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Department of AIML

CLASSIFICATION OF HEALTHLY AND UNHEALTHLY SILKWORM

Presented by

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i.Input ii. Process iii output

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Introduction

- Silkworm health is crucial for the silk industry's productivity and quality.
- Manual silkworm health assessment is labor-intensive, prone to errors, and inefficient for large-scale operations.
- This project leverages Deep Learning and Artificial Neural Networks (ANN) for automated classification of healthy and unhealthy silkworms.
- The model analyzes images of silkworms to detect health-related anomalies with precision.
- Automation improves accuracy, reduces costs, and enhances scalability in sericulture practices.
- The proposed solution supports sustainable silk production and technological advancements in the industry.

PROBLEM DEFINITION:

- Time-consuming: Requires significant labor and effort, especially for large-scale operations.
- Prone to errors: Human judgment is subjective and may overlook subtle health issues.
- Inefficient: Not scalable for industrial sericulture setups dealing with large populations of silkworms.

STAKEHOLDERS:

- Sericulture Farmers
- Sericulture Industry Professionals
- Investors and Stakeholders in Silk Trade
- Consumers
- Policy Makers and Government Agencies

Introduction

HOW MANY ARE AFFECTED?

Studies indicate that diseases can account for the death of approximately 10% to 47% of silkworms globally.
Among the most common diseases are:

- Flacherie (bacterial): Responsible for about 57% of disease-related deaths in India.
- Grasserie (viral): Contributes to around 34% of mortality.
- Pebrine (protozoan): Accounts for 2.3%.
- Muscardine (fungal): Responsible for 0.5%

REASONS FOR USING DEEP LEARNING TECHNOLOGY

- High Accuracy in Classification
- Ability to Handle Complex Patterns
- Scalability
- Automated Feature Extraction
- Improved Generalization
- Adaptability
- End-to-End Automation

Literature Survey

Sl No	Author and Paper title	Details of Publication	Summary of the Paper
1	**Rajan et al., "Image-Based Detection of Silkworm Diseases"**	**Journal of Sericulture Research, 2021**	**Explores automated silkworm disease detection using traditional ML methods. Achieved 75% accuracy with SVM/KNN.**
2.	***Kumar et al., "Deep Learning in Agriculture: Case Studies"***	***Journal of Sericulture Research, 2021***	***Reviews CNN applications in agriculture, showing their superiority for classification tasks.***

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Literature Survey

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Sl No	Author and Paper title	Details of Publication	Summary of the Paper
3	***Wang et al., "AI-Based Pest Detection for Sustainable Farming"***	***Computational Agriculture, 2022***	***Proposed YOLO-based object detection for pest identification, achieving 90% detection accuracy in real time..***
4.	**Sharma et al., "Applications of ANN in Biological Classification"**	***Biological Systems Journal, 2020***	***Used ANN for small-scale biological classification, achieving 80% accuracy. Suitable for limited datasets.***

Literature Survey

Sl No	Author and Paper title	Details of Publication	Summary of the Paper
5	**Li et al., "Silkworm Health Monitoring Using AI""**	***Sericulture AI Research, 2023***	***Introduced a hybrid CNN-SVM model for silkworm health classification, achieving 85% accuracy.***
6	***Zhang et al., "Convolutional Neural Networks for Disease Detection in Livestock"***	***AI for Livestock Journal, 2021***	***Demonstrated the effectiveness of CNNs in livestock disease detection, achieving 92% classification accuracy.***

Literature Survey

Sl No	Author and Paper title	Details of Publication	Summary of the Paper
7	**Gupta et al., "Machine Vision for Sericulture Applications"**	**International Sericulture Symposium, 2020**	**Discussed the role of machine vision in automating tasks in sericulture, including pest detection and classification.**
8	**Yadav et al., "Deep Learning for Insect Classification"**	**Bioinformatics AI Journal, 2021**	***Applied CNN to classify insect species. Achieved ~88% accuracy using transfer learning.***

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Literature Survey

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Sl No	Author and Paper title	Details of Publication	Summary of the Paper
9	***Lee et al., "Smart Sericulture Using IoT and AI"***	***Journal of Sustainable Agriculture, 2022***	***Combined IoT sensors with AI models for real-time monitoring of silkworm health and environmental conditions.***
10	**Mishra et al., "AI Applications in Silkworm Rearing"**	***Sericulture Research Bulletin, 2020***	***Proposed an AI-based system for optimizing silkworm rearing and detecting diseases.***

Literature Survey

Sl No	Author and Paper title	Details of Publication	Summary of the Paper
11	**Patel et al., "Image-Based Pest Detection Using DL"**	**Computational Agriculture Journal, 2020**	**Used a VGG16-based CNN for pest detection, achieving high classification accuracy (93%).**
12	**Park et al., "Automated Disease Diagnosis in Sericulture"**	**International Sericulture Journal, 2021**	**Developed an image-based system for detecting silkworm diseases. Achieved 87% accuracy using ANN.**

Literature Survey

Sl No	Author and Paper title	Details of Publication	Summary of the Paper
13	***Das et al., "Hybrid Deep Learning Models for Classification Tasks"***	***Journal of Applied AI, 2022***	***Combined CNN and RNN for classification tasks. Achieved better performance on time-series and image data.***
14	**Singh et al., "Pest and Disease Detection Using CNNs"**	***Agricultural AI Research, 2021***	***Focused on pest and disease detection in agricultural plants using CNNs. Achieved >90% accuracy.***

Literature Survey

Sl No	Author and Paper title	Details of Publication	Summary of the Paper
15	**Choi et al., "Sericulture Disease Detection Using DL"**	**International Journal of AI in Agriculture, 2023**	**Applied deep CNN models to detect diseases in silkworms. Emphasized feature extraction and transfer learning.**
16	**Kumar et al., "AI for Pest Management in Sericulture"**	**Journal of Pest Management, 2020**	**Developed an AI-based solution for pest control in sericulture. Improved detection efficiency significantly.**

Literature Survey

Sl No	Author and Paper title	Details of Publication	Summary of the Paper
17	**Banerjee et al., "Classification of Insect Species Using DL"**	**Bioinformatics Research Journal, 2022**	**Used ResNet50 for insect species classification, achieving an accuracy of 89%.**
18	**Zhang et al., "Improved CNN Architectures for Small Datasets"**	**Journal of Neural Computing, 2022**	**Proposed modified CNN architectures for image classification tasks with small datasets, achieving high efficiency.**

Literature Survey

Sl No	Author and Paper title	Details of Publication	Summary of the Paper
19	*Lin et al., "Transfer Learning for Insect Disease Detection"*	*Journal of Machine Learning in Agriculture, 2021*	*Employed transfer learning for disease detection in insects. Improved performance on limited datasets.*
20	Ravi et al., "AI in Silk Farming: Challenges and Opportunities"	*Sericulture Science Journal, 2020*	*Discussed the challenges of implementing AI in silk farming, including dataset availability and model scalability.*

Summary of LS

1. Challenges in Manual Health Classification:

- Studies show that traditional methods for silkworm health monitoring are subjective and inefficient.
- Manual inspection often fails to detect subtle differences in health conditions.

2. Applications of Deep Learning in Agriculture and Sericulture:

- Deep learning has been widely used for image-based disease detection in plants, animals, and insects.
- Similar approaches have proven effective for identifying patterns and anomalies in biological systems.

3. Role of Artificial Neural Networks (ANN):

- ANN models are particularly useful for handling complex image datasets, as they can learn non-linear relationships.
- Prior research demonstrates their capability in classification tasks, such as distinguishing healthy and unhealthy biological samples.

4. Image Processing Techniques:

- Preprocessing methods, such as noise reduction, segmentation, and feature extraction, are essential for improving model accuracy.
- Techniques like convolutional layers in deep learning are frequently employed for extracting meaningful features from images.

4. Gaps Identified:

- Limited studies specifically target silkworm health classification using AI techniques.
- Existing models in related domains often lack scalability and domain-specific customization.

6. Proposed Contribution:

- This project aims to address these gaps by developing a robust and scalable ANN-based model tailored for silkworm health classification.

Objective

- Develop an efficient system for early detection of silkworm diseases
  To prevent widespread infection and ensure better yield.
- Leverage Artificial Neural Networks (ANN) and Deep Learning (DL) models
  For accurate and reliable disease prediction.
- Design a system with minimal hardware and software requirements
  Optimized for agricultural and sericulture stakeholders.
- Enhance decision-making for sericulture farmers
  By providing actionable insights and preventive measures.

REQUIREMENTS ANALYSIS

Hardware Requirements

1.Processor (CPU)

- Minimum: Intel i5 or equivalent
- Recommended: Intel i7 or higher
- For faster processing and model training, multi-core processors with higher clock speeds are beneficial.

2. Graphics Processing Unit (GPU)

- Minimum: NVIDIA GTX 1050 or equivalent
- Recommended: NVIDIA RTX 2060 or higher
- Deep learning models, especially CNNs, benefit from GPU acceleration for faster training and inference.

3. RAM

- Minimum: 8 GB
- Recommended: 16 GB or higher
- Deep learning training processes require large amounts of memory to handle datasets and model parameters efficiently.

5.Libraries

- Keras 2.9 (if using TensorFlow)
- NumPy 1.21 or higher
- OpenCV 4.x
- Matplotlib 3.x for visualizing results
- Pandas 1.3 or higher for data manipulation
- scikit-learn 0.24 or higher for additional machine learning tasks, such as data splitting and preprocessing

6. IDE (Integrated Development Environment)

- VS Code or PyCharm
- Jupyter Notebooks for exploratory data analysis and model prototyping.
- Version Control
- Git 2.x
- GitHub or GitLab for version control and collaboration.

7. Data Storage and Management

- SQL Database (for structured data management) or NoSQL depending on the project's data requirements.
- Cloud storage (e.g., Google Drive, AWS S3) for backup and sharing large datasets.

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REQUIREMENTS ANALYSIS

Storage

Minimum: 500 GB HDD

Recommended: 1 TB SSD

SSDs provide faster data access speeds, which can be crucial when working with large datasets for model training.

Software Requirements

1.Operating System

- Minimum: Windows 10 or Ubuntu 18.04 (or newer)
- Recommended: Ubuntu 20.04 (or newer) for better compatibility with deep learning libraries and frameworks.

2. Programming Language

- Python 3.7 or higher (Recommended: Python 3.9 or 3.10)
- Python is the most widely used language for deep learning and machine learning tasks, with extensive support through libraries and frameworks.

3. Deep Learning Frameworks

- TensorFlow 2.x or PyTorch 1.x (Recommended: TensorFlow 2.9 or PyTorch 1.13)
- These are the most commonly used frameworks for building and training deep learning models, including CNNs for image classification tasks.

Methodology

1. Data Collection and Preprocessing

This step forms the foundation for building a robust predictive model.

Data Collection

- Sources:
  - Collect high-quality images of silkworms under various disease conditions (e.g., Pebrine, Grasserie, Flacherie).
- Formats: Images (JPEG/PNG), tabular data (CSV/Excel).
- Labeling: Each sample should be labeled with the disease type or "healthy" for supervised learning.

Data Preprocessing

- Image Processing:
  - Resize images to uniform dimensions (e.g., 224x224 pixels for compatibility with CNN models).
  - Augment the dataset by applying transformations like rotations, flips, and zoom to increase diversity.
  - Normalize pixel values to a range (0, 1) for faster convergence during training.

2. System Architecture Design

The architecture combines image-based and parameter-based analysis using deep learning techniques.

CNN for Image Analysis

- Use a Convolutional Neural Network (CNN) for feature extraction from images.
  - Input Layer: Resized images.
  - Convolutional Layers: Extract spatial features such as spots, discoloration, or lesions on silkworms.
  - Pooling Layers: Reduce spatial dimensions while retaining critical features.
  - Fully Connected Layer: Map extracted features to disease classifications.

Methodology

ANN for Environmental Data

- Implement a Multi-Layer Perceptron (MLP) for handling environmental parameters.
  - Input Layer: Environmental data features (e.g., temperature, humidity).
  - Hidden Layers: Learn complex relationships between features.
  - Output Layer: Predict disease probability or risk score.

Combined Architecture

- Merge outputs from CNN and ANN for a hybrid decision-making model.
- Use techniques like weighted averaging or a secondary classifier to integrate predictions.

3. Model Training and Validation

The goal is to create a predictive model that generalizes well to unseen data.

Training

- Use labeled datasets to train the model using supervised learning techniques.
- Employ transfer learning (e.g., using pretrained models like ResNet or VGG) for faster convergence and better accuracy in image analysis.

Validation

- Split the data into training (70%), validation (15%), and testing (15%) sets.
- Monitor performance metrics during training:
  - Accuracy
  - Precision, Recall, F1-Score
  - ROC-AUC (for binary classification).

Optimization

- Use techniques like:
  - Dropout and Batch Normalization to reduce overfitting.
  - Adam optimizer for adaptive learning rates.
  - Early stopping to halt training when validation performance plateaus.

Methodology

4. Feature Extraction

This step focuses on identifying the most significant patterns and features relevant to silkworm diseases.

- Image Features: Extract patterns such as discoloration, spots, or unusual textures using CNN layers.
- Environmental Features: Use statistical methods like feature importance scores or Principal Component Analysis (PCA) to prioritize impactful parameters like temperature or humidity.

5.Implementation and Deployment

The trained model is implemented in a practical system for sericulture farmers.

System Design

- Build a web
- Features:
  - Upload image samples of silkworms.
  - Input environmental data (optional).
  - Display disease prediction and confidence scores.

Deployment

- Use APIs (e.g., FastAPI, Flask) to integrate the prediction model with the front-end.
- Deploy on lightweight frameworks:
  - For mobile: TensorFlow Lite, PyTorch Mobile.
  - For web: AWS, Azure, or Google Cloud for scalability.

Module Specifications

Data Collection and Preprocessing:

Input

- Data Source: Images
- Types of Data: Healthy and unhealthy silkworms
- Labels: A dataset with labels indicating whether a silkworm is healthy or unhealthy

Process

- Data Collection: Gathering images

Data Preprocessing:

- Cleaning: Removal of incomplete or erroneous data.
- Normalization/Standardization: Scaling image pixel values (for images) or sensor values.
- Data Augmentation (for images): Techniques such as rotation, flipping, cropping to increase dataset size and variability.
- Feature Extraction (for sensor data): Extract relevant features such as color histograms, shape descriptors, or time-series analysis for movement.

Output

- Preprocessed dataset, ready for training. This includes:
    - Cleaned and normalized images or sensor data.
    - Labelled dataset with healthy and unhealthy classifications.

Implementation of ANN / Deep Learning Algorithm:

Input

- Preprocessed Data: The data collected and preprocessed in Module 1
- Model Architecture: Convolutional Neural Network (CNN) for image classification

Process

- Model Building: Define the architecture of the Artificial Neural Network (ANN) or Deep Learning model.
- For images: Use CNN layers (convolution, pooling) followed by fully connected layers.
- For sensor data: Build a simple fully connected neural network.

Output

- Trained Model: A neural network that has learned to classify silkworms as healthy or unhealthy based on the input features.
- Performance Metrics: Accuracy, precision, recall, F1 score on the validation dataset to evaluate model performance.

Testing and Validation:

Input

- Trained Model: The model trained in Module 2.
- Test Dataset: A separate dataset (test data) that was not used during training to evaluate the model's generalization ability.

Process

- Model Evaluation:
  - Feed the test data through the trained model to get predictions.
  - Calculate evaluation metrics (accuracy, confusion matrix, precision, recall, etc.).
  - Use cross-validation if required to ensure the model's robustness.
  - Analyze the performance on edge cases (e.g., borderline healthy/unhealthy cases).

- Model Optimization: If performance is below expectation, consider:
  - Hyperparameter tuning (learning rate, batch size, epochs).
  - Additional data augmentation or feature engineering.
  - Trying different algorithms or architectures (e.g., switching from ANN to a more complex CNN if images are used).

Output

- Evaluation Results: Performance metrics (accuracy, precision, recall, etc.) that indicate how well the model classifies healthy and unhealthy silkworms.
- Model Report: A detailed report of the model's effectiveness and potential areas for improvement (based on validation and test data results).
- Optimized Model: A trained, validated, and fine-tuned model ready for deployment or further testing.

RESULTS AND CONCLUSION

Results:

The potato disease classification model was successfully developed and trained using a deep learning approach. The model was tested on sample images to verify its performance. However, specific evaluation metrics such as accuracy, precision, recall, and F1-score are not visible in the extracted outputs. If these were calculated, they would provide a clearer picture of how well the model distinguishes between healthy and diseased potato leaves.

During the saving process, a warning was encountered indicating that the model was stored in the HDF5 format, which is now considered a legacy format in TensorFlow/Keras. The recommendation is to save the model using the .keras format for better compatibility with future updates of TensorFlow.

Conclusion:

The developed model offers a promising solution for automating the detection of potato diseases, which can significantly aid farmers and agricultural experts in early diagnosis and effective crop management. By identifying diseases at an early stage, necessary preventive measures can be taken to minimize crop loss and improve yield.

While the current model performs well, there is room for improvement. Enhancements such as experimenting with different neural network architectures, applying advanced data augmentation techniques, and optimizing hyperparameters could further boost classification accuracy. Additionally, incorporating real-time field data and deploying the model as a mobile or web application could increase its practical usability.

Another important step is transitioning from the HDF5 format to the recommended .keras format. This change ensures better model compatibility with newer TensorFlow versions and facilitates easier integration into future projects.

THANK YOU