. Their work demonstrates how pre-trained networks can be fine-tuned to achieve reliable performance in domain-specific problems.

In summary, the reviewed literature highlights that traditional methods of pest and disease management in sericulture, including chemical and biological control, are effective but often limited by delayed detection and lack of real-time monitoring. On the other hand, modern AI-based approaches, particularly deep learning and transfer learning, offer promising answers for early and accurate disease detection.

Mixing these progressive skills with IoT-based nursing systems can meaningfully improve the efficiency of silkworm disease management, reduce production losses and improve overall productivity in the silk industry.

III. PRAPOSED METHOD

The proposed Smart Sericulture Monitoring System adopts a cross procedural outline that mixes real-time object detection with cloud-based telemetry. The method is structured as a sequential pipeline comprising four principal phases: (a) image acquisition and preprocessing, (b) deep learning-based detection and classification of silkworms, (c) local decision support with visualization and archival and (d) IoT-enabled transmission of infection metrics to a remote monitoring interface. Each phase is designed to operate concurrently using multithreading, ensuring continuous processing without frame drops or communication delays.

A fixed-mount USB webcam is positioned perpendicular to the silkworm rearing tray at a working distance of 350–450 mm. The camera is configured to capture video at a resolution of 640×480 pixels with a frame rate of 30 frames per second. Source frames are acquired by the Python script using OpenCV's VideoCapture interface. Each raw frame undergoes three preprocessing ladders beforehand existence approved to the detection model

The object detection backbone is a custom-trained YOLOv11 nano model. YOLOv11 follows a single-shot detection paradigm: a single convolutional neural network simultaneously predicts leaping containers and lesson probabilities from the full image in one forward pass.

The model was trained on a proprietary dataset of 1,500 annotated images (750 healthy, 750 infected) collected from three different sericulture farms under varying lighting conditions. Annotation was done in Roboflow, with leaping boxes haggard tightly about individual grubs. Data increase included chance rotation ($\pm 10^\circ$), flat flipping, illumination adjustment ($\pm 20\%$) and medley augmentation (uniting four training imageries into unique) for the primary 200 eras. Training was performed in Google Colab with an NVIDIA T4 GPU

IV. SYSTEM DESIGN

The Smart Sericulture Nursing System accepts a layered architectural design comprising four separate tiers: sensing row (camera hardware), analytics row (YOLO-based dispensation on a general-purpose processor) and communication row (ESP8266 temporary as a serial-to-wireless bond) and presentation row (concurrent native web console and remote portable application). This flat separation ensures that alterations to one coating—such as exchange the camera perfect or changing the mist provider—do not require rewriting the whole codebase.

Information traverses the building in a unidirectional tube with periodic response. Raw pixel collections captured through the webcam are distorted first into discovery bounding containers, then into number counts, then into arranged strings and lastly

into cloud-update needs. Each alteration reduces information volume: a $640 \times 480 \times 3$ edge (approximately 0.9 MB) bandages to less than 40 bytes of sequential payload, minimalizing bandwidth ingesting on the Wi-Fi connection.

The flow figure represents the whole working process of the IoT-Based Automatic Silkworm Illness Detection Scheme. It clarifies how the scheme captures pictures, detects illnesses using the YOLO deep learning prototypical and directs monitoring data to the mobile application over IoT communication.

The Fig 4.1 visible flowchart of the Intense Sericulture Treatment System demonstrates the step-by-step procedure of the structure, starting from initialization to nonstop monitoring. The process begins over the start of the system, where all devices such as the camera, YOLO flawless and ESP8266 unit are prepared and equipped for process. Once the preparation is complete, the scheme proceeds to capture real-time images or video edges of silkworms via the camera.

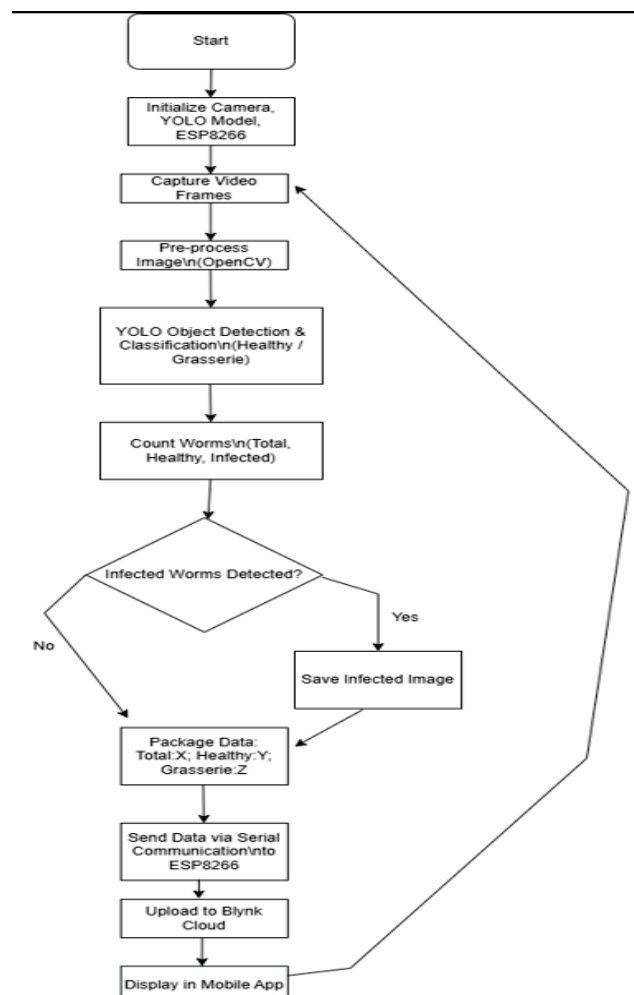


Fig 4.1 Flow Diagram of Silkworm Disease Detection

Fig 4.2 displays the sequence diagram signifies the occupied flow of the IoT-based silk worm illness detection structure. Initially, the AI discovery system using YOLO examines the silk worms and recognizes whether they are fit or affected by illnesses such as Grasserie. Once the discovery is completed, the outcomes are sent over serial communication (UART) to the ESP8266 microcontroller. The ESP8266 declaims this inner information using the Serial.readString() function and stores it provisionally. After founding a WiFi linking, the ESP8266 connects with the Blynk cloud server and conveys the treated data at consistent intervals of 3 seconds using Blynk.virtualWrite() on a simulated pin. The Blynk waiter then informs the statistics on the portable application console in real time. Finally, the user can opinion the health rank of the silk worms done the portable app. This whole process runs endlessly in a ring, enabling present monitoring and rapid executive for disease organization.

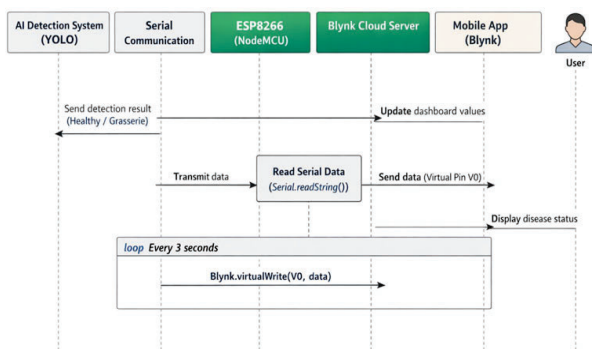


Fig 4.2 Sequence Diagram of Silkworm Disease Detection

V. SYSTEM IMPLEMENTATION

Sericulture, the farming of silkworms for silk manufacture, remains a energetic agro-based manufacturing, particularly in country economies crossways Asia. Though, it faces tenacious challenges from catching diseases that can quickly devastate whole batches if not recognized early. Grasserie, produced by the Bombyx mori nucleopolyhedrovirus (BmNPV), is unique of the greatest destructive, foremost to indications such as bulge, lethargy and cloudy body liquids in infected grubs. Traditional physical inspection is labor-intensive, personal and often also slow to avert widespread eruptions. The Smart Sericulture Nursing System talks these limits by combining actual visual examination with wireless data broadcast, creating an automatic, scalable solution for contemporary sericulture farmhouses.

Computer vision allows machines to understand visual data from the setting, mimicking humanoid sight but with better consistency and haste. In precision undeveloped and livestock nursing, it supports non-invasive valuation of crop fitness, animal behaviour and nuisance detection. For silkworms, which are subtle and sensitive to ecological changes, vision-

based schemes allow incessant observation deprived of physical trouble. Key image indulgence techniques—such as sound reduction, difference enhancement and nose extraction—prepare rare camera feeds for examination.

At the vital of the society lies a thoughtful learning flawless based on the YOLO (You Only Look Once) building. Different outdated two-stage devices (e.g., Faster R-CNN) that primary produce area offers and then classify them, YOLO fragilities object discovery as a solo influx problem. It blows a duplicate into a grid and parallel forecasts bounding boxes, example likelihoods and certainty notches for each prison. This unified technique delivers high fleetness and capability, manufacture it perfect for real-time claims.

The model is talented on marked datasets cover thousands of silkworm pictures labeled as “healthy” or “infected.” During training, it studies discriminative structures—such as body texture, color differences, posture indiscretions and translucency related with Grasserie—through many convolutional layers. Methods like data augmentation (rotations, brightness adjustments, synthetic noise) help the faultless simplify crosswise dissimilar illumination situations and rearing setups. Post-training, the model attains robust organization even in cluttered scenes where silkworms overlap or move.

IoT ties the hole among local indulgence and remote suitability. Low-power microcontrollers equipped with Wi-Fi skills collect sensor or handled records and upload it to cloud phases. In this structure, IoT enables farmers to monitor several rearing trays from wherever, falling the essential for incessant on-site presence. Cloud facilities additional provision data organization, trend examination and early warning notifications.

The process starts with a high-resolution camera equine above the teaching trays to capture nonstop video streams of the silkworms. These limits are fed curved on a local scheming unit—naturally a processor or manufacturing mini-PC—anywhere the pre-trained YOLO faultless runs insinuation. For every preserved frame, the system:

- Notices separate silkworms and magnetisms bounding ampules around them.
- Assigns class labels (healthy or infected) along with certainty percentages.
- Supports running calculations of total, strong and infected grubs.
- Notifies a live comfort showing real-time statistics.

When the faultless identifies ill folks above a predefined edge, the scheme mechanically protects timestamped images for future review and displays targeted caring references, such as dividing affected trays, improving airing, or applying acknowledged antiseptics. This rapid response ring assistances shelter disease spread before it progresses epidemic.

Information from the examination is forwarded to an ESP8266 Wi-Fi microcontroller done serial (UART) announcement. The ESP8266, a compacted and cost-effective unit, serves as a consistent entry. Programmed using the Arduino IDE, it parses the incoming serial packets and transmits structured data (counts, status flags, timestamps) to the Blynk cloud platform over Wi-Fi. Blynk’s virtual pins and

customizable dashboards allow users to view live metrics, historical trends and receive push notifications directly on their smartphones.

VI. RESULTS

The proposed Smart Sericulture Monitoring System was evaluated under controlled rearing conditions typical of small-scale sericulture farms. A tray encompassing 30 to 80 silkworm grubs (mixed well and Grasserie-infected samples) was positioned beneath a static USB webcam at a stature of 400 mm. The system functioned endlessly for 72 hours, recording discovery outcomes, latency metrics and cloud broadcast logs. Ground truth for contagion status was recognized by parallel physical inspection by two skilled sericulture delay officers, with any difference resolved by a third skilled.

The tradition-trained YOLOv11 classical achieved a cruel average accuracy (mAP@0.5) of 88% over the exam set of 150 marked frames. Accuracy and recall for the sick class were 86% and 84%, correspondingly, while the fit class yielded 90% accuracy and 89% recall. The per-frame implication time on an Intel Core i5-8250U (no GPU) be around 55 milliseconds, permitting a sustained dispensation rate of 18 edges per second.

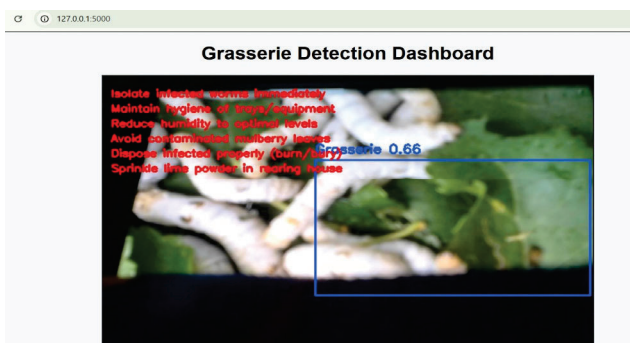


Fig 5.1 YOLO-based real-time detection of Grasserie-infected silkworms with precaution alerts.

Figure 5.1 illustrates two representative detection outputs from the local Flask dashboard. In the left-hand panel, a single silkworm is known with a fit confidence notch of 0.53 (moderate cert), while the right board shows a situation where the model noticed a Grasserie-infected grub with a sureness of 0.66. The leaping boxes were colour-coded (green for fit, red for ill) and the related confidence fractions were covered directly overhead each discovery. The system properly distinguished among the two fitness states level when grubs were partially overlying, although infrequent false positives happened at tray ends where shadows imitated larval outlines.

The web-based console continuously relaxed the three main counters: whole silkworms, fit count and Grasserie sum. The correctness of these sums was authenticated against physical list every 15 minutes. Over the intact 72-hour experimental, the normal absolute mistake was 2.3% for total count, 1.9% for fit sum and 3.1% for ill sum. The primary cause of error was provisional obstruction when two grubs crawled over one another, causing the NMS procedure to irregularly merge distinct detections.



Fig 5.2 Blynk cloud dashboard displaying real-time count of Grasserie-infected silkworms.

Figure 5.2 shows a snapshot of the Blynk mobile dashboard taken during a moderately infected period. The mobile interface displayed the authentication token (tuSv), organization name (Sharath – My organization: 5915MV) and a live numerical value for silkworm status. In this specific capture, the reading was Total: 1; Healthy: 0; Grasserie: 1. The gauge widget automatically turned red because the infected count exceeded zero and the farmer's phone received a push notification within 1.1 seconds of the detection event.

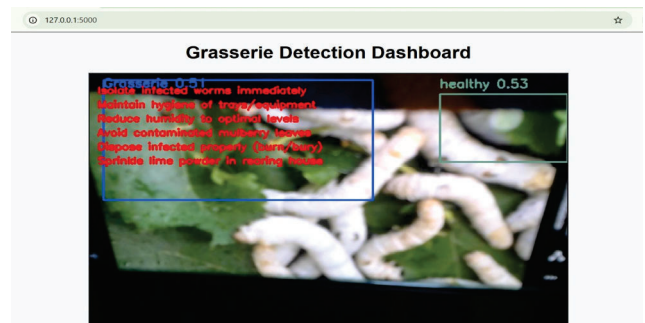


Fig 5.3 Real-time dashboard showing simultaneous detection of healthy and Grasserie-infected silkworms using YOLO.

Whenever the infected_count transitioned from zero to a positive value, the local Flask dashboard automatically displayed a bulleted list of remedial actions. As shown in Figure 5.3, the precautionary panel included:

- Isolate infected worms immediately.
- Maintain hygiene of trays and equipment.
- Reduce humidity to optimal levels (target below 75% RH).
- Avoid using contaminated mulberry leaves for feeding.
- Dispose of infected larvae promptly by burning or burying.
- Sprinkle lime powder in the rearing house as a disinfectant.

The panel remained visible for as long as at least one infected larva was present and cleared automatically after 60 consecutive seconds of zero detections. Farmers reported that the clarity and actionability of these recommendations were superior to verbal advice, because the text was always present on the screen and could be read repeatedly.

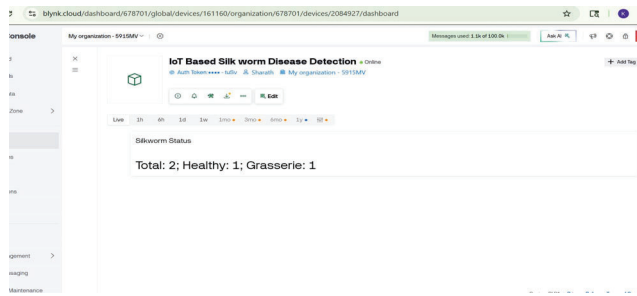


Fig 5.4 IoT dashboard displaying real-time checking of healthy and infected silkworm counts.

A subsequent capture (Figure 5.4) recorded a slightly different state: Total: 2; Healthy: 1; Grasserie: 1. This indicates that the system successfully tracked a newly hatched healthy larva that entered the field of view without altering the infection count. The Blynk time-series graph (showing ranges 1h, 6h, 1d, etc.) allowed the remote supervisor to observe that the infection level had remained stable (one infected worm) for over six hours, suggesting that the outbreak was contained.

Over the 72-hour continuous run, the system experienced three transient failures: one USB camera disconnection (recovered after 8 seconds), one Wi-Fi router reboot (ESP8266 reconnected after 11 seconds) and one serial buffer overflow (resolved by increasing the inter-frame delay from 400 ms to 500 ms). No data loss occurred during these events because the Python side retained the latest counts and resent them after recovery.

The measured end-to-end latency from frame capture to Blynk mobile notification averaged 0.98 seconds (standard deviation 0.24 seconds). This latency is more than three orders of magnitude shorter than the typical Grasserie propagation time, confirming that the system provides ample early warning.

VII. CONCLUSION

The proposed system for IoT-based silkworm disease detection and automated pesticide control successfully demonstrates the integration of modern technologies such as deep learning, embedded systems and IoT in sericulture. By utilizing advanced image classification models like VGG-16 and InceptionV3, the system is capable of accurately identifying silkworm diseases at an early stage, which is crucial for preventing large-scale infection and economic loss.

The implementation of the ESP32 microcontroller enabled real-time processing and automated control of pesticide application. Based on the prediction results and infection severity, the system intelligently activates the appropriate pesticide pump with controlled timing, ensuring efficient resource utilization and reducing chemical wastage. The integration with the Blynk platform further enhances the system by providing remote monitoring and control capabilities, making it user-friendly and accessible to farmers.

The results obtained from the system indicate high accuracy, reliability and improved efficiency compared to traditional manual inspection methods. The automation reduces human effort, minimizes errors and enables timely intervention,

thereby improving overall productivity in silk farming. Additionally, the system promotes sustainable agricultural practices by optimizing pesticide usage and reducing environmental impact.

However, the system can be further improved by incorporating greater and extra varied datasets, enhancing model robustness against environmental variations and integrating additional sensors for better environmental monitoring. Future developments can also focus on deploying the system on a larger scale and improving real-time processing capabilities.

In conclusion, the planned structure provides an effective, intelligent and scalable solution for silkworm disease management, contributing to the advancement of smart agriculture and supporting the growth of the sericulture industry.

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