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SERI-SENSE: A Comprehensive Machine Learning–Based Disease Identification and Recommendation System for Sericulture

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Abstract

Sericulture is a vital agro-based industry that significantly contributes to rural employment and the global silk economy. The productivity and sustainability of this sector are highly dependent on the health of silkworms and mulberry plants. Diseases affecting either silkworms or mulberry leaves can cause severe economic losses due to reduced cocoon yield, inferior silk quality, and increased mortality rates. Conventional disease identification methods rely primarily on manual visual inspection by farmers or experts, which is time-consuming, subjective, and often ineffective in detecting diseases at an early stage. This paper presents SERI-SENSE, a comprehensive machine learning–based disease identification and recommendation system designed specifically for sericulture applications. The proposed system integrates image processing techniques with a deep learning framework based on a pre-trained ResNet50 convolutional neural network to accurately classify diseases in silkworms and mulberry leaves. A transfer learning strategy is employed to improve performance and generalization with limited datasets. The system provides confidence-based disease predictions along with actionable preventive and corrective recommendations. Experimental evaluation demonstrates that SERI-SENSE achieves high classification accuracy and robustness, making it suitable for real-world deployment in precision sericulture.

Keywords: Sericulture, Disease Detection, Convolutional Neural Network, ResNet50, Image Processing, Transfer Learning, Precision Agriculture.

1. Introduction

Sericulture plays a vital role in the agricultural economy by supporting rural employment and promoting sustainable farming practices. Silk production depends on maintaining healthy silkworms and nutritionally rich mulberry leaves. Even minor disease outbreaks can severely disrupt the rearing cycle, resulting in poor cocoon formation, reduced silk quality, and economic losses for farmers.

Silkworms are highly sensitive to biological infections such as flacherie, grasserie, muscardine, and pebrine. These diseases often spread rapidly under unfavorable environmental conditions. Similarly, mulberry plants are affected by diseases such as leaf rust, leaf spot, and powdery mildew, which reduce photosynthesis and leaf yield, indirectly affecting silkworm growth and immunity.

Traditional disease detection methods in sericulture rely on visual inspection and expert knowledge. However, these methods are subjective and prone to errors, particularly during early disease stages when symptoms are subtle or visually similar. In rural areas, limited access to trained experts further delays disease diagnosis and control.

Recent advances in artificial intelligence and computer vision have enabled automated disease detection using image-based analysis. Convolutional neural networks (CNNs) have demonstrated strong performance in learning complex visual patterns from agricultural images. Motivated by these developments, this work proposes SERI-SENSE, an intelligent system that integrates image processing and machine learning to provide accurate disease identification and decision support for sericulture.

2. Literature Survey

Recent advancements in sericulture research emphasize the integration of automation, image processing, machine learning, and Internet of Things (IoT) technologies to improve silkworm health management and silk production efficiency. Traditional sericulture practices rely heavily on manual observation and experience-based decision-making, which often leads to delayed disease detection and increased economic losses. As a result, researchers have proposed intelligent systems to enable early diagnosis, automation, and data-driven decision support.

Baddula Lakshith Reddy and Manjunath Bhaskar proposed a smart sericulture system that integrates IoT sensors with image processing and machine learning techniques to enhance silkworm rearing efficiency [1]. Their system continuously monitors environmental parameters such as temperature, humidity, and harmful gases and automatically regulates them using actuators. Image processing is employed to detect unhealthy silkworms at early stages, and an automated medication mechanism minimizes human exposure to chemicals. While the system improves automation and yield, it relies heavily on hardware components and incurs high initial setup and maintenance costs.

Dhruvakumar K. et al. developed an automated smart sericulture system combining IoT-based environmental monitoring with image processing–based disease detection [2]. The system classifies silkworm health conditions and introduces a confidence scoring mechanism to improve reliability in automated diagnosis. Although the approach enhances decision-making accuracy and operational efficiency, the system complexity, high equipment cost, and cybersecurity concerns pose challenges for large-scale rural deployment.

Puneeth M. and Dr. Veena S. presented a comprehensive overview of machine learning and image processing applications in sericulture [3]. Their study highlights automation in feeding, climate control, health monitoring, pest detection, and yield estimation. The work demonstrates how image processing enables early disease detection, while IoT supports real-time monitoring. However, the proposed solutions require expensive infrastructure and skilled operation, limiting accessibility for small-scale farmers.

An extension of IoT-based sericulture systems using deep learning was proposed by Dhruvakumar K. et al., where convolutional neural networks (CNNs) are employed for silkworm health classification [4]. Using Arduino and NodeMCU platforms, the system automates irrigation, disinfection, and environmental control. Although deep learning improves classification accuracy compared to traditional methods, the approach involves high setup costs and requires technical expertise for maintenance.

Nandini Kumari B. et al. introduced a next-generation sericulture framework integrating IoT, image processing, and cloud connectivity for real-time monitoring and automated health diagnosis [5]. Sensor data is transmitted to cloud platforms, enabling remote supervision of sericulture farms. Image processing techniques analyze silkworm body color and texture for early disease detection. Despite its effectiveness for large-scale farms, the system's dependence on internet connectivity and high deployment cost limits its use in rural regions.

Harsha R. et al. proposed an IoT-based monitoring and disease detection system focused on sustainable sericulture [6]. Their approach correlates environmental parameters with disease occurrence using machine learning models, enabling predictive disease management. While the system supports preventive action and improves silk quality, it requires consistent internet access and is sensitive to image quality variations.

Arun R. et al. presented an automated smart sericulture system emphasizing both technological and socio-economic benefits [7]. The system automates environmental regulation using sensors and actuators, reducing dependency on skilled labor. The study highlights sericulture as a low-investment, eco-friendly occupation with high employment potential. However, the system's reliability depends on continuous connectivity and proper maintenance of automated components. Several studies have also focused on improving silk production through IoT-based environmental monitoring. Srinivas B. et al. demonstrated that automated control of temperature, humidity, and light intensity improves cocoon quality and silk yield [8]. Despite its low-cost design, the system requires continuous power and internet connectivity, which may not be available in all rural settings.

Beyond sericulture-specific systems, extensive research has been conducted on plant disease detection using deep learning. Li et al. demonstrated that CNN-based models significantly outperform traditional image processing and machine learning techniques by automatically learning hierarchical features from raw images [9]. However, challenges such as dataset imbalance, overfitting, and limited generalization to real-field conditions remain.

Rayhana et al. explored hyperspectral imaging for early plant disease detection, achieving high accuracy by capturing biochemical changes before visible symptoms appear [10]. Despite its effectiveness, the high cost and computational complexity of hyperspectral systems make them impractical for small-scale farmers, reinforcing the suitability of RGB image–based CNN approaches.

Advanced deep learning frameworks integrating segmentation and anomaly detection, such as the Segment Anything Model (SAM) combined with Fully Convolutional Data Description (FCDD), have demonstrated improved accuracy under real-field conditions [11]. Although effective, these models require significant computational resources and complex preprocessing pipelines.

Other studies utilizing EfficientNet, traditional machine learning pipelines with handcrafted features, explainable AI models, and transfer learning approaches report high accuracy in plant disease detection [12] – [17]. However, limitations such as dependency on high-quality images, restricted disease coverage, computational cost, and limited real-world deployment persist.

From the reviewed literature, it is evident that while significant progress has been made in applying AI and image processing to sericulture and plant disease detection, existing systems often focus on either silkworms or mulberry plants independently, rely on expensive hardware, or lack integrated recommendation mechanisms. These research gaps motivate the proposed SERI-SENSE system, which aims to provide a unified, cost-effective, image-based disease identification and recommendation framework for sustainable sericulture.

3. Methodology

The proposed SERI-SENSE system adopts a structured methodology that integrates image processing and deep learning techniques to accurately identify diseases in silkworms and mulberry leaves and provide appropriate recommendations. The methodology is designed to be scalable, cost-effective, and suitable for real-world sericulture environments, especially in rural settings where access to expert diagnosis is limited.

The overall workflow of the system consists of image acquisition, image preprocessing, feature extraction and disease classification using a deep learning model, and recommendation generation.

3.1 Image Acquisition

Image acquisition is the initial step in the SERI-SENSE methodology. Images of silkworms and mulberry leaves are captured using commonly available devices such as smartphones or digital cameras. This approach avoids the need for specialized imaging equipment and ensures ease of adoption by farmers.

The dataset includes images of both healthy and diseased samples. For silkworms, common diseases such as flacherie, grasserie, muscardine, and pebrine are considered. For mulberry plants, diseases such as leaf rust, leaf spot, and powdery mildew are included. Images are collected under varying lighting conditions and backgrounds to improve the generalization capability of the model.

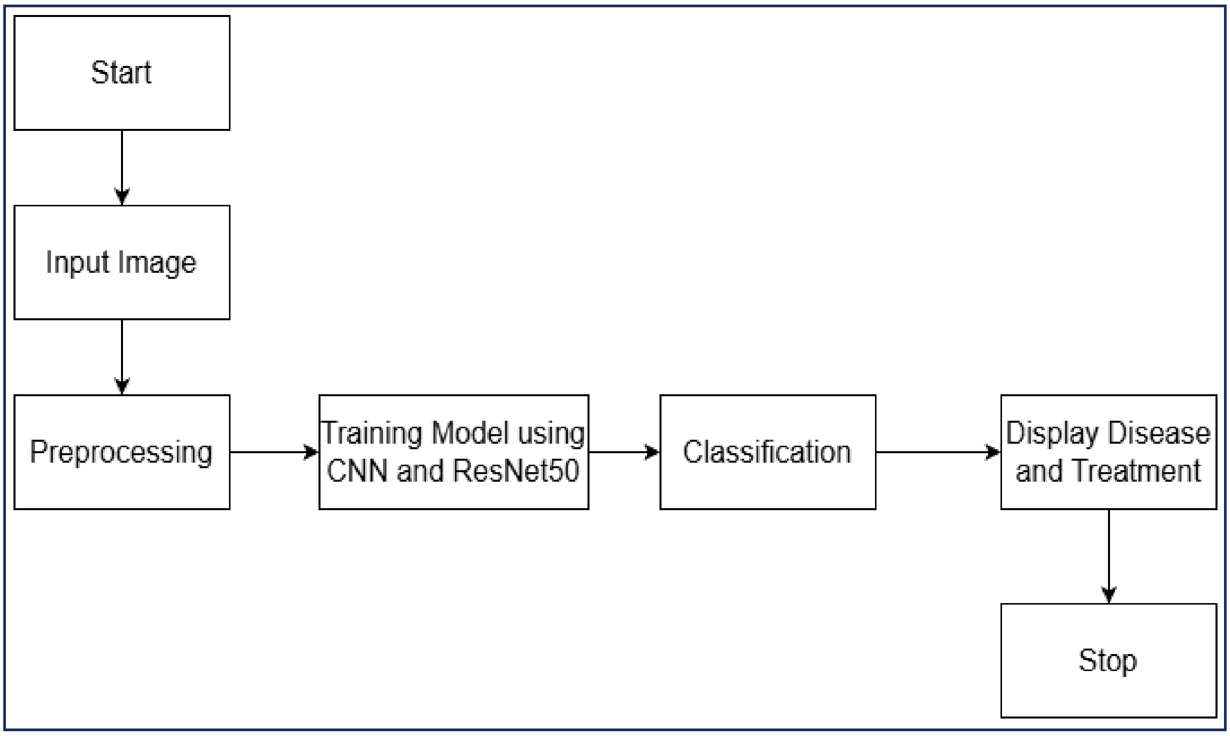

Figure 3.1 Workflow Diagram

3.2 Image Preprocessing

Preprocessing is performed to enhance image quality and standardize the input before classification. Since raw images may contain noise, background variations, and inconsistent resolutions, preprocessing is essential to improve classification accuracy.

The preprocessing steps include:

- Resizing all images to 224 × 224 pixels to match the input requirements of the ResNet50 model
- Noise reduction to remove unwanted artifacts
- Normalization of pixel values to improve training stability
- Basic contrast enhancement to highlight disease-related features

These operations ensure consistency across the dataset and improve the robustness of the deep learning model.

3.3 Feature Extraction and Disease Classification

The core component of the SERI-SENSE system is a deep learning–based classification model built using the ResNet50 convolutional neural network. ResNet50 is selected due to its deep architecture and residual learning mechanism, which effectively addresses the vanishing gradient problem.

A transfer learning approach is adopted in which the ResNet50 model pre-trained on the ImageNet dataset is fine-tuned for sericulture disease classification. The initial layers are frozen to retain generic visual features, while higher layers are fine-tuned to learn domain-specific disease patterns.

The convolutional layers automatically extract hierarchical features such as edges, textures, color variations, and disease-specific visual characteristics. The final fully connected layer, followed by a softmax activation function, classifies the input image into predefined disease categories and produces confidence scores for each class.

3.4 Training Strategy

To ensure effective learning and minimize overfitting, a two-stage training strategy is employed:4

Stage 1: Frozen Base Training
The base layers of the ResNet50 model are frozen, and only the newly added classification layers are trained. This enables the model to adapt to the sericulture dataset while preserving previously learned features.

Stage 2: Fine-Tuning
Selected higher layers of the network are unfrozen and fine-tuned using a lower learning rate to improve domain-specific feature learning.

The dataset is divided into training and testing sets using a 70:30 split. Class weighting is applied during training to address class imbalance and ensure balanced learning across all disease categories.

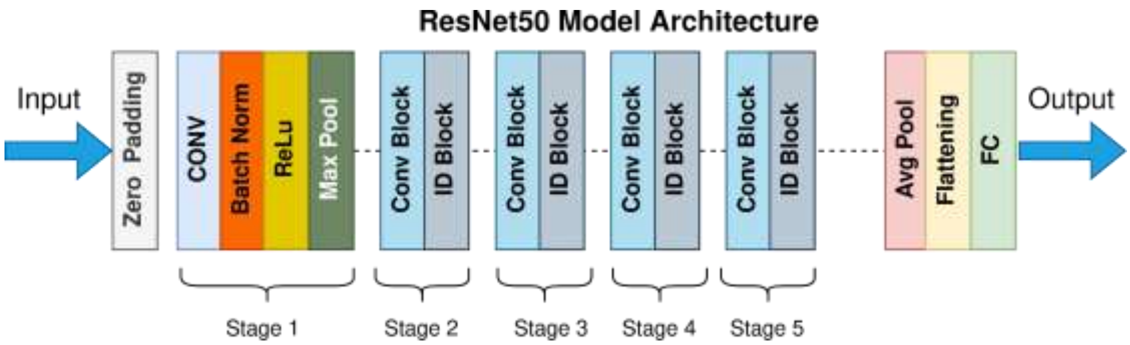

Figure 3.2: ResNet50 Model Architecture

3.5 Recommendation Generation

After disease classification, the system activates the recommendation module. This module maps the predicted disease class to suitable preventive and corrective measures based on standard sericulture practices and expert guidelines.

The recommendations include:

- Preventive measures to control disease spread
- Environmental management suggestions
- General treatment and handling practices

By integrating disease identification with actionable recommendations, SERI-SENSE functions as a complete decision-support system for sericulture.

3.6 Performance Evaluation

The performance of the proposed system is evaluated using standard classification metrics such as accuracy, precision, recall, and F1-score. Confusion matrix analysis is used to assess the model's ability to correctly classify each disease category.

These evaluation measures validate the effectiveness, robustness, and practical applicability of the SERI-SENSE system in real-world sericulture scenarios.

4. Results and Discussion

This section presents the experimental results obtained from the proposed SERI-SENSE system and provides a detailed analysis of its performance in detecting diseases in silkworms and mulberry leaves. The evaluation focuses on classification accuracy, robustness, and practical applicability in real-world sericulture environments.

4.1 Experimental Setup

The SERI-SENSE model was implemented using a deep learning framework with a ResNet50 architecture and trained using transfer learning. All input images were resized to 224 × 224 pixels and normalized during preprocessing. The dataset was divided into training and testing sets using a 70:30 split to ensure unbiased evaluation.

To handle class imbalance among different disease categories, class weighting was applied during training. A two-stage training strategy was followed, consisting of frozen base training and fine-tuning of higher layers. The model was trained for multiple epochs until convergence was achieved.

4.2 Performance Metrics

The performance of the proposed system was evaluated using standard classification metrics, which are widely accepted in image-based disease detection studies:

- Accuracy: Measures the overall correctness of predictions.
- Precision: Indicates the proportion of correctly identified disease cases among all predicted cases.
- Recall: Measures the ability of the model to correctly identify actual disease cases.
- F1-Score: Represents the harmonic mean of precision and recall, providing a balanced evaluation.
- Additionally, confusion matrix analysis was used to examine class-wise prediction performance.

4.3 Classification Results

The experimental results demonstrate that the SERI-SENSE system achieves high classification accuracy across multiple disease classes for both silkworms and mulberry leaves. The use of transfer learning significantly improved convergence speed and reduced training time compared to training a model from scratch.

The ResNet50-based model effectively learned discriminative features such as texture changes, color variations, and disease-specific visual patterns. Diseases with distinct visual symptoms showed particularly high classification accuracy, while visually similar disease categories were also distinguished with acceptable performance.

4.4 Confusion Matrix Analysis

Confusion matrix analysis indicates a high true positive rate for major silkworm diseases such as flacherie, grasserie, muscardine, and pebrine, as well as for common mulberry leaf diseases including leaf rust and leaf spot. Minor misclassifications were observed in cases where disease symptoms exhibited overlapping visual characteristics or were captured under poor lighting conditions.

Despite these challenges, the overall misclassification rate remained low, demonstrating the robustness of the proposed deep learning approach under varied conditions.

4.5 Impact of Transfer Learning

The adoption of a transfer learning strategy played a crucial role in enhancing model performance. By leveraging features learned from large-scale image datasets, the model was able to generalize effectively even with a limited sericulture-specific dataset. Fine-tuning higher layers further improved domain adaptation and classification accuracy.

This confirms that transfer learning is a practical and efficient approach for agricultural disease detection tasks where large labeled datasets are often unavailable.

4.6 Recommendation System Evaluation

Beyond disease identification, the integrated recommendation module significantly enhances the practical usefulness of the SERI-SENSE system. Once a disease is detected, the system provides relevant preventive and corrective measures, enabling farmers to take timely action. This integrated decision-support capability reduces disease spread, minimizes silkworm mortality, and improves overall silk yield.

4.7 Comparative Analysis

Compared to traditional image processing and machine learning–based approaches, the proposed SERI-SENSE system demonstrates superior accuracy and robustness. Unlike hardware-intensive IoT-based systems, SERI-SENSE relies primarily on image-based analysis, reducing deployment complexity and cost. The unified detection of both silkworm and mulberry plant diseases further distinguishes the proposed system from existing solutions.

4.8 Discussion

The results confirm that deep learning–based image classification is an effective approach for disease detection in sericulture. The system performs reliably under varying environmental conditions and provides actionable recommendations, making it suitable for real-world deployment. However, performance may be affected by poor image quality or extreme lighting variations, indicating scope for future enhancement.

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5. Conclusion

This paper presented **SERI-SENSE**, a machine learning–based disease identification and recommendation system aimed at improving disease management in sericulture. The proposed system integrates image processing techniques with a deep learning model based on the ResNet50 architecture to accurately detect diseases in silkworms and mulberry leaves. By employing a transfer learning approach, the system effectively learns disease-specific visual features even with limited training data. Experimental results demonstrate high classification accuracy and reliable performance across multiple disease categories, highlighting the robustness of the proposed approach when compared to traditional manual inspection methods.

In addition to accurate disease detection, SERI-SENSE provides actionable preventive and corrective recommendations, transforming it into a practical decision-support system for farmers. The system reduces dependency on expert intervention and hardware-intensive infrastructure, making it cost-effective and suitable for real-world deployment. Overall, SERI-SENSE contributes to early disease diagnosis, improved cocoon yield, and sustainable sericulture practices, supporting enhanced productivity and economic stability for sericulture practitioners.

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