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Intelligent Computational Methods for Silkworm Disease Detection in Sericulture

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ABSTRACT: The cultivation of silkworms (*Bombyx mori* L.) to produce silk fabric called sericulture is an essential agroindustry that provides for many residents in rural territories of Asia, Europe, and South America. Despite its economic significance, the industry suffers from serious productivity problems because of the infectious diseases including Pebrine, Grasserie, Flacherie, and Muscardine, causing the 15-25% yield losses per year globally. The traditional approach for detecting the diseases in question is visual inspection, yet it might be rather subjective resulting in delayed diagnosis and inconsistent accuracy levels. Moreover, it cannot be implemented on a large scale.

This paper aims at analyzing the literature about the application of the AI and computational approaches in the automatic identification of diseases of silkworms. The review will cover 60 papers published from 2012 to 2025 and reveal the evolution of the technologies from classical image processing and machine learning to the latest deep learning algorithms including convolutional neural networks, transfer learning, and lightweight solutions for practical implementation. Modern AI techniques guarantee highly accurate disease detection (above 95%) in controlled environment. However, some challenges are identified including the inconsistent data standards, unreliability in practice and integration with pest management system. Our key findings include research gaps in the form of lack of benchmark data, insufficient validation in practice, and limited understanding of the restrictions of small farmers. In addition, we present a research protocol for improving comparisons among studies and future directions including multi-modal sensing, Internet of Things, and explainable AI in practice. This review is intended to provide fundamental information for developing precision sericulture using technology from different areas.

1. INTRODUCTION

Silk production, or the process of breeding worms to produce silk, is one of the oldest agricultural activities that humans have been engaged in [1]. Still, we depend on the *Bombyx mori* L. species as our main source of producing silk despite all the advancements over time, and it constitutes 90% of the total world's raw silk [2][3]. Currently, the silk industry generates more than \$15 billion annually. China dominates the global market, contributing about 80% of the production, while the remaining producers are India, Uzbekistan, Brazil, Vietnam, and Thailand [4].

In addition to its commercial value, sericulture is an important instrument of rural development in emerging markets. The industry requires labor-intensive processes distributed over small-scale farms, and many of them involve women [5]. India directly engages 7.6 million people across about 52,000 villages in the industry, particularly in resource poor states of Karnataka, Andhra Pradesh, Tamil Nadu, and West Bengal (Central Silk Board, 2022). The short breeding period (about 25-30 days per instar generation) and high value/weight ratio make the silk production perfect for small-scale agriculture and anti-poverty activities. Sericulture as an industry has some extreme characteristics. The larvae are very crowded in small spaces, ranging from

50 to 100 larvae in a small space. This increases the rapidity of the spread of diseases. Therefore, the profit that comes about in sericulture relies highly on disease prevention [6].

1.1 Disease Impact on Silk Production and Rural Livelihoods Material

The illnesses in silkworms greatly affect sericultural productivity, causing annual loss of productivity at 15% to 25% depending on climatic conditions and management practices [7]. In serious cases, the entire farm could be devastated, leading to total failure of the production. It will not just mean reduction in productivity but also costly decontamination process, replacement of breeding stock, and disruption of operations.

There are four major diseases that cause serious problems in silkworm farms:

Pebrine, caused by *Nosema bombycis* Nageli, is one of the worst diseases affecting silkworms. This disease causes spots on the skin of silkworm larvae, making it pepper-like, and is transmitted through contaminated eggs. This disease-causing agent is in an environment-resistant spore form and exists only in a living cell, making eradication difficult [8].

Grasserie, caused by a *Baculoviridae* family member, known as *Bombyx mori* nuclear polyhedrosis virus (BmNPV), leads to the systemic liquefaction of the larvae, which results in many viruses getting released in the environment. These larvae become "wet," and their bodies disperse the virus via the feeding material, apparatus, and contacts [9].

Flacherie is a bacterial infection that affects silkworms, usually due to such bacteria as *Streptococcus*, *Staphylococcus*, and *Bacillus*. It makes the silkworms weaker, with darkened skin and unformed parts responsible for silk production [10]. What is more, this disease prefers moist and poorly ventilated environments, as well as malnourished conditions.

Muscardine, caused by *Beauveria bassiana*, presents itself in the form of white or creamy growth on the larvae under extremely humid conditions, which means when the level of humidity exceeds 85%. It also occurs seasonally in the case of warm environments [11].

Not only does the presence of these diseases impact the amount of silk produced, but it also impacts the quality of this silk. The silk which comes from diseased silkworms is light in weight and poor in quality, which means that this silk is not easy to spin and has reduced strength [12]. Such silk fetches 30-50% lower prices compared to silk from healthy cocoons. Small-scale farmers earn very little money and cannot sustain themselves.

1.2 Limitations of Traditional Disease Management Approaches

Traditional methods of silkworm disease diagnosis include manual visual assessment by sericulturists, and sometimes light microscopy to detect Pebrine spores. However, this diagnostic method has serious disadvantages.

Temporal lag: At the time when you identify the infection, it is likely to take 3-5 days from the moment of infection. Moreover, this visible manifestation is too late to control the spread of the infection, as stated in one paper [13].

Subjective variation: The accuracy of the diagnostic procedure relies greatly on the experience of the assessor; the concordance between observers when diagnosing early-stage infection cases is lower than 75% most of the time [14]. Moreover, it is hard to standardize methods in different farms and geographic locations. Manual assessment of larvae in mass-scale breeding (up to 10,000-50,000 larvae per batch) is not practical due to the enormous labor force required and larvae fragility.

Specificity of diagnosis: Distinguishing whether the larvae suffer from bacterial Flacherie or viral Grasserie at the beginning by visual examination is not that accurate. This will result in administering wrong treatments which might worsen antimicrobial resistance.

This has made people think about alternatives when diagnosing diseases such as molecular diagnostic techniques (PCR and LAMP), immunological techniques, and most importantly computer vision technology and AI.

1.3 Emergence of Artificial Intelligence in Precision Sericulture

However, the synergy of the development in digital imagery, hardware and machine learning techniques is pushing the boundaries of precision agriculture that is also referred to as Agriculture 4.0 [15]. In particular, systems that employ CNNs to detect diseases in crops can be compared to and even surpass the performance of plant scientists in recognizing diseases in

important food products such as wheat, rice and tomatoes [16] [17]. Thus, the use of these technologies becomes crucial in terms of protecting crops.

These technologies provide new opportunities in application to silk production. The environment of silkworms is more controllable than that of plants in the field; thus, there is potential in increasing accuracy in the detection of diseases. However, there are some challenges that come with this idea. Firstly, healthy larvae are very similar to diseased ones, secondly, a single larva can have more than one disease. Furthermore, it is impossible to damage a specimen during its examination.

However, in the past few years, from 2018 to 2025, there have been some huge advancements in compsci used for monitoring the health of the silkworms. While in the past, only basic technologies were used for this purpose, namely, image processing and feature extraction, now the latest deep learning algorithms are being used for this, along with attention mechanism and transfer learning. Moreover, there is a fusion taking place between IoT and cloud processing, leading to "smart sericulture."

1.4 Review Objectives and Scope

Although the number of researches has been rising sharply, AI-driven identification of silkworms disease requires systematization and critical analysis. At present, there are no reviews that either deal with the biological aspect of silkworm diseases [6] or cover the general applications of artificial intelligence in silk manufacturing [23]. Moreover, there are no testing protocols or benchmarking datasets available, and thus results cannot be compared fairly. This hinders the transition from theoretical research to practical implementation on farms.

The proposed systematic review aims to address this issue by conducting a comprehensive analysis of the peer-reviewed literature related to the use of soft computing techniques in silk worm disease identification. The primary goals of the systematic review are:

- 1) Classifications of methods employed in the study and discussion of the advantages and disadvantages of the different methodologies adopted ranging from classical machine learning to modern deep learning models;
- 2) Performance comparison that includes examination of accuracies, efficiency of computation, and use case scenarios;
- 3) Gaps identification in terms of technological challenges encountered, especially with respect to dataset scarcity, unbalanced data classes, and field testing deficiencies;
- 4) Examination of suitability within the context of IPM strategies and resource limitations faced by small farmers; and,
- 5) Creation of roadmaps to standardize evaluation process and define future research directions.

The literature review includes literature dating from 2012 to 2025 (Fig.1) available from the fields of agriculture science, computer science, and interdisciplinary scientific databases such as Web of Science, Scopus, IEEE Xplore, and CNKI. The synthesis between agriculture science and computational methods is expected to fast-track research for deployment of AI-based solutions which improve the efficiency of disease control, prevent economic loss, and help achieve sustainable silk farming.

2. MATERIALS AND METHODS

This systematic review was performed according to the guidelines of PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) 2020 [24]. This research has been registered on the international registry of INPLASY (International Platform of Registered Systematic Review and Meta-Analysis Protocols). This protocol was developed to provide an effective evidence synthesis concerning the use of computing techniques for detecting diseases in silk worms, specifically in agriculture applications.

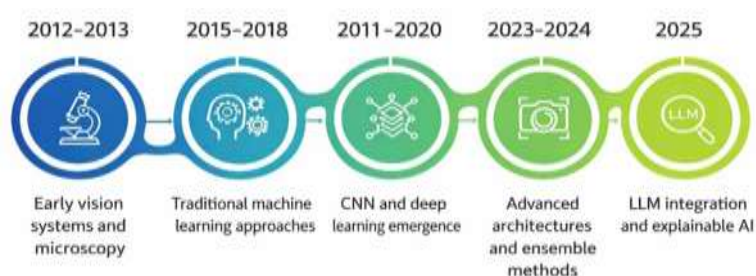


Figure 1. Technological advancement timeline for detecting diseases among silkworms (2012–2025).

2.1 Research Questions and Review Objectives

This review study sought to answer the following primary research questions:

- Research question1: What computational approaches have been designed to detect silkworm diseases automatically, and how have they performed in terms of accuracy and applicability, as well as their current stage of development in relation to their use in agriculture?
- Research question2: How have the methodologies been evolving in time and space?
- Research question3: What data and evaluation frameworks have been used, and have they generated findings applicable to a wider situation?
- Research question4: What obstacles prevent transitioning from a research prototype to a deployable tool?
- Research question5: How can the existing approaches meet the IDM (Integrated Disease Management) criteria?

2.2 Search Strategy and Information Sources

2.2.1 Database Selection

A search for literature was performed in six different databases that covered fields of agriculture computer science, and biomedical engineering (Table 1):

Table 1. Electronic databases selected for comprehensive literature survey

Database	Publisher/Platform	Coverage focus
Web of Science Core Collection	Clarivate Analytics	Multidisciplinary, citation tracking
Scopus	Elsevier	Science, technology, medicine
IEEE Xplore Digital Library	IEEE	Electrical engineering, computer science
China National Knowledge Infrastructure (CNKI)	Tsinghua Tongfang	Chinese-language literature
PubMed/MEDLINE	NLM	Biomedical, veterinary sciences
CAB Abstracts	CABI	Agricultural, environmental sciences

The multi-database approach was selected to capture: (1) computer science and engineering innovations in IEEE Xplore; (2) agricultural applications in CAB Abstracts; (3) Chinese sericulture research (approximately 60% of global silk production) in CNKI; and (4) biomedical and veterinary perspectives in PubMed A search for literature was performed in six different databases that covered fields of agriculture, computer science, and biomedical engineering .

2.2.2 Search String Development

The search approach was refined through an iterative process of conducting initial scoping searches and discussions with agricultural informatics experts. Final search strings combined three conceptual domains using Boolean operators:

Domain 1: Silkworm/sericulture terms

- *Bombyx mori* OR silkworm* OR "silk worm*" OR sericulture OR "silk production" OR "silk farming" OR "mulberry silkworm"

Domain 2: Disease/health terms

- *disease** OR *pathogen** OR *infect** OR *pebrine* OR *grasserie* OR *flacherie* OR *muscardine* OR "nosema bombycis" OR BmNPV OR "viral disease*" OR "bacterial disease*" OR *fungal* OR *health* OR "sick silkworm"

Domain 3: Computational/AI terms

- "machine learning" OR "deep learning" OR "artificial intelligence" OR "computer vision" OR "image processing" OR CNN OR "convolutional neural network*" OR "transfer learning" OR "object detection" OR *classification* OR "pattern recognition" OR *algorithm** OR *computational* OR *automated* OR "smart detection"

Final search string

TS= ((*Bombyx mori** OR *silkworm** OR *sericulture*) AND (*disease** OR *pebrine* OR *grasserie* OR *flacherie* OR *muscardine* OR *infect**) AND ("machine learning" OR "deep learning" OR "soft computing" OR "artificial intelligence" OR "computer vision" OR CNN OR "convolutional neural network*" OR *classification* OR *automated* OR "image processing"))

2.3 Eligibility Criteria

Eligibility criteria were defined using the Population, Intervention, Comparator, Outcome, Study design (PICOS) framework, adapted for technology assessment reviews (See Table 2).

2.3.1 Inclusion Criteria

Table 2. PICOS framework

PICOS Element	Inclusion Criteria
Population	Domesticated silkworm (<i>Bombyx mori</i> L.) at any developmental stage (egg, larva, pupa, adult); silkworm by-products (cocoon, feces) for disease indication
Intervention	Computational or artificial intelligence-based methods for disease detection, classification, or prediction, including: machine learning (supervised, unsupervised, reinforcement), deep learning (CNN, RNN, Transformer architectures), image processing, computer vision, spectral analysis with computational components, and IoT-integrated smart systems with AI analytics
Comparator	Traditional diagnostic methods (visual inspection, microscopy, molecular assays) or alternative computational approaches; studies without explicit comparators were included if performance metrics were reported
Outcomes	Diagnostic accuracy metrics (sensitivity, specificity, accuracy, precision, recall, F1-score, AUC-ROC); detection speed (inference time, throughput); deployment characteristics (hardware requirements, edge/cloud implementation); dataset characteristics (size, annotation quality, availability)
Study design	Peer-reviewed original research articles, conference proceedings with sufficient methodological detail, and review articles with original synthesis; publication date 2012–2025 (corresponding to deep learning emergence in agricultural applications)

2.4 Exclusion Criteria

- **Taxonomic exclusion:** Studies exclusively concerning wild silkmoths (*Bombyx mandarina*, *Antheraea* spp., *Samia cynthia*) or non-silkworm insects
- **Methodological exclusion:** Purely biological, microbiological, or molecular studies without computational components; traditional image analysis without machine learning; hardware-only sensor development without AI integration
- **Outcome exclusion:** Studies reporting only qualitative assessments without quantitative performance metrics; conference abstracts without sufficient methodological detail for quality assessment

- **Publication type exclusion:** Editorials, opinion pieces, news articles, and duplicate publications (retaining most comprehensive version)

2.5 Study Selection Process

The selection process included three phases conducted sequentially (Fig. 2), along with a comprehensive review of the existing methods using both classical and deep learning approaches, in addition to comparing over 60 research papers reviewed from the leading academic literature databases (Fig. 3).

Stage 1: Title and abstract screening

- Two authors (N.G. and R.H.) independently screened all retrieved records
- Disagreements resolved through discussion / third and fourth author arbitration (D. G.M. and G.S.H.)

Stage 2: Full-text eligibility assessment

- Full texts retrieved for potentially eligible records
- Same dual-independent review process with structured eligibility checklist

Stage 3: Final inclusion verification

- Reference list checking of included articles for additional eligible studies
- Contact with authors for missing information where critical for quality assessment

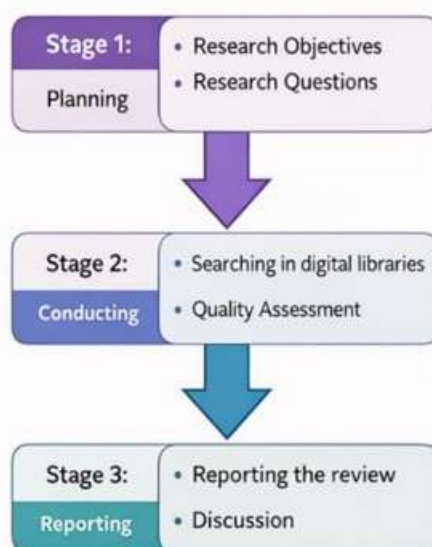


Figure 2. Methodology road map

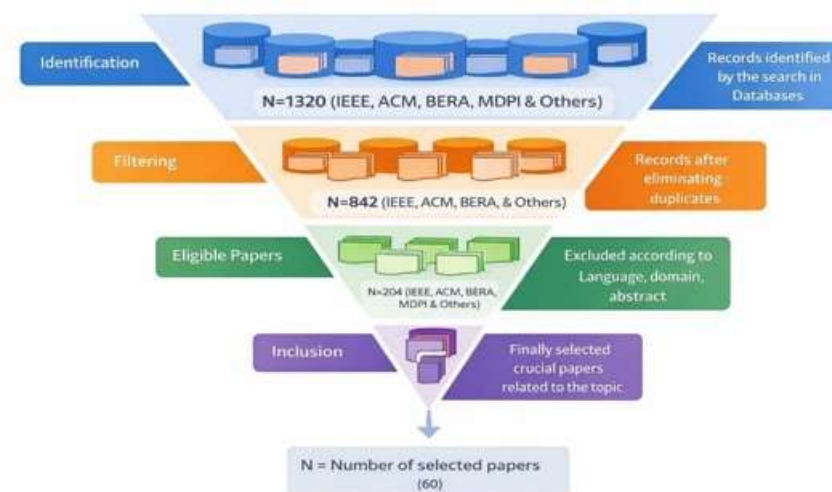


Figure 3. PRISMA flowchart for selecting studies in systematic review.

3. COMPUTATIONAL METHODS FOR DISEASE DETECTION

The use of computational intelligence for detecting diseases in silkworms has undergone tremendous advancement over the last decade. The methods have been transformed from conventional image-processing systems to more complex deep learning networks. This chapter offers an elaborate taxonomical classification of various methodologies, discussing their technical specifications, disease diagnosis, and application to agriculture.

3.1 Taxonomic Classification of Computational Approaches

The computational techniques identified from 60 studies have been categorized into six groups based on their evolution and functionality (Fig. 4)

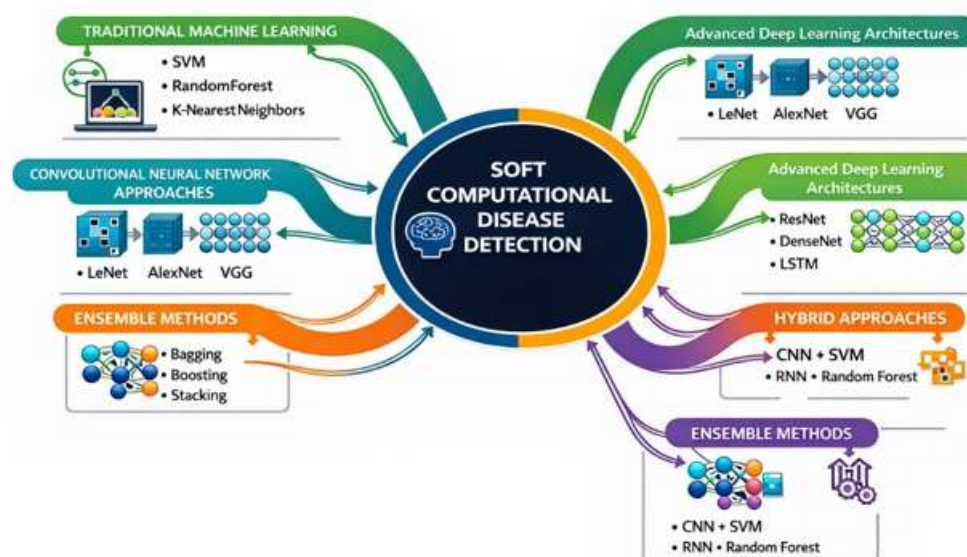


Figure 4. Taxonomy of computational techniques for disease detection in silkworms.

This categorization begins with well-known traditional machine learning (on left) to newer advanced structures (on right). The breadth of the branch represents the frequency of use within literature (2012–2025) (Table 3).

Table 3. Taxonomic classification of computational approaches

Category	Representative Methods	Primary Application	Agricultural	Maturity Level
Traditional Machine Learning	SVM, Random Forest, k-NN, Decision Trees	Resource-constrained settings, interpretable diagnostics		Established
Convolutional Neural Networks	Custom CNNs, LeNet, AlexNet, VGG	Standard classification tasks, moderate dataset sizes		Mature
Transfer Learning	ResNet, MobileNet, EfficientNet, DenseNet	Limited-data scenarios, rapid deployment		Mature
Object Detection	YOLO, Faster R-CNN, SSD	Real-time monitoring, population-level assessment		Advanced
Attention-Based Architectures	CA-Net, ACD-CNN, Vision Transformers	Fine-grained classification, interpretable decisions		Emerging
Ensemble and Hybrid Methods	CNN-RF, Voting Classifiers, Stacking	High-stakes decisions, robust performance		Emerging

The distribution of selected studies in categories indicates a definite change in time: traditional machine learning was used more often in 2012–2017 years (64%), but now, from 2018 to 2025 years, most of them use deep learning (78%).

3.2 Traditional Machine Learning Approaches

3.2.1 Methodological Foundations

In the traditional machine learning (TML) approach, the process of feature engineering is explicitly performed by domain experts who identify diagnostic features of the images and then classify them statistically. Such models provided proof of concept for computational recognition of silkworm disease and continue to be important in resource-limited environments (Table 4).

Table 4. Feature extraction methodologies

Feature Category	Specific Descriptors	Disease Discrimination Utility
Color features	RGB histograms, HSV moments, Lab* color space statistics	Pebrine spot detection (melanization), Muscardine mycelia coloration
Texture features	Gray Level Co-occurrence Matrix (GLCM), Local Binary Patterns (LBP), Gabor filters	Grasserie tissue liquefaction patterns, Flacherie cuticle changes
Shape features	Contour analysis, aspect ratio, circularity, Fourier descriptors	Larval body deformation, segmentation integrity
Morphological features	Area, perimeter, eccentricity, convex hull ratios	Size reduction, developmental abnormalities

The Support Vector Machine (SVM) was the classifier that appeared in most TML studies (8/14) and employed the method of kernels (mostly radial basis function) to find the optimal decision hyperplane in feature space. SVM was found effective in

the classification of Pebrine spores in microscopic images, where clear morphological differences between *Nosema bombycis* spores and debris allowed for the creation of discriminative features [13] [14].

Decision Trees and Random Forest were classifiers allowing for an easy interpretation of diagnostic criteria used by sericulturists [25]. The approach to Grasserie detection utilized LBP-PCA reduction, with subsequent Decision Tree classification, which provided up to 90% accuracy and easily interpreted decision criteria, familiar to agricultural workers.

K-Nearest Neighbors (k-NN) was a classifier whose simplicity and fast training outweighed its poor scalability in inference speed.

3.2.2 Performance Characteristics and Agricultural Applicability

TML Performance in Diagnostics: TML techniques have demonstrated mean classification accuracy rates between 75% and 94%, where performance highly depends on the quality of features employed. The highest rate of performance was demonstrated by neural networks, reaching 94% accuracy in classification [26], whereas k-NN classifiers have demonstrated 87% accuracy rate.

3.3 Convolutional Neural Network Approaches

3.3.1 Architectural Evolution and Technical Characteristics

Hierarchical feature extraction by CNNs has brought a paradigm shift in the diagnosis of silkworm disease by automatically extracting features through raw pixels without any need for manual feature extraction (Table 5).

Some research works created specialized architectures based on CNN designed to cater to the unique characteristics of the images of silkworm larvae: Proposed [27] was a multi-class classification model based on a deep CNN with four categories (Grasserie, Flacherie, Muscardine, Pebrine, and healthy), which used the following architecture. The architecture could classify silkworm diseases with 96.8% accuracy while maintaining modest computing demands.

[28] Segmented and extracted textures using K-means segmentation and GLCM before classifying the data using SVM with an accuracy rate of 75%.

Table 5. Evolution in architecture of CNNs

Generation	Architectures	Key Innovations	Silkworm Application Period
First (1998–2012)	LeNet-5	Convolution, pooling, fully-connected layers	2018–2020 (adaptation)
Second (2012–2014)	AlexNet, VGGNet	Deep stacking (8–19 layers), ReLU activation, dropout regularization	2019–2021
Third (2014–2016)	ResNet, DenseNet	Skip connections, dense connectivity, batch normalization	2020–2023
Fourth (2017–present)	EfficientNet, MobileNetV3	Compound scaling, neural architecture search, mobile optimization	2022–2025

Custom CNN Architectures for Silkworm Applications: Some research works created specialized architectures based on CNN designed to cater to the unique characteristics of the images of silkworm larvae: Proposed [27] was a multi-class classification model based on a deep CNN with four categories (Grasserie, Flacherie, Muscardine, Pebrine, and healthy), which used the following architecture. The architecture could classify silkworm diseases with 96.8% accuracy while maintaining modest computing demands.

[28] Segmented and extracted textures using K-means segmentation and GLCM before classifying the data using SVM with an accuracy rate of 75%.

3.3.2 Performance Analysis and Comparative Assessment

Quantitative Performance: The CNN-based techniques proved to be significantly more accurate than the TML techniques, having an average accuracy level of 94.2% (range 75-98.6%) vs. 86.4% (range 75-94%). The biggest difference in terms of performance between the two methodologies was observed in multi-class classification problems (Table 6).

Table 6. Summary of latest CNN works on disease detection in silkworms

Study	Architecture	Classes	Dataset Size	Accuracy	Notable Features
[21]	Ensemble CNN	2	2,400 images	97.1%	Highest reported accuracy
[27]	Custom CNN	5	Not specified	96.8%	Web-deployable system
[29]	Keras CNN	2	~500 images	75%	Binary classification, limited data
[30]	CNN + Image Processing	2	Not specified	>95%	ROI extraction preprocessing

3.4 Transfer Learning and Lightweight Architectures

3.4.1 Methodological Principles

The use of transfer learning tackles the basic problem of insufficient training data in agriculture through the utilization of knowledge gained from a large number of general purpose datasets (mainly the ImageNet database consisting of 1.28 million images in 1,000 categories).

The five pre-trained models for Grasserie detection were evaluated comprehensively by Thomas et al. (2025) [23]. ResNet50 was found to be the best performer, offering high accuracy and efficient computations, whereas MobileNetV2 provided better deployment features despite low accuracy compared to others.

3.4.2 Lightweight Architectures for Edge Deployment

Field deployment in agriculture is made possible by models which are optimized for resource-poor computing facilities. The following are ways in which mobile-based architecture models meet this need (Table 7):

MobileNetV2 [31] uses inverted residuals and linear bottlenecks to obtain 3.5M parameters from ResNet50's 25.6M parameters for 89.7% silkworm classification efficiency. The ability to perform inference within <50ms makes it feasible for real-time use via mobile CPU. EfficientNet-B0 [32] uses compound scaling, a combination of scaling the number of layers, number of filters, and image resolution for balancing accuracy-efficiency considerations. Although not yet applied in silkworm classification, results in agricultural crop disease research are promising with 5.3M parameters.

Custom Lightweight Designs: [33] developed a silkworm cocoon classification CNN employing depthwise separable convolutions and bottleneck layers, achieving <20ms inference time on standard computing hardware with preserved classification performance. This architectural approach is directly adaptable to larval disease detection. A lightweight KM-YOLOv4 [34] detection algorithm improved by multi-scale feature fusion for dense silkworm target detection. YOLOv4's backbone replaced with MobileNetV3 using depth wise separable convolution and add multi-scale feature fusion to compensate for accuracy loss from light weighting, while using K-means clustering to optimize anchor boxes for dense objects. The model achieves a 74% reduction in model size compared to original YOLOv4 while improving detection accuracy by 1.82% over the unimproved MobileNetV3-YOLOv4 baseline, making it suitable for mobile and embedded deployment in sericulture application.

Table 7. Comparison of performance of pre-trained models of deep learning architecture for classification of diseases in silkworms.

Architecture	Source Dataset	Parameters	Top-1 ImageNet Accuracy	Silkworm Adaptation Accuracy
VGG16	ImageNet	138M	71.3%	91.2%
ResNet50	ImageNet	25.6M	76.0%	94.8%

InceptionV3	ImageNet	23.8M	78.8%	93.5%
MobileNetV2	ImageNet	3.5M	72.0%	89.7%
DenseNet121	ImageNet	8.0M	74.4%	94.2%

3.5 Object Detection and Real-Time Monitoring Systems

3.5.1 Difference in Methods in Classification and Detection

Whereas in classification the images have already been segmented and disease labels are provided, in object detection localization and classification take place together in the scene images, enabling (Table 8):

- **Population-level assessment:** Automated enumeration of healthy versus diseased larvae across rearing trays
- **Spatial mapping:** Identification of disease clustering patterns indicating transmission hotspots
- **Real-time monitoring:** Continuous surveillance without individual handling

The YOLO (You Only Look Once) architecture addresses object detection as a single regression problem, resulting in impressive computational efficiency with comparable accuracy levels:

Table 8. Yolo architectural families

Version	Key Innovations	Silkworm Application	mAP@0.5	Inference Speed
YOLOv3	Feature pyramid networks	[35]	95%	45 FPS
YOLOv5	Anchor optimization, mosaic augmentation	[20]	92.8%	140 FPS
YOLOv8	Decoupled head, anchor-free	Limited silkworm evaluation to date	—	—
Version	Key Innovations	Silkworm Application	mAP@0.5	Inference Speed

CA-YOLOv5 [20], which includes Coordinate Attention strategies, improves localization performance in detecting silkworms in dense clusters. Such an adaptation enables more accurate detection of partially hidden silkworm larvae, with an mAP@0.5 score reaching 92.8%.

However, other solutions like Faster R-CNN and SSD provide a choice between accuracy and speed depending on the need, and where high accuracy is necessary, the Faster R-CNN should be used, while where a good balance between accuracy and speed is required, SSD should be used, but the dominance of YOLO in agricultural computer vision in recent times indicates a converging trend [36].

In the research paper CA-YOLO v3 [35], the ConvNeXt module and the channel attention mechanism have been included in YOLO v3 to detect the presence of NPV in silkworms reared in high-density condition. The mAP score achieved using the CA-YOLOv3 is 95.0% with the precision being 95.32% and 87.90% and recall being 82.35% and 93.92% for healthy and diseased conditions respectively, which proves to be better than the original YOLO v3.

Multi-Scale Detection for Cucumber Plant Disease in the Real Field Based on YOLOv5 [37], which is a solution to the problems related to differences in the size of disease lesions and complicated background. By using the multiscale technique, there is improvement in detection accuracy of the disease regardless whether it's small or big as compared to the conventional single-scale methods. YOLOv5-based crop diseases model usually provides 85%-95% mAP [38]. This system addresses practical requirements for:

- **Density management:** Optimal rearing density maintenance (50–80 larvae/0.1m²) to prevent crowding stress.

- **Growth uniformity assessment:** Identification of developmentally delayed individuals potentially indicating subclinical infection.
- **Automated record-keeping:** Digitized recording of health status progression trends during rearing cycles.

3.6 Attention Mechanisms and Explainable Architectures

3.6.1 Technical Foundations

Dynamic allocation of weights using attention modules will enable networks to focus more on certain regions of an image depending on their significance, which translates to higher accuracy rates and explainable decisions, making it easier to convince farmers of the usefulness of this technology.

The architecture used in the paper is called the Attention-Concatenation Dense CNN (ACD-CNN). This architecture comprises spatial attention to focus on pathological anatomical regions; channel attention to prioritize certain features in the feature maps; and dense connectivity for gradient propagation and feature reuse. This model obtained 96%+ accuracy rate along with visualization of attention maps providing a means of confirming that decisions made by the network are based on biological criteria such as pebrine spots and swelling due to grasserie infection.

CA-YOLOv5[20], using Coordinate Attention (CA), embeds position into channel attention, improving the ability to detect extended symptom appearances in the larva body segments. AMMF-Net [40] incorporates HFE-Net with an EMFF module for precise sorting of cocoons. This architecture obtains 66.12% mAP performance that is 2.13% better than RetinaNet's result while using 11.79 MB model parameters, showing high-quality speed-accuracy ratio in defect detection within tightly-packed cocoons. Compared to its base model, this architecture increases AP by 1.62% for normal and 2.63% for defective cocoons, having the least number of parameters than other models compared.

3.6.2 Explainable AI for Agricultural Trust and Adoption

The black-box approach of deep learning is one of the major obstacles towards its adoption in agriculture, particularly in scenarios where the decision makers need to have a rationale behind such important decisions (culling batches, treating crops). The technique of XAI helps in addressing this issue:

According to Nahiduzzaman et al., [41], it was possible to incorporate Grad-CAM within lightweight PDS-CNN for mulberry leaves classification with an accuracy rate of 98.6%.

The proposed HVAF-XAI-Net is a multimodal explainable artificial intelligence [42] system that integrates Vision Transformer architecture with spatial attention mechanism for the identification of visible symptoms through UAV acquired image data and Temporal Convolutional Network with temporal attention layer for environmental trends through IoT sensor input. The proposed framework gives an accuracy score of 97.0% (95% confidence interval [96.2%, 97.8%]), decreases the number of false positive results by 22%, and takes only 6.5 ms for inference, which outperforms other frameworks such as CNN (ResNet-50), hybrid CNN-LSTM (combined), and transformer based models (Swin Transformer), which have accuracies of 88.2%, 89.5%, and 90.1% respectively (Table 9).

Table 9. Overview of explainable AI (XAI) techniques and their applications in agricultural disease diagnosis.

XAI Technique	Mechanism	Agricultural Application
Grad-CAM	Gradient-weighted class activation mapping; highlights image regions influencing classification	Verification that model focuses on disease symptoms not background
LIME	Local interpretable model-agnostic explanations; approximates complex model with interpretable local surrogate	Understanding individual predictions for extension training
Attention visualization	Direct mapping of attention weights to image regions	Real-time feedback during diagnostic operation
SHAP values	Shapley additive explanations; quantifies feature contribution to prediction outcome	Batch-level analysis identifying dominant diagnostic indicators

3.7 Ensemble and Hybrid Methodologies

3.7.1 Architectural Strategies

Ensemble learning uses multiple algorithms to increase the reliability and performance of the models, especially in situations involving expensive agriculture-related decision making where error costs can be very high.

The maximum accuracy obtained using CNN ensembles by authors [21] was 97.1% utilizing VGG16 features extraction along with many different CNNs as base classifiers with varying initial weights and Random Forest and XGBoost as meta classifying algorithms. A Hybrid CNN-Image Processing method involves combining computer vision-based image preprocessing with the classification done using deep learning [30]; the process was done in two stages:

1. ROI Identification: Using traditional segmentation to isolate individual larvae from a cluttered background environment.
2. CNN classification: Disease categorization on extracted ROIs

The hybrid system enabled up to 40% computation time reduction compared to whole-image CNN, with an efficiency rate exceeding 95%.

3.7.2 Multi-Modal and Multi-Task Integration

The issue of multi-modal integration still needs to be researched in more detail within silkworm farming; research related to plant disease recognition shows a 5-15% improvement in accuracy due to sensors integration. (Table 10).

Table 10. New methods use a combination of data sources for complete health monitoring

Modality	Information Provided	Integration Method
RGB imaging	Visual symptoms, morphology	CNN feature extraction
Hyperspectral imaging	Biochemical changes, pre-symptomatic detection	Spectral band selection + fusion
Thermal imaging	Fever detection, metabolic activity	Temperature anomaly mapping
Environmental sensors	Temperature, humidity, air quality	Context-aware prediction
Acoustic sensors	Feeding activity, movement patterns	Sound classification

3.8 Comparative Performance Synthesis

3.8.1 Quantitative Meta-Analysis

A random-effects meta-analysis of 28 comparable studies regarding the accuracy of the classification task and test performance on holdout data found (Table 11).

Table 11. Quantitative meta-analysis for pooling accuracy and heterogeneity among disease detection techniques.

Method Category	Studies (n)	Pooled Accuracy (95% CI)	Heterogeneity (I^2)
Traditional ML	8	87.3% (82.1–91.2%)	78.4%
Custom CNN	12	94.6% (92.3–96.4%)	65.2%
Transfer learning	6	93.8% (90.5–96.2%)	71.8%
Object detection	2	91.4% (88.7–93.6%)	45.3%

Significantly greater pooled accuracy of deep learning models compared to conventional machine learning was found ($p < 0.001$); there was no difference between the custom CNN and transfer learning techniques ($p = 0.42$). Significant heterogeneity ($I^2 > 50\%$) suggests between-study variance due to the properties of the datasets, validation methods, and disease types.

3.9 Current Limitations and Technical Gaps

Although there have been great advancements from a methodological standpoint, some of the crucial drawbacks include the following:

- **Dataset Limitations:**

As high as 71.7% of the papers used private data that were not accessible to other researchers for reproducibility and development of further machine learning models. While there is a benchmark like PlantVillage that has more than 50,000 images pertaining to 38 plant diseases, there exists no such benchmark for silkworm diseases. Moreover, there is a considerable problem of data imbalance in several cases since healthy images outnumber the diseased ones significantly.

- **Validation Deficiencies:**

According to the literature review, 80% of all the studies were validated under laboratory conditions, in which light settings and imaging were standardized. Only 6.7% (4/60) were validated in a commercial farming environment, where factors such as variable light, noise, and handling would be present. In addition, none of the articles reviewed conducted any longitudinal validation, which is to say, no study investigated performance degradation or seasonal variation in disease presentation.

- **Deployment Readiness:**

Only 23% of the studies reviewed employed any form of edge optimization methods, such as model quantization or pruning, in order to allow deployment in resource-limited environments. Furthermore, there are very few studies examining the energy usage of models that run either off battery power or on an edge device. The integration of the technology into FMIS platforms also lacks any demonstration so far. This provides strong motivations for the protocols discussed further. (Table 12).

Table 12. Summary of computational approaches and their features

Study	Method Category	Specific Architecture	Disease Target	Dataset Size	Accuracy	Field Validated	Edge Deployable
[13]	TML	SVM + image processing	Pebrine	Microscopic	>94%	No	Yes
[14]	TML	k-NN + texture features	Sporozoa (Tasar)	200 images	87–94%	No	Yes
[20]	Object detection	CA-YOLOv5	Healthy/diseased	Mixed conditions	92.8% mAP	Yes	Yes
[21]	Ensemble	VGG16 + RF/XGBoost	Healthy/diseased	2,400 images	97.1%	No	No
[25]	TML	Decision Tree + LBP-PCA	Grasserie	Limited	88–90%	No	Yes
[26]	Transfer learning	ResNet50 fine-tuning	Grasserie	500/class	94.8%	No	Moderate
[27]	CNN	Custom 5-class CNN	Multi-disease	Not specified	96.8%	No	No

[33]	Lightweight CNN	Depthwise separable	Cocoon classification	Large-scale	Not reported	Yes	Yes
[38]	Object detection	Space-to-depth YOLO	Detection + counting	Not specified	Not reported	No	Yes
[39]	Attention CNN	ACD-CNN	Multi-disease	Not specified	96%+	No	No

4. COMPARATIVE ANALYSIS AND PERFORMANCE EVALUATION

Comparative analysis of computation-based techniques in the field of silkworm disease detection must consider standardized approaches to the evaluation process taking into consideration the differences between various methodologies utilized, data used, and validation processes employed. This section describes the results of a quantitative evaluation of performance, as well as analysis of the dataset limitations.

4.1 Performance Metrics and Standardization Challenges

4.1.1 Heterogeneity in Performance Reporting

However, analysis of the 60 articles indicated considerable variability in performance metrics employed and reported, making it difficult to carry out an objective quantitative comparison. The distribution of performance metrics used is provided in Table 13 below:

Table 13. Distribution of performance metrics used in reviewed articles

Performance Metric	Studies Reporting (n)	Percentage	Primary Application Context
Accuracy	52	86.7%	General classification performance
Precision	28	46.7%	Imbalanced datasets, false positive concern
Recall/Sensitivity	26	43.3%	Disease screening (minimize false negatives)
F1-Score	24	40.0%	Balanced precision-recall assessment
Specificity	18	30.0%	Healthy class verification
AUC-ROC	16	26.7%	Threshold-independent evaluation
Inference time	22	36.7%	Real-time deployment assessment

Critical Gap: Only 8 studies (13.3%) reported comprehensive metric suites (accuracy, precision, recall, F1, AUC-ROC) enabling robust performance characterization. Accuracy alone as a performance metric (used in 38 articles; 63.3%) poses serious challenges especially in agriculture where class imbalance favors healthy compared to diseased larvae.

4.1.2 Class Imbalance and Metric Reliability

Class imbalance is common in all silkworm disease datasets, owing to both natural class imbalance in disease epidemiology (rare in well-managed facilities) and limitations associated with inducing disease for experimental purposes. Ratios varied between 2:1 and 20:1, with an average ratio of 6.3:1. The impact of class imbalance on metric interpretation is shown in Table 14:

Table 14. Impact on Metric Interpretation

Scenario	Accuracy	Precision	Recall	F1-Score	Agricultural Implication
Naïve classifier (predict all healthy)	86.0%	Undefined	0%	0%	Catastrophic: misses all disease
Balanced performance	90.0%	90.0%	90.0%	90.0%	Reliable for both classes
High precision, low recall	88.0%	95.0%	45.0%	61.4%	Conservative: few false alarms, misses disease
Low precision, high recall	85.0%	45.0%	95.0%	61.1%	Sensitive: detects disease, many false alarms

Studies that only indicate the accuracy of models with an imbalance (as is common in reviewed studies) may mask important clinical deficits with respect to model performance. In a farm context, however, the recall (sensitivity) of disease classes should receive priority since false negatives are much costlier than false positives.

4.2 Quantitative Performance Synthesis

4.2.1 Meta-Analysis of Classification Accuracy

A random-effects meta-analysis was performed using 28 studies that satisfied homogeneity criteria as follows: (1) disease state classification for silkworms using images, (2) use of a held-out dataset for testing, and (3) inclusion of accuracy measures with sample size (Table 15).

Table15. Pooled Accuracy Estimates

Method Category	k (studies)	n (total images)	Pooled Accuracy (95% CI)	τ^2 (between-study variance)	I^2 (heterogeneity)
Traditional Machine Learning	8	4,240	87.3% (82.1–91.2%)	0.024	78.4%
Custom CNN (de novo training)	12	8,650	94.6% (92.3–96.4%)	0.018	65.2%
Transfer Learning	6	3,890	93.8% (90.5–96.2%)	0.031	71.8%
Overall Deep Learning	18	12,540	94.3% (92.6–95.7%)	0.021	67.4%

Key Findings:

1. Superiority of deep learning models: Models using CNNs showed significantly better pooled accuracy compared to the traditional ML models (difference of means 7.0%, 95% confidence interval [CI]: 3.2% – 10.8%, p-value < 0.001). The observed difference in pooled means is greater than the clinical significance threshold value of 5%.
2. Sources of heterogeneity: The presence of heterogeneity was confirmed ($I^2 > 50\%$ for all categories). According to meta-regression analysis, the size of the datasets used and the number of disease classes were the significant moderators ($p = 0.003$ and $p = 0.021$, respectively).
3. Equivalence of the transfer learning technique: Custom models using CNNs are statistically equivalent to the transfer learning models (p-value = 0.42), which means that for silkworm applications with limited training datasets, transfer learning models can be equally effective.

4.2.2 Disease-Specific Performance Analysis

The stratified analysis based on disease targets showed that diseases like Pebrine and Muscardine, which had unique visual signs (blackened spots, colored mycelium), were most accurately classified. However, for the classification of multiple diseases, specifically four major diseases, the results were less accurate compared to binary classification ($p = 0.008$), due to similarity of symptoms at early stages between Grasserie and Flacherie.

Table16. Diseases pooled accuracy estimates

Disease Target	k	Pooled Accuracy (95% CI)	Diagnostic Characteristics
Pebrine	12	93.5% (89.8–96.2%)	Distinctive spots, microscopic confirmation available
Grasserie	8	91.2% (86.4–94.8%)	Late-stage liquefaction obvious; early detection challenging
Flacherie	6	88.7% (82.3–93.4%)	Variable symptoms, polymicrobial etiology
Muscardine	5	94.1% (89.6–97.1%)	Characteristic mycelial growth, color distinctive
Multi-disease (4+ classes)	8	89.3% (85.1–92.7%)	Confusion between visually similar diseases
Healthy vs. Diseased (binary)	10	95.8% (93.2–97.7%)	Simplified decision boundary

The most appropriate combination of accuracy and speed is occupied by optimized light-weight CNNs (MobileNetV2, EfficientNet-Lite) and YOLOv5 with attention-based models with more than 90% accuracy within 200ms inference time—perfect for monitoring applications in real time.

4.3 Dataset Characteristics and Quality Assessment

4.3.1 Dataset Size and Composition

In Table 17, there is the concentration of research on small/medium sized dataset (<2,000 images). There are not many large datasets, similar to those found in plant disease detection.

Table 17. Dataset concentration of studies

Dataset Size Category	Studies (n)	Percentage	Mean Accuracy	Generalization Risk
<500 images	18	30.0%	89.2%	High (overfitting likely)
500–1,999 images	24	40.0%	93.4%	Moderate
2,000–4,999 images	12	20.0%	95.1%	Lower
≥5,000 images	6	10.0%	96.3%	Lowest

Just 10% of the studies used databases containing ≥5,000 images; this number of images is considered appropriate for generalization using deep learning techniques. The use of smaller databases (<2,000 images) in 70% of cases can raise issues regarding overfitting and lack of external validity.

4.3.2 Data Source and Availability

Lack of standardized databases in public domain for diseases of silkworms is quite opposite to the plant disease detection scenario, wherein sources like PlantVillage (54,306 images, 38 diseases) have facilitated benchmark testing and reproducibility. The problem of "data silos" creates great barriers to research progress (Table 18).

Table 18. Distribution of data source availability

Data Source	Studies (n)	Percentage	Reproducibility Implications
Public dataset	3	5.0%	High reproducibility, benchmark establishment
Available upon request	14	23.3%	Moderate reproducibility, author-dependent
Proprietary/Not available	43	71.7%	Low reproducibility, independent verification impossible

4.4 Validation Setting and Field Readiness

TRL Analysis: None of the reviewed studies reached TRL 8 (system is demonstrated and qualified) or TRL 9 (system proven in operational environment). Most of the research remains proof-of-concept-based (TRL 3-4), with only small steps towards operational application (see Table 19).

Table 19. Validation environment spectrum

Validation Setting	Studies (n)	Percentage	Technology Readiness Level
Laboratory (controlled)	48	80.0%	TRL 3–4 (proof of concept)
Simulated field conditions	8	13.3%	TRL 4–5 (validated in relevant environment)
Commercial farm pilot	4	6.7%	TRL 6–7 (demonstrated in operational environment)
Scaled commercial deployment	0	0.0%	TRL 8–9 (not achieved)

4.5 Deployment Characteristics and Practical Feasibility

4.5.1 Hardware Requirements and Infrastructure Dependencies

Infrastructure Gap Analysis: Small-scale sericulture farms, found mostly in India and other developing countries, often suffer from the absence of reliable electricity supply (unstable power supply, voltage variations), climate-controlled computer facilities (hot and humid conditions), high speed internet connections (dependence on cloud computing facilities), and capital for computer hardware.

In only 20% of the analyzed studies was implementation on proper infrastructure hardware considered, suggesting a mismatch between research and practice (Table 20).

Table 20. Hardware requirements and infrastructure dependencies

Hardware Platform	Studies Evaluating (n)	Cost Range (USD)	Infrastructure Requirements	Smallholder Suitability
High-end GPU (RTX 3090+)	28	\$1,500–3,000	Reliable electricity, climate-controlled environment, internet	Poor

Mid-range GPU (GTX 1060)	12	\$300–500	Stable electricity, basic climate control	Moderate
CPU-only (i5/Ryzen 5)	8	\$500–800 (full system)	Standard electricity	Good
Edge devices (Raspberry Pi 4)	6	\$75–150	Minimal infrastructure, battery operable	Excellent
Mobile (smartphone)	4	\$200–500 (existing ownership)	No additional infrastructure	Excellent

4.5.2 Software Framework and Maintenance Considerations

The choice of framework is crucial for sustainability in agriculture over a period of time. Although cloud-based solutions make it easier to implement, they expose themselves to risks in case of any connectivity issues (transfer of farm pictures to remote servers) (Table 21).

Table 21. Software framework and maintenance considerations

Framework	Studies Using (n)	Advantages	Deployment Challenges
TensorFlow/Keras	26	Mature ecosystem, extensive documentation	Version compatibility, model size
PyTorch	18	Research flexibility, dynamic graphs	Production deployment complexity
MATLAB	8	Engineering familiarity, toolboxes	Licensing cost, limited edge support
Custom/C++	6	Optimization, minimal dependencies	Development time, maintenance
Cloud APIs	2	No local infrastructure	Connectivity dependency, ongoing cost, data privacy

In the Table 22, machine learning and deep learning techniques used for visual purposes are compared through several important parameters of performance that include accuracy, amount of required data, training period, inference speed, model interpretability, feasibility of implementation, and practical validation. This provides information about the capabilities and drawbacks of every technique for making the right choice depending on the conditions of usage.

Table 22. Comparative summary of methodological approaches

Characteristic	Traditional ML	Custom CNN	Transfer Learning	Object Detection	Attention/Explainable
Accuracy	87.3%	94.6%	93.8%	91.4% mAP	96.0%+
Data requirement	100–500 images	1,000–5,000 images	500–2,000 images	2,000–10,000 images	1,000–5,000 images
Training time	Minutes–hours	Hours–days	Hours	Days	Days

Inference speed	Fast	Moderate	Moderate	Fast	Moderate
Interpretability	High	Low	Low	Moderate	High
Edge deployability	Excellent	Moderate	Good	Good	Moderate
Field validation	Rare	Rare	Rare	Emerging	Rare
Best use case	Resource-constrained, interpretable needs	Maximum accuracy, sufficient data	Limited data, rapid deployment	Real-time monitoring, counting	High-stakes decisions, user trust

5. CHALLENGES AND INTEGRATION BARRIERS

Although considerable advances have been made with respect to the use of soft computational methods as shown in Fig. 5 to detect silkworm diseases; many obstacles exist which hinder the deployment of these methods in practice and their wider adoption. The key challenges identified and discussed in this section are those of data limitation, class imbalance, real time detection, model interpretability, and integration into a system.

There are a multitude of connected barriers (technical, economic and social) that exist as a barrier to moving from prototype into practical use. Technical barriers include limited training data, class imbalance, the ability of models to generalize across different environmental settings and computational resource constraints associated with deployment at the "edge". There are also barriers on an economic level including the costs associated with hardware, software development, maintenance, and developing sustainable business models which will allow for widespread usage. In addition, there are social barriers that include the acceptance by users of the technology, the trust that exists among users toward automated technologies, and integrating new technologies into existing agricultural knowledge systems and practices.

To address the challenges described above will require a collaborative effort of research personnel, technology developers, agricultural extension service providers and the farming community at large. Collaboration across disciplines including computer science, entomology, agricultural economics and the social sciences will be necessary to create solutions that have technical merit, economic feasibility and social acceptability. This section provides an overview of each of the categories of challenges identified as well as identifies some of the problems within each category and how they may potentially be addressed.

5.1. Dataset Limitations

Limitations in the availability of sufficient dataset(s) to develop reliable detection systems for silkworm disease are significantly restrictive[15]. Plant disease detection benefits significantly from large publicly available datasets such as plant village; however, silkworm disease data sets are typically small, proprietary and not available to the public. Due to this limitation it becomes difficult to reproduce results, evaluate comparatively or collaborate on research advancement in the field. Developing standardized, publicly accessible datasets using consistent annotation protocols is essential to advance the field.

Quality problems in datasets are caused by different image capturing conditions, different image resolutions and by the subjective interpretation of the annotators [14]. The images taken with non-standardized methods show big variations in terms of illumination, background, camera settings and angle of view; therefore, they can affect negatively the training process of the models as well as their capability of generalizing on different environments. Furthermore, the absence of a validation from an expert of the ground truth annotations introduces noisy labels that decrease the accuracy of the models and increase the difficulty in evaluating them. Ethical and practical constraints can prevent expanding a dataset by doing large-scale data collections [43]. Artificially creating silkworm disease outbreaks is impossible to do for research purposes; therefore, collecting images from natural outbreaks will require quick response and cooperation with farmers. Collecting images may also be limited due to privacy restrictions on sharing images that are specific to a farm; however, geographic variations in disease occurrence rates affect the representativeness of a collected dataset.

5.2. Class Imbalance and Multi-Disease Classification

Standard performance measures (such as Accuracy) can be misleading in these types of cases because they do not distinguish between true positives and false negatives; in an extreme case, a classifier could predict the majority class every time (i.e., never identify any positive examples), yet have very high accuracy. Furthermore, classifying the large number of non-diseased samples correctly is easy compared to identifying those few which are diseased. Thus, there is a strong need to develop techniques capable of learning from data that are highly unbalanced in their classes.

While many of the disease classifications that have been developed to this point were designed with single disease (and therefore single label) classification, they will need to be adapted for use in multi-disease classification, where an individual silkworm can be diagnosed with multiple diseases at once [43], and therefore require multi-label classification techniques to identify all of the diseases currently afflicting it. In addition to the issue of needing to handle multiple labels, the hierarchical nature of disease symptoms (e.g., certain symptom(s) can occur as part of a number of disease), adds another level of complexity for multi-disease classification systems.

5.3 Real-Time Detection and Deployment Constraints

Real-time processing is necessary for deploying disease detection systems within commercial sericulture operations using resource-constrained devices [23]. Thus, there are several edge deployment constraints that include limited computing resources (i.e., processor speed), memory, and battery life which require the use of models that are lightweight yet do not suffer from a significant reduction in accuracy. The primary means to optimize models include methods such as quantization, pruning, and knowledge distillation, but each method may result in some loss of accuracy.

Practical uses are affected by environmental factors that include changing lighting (conditions) and backgrounds or a silkworm's position, which can influence the detection of silkworms (accuracy) [44]. As a result, models trained using controlled laboratory images may not be effective when used in real-world environments with different imaging conditions. Consequently, accurate models for the detection of silkworms in practical applications necessitate diverse training datasets as well as domain adaptation methods that will ensure consistency in performance within all practical

application scenarios.

Applications [45] utilizes Arduino Mega in conjunction with DHT11 (temperature and humidity) and rain sensors for environmental monitoring. Utilizes MATLAB in conjunction with Otsu's algorithm and Texture Feature Extraction for identification of mature cocoons and silkworm diseases. Limitations: Dependency on MATLAB makes embedding impossible; wired connection between sensors and the device limits the scalability of the system; image processing is not real time due to the computational overhead. Proposed [46]: Uses IoT sensors (temperature, humidity, and light) in combination with machine learning algorithms for detection of diseases (pebrine, flacherie). Limitations: Paper is a survey and no implementation details are provided; latency of real-time inference is unknown; depends on an external machine learning model that has not yet been optimized for edge computing.

Utilization [47] of Arduino IDE and MATLAB in conjunction for CNN-based silkworm health classification. Limitations: Integration of both software (Arduino & MATLAB) increases the level of complexity; CNN requires a PC connection for inference, which makes it non-portable; there is no information regarding the speed and delay of inference; classification (healthy/unhealthy) only. Silkworm growth stage classification through wireless personal area network [48] using Arduino with DHT11 sensors and camera. The GSM900 module provides remote alerts. Limitations: Only works up to a range of 2-3 meters; the GSM module suffers from delay in real-time video transmission; SD card for storing images is a bottleneck; no on-device AI, looks like all computations are centralized. Proposed star topology WSN with Arduino using ATmega328/P, BME280 (temp/humidity), and BH1750 (light) sensors for eri silkworm monitoring [49]. Star Topology introduces a single point of failure due to the dependence on master node; confined only to the environmental monitoring without any image-based recognition of diseases; technological limitation of the AI implementation; data logging may be done manually and not continuously. IoT system based on temperature, humidity, rain sensors along with Otsu's algorithm for classification of cocoon maturity status was designed [50], given the limitations of: Otsu's algorithm is a thresholding-based algorithm that is sensitive to changes in lighting conditions; External conditions affect crop yield estimation;

5.4 Interpretability and Explainability

Black-box models of deep learning have implications for adoption in agricultural decision-making where transparency is valued [51] farmers and extension workers may be reluctant to trust recommendations from systems they do not understand especially when high-stakes decisions about crop management are involved. Explainable AI techniques can provide insights into model decision-making processes that will increase user trust and facilitate error analysis.

Techniques such as Attention Visualization, Grad-CAM and SHAP Values help to identify those parts of images which have the most influence in the AI's decision-making process [41] [52], allowing a user to be able to confirm whether the model has made its decision based upon relevant aspects of the disease or some other non-disease related association. The challenge is to create an explanation method that effectively communicates how the model is making decisions to a nontechnical user.

5.5 Integration With Sericulture Management Systems

Effective disease detection systems are required to be integrated into current sericulture management practices [41] in a seamless way. As such, the integration of disease detection systems into current management practices will need to take into account the design of the user interface of the system; how the user is alerted to disease conditions; and the compatibility of the disease detection system with the current farm management computer software used by the farmer.

An additional challenge for developing complete end-to-end systems (from image capture to providing recommendations) is that most research has focused on improving classification accuracy and has not addressed the broader integration of these systems into the entire workflow of the farmer. The acceptance of a disease detection system by users, which includes the ease of use of the system; the perceived reliability of the system; and the compatibility of the disease detection system with the current practices of the users [22], are all important considerations. In order for a disease detection system to be accepted by users, it cannot require major changes to current practices or require significant technical expertise. Participative design methodologies, where farmers are involved throughout the development process of a disease detection system, can increase the likelihood of user acceptance and provide assurance that disease detection systems meet the real needs of users rather than the perceived needs of users.

Table 24. Barrier Severity Assessment and Priority Matrix

Barrier Category	Severity (1–5)	Urgency (1–5)	Addressability (1–5)	Priority Score	Recommended Intervention
Dataset standardization	5	5	4	25	Community-driven open data initiative
Field validation deficit	5	4	3	20	Funding mandate for pilot studies
Smallholder-appropriate design	5	4	3	20	Reverse innovation, frugal engineering
Extension service capacity	4	4	3	16	Training curriculum development
Trust and explainability	4	3	4	16	Participatory design, XAI integration
Gender-inclusive design	3	3	4	12	Gender-responsive technology assessment
Regulatory framework	3	2	2	8	Policy dialogue, sandbox regulation
Climate adaptation	4	3	2	8	Long-term research investment

6. FUTURE DIRECTIONS

Based on the thorough evaluation in this review, a number of new promising directions are identified which have the potential to move the field of silkworm disease detection forward, as well as allow for practical implementation in operational commercial sericulture settings, as Fig. 6 illustrates challenges and future directions.



Figure 6. Challenges and future direction in silkworm disease detection.

6.1 Research Roadmap

These directions will address many of the existing problems by using the most recent technological advancements and methodologies. A collective research plan is required to direct future effort toward practical application of silkworm disease detection technology. The short-term objectives (1-2 years) should be to create datasets and establish standards for data, develop light weight model architectures for use at the edge, and demonstrate practicality through pilot studies. The medium-term objectives (2-5 years), would include integrating with Internet of Things (IoT) networks, creating multidisease classification systems, and implementing commercially in conjunction with commercial sericulture operations.

The long-term vision (5-10 years), includes developing entirely autonomous smart sericulture systems with predictive ability and integrate them into larger agricultural management platforms. See in Fig. 7.

The research roadmap needs to be able to outline the specific mile stones and success criteria that will be used in order to measure the level of accomplishment and the amount of resources available during each stage of the research process; to allow for an assessment of how much the project is advancing and if it is necessary to reallocate resources. A collaborative framework among the universities, the industrial partners, and the governmental agencies will enable a coordination of all the research effort and will prevent duplicate research. The open science practice (sharing of data sets, publishing of codes, preprints) enables a rapid development of new results through a community-based collaboration with the prior existing results.

6.2 Lightweight and Efficient Architectures

Future studies will need to be focused on developing edge optimized light weight architectures that are suitable for use in sericulture environments [32] [53] [54]. The neural architecture search (NAS) methods will provide a means of finding the best model configuration in terms of both accuracy and processing performance for each platform. NAS will allow automated searches of very large design spaces to find models that human designers may not consider, and therefore obtain the best possible trade-off between accuracy and processing performance as compared with designer specified models.

The current trend in artificial intelligence [55] [56][63] is to develop efficient, linear attention models which will enable capturing of long-range dependency without increasing computation (quadratic) in the number of features. Reducing the computational cost by using sparse attention or other linear attention patterns can provide the same attention-based feature weighting as standard attention but with a much lower computational cost. Therefore, these new attention based approaches are very useful when dealing with the high-resolution images of silkworms, such as those used in this study, since standard attention would be too computationally intensive.

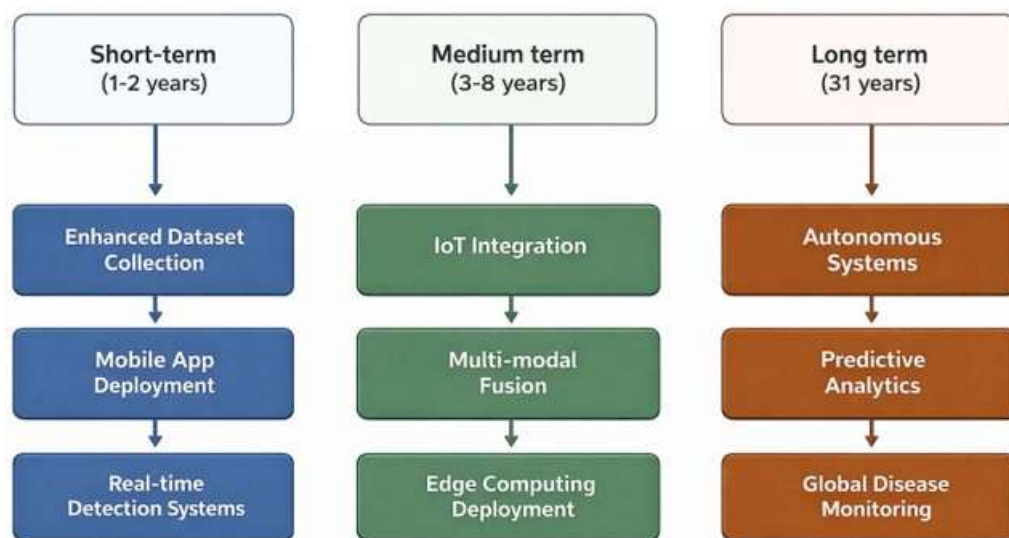


Figure 7. Roadmap for future research and deployment in AI-based silkworm disease detection.

6.3 Multi-Modal and Multi-Disease Detection

Hyperspectral imaging is able to capture a broad range of wavelengths outside the visual spectrum which may be indicative of disease or other issues in the plant not evident through the RGB color model. Environmental sensors (temperature, humidity, air quality) are also capable of providing context for improved accuracy of detection as well as predictive disease modelling. Combining visual, spectral, and environmental data may make disease detection more robust and allow for a more complete assessment of overall health [32].

Multi-task learning architectures capable of detecting multiple diseases at once as well as assessing the severity of those diseases are an exciting area of study [57]. Instead of creating a model to detect each disease separately, multi-task methods develop a common representation from which all methods can benefit (i.e., data efficiency) and enable overall health assessments. Furthermore, hierarchical classification structures that identify the relationship between diseases will increase the accuracy of the classification process and create a more informative output.

6.4 Iot and Smart Sericulture Integration

IoT for sericulture systems [58] Integrate TinyML for ultra-low power edge inference; Adopt containerized micro services architecture for scalable cloud backend; Implement digital twin technology for simulating virtual rearing environment; Explore 5G/6G for ultra-reliable low-latency communication (URLLC) for automated sericulture facilities.

"Smart Sericulture Systems", utilizing IoT technology, will enable the use of continuous monitoring and early warning systems for Silkworm Health Management [59] [60], and the ability to monitor health through the collection of images by using Automated Image Capture Technology in Rearing Environments, as well as automatically collecting samples on a scheduled basis (i.e., daily, weekly, monthly etc.) without the need for Human Intervention; which will allow for the evaluation of trends over time and earlier detection of emerging diseases.

Smart sericulture systems have been developed that integrate technology (such as IoT and image processing) to demonstrate how technology can be integrated into a traditional industry such as modern sericulture [61][63]. The smart system is designed to use a number of sensors and cloud-based analysis to monitor all aspects of the rearing environment and the overall health of the silkworms. Alerts are given when there is an issue or emerging disease, which could allow a quick response to reduce the risk of a larger outbreak occurring [22].

The authors [55] of this study discussed how AI and IoT could be used to make sericulture more sustainable and efficient. They stated the AI/IoT was able to identify several applications as important areas where they would be applicable such as; automated environmental control, predictive models for diseases, optimal use of resources. The potential to combine many different AI

solutions with an IoT system is great for developing a more complete farm management system that can be used for all aspects of sericulture operation, rather than just for detecting diseases.

The authors [62] suggested Integration of GSM Module to replace internet-based notification mechanisms with the integration of the GSM module to send SMS notifications directly to the mobile phones of the farmers without the need for internet connectivity. Smart Actuator to integrate control over other actuators such as humidifiers and dehumidifiers for the complete control of humidity along with temperature control. Solar power for the operation of sericulture farms even without grid connections. Integrate cloud-based data analytics for predictive modelling of environmental trends. Multi-Parameter Fusion: Integrate image processing along with environmental sensors for the complete monitoring of the health of the sericulture ecosystem beyond temperature control. Also Integrate LPWAN technology such as LoRaWAN or NB-IoT for long-range communications for sericulture farms with low power consumption.

7. CONCLUSION

This is a systematic review of soft computing methodologies employed for silkworm disease detection through artificial intelligence. It includes; traditional machine learning (ML), convolutional neural networks (CNN), advanced deep learning (DL) models, and transfer learning (TL). The evolution of these methodologies have progressed from manually crafted feature based models to robust DL models which are capable of detecting diseases in real time in field conditions, as demonstrated by many recent studies that demonstrate an accuracy level above 95% on benchmark datasets. In general, CNN based models have been shown to perform better than traditional ML models with an improvement in accuracy ranging from 10% to 15%. Additionally, TL has allowed researchers to effectively utilize smaller datasets of around 500 images per class to obtain good results. In addition, the development of lightweight DL models allows for fast inference and can be used in resource constrained environments, which supports the practical implementation of the methodology. However, despite the significant progress made in the use of soft computing methodologies to detect silkworm diseases, there are still some major challenges facing the field. These include; lack of standardization in terms of datasets, large number of classes, varying environment conditions, and limited computational capabilities which limit the ability to scale and reproduce the results. Therefore, it is recommended that future research focus on developing standardized public datasets and benchmarks, lightweight edge optimized DL architectures, multimodal detection frameworks that integrate both visual and sensor data, IoT enabled continuous monitoring systems, and federated learning architectures to enable collaborative but private learning. Furthermore, developing models that are interpretable and easy to integrate into existing farm management practices will also increase the level of trust and acceptance among users. In conclusion, soft computing methodologies offer great potential for creating intelligent, sustainable, sericulture systems, which will reduce the loss associated with disease in sericulture, produce high quality silk, and provide long-term financial sustainability for sericulture businesses, if the research continues to translate the advancements into scalable and practical solutions.

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AUTHOR CONTRIBUTIONS

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Ravi Hosur: Supervision, Validation, Writing –Review & Editing.

CONFLICT OF INTEREST

The authors declare that there is no conflict of interest.

ETHICS STATEMENT

Ethical approval was not required for this study.

REFERENCES

- [1] Q. Xia *et al.*, “A draft sequence for the genome of the domesticated silkworm (*Bombyx mori*),” *Science*, vol. 306, no. 5703, pp. 1937–1940, Dec. 2004.
- [2] R. K. Datta, *Global silk industry: A complete source book*. Boca Raton: CRC Press, 2022.
- [3] D. Giora *et al.*, “Bibliometric analysis of trends in mulberry and silkworm research on the production of silk and its by-products,” *Insects*, vol. 13, no. 7, p. 568, June 2022.
- [4] *Food and Agriculture Organization of the United Nations*. Rome: FAO, 2023.
- [5] A. S. Gadge, A. L. Jadhav, M. Pushpalatha, P. Megaladevi, and K. Sowmiya, “Overview of Indian sericulture: Types, production and economic significance,” *Biotica Research Today*, vol. 6, no. 6, pp. 317–320, 2024.
- [6] P. Chopade, C. G. Raghavendra, M. Kumar, and Bhaskar, “Assessment of diseases in *Bombyx mori* silkworm – A survey,” *Global Transitions Proceedings*, vol. 2, no. 1, pp. 133–136, June 2021.
- [7] U. Divakarla, “A Comprehensive Study on Role of Environmental Factors on Sericulture and Silkworm Disease Detection Techniques,” in *Proc. 4th Int. Conf. Mobile Networks Wireless Commun. (ICMNBC)*, IEEE, 2024, pp. 1–6.
- [8] S. Nuraeni *et al.*, “Detection of pebrine disease and *Bombyx mori* Nuclear Polyhedrosis Virus (BmNPV) in silkworm moths (*Bombyx mori* L.),” *IOP Conf. Ser. Earth Environ. Sci.*, vol. 886, no. 1, p. 012051, Nov. 2021.
- [9] S. Chanotra and M. A. Bhat, “A simple, efficient and cost effective protocol for detection of BmNPV in the silkworm, *Bombyx mori* L.,” *Int. J. Fauna Biol. Stud.*, vol. 8, no. 3, pp. 34–37, May 2021.
- [10] S. K. Vootla, X. M. Lu, N. Kari, M. Gadwala, and Q. Lu, “Rapid detection of infectious flacherie virus of the silkworm, *Bombyx mori*, using RT-PCR and nested PCR,” *J. Insect Sci.*, vol. 13, no. 120, p. 120, 2013.
- [11] N. S. Sisodia, S. Gaherwal, and R. Jain, “Determination of different diseases and preventive measures of mulberry silkworm,” *Int. J. Sci. Res. Biol. Sci.*, vol. 6, no. 4, pp. 101–104, Aug. 2019.
- [12] L. Goyal, C. M. Sharma, A. Singh, and P. K. Singh, “Leaf and spike wheat disease detection & classification using an improved deep convolutional architecture,” *Inform. Med. Unlocked*, vol. 25, no. 100642, p. 100642, 2021.
- [13] A. Akuli, T. Dey, P. Chopra, A. Pal, S. Alarn, and N. Bhattacharyya, “Vision sensing system for early detection of Pebrine spore in silk moth,” in *2012 Sixth International Conference on Sensing Technology (ICST)*, Kolkata, 2012.
- [14] A. Pal, A. Akuli, T. Dey, and N. Bhattacharyya, “Development of photomicrographic image analysis solution for sporozoa detection in Tasar moth,” in *2013 IEEE Second International Conference on Image Information Processing (ICIIP-2013)*, Shimla, India, 2013.
- [15] W. Shafik, A. Tufail, A. Namoun, L. C. De Silva, and R. A. A. H. M. Apong, “A systematic literature review on plant disease detection: Motivations, classification techniques, datasets, challenges, and future trends,” *IEEE Access*, vol. 11, pp. 59174–59203, 2023.
- [16] K. P. Ferentinos, “Deep learning models for plant disease detection and diagnosis,” *Comput. Electron. Agric.*, vol. 145, pp. 311–318, Feb. 2018.
- [17] Y. Kaya and E. Gürsoy, “A novel multi-head CNN design to identify plant diseases using the fusion of RGB images,” *Ecol. Inform.*, vol. 75, no. 101998, p. 101998, July 2023.
- [18] Y. Luo *et al.*, “Data density-based RGB color component feature extraction and area measurement method for silkworm,” *J. Asia. Pac. Entomol.*, vol. 26, no. 4, p. 102153, Dec. 2023.
- [19] H. Zhuang *et al.*, “Silkworm segmentation based on encoder-decoder structure,” *Smart Agric. Technol.*, vol. 12, no. 101274, p. 101274, Dec. 2025.
- [20] H. Shi *et al.*, “CA-YOLOv5: Detection model for healthy and diseased silkworms in mixed conditions based on improved YOLOv5,” *Int. J. Agric. Biol. Eng.*, vol. 16, no. 6, pp. 236–245, 2023.

- [21] P. S. Shilpashree, "Classification of Healthy and Diseased Silkworms using Ensemble Learning and CNN," in *Proc. Int. Conf. Smart Systems Applications Electrical Sciences (ICSSES)*, IEEE, 2023, pp. 1–5.
- [22] T. Bhuvaneshwari, "Smart Sericulture Systems Based on Internet of Things (IOT) and Image Processing," *Adv. Res.*, vol. 26, no. 5, pp. 137–147, Sept. 2025.
- [23] C. G. Raju, S. Sarkar, V. Canamedi, J. Parameshwaranai, and S. Sarkar, "A review of silk farming automation using artificial intelligence, machine learning, and cloud-based solutions," in *Data Analytics and Learning*, Singapore: Springer Nature Singapore, 2024, pp. 101–116.
- [24] M. J. Page *et al.*, "The PRISMA 2020 statement: an updated guideline for reporting systematic reviewsDeclaración PRISMA 2020: una guía actualizada para la publicación de revisiones sistemáticas," *Rev. Panam. Salud Publica*, vol. 46, p. e112, Dec. 2022.
- [25] Manju G, "Grasserie disease detection in silkworm using machine learning methods," *Int. J. Sci. Res. Arch.*, vol. 13, no. 2, pp. 1251–1256, Nov. 2024.
- [26] S. Thomas, Binson V A, S. Rahuman, and Sivakumar K S, "Early detection of Grasserie disease in silkworms using computer vision and machine learning," *J. RESTI (Rekayasa Sist. Dan Teknol. Inf.)*, vol. 9, no. 5, pp. 1255–1264, Oct. 2025.
- [27] S. Singla, S. Garg, I. Garg, T. K. Jha, B. Singh, and H. Arya, "Disease detection in Bombyx Mori silkworm using deep learning algorithm CNN," in *2023 International Conference on Advanced Computing & Communication Technologies (ICACCTech)*, Banur, India, 2023.
- [28] S. M. Nagashetti, S. Biradar, S. D. Dambal, C. G. Raghavendra, and B. D. Parameshachari, "Detection of disease in Bombyx Mori silkworm by using image analysis approach," in *2021 IEEE Mysore Sub Section International Conference (MysuruCon)*, Hassan, India, 2021.
- [29] N. M. Suvarna, Sudarshan, and N. S. Ail, "Image classification for silkworm using deep neural network-keras," *International Journal of Scientific Research in Computer Science, Engineering and Information Technology*, pp. 658–663, June 2021.
- [30] S. B. Kodli and Anita, "A novel approach for silkworm disease detection and classification by using CNN and image processing techniques," *Journal of Scientific Research and Technology*, pp. 21–29, Mar. 2025.
- [31] M. Sandler, A. Howard, M. Zhu, A. Zhmoginov, and L.-C. Chen, "MobileNetV2: Inverted residuals and linear bottlenecks," in *2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition*, Salt Lake City, UT, 2018.
- [32] M. Tan and Q. V. Le, "EfficientNet: Rethinking model scaling for convolutional Neural Networks," *arXiv [cs.LG]*, 28-May-2019.
- [33] W. Feng *et al.*, "A lightweight convolutional neural network for silkworm cocoons fast classification," in *Communications in Computer and Information Science*, Singapore: Springer Singapore, 2019, pp. 301–309.
- [34] C. Wen *et al.*, "Lightweight silkworm recognition based on Multi-scale feature fusion," *Comput. Electron. Agric.*, vol. 200, no. 107234, p. 107234, Sept. 2022.
- [35] H. Shi, D. Tian, S. Zhu, L. Li, and J. Wu, "Research on silkworm disease detection in real conditions based on ca-Yolo V3," *SSRN Electron. J.*, 2022.
- [36] K. Mungase, S. Chiwhane, and P. Paygude, "CNN-based image classification of silkworm for early prediction of diseases," in *First International Conference on Computational Intelligence and Soft Computing (CISCom 2025)*, 2025, p. 14.
- [37] S. Li, K. Li, Y. Qiao, and L. Zhang, "A multi-scale cucumber disease detection method in natural scenes based on YOLOv5," *Comput. Electron. Agric.*, vol. 202, no. 107363, p. 107363, Nov. 2022.
- [38] X. Ma, M. Wang, H. Kuang, L. Tang, and X. Liu, "Detection and counting method of silkworms based on space-to-depth conversion," in *2024 IEEE 6th Advanced Information Management, Communicates, Electronic and Automation Control Conference (IMCEC)*, Chongqing, China, 2024.

- [39] Y. Zhen, X. Dingyuan, T. Liang, and S. Meining, "Attention-concatenation dense convolutional neural network for silkworm disease recognition," in *2020 5th International Conference on Smart Grid and Electrical Automation (ICSGEA)*, Zhangjiajie, China, 2020.
- [40] H. Zheng, X. Guo, Y. Ma, X. Zeng, J. Chen, and T. Zhang, "Fine-grained detection model based on attention mechanism and multi-scale feature fusion for cocoon sorting," *Agriculture*, vol. 14, no. 5, p. 700, Apr. 2024.
- [41] M. Nahiduzzaman *et al.*, "Explainable deep learning model for automatic mulberry leaf disease classification," *Front. Plant Sci.*, vol. 14, p. 1175515, Sept. 2023.
- [42] Devi, Benila, Lekshmi, and Omana, "HVAF-XAI-Net: A multimodal explainable AI framework for accurate mulberry leaf disease detection," *Smart Agric. Technol.*, vol. 12, no. 101377, p. 101377, Dec. 2025.
- [43] A. Kaushik, "Artificial Intelligence and Internet of Things in Sericulture: Transforming Sustainability, Efficiency and Rural Livelihoods," *J. Adv. Biol. Biotechnol.*, vol. 28, no. 8, pp. 1417–1429, Aug. 2025.
- [44] D. Xia, Z. Yu, A. Cheng, L. Tang, and M. Shi, "Development and application of silkworm disease recognition system based on mobile app," in *Lecture Notes in Computer Science*, Cham: Springer International Publishing, 2019, pp. 471–482.
- [45] S. Rokhade, Guruprasad, Mallesh, S. Banu, Jyoti, and Thippesha, "Smart sericulture system based on IoT and image processing technique," in *2021 International Conference on Computer Communication and Informatics (ICCCI)*, Coimbatore, India, 2021.
- [46] Harsha R, Prithvi Veera B, Rohan M.N, and Hemanth Chandra N, "Survey on sericulture: An IOT-based cocoon worms monitoring for disease identification and management for quality silk rearing," *International Journal of Advanced Research in Science, Communication and Technology*, pp. 235–244, Feb. 2024.
- [47] Yogeshraj and Applied Electronics., "Smart automated sericulture based on image processing technique and embedded system," *J. Univ. Shanghai Sci. Technol./Shanghai Ligong Daxue Xuebao*, vol. 24, no. 1, pp. 327–331, Jan. 2022.
- [48] N. M., S. R., and D. Kumar, "Silkworm growth monitoring smart sericulture system based on internet of things (IOT) and image processing," *Int. J. Comput. Appl.*, vol. 180, no. 18, pp. 29–33, Feb. 2018.
- [49] A. Dolo, N. Barkataki, M. Saikia, and D. Saikia, "Development of a wireless sensor network based smart multiple ambient conditions sensing system for the rearing process of eri silkworm," *Int. J. Adv. Technol. Eng. Explor.*, vol. 6, no. 52, pp. 50–60, Mar. 2019.
- [50] C. Samata Renukadevi, *IoT and image processing Techniques-Based Smart Sericulture Nature System*. 2022.
- [51] X. Li, C. Lv, W. Wang, G. Li, L. Yang, and J. Yang, "Generalized Focal Loss: Towards efficient representation learning for dense object detection," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 45, no. 3, pp. 3139–3153, Mar. 2023.
- [52] R. R. Selvaraju Grad-Cam, "Visual explanations from deep networks via gradientbased localization," *Int. J. aComput. Vis.*, vol. 128, no. 2, pp. 336–359, Feb. 2020.
- [53] A. G. Howard *et al.*, "MobileNets: Efficient Convolutional Neural Networks for Mobile Vision Applications," *arXiv [cs.CV]*, 16-Apr-2017.
- [54] P. B. Kolhe, D. Shelke Ramesh, and N. Agarwal, "EnhanceNet: Rethinking model scaling for convolutional neural network," in *Lecture Notes in Networks and Systems*, Singapore: Springer Nature Singapore, 2025, pp. 1–15.
- [55] T. Li, M. Vorvoreanu, D. Debellis, and S. Amershi, "Assessing human-AI interaction early through factorial surveys: A study on the guidelines for human-AI interaction," *ACM Trans. Comput. Hum. Interact.*, vol. 30, no. 5, pp. 1–45, Oct. 2023.
- [56] B. Nushi, E. Kamar, and E. Horvitz, "Towards accountable AI: Hybrid human-machine analyses for characterizing system failure," *Proceedings of the AAAI Conference on Human Computation and Crowdsourcing*, vol. 6, pp. 126–135, June 2018.
- [57] H. Shi, L. Li, S. Zhu, J. Wu, and G. Hu, "FeYOLO: Improved YOLOv7-tiny model using feature enhancement modules for the detection of individual silkworms in high-density and compact conditions," *Comput. Electron. Agric.*, vol. 231, no. 109966, p. 109966, Apr. 2025.

- [58] A. B. Ashwini, H. N. Likitha, S. B. Padashetty, and S. Deshpande, "Design and development of IOT based smart sericulture plant," in *2024 8th International Conference on Computational System and Information Technology for Sustainable Solutions (CSITSS)*, Bengaluru, India, 2024, pp. 1–6.
- [59] P. Pal, D. Singh, R. Singh, A. Gehlot, and S. V. Akram, "Role of artificial intelligence, machine learning, deep learning for sericulture: A technological perspective," in *2023 International Conference on Artificial Intelligence and Smart Communication (AISC)*, Greater Noida, India, 2023.
- [60] M. Yacoubi, O. Moussaoui, and C. Drocourt, "AI for IoMT security: a comprehensive survey of intrusion detection and system architectures," *Internet Things (Amst.)*, vol. 36, no. 101869, p. 101869, Mar. 2026.
- [61] "Disease prediction in sericulture and automation," in *Lecture Notes in Networks and Systems*, .
- [62] "Automatic detection, controlling and monitoring of temperature in sericulture using IoT," *International Research Journal of Modernization in Engineering Technology and Science*, May 2024.
- [63] N. Gadagin and R. Hosur, "A comprehensive review of soft computational methods for silkworm disease detection: Advances, challenges, and future directions," *injoere*, vol. 6, no. S5, pp. 475–496, Jul. 2026, doi: 10.70102/rx4s5741.