International Journal for Multidisciplinary Research

Two-Day National Conference on WOMEN LED DEVELOPMENT: Pathways to Inclusive, Sustainable & Equitable Growth

Organized by De Paul College, Mysore & Center for Women Studies and Research, Mandya University, Mandya on 14th & 15th March 2026

E-ISSN: 2582-2160 ● Website: www.ijfmr.com ● Impact Factor: 9.24

Silk Vision: An AI-Powered Web Platform for Automated Silkworm Disease Detection Using Deep Learning

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Abstract

Silkworm cultivation serves as a fundamental economic pillar in many rural regions, providing agricultural households with vital opportunities for income diversification. However, the high susceptibility of silkworms to various infectious diseases presents a constant threat of catastrophic population declines and significant economic distress. Early identification of these issues is currently hindered by a reliance on traditional visual inspections conducted by trained professionals—an approach that is often cost-prohibitive and inaccessible for small-scale farming operations. Such diagnostic delays lead to increased mortality rates and decreased production standards.This paper proposes an automated, AI-driven web-based platform designed to provide accessible pathological assessment through computational intelligence and pattern recognition. The system features a secure user interface where farmers can upload digital images of silkworm specimens to receive immediate analytical feedback. By employing a technical methodology cantered on advanced image processing, data augmentation, and Convolutional Neural Network (CNN) based classification, the platform automatically detects visual indicators of common ailments such as Pebrine, Grasserie, Flacherie, and Muscardine. Results demonstrate that these techniques enhance classification accuracy and system performance across diverse environments, effectively reducing dependence on manual expertise and supporting sustainable sericulture through smart agriculture.

1. Introduction

1.1 Background Overview

Silk production serves as a fundamental pillar supporting rural economic stability, creating vital income opportunities for numerous agricultural families. The prosperity of silk manufacturing depends critically on preserving robust silkworm colonies. Regrettably, these fragile organisms encounter persistent challenges from environmental pressures and infectious conditions such as Pebrine, Flacherie, Grasserie, and Muscardine. When these disorders emerge, they can rapidly destroy complete production cycles, causing significant economic distress for cultivators.

1.2 Current Diagnostic Methodologies

Existing diagnostic methodologies rely extensively on skilled professionals performing visual evaluations. This manual approach proves both costly and unfeasible for smaller farming operations. Furthermore, traditional identification methods depend on human knowledge and practical experience, which can be inconsistent and susceptible to errors. These conventional processes are often unavailable in remote agricultural regions, leading to critical delays in treatment.

1.3 Technological Opportunities

Contemporary advances in computational intelligence and automated learning systems have created unprecedented opportunities for photographic disease recognition platforms. Sophisticated systems can now analyze silkworm images and identify pathological indicators through pattern recognition of distinctive visual features. Such technological approaches minimize dependence on specialized expertise while facilitating faster, more reliable diagnostic results.

1.4 System Overview

The developed Silkworm Health Assessment System harnesses machine learning technologies to optimize identification procedures through automated image analysis. The application provides an accessible interface enabling farming professionals to establish accounts, log in securely, and upload silkworm photographs for evaluation. Using advanced algorithmic processing and neural network architectures, the system examines uploaded imagery to determine potential disease states.

1.5 Objective

The primary objective of this Silkworm Disease Detection system is to deliver an intelligent, automated, and dependable approach for early-stage disease identification. By utilizing advanced image processing and machine learning methodologies, the system aims to:

- Reduce dependence on manual examination and specialist consultation.
- Help prevent rapid disease transmission through immediate diagnostic feedback.
- Assist farmers in making well-informed, timely decisions regarding treatment protocols.
- Encourage the implementation of contemporary AI-driven technologies within the agricultural sector.

1.6 Goal

The central goal of this initiative involves creating and implementing an AI and Machine Learning-powered system capable of detecting and forecasting silkworm diseases through image evaluation. This empowers farmers and sericulture specialists to execute timely preventive and remedial measures, ultimately enhancing silk production and quality outcomes.

1.7 Challenge Definition

Silkworm cultivation faces significant vulnerability to diseases like Pebrine and Flacherie, which demonstrate rapid transmission capabilities. The absence of early detection mechanisms leads to treatment delays, elevated silkworm mortality rates, and considerable financial losses. Consequently, there exists a critical need for an automated, precise, and user-friendly system capable of recognizing ailments during initial stages to promote sustainable sericulture.

2. Literature Survey

The literature survey reviews existing research on silkworm disease detection using image processing, machine learning (ML), and deep learning techniques. This section highlights the methodologies, findings, and limitations of previous studies that form the foundation for the proposed AI-driven system.

2.1 Review of Existing Methodologies

Current research in sericulture has evolved from manual inspection to automated digital analysis. Key methodologies include:

- Image Processing: Focused on enhancement, segmentation, and manual feature extraction of visual symptoms like color and texture.
- Machine Learning: Utilizing traditional classifiers such as Support Vector Machines (SVM) and Random Forests to categorize disease states based on extracted physical characteristics.
- Deep Learning: Implementing Convolutional Neural Networks (CNN) to automatically learn pathological features directly from raw image data.

2.2 Comparative Analysis of Previous Research

2.2.1 Traditional Image Processing and Feature Extraction

Previous studies leveraged image enhancement and segmentation to identify visual symptoms like size changes and color variation in infected silkworms.

- Findings: Systems successfully detected common diseases like Pebrine and Grasserie with moderate accuracy.
- Limitations: Accuracy was restricted by the need for manual feature extraction and high sensitivity to varying lighting conditions.

2.2.2 Standard Machine Learning Classifiers (SVM, Random Forest)

Academic research groups have proposed models using shape and texture histograms fed into Decision Trees or Random Forest classifiers.

- Findings: These models offered varying degrees of improvement over traditional manual inspection.
- Limitations: Required extensive data preprocessing and performed poorly when tested with real-world, noisy agricultural images.

2.2.3 Deep Learning (CNN) Approaches for Feature Learning

Recent scholars introduced CNNs for automated recognition, eliminating the need for manual feature engineering.

- Findings: These models achieved higher accuracy and better generalization compared to traditional ML methods.
- Limitations: High computational resources and large labeled datasets are required for effective training.

2.2.4 Integrated Smart Agriculture Systems

Some research integrated disease detection into broader "Smart Agriculture" frameworks that include environmental monitoring.

- Findings: Demonstrated significant reductions in detection time and improvements in overall

productivity.
- Limitations: High implementation costs and system complexity made these solutions less suitable for small-scale farmers.

2.2.5 Web-Based Diagnostic Platforms

Engineering researchers developed web-based prediction systems allowing users to upload images for instantaneous diagnostic feedback via cloud infrastructure.

- Findings: Enhanced user accessibility across different farming environments with rapid performance.
- Constraints: These platforms are limited by internet connectivity requirements and a lack of multi-language support.

2.3 Advantages of the Proposed System

The proposed system addresses the shortcomings of existing methodologies by providing a cost-effective, automated, and high-accuracy solution.

- Early and Accurate Detection: Provides real-time prediction to prevent rapid disease transmission.
- Reduced Expert Dependency: Minimizes the need for manual inspection by scarce sericulture specialists.
- High Precision: Utilizes advanced CNN models that work effectively with real-world images and varying conditions.
- Economic Sustainability: Reduces financial losses by supporting early preventive measures and improving overall silk production standards.

3. Dataset Analysis

3.1 Image Collection

The project utilizes a comprehensive collection of classified silkworm photographs, which are essential for the performance and accuracy of the AI/ML framework. The dataset is organized into two primary categories: healthy specimens and affected categories. The affected classifications encompass prevalent disorders such as Pebrine, Grasserie, Flacherie, and Muscardine. These images were sourced from established academic research repositories and agricultural databases to document observable manifestations of silkworm health.

3.2 Data Processing

To optimize model effectiveness and enhance visual quality, all photographs undergo rigorous processing procedures. These steps include:

- Dimensional Standardization: Ensuring all images have uniform height and width.
- Pixel Value Normalization: Standardizing pixel intensity to facilitate efficient feature recognition.
- Artifact Elimination: Removing noise and excluding corrupted or redundant images to maintain high data integrity.

3.3 Enhancement Strategies

Data enhancement methodologies are applied to expand dataset variety and prevent model overfitting. These augmentation techniques improve the model's adaptability when processing real-world photographs captured under diverse environmental circumstances. Key techniques used include:

- Geometric Transformations: Image rotation, horizontal/vertical flipping, and scaling adjustments.
- Illumination Modifications: Adjusting lighting and brightness values to simulate different environmental conditions.

3.4 Dataset Challenges

Achieving high diagnostic precision is complex due to several inherent challenges in agricultural data collection. The most significant hurdles include:

- Visual Variabilities: Differences in photograph quality, background noise, and varying lighting conditions.
- Data Scarcity: Class imbalance and the limited availability of accurately labeled images for specific diseases.
- Classification Complexity: Strong visual similarities between certain diseases require the use of robust deep learning architectures for accurate differentiation.

4. Detailed Design & Methodology

The detailed design phase defines the internal framework of the Silkworm Disease Detection System, outlining how information flows between components and how each is implemented. This section provides clarity on the architectural, modular, and logical structures of the platform.

Fig 1: System Architecture Design

The platform is built on a robust three-tier architecture:

- Presentation Layer: A responsive web interface developed with HTML, CSS, Bootstrap, and JavaScript for user interactions like registration and result visualization.
- Application Layer: Implemented using ASP.NET (C#), this layer manages core business logic, user authentication, and coordinates communication with the AI model.
- Data Layer: Utilizing SQL Server, this layer securely stores user profiles, submitted images, and historical diagnostic results.

4.1 Module Design

The system is divided into functional modules to ensure modularity and ease of maintenance:

- User Management: Modules for account creation and secure credential authentication through session management.
- Image Handling: An upload module that validates file formats followed by a preprocessing module to resize, normalize, and de-noise images for analysis.
- Analysis Engine: A Convolutional Neural Network (CNN) module that automatically extracts features to classify the silkworm condition and generate a confidence score.
- Output Module: Displays the identified disease name and confidence level while archiving the history in the database.

4.2 Process Flow

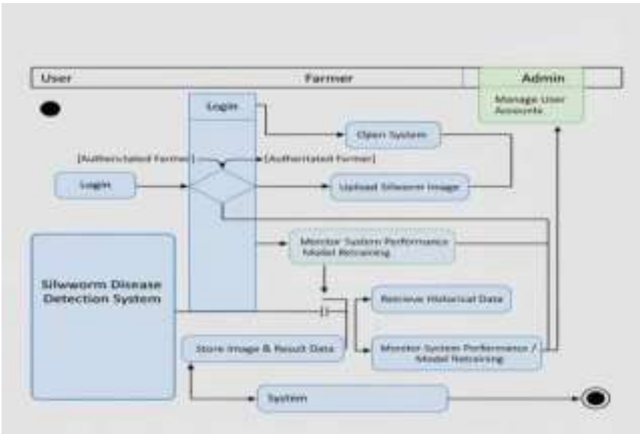

Fig 2– Data Flow Diagram of Silkworm Disease Detection System

Information moves through the system in a structured sequence:

1. Authentication: The user logs in to access the secure dashboard.
2. Submission: A digital photograph of a silkworm specimen is uploaded and temporarily held for processing.
3. Refinement: Images undergo size modification and standardization to ensure uniformity for the AI model.
4. Diagnostics: The AI model analyzes visual features to classify the sample as healthy or diseased.
5. Reporting: Final findings and reliability scores are saved to the database and displayed to the user.

4.3 Diagrammatic Representations

- 6.4.1 Context and Data Flow Diagrams (DFD): Illustrates how data moves from external users through operational processes into information repositories.
- 6.4.2 Process and Sequence Diagrams: Represents the step-by-step functional behavior and time-based interaction between system components from engagement to output.
- 6.4.3 Entity-Relationship (ER) Diagram: Defines the logical structure of the database, showing the relationships between Users, Images, ML Models, and Treatment Recommendations.

5. Platform Development & Implementation

The platform development phase involves transforming design specifications into a functional software solution by integrating web technologies with artificial intelligence. This phase focuses on constructing a seamless pipeline from user interaction to deep learning-based diagnostic output.

5.1 Development Environment

The backend infrastructure is built using the ASP.NET (C#) framework to manage application logic and server-side operations. SQL Server serves as the primary data management system, ensuring the protected storage and administration of user profiles, submitted photographs, and diagnostic history. The environment is configured to facilitate modularity, incorporating components for account management, image processing, and disease analysis.

5.2 Frontend Implementation

The user interface is engineered to be intuitive and accessible for agricultural practitioners with varying levels of technical expertise.

- Technologies: Developed using a combination of HTML, CSS, Bootstrap, and JavaScript.
- Functionality: Provides a user-friendly environment for account creation, secure authentication, and a dedicated portal for photograph submission.
- Visualization: Diagnostic results are presented in clear, comprehensible formats that include identified condition names and confidence levels.

5.3 AI/ML Integration

A core component of the platform is the integration of the trained Convolutional Neural Network (CNN) within the web framework.

- Architecture: CNN was selected due to its superior performance in visual recognition and pattern recognition tasks.
- Workflow: Once a user submits an image, it is automatically forwarded to the CNN framework, which leverages patterns acquired during training to generate predictions.
- Implementation: The model identifies prevalent silkworm conditions such as Pebrine, Grasserie, Flacherie, and Muscardine, providing immediate diagnostic measurement.

5.4 Security and Session Management

Robust security protocols are implemented to safeguard sensitive user data and maintain platform integrity.

- Authentication: User verification systems and secure login protocols ensure that only authorized individuals can access the diagnostic tools.
- Session Control: The platform incorporates advanced session management to maintain active authentication states during use and ensures secure termination of sessions upon logout.
- Data Integrity: Submission validation protocols are in place to verify appropriate image formats and dimensions, preventing system errors and ensuring stable performance.

6. Conclusion & Future Scope

6.1 Summary of Findings

The Silkworm Disease Detection System using AI & ML provides an efficient and automated solution for identifying diseases in silkworms. By combining image analysis, neural network methodologies, and web-based interfaces, the platform empowers agricultural practitioners to identify prevalent conditions such as Pebrine, Grasserie, Flacherie, and Muscardine through immediate diagnostic capabilities.

- The project successfully delivers an economical, accurate, and expandable solution for silkworm health monitoring.
- It illustrates the significant potential of AI and ML within agricultural implementations.
- The system establishes a foundation for subsequent improvements, including expanded condition databases and enhanced model precision.
- The automated nature of the tool reduces the historical dependency on scarce manual expertise and costly laboratory analysis.

6.2 Advancement Opportunities

While the platform establishes robust foundations for automated condition identification, several areas exist for further development to enhance functionality and accessibility.

- **Continuous Monitoring**: The platform may be extended to provide real-time notification systems to alert users of potential outbreaks and preventive strategies.
- **Analytical Dashboards**: Incorporating visual dashboards for condition trends and historical predictions can assist farmers in making data-driven decisions.
- **Localization**: Implementing multi-language functionality and voice-assisted capabilities can enhance accessibility for broader user demographics.
- **Mobile Integration**: Developing mobile-native applications would allow for easier accessibility and immediate identification directly in the field.
- **Intelligent Infrastructure**: These advancements would allow the platform to evolve into a comprehensive, scalable infrastructure for sustainable silkworm health management.

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