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“Silk Shield: AI-powered Sericulture Disease Detection and Climate- based Cocoon Optimization”

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Abstract : This paper presents a deep learning-based solution developed to detect silkworm diseases and optimize rearing environments using image inputs. The system, called Silk Shield, utilizes a fine-tuned EfficientNetB3 model capable of classifying silkworm conditions including Pebrine, Grasserie, Muscardine, and Flacherie by analyzing physical traits from images. It also estimates optimal temperature and humidity for cocoon development using climate-aware intelligence. Unlike conventional systems requiring manual inspection or external sensors, Silk Shield uses vision-based learning, making it highly scalable and affordable. With high prediction accuracy across categories, it is integrated into a real-time interface that provides farmers with quick, actionable insights. This work highlights how AI can transform sericulture into a smarter, sensor-free process.

I. INTRODUCTION

Silkworm farming plays a vital role in supporting India’s rural economy, particularly among small-scale farmers involved in sericulture. The success of this industry depends heavily on the health and productivity of silkworms, which are highly susceptible to a variety of infectious diseases such as Pebrine, Grasserie, Muscardine, and Flacherie. These diseases, if not detected early, can rapidly spread through rearing units and lead to significant crop loss, affecting both cocoon yield and overall silk quality. Traditionally, farmers rely on manual visual inspection to identify infections, a method that is slow, error-prone, and dependent on expert knowledge— making it impractical for real-time decision-making.

With advancements in AI and computer vision, new possibilities have emerged to automate this critical task. The Silk Shield system leverages image-based disease detection using a deep learning model trained to identify infected silkworms from a single image. It uses a fine-tuned EfficientNetB3 network to capture disease-specific features without requiring lab tests or physical sensors. By analyzing texture, color, and lesion patterns on the silkworm’s body, it enables early, accurate, and fast diagnosis. The system is deployed through a real-time interface that helps farmers take timely action.

Silk Shield is designed to empower sericulturists by replacing guesswork with intelligent automation. It reflects the broader goal of integrating modern AI technology into traditional farming to make sericulture more precise, accessible, and scalable. Moreover, by removing the dependency on lab infrastructure and ensuring faster intervention, the system contributes to sustainable agriculture and improved rural livelihoods. The project emphasizes the need for affordable smart tools that can be scaled to benefit diverse farming communities across various sericultural zones in India.

II. PROBLEM STATEMENT AND OBJECTIVE

A. PROBLEAM STATEMENT

The Silk Shield system is developed using a modular deep learning framework tailored for silkworm disease detection and cocoon rearing optimization. The system begins with image capture through a smartphone or digital device, where farmers upload a clear photo of the silkworm.

The image is passed into a preprocessing module that handles resizing, noise reduction, and normalization to match model input requirements. This processed image is then analyzed by an EfficientNetB3-based convolutional neural network, which has been fine- tuned to identify infections such as Grasserie, Pebrine, Muscardine, and Flacherie. Once classified, the system cross-references the prediction with a treatment database and generates disease-specific remedies and care tips in real time. To support environmental monitoring, a lightweight engine evaluates ambient

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temperature and humidity to recommend optimal cocoon rearing conditions. Additionally, a built-in web scraping module fetches up-to-date cocoon market prices from official sericulture department PDFs.

All outputs are displayed via a responsive and intuitive Streamlit or Flask interface, designed to provide accessible, multilingual, and low-latency interaction for farmers across different skill levels and connectivity zones.

B. OBJECTIVE

The primary goal of the Silk Shield project is to develop an intelligent, automated system capable of identifying silkworm diseases and recommending climate-aware rearing practices using a single image input. Traditional disease identification methods in sericulture are labor-intensive, depend heavily on expert judgment, and require dedicated monitoring environments—factors that are often unavailable to rural farmers.

Silk Shield is designed to overcome these limitations by providing a deep learning-based, real-time solution that is efficient, accurate, and accessible. The core focus of the project is on capturing high-quality images of silkworms and detecting disease indicators such as color change, abnormal texture, and visible lesions. These features are processed through an EfficientNetB3 model trained to classify infections and output specific disease categories with confidence.

The system is also equipped to evaluate environmental conditions like temperature and humidity and deliver rearing suggestions accordingly. Its intuitive interface is designed for practical use in farming environments and enables farmers to make timely decisions, reduce losses, and improve cocoon yield through smart, data-driven sericulture.

III. SYSTEM DESIGN

The Silk Shield system has been structured around a flexible and intelligent design that enables it to detect diseases in silkworms and simultaneously offer climate-based rearing recommendations using a single image input. Central to the design is a deep learning framework that combines image classification with environmental data assessment in one cohesive pipeline. The system begins when a farmer captures an image of a silkworm using a mobile device. This image is then automatically processed and standardized through a preprocessing unit that adjusts brightness, resizes the image, and ensures consistent formatting for prediction.

A fine-tuned EfficientNetB3 convolutional neural network acts as the main processing engine. This model receives the preprocessed image and extracts key visual features such as body texture, color tone, and lesion patterns. These deep features are then passed to a classification head that determines the health condition of the silkworm—identifying whether it is affected by Pebrine, Grasserie, Muscardine, or Flacherie. Once the prediction is made, a recommendation module is triggered. This module provides real-time feedback to the user, including potential remedies, care instructions, and warnings based on the diagnosed condition.

The system does not stop at disease detection. It incorporates a lightweight environmental suggestion engine that evaluates conditions such as temperature and humidity—either from user input or sensors— and offers ideal rearing parameters to promote healthy cocoon development. In addition to disease and climate analysis, Silk Shield integrates a market intelligence layer. A PDF scraping module retrieves up-to-date cocoon prices from the Karnataka Sericulture Department's official reports and presents them to the farmer, helping them understand economic conditions in parallel.

All operations and results are displayed through an interactive interface developed using Streamlit or Flask. This interface is simple, responsive, and capable of running on low-end hardware. It allows users to upload images, view results, and receive tailored recommendations instantly. The design also includes multilingual support for better accessibility in rural areas. Overall, the system offers modularity, ease of use, and real-time feedback, making it suitable for deployment in real-world sericulture environments.

IV. METHODOLOGY

The approach for this project is based on an image-driven deep learning strategy aimed at detecting silkworm diseases and suggesting climate- based cocoon optimization through a single image input. First, a custom dataset was created by collecting real-world images of both healthy and diseased silkworms, capturing different stages and symptoms of infections like Pebrine, Grasserie, Muscardine, and Flacherie. Each image was carefully annotated and labeled based on visible traits such as body color, texture, growth deformities, and lesion patterns using expert-verified references.

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To enhance the robustness and generalization ability of the model, the dataset was augmented using rotation, horizontal flipping, brightness adjustments, and zoom transformations. This not only increased the number of samples but also helped the model handle diverse lighting and orientation conditions.

For model training, a transfer learning approach was adopted using EfficientNetB3 as the base feature extractor. The pre-trained network was fine-tuned on the silkworm dataset using a softmax classification head to distinguish between disease types. Images were resized and normalized during preprocessing to ensure input consistency. A custom labeling strategy was implemented to ensure uniform annotations across disease classes. In parallel, historical climate data—specifically temperature and humidity trends—were used to train a lightweight regression model that predicts ideal rearing conditions. Both components were optimized using categorical cross- entropy for classification and mean squared error for regression. The overall system was trained using stratified k-fold cross-validation, and its performance was evaluated using accuracy, recall, F -score, and inference time. The trained model was then deployed within a Streamlit-based user interface for real-time use.

The system can be represented using algorithms and algorithms are designed using flowcharts.

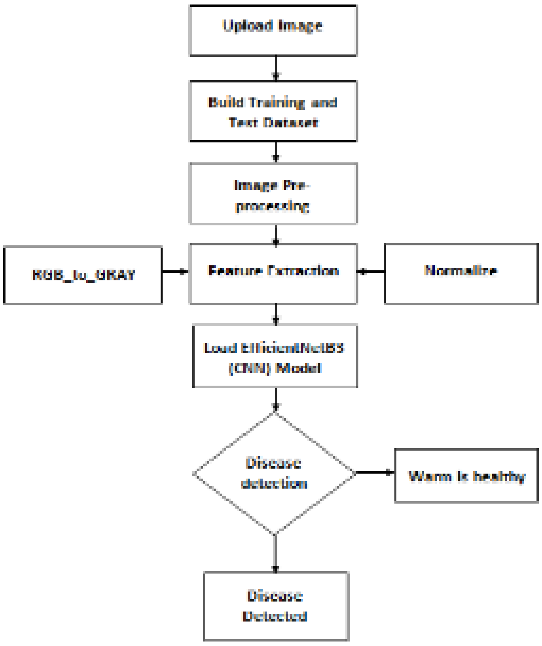

Fig: - Flow Chart.

Step 1: User uploads an image of a silkworm through the interface.
Step 2: Image is received by the Image Collection module.
Step 3: Preprocessing Module cleans, resizes, and normalizes the image.
Step 4: The processed image is passed to the EfficientNetB3-based prediction model.
Step 5: The model identifies the disease and analyzes climate conditions for cocoon optimization.
Step 6: Results including diagnosis, remedy, and environmental suggestions are passed to the output module.
Step 7: Final recommendations and predicted cocoon yield conditions are displayed to the user in real time.

V. IMPLEMENTATION

Integrating data preprocessing, model training, and deployment into a unified pipeline is central to implementing the Silk Shield system. Python was the primary development language, using libraries such as TensorFlow and Keras for deep learning, OpenCV and PIL for image handling, and NumPy and Pandas for data management. The model is built on the EfficientNetB3 architecture and trained to perform multi-class classification of silkworm diseases. The feature extractor captures hierarchical features, and the final prediction layer outputs probability scores for each disease category. A consolidated training script was developed to handle data loading, augmentation, model fitting, and evaluation in a synchronized process.

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After training and validation, the model was deployed through a Streamlit-based web application that enables users to upload silkworm images and receive predictions in real time. The interface is lightweight, intuitive, and accessible even for non-technical users, including farmers and agricultural field workers. Additional utility scripts were created for visualization of training metrics and system testing. The overall architecture is modular and allows for future updates or the addition of new diseases without rewriting the entire codebase.

VI. SYSTEM REQUIREMENTS

Installation of the Silk Shield system requires a computing environment capable of handling deep earning tasks, real-time prediction, and smooth user interface operations. For basic model inference and interface interaction, a system with an Intel i5 processor, 8 GB of RAM, and 0 GB of free disk space is sufficient. However, for training or fine-tuning the model on larger datasets or adding additional features, a system equipped with an Intel i7 or AMD Ryzen 7 processor, 6 GB of RAM, and an NVIDIA GPU with CUDA support (such as the GTX 660 or RTX 2060) is recommended. The use of SSD storage is advised to speed up data loading and model performance. On the software side, the system is developed using Python 3.8 or later and utilizes essential libraries including TensorFlow and Keras for deep learning, OpenCV and Pillow for image processing, and NumPy and Pandas for data handling. Streamlit or Flask is used to build the user interface and handle backend operations. Additional dependencies include PyMuPDF for PDF scraping, and Matplotlib for visualizing results. The application is cross-platform and runs smoothly on Windows, Linux (Ubuntu 20.04+), and Android (via browser-based access). A modern web browser is sufficient to use the interface with minimal setup.

VII. CONCLUSION

The silkworm disease detection and cocoon optimization system developed under the Silk Shield project demonstrates the effectiveness of applying deep learning technologies to real-world agricultural challenges. Using a single silkworm image, the system leverages a fine-tuned EfficientNetB3 model to accurately classify diseases such as Pebrine, Grasserie, Muscardine, and Flacherie, and also offers environment-specific rearing suggestions. This image-based approach eliminates the need for manual diagnosis or expensive sensor infrastructure, significantly reducing costs and making the system accessible to farmers with limited resources. The integration of vision-based prediction with environmental intelligence ensures both scalability and precision in rural deployment scenarios.

The deployment of the trained model through a lightweight and user-friendly web interface enhances usability for farmers, field experts, and support personnel. Through simple image uploads, users can receive instant, actionable feedback that improves decision-making in disease control and cocoon production. Overall, the Silk Shield system bridges the gap between cutting-edge AI tools and traditional sericulture, driving forward the vision of smart, data-driven agriculture in resource-constrained communities.

VIII. FUTURE ENHANCEMENTS

Though the present system gives precise and fast predictions only from image input, there are some upgrades that can extend its usability and functionality even more. One of the major upgrades would be fusing real-time sensor inputs like temperature, humidity, and moisture from IoT sensors to support image-based predictions.

This hybrid model would improve prediction accuracy, particularly in varying environmental situations. Also, increasing the dataset to cover additional seed types and larger Though the current Silk Shield system delivers fast and accurate predictions using only image input, several enhancements can further improve its utility, scalability, and adaptability. One of the most impactful upgrades would be the integration of real-time sensor inputs, such as temperature, humidity, and moisture data from IoT devices, to complement image-based predictions and enhance contextual accuracy. Incorporating sensor data would allow the model to make more informed decisions, particularly in dynamic or unpredictable environmental conditions. Additionally, expanding the dataset to include a wider range of silkworm species, diseases, and regional variations would improve the model's generalization and reliability across diverse climates and geographies.

From the usability perspective, developing a dedicated Android mobile application would make the system more accessible to farmers, allowing them to capture and upload images on the go. Adding voice-based interaction and support for regional languages like Kannada, Tamil, and Hindi would improve accessibility further. Offline prediction capabilities could benefit users in remote areas without reliable internet. Finally, embedding explainable AI features would build trust by showing the basis for each prediction, while integration with government platforms could support broader adoption and policy- level decision-making in the sericulture sector.

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