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Artificial Intelligence Driven Silkworm and Mulberry Plant Disease Detection with Smart Prevention Recommendations

Dr. Santosh K C[1], Manoj P J[2], Dishan J Alur[3], Nithish S M[4], Hitesh G P[5]

[1]Associate Professor, CSE dept. Bapuji Institute of Engineering and Technology, Davangere-04 [2-5] U G Students, CSE dept. Bapuji Institute of Engineering and Technology, Davangere-04

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ABSTRACT — Initiating a paradigm shift in sericulture practices, our ground breaking initiative takes a holistic approach to disease management in silkworms and mulberry plants, with a clear emphasis on preventive measures. Drawing inspiration from plant leaf detection methodologies, our system seamlessly integrates state-of- the-art image processing and machine learning techniques, employing deep convolutional networks (CNNs) for precise disease recognition. Through this, we establish an extensive disease database covering diverse ailments in silkworms and mulberry plants, aligned with expert assessments. Emulating the simplicity of plant leaf detection, our system, utilizing CNNs and image processing, effectively discerns between diseased and healthy leaves or environmental elements, showcasing innovative solutions. Beyond identification, our solution provides immediate resources, offering literature on the identified disease and preventive measures, while also enabling direct communication with relevant experts. This holistic approach not only strengthens disease management but optimizes cocoon production and ensures sustainable growth in sericulture. By translating advancements from plant leaf detection to sericulture, our article contributes not only to disease identification but also provides crucial resources and expert contacts, offering unparalleled support for sericulture practitioners aiming for sustainable and efficient silk production.

Keywords— Sericulture, Disease Management, Preventive Measures, Image Processing, Machine Learning, Deep Convolutional Networks (CNNs).

I. INTRODUCTION

The sericulture industry, crucial to the global silk trade, grapples with challenges in controlling diseases affecting silkworms and mulberry plants. To address these issues comprehensively, our paper integrates advanced image processing and machine learning. The sericulture industry, a cornerstone of the global silk trade, faces significant challenges in the effective control of diseases affecting silkworms and mulberry plants.

In this paper, we propose a comprehensive solution that integrates advanced image processing and machine learning techniques to enhance disease detection and prevention strategies. Our approach leverages the power of convolutional neural networks (CNNs) for accurate feature extraction from images, coupled with sophisticated image processing algorithms. The fusion of these technologies aims to provide a robust and automated system for early disease identification and smart prevention measures.

Our primary goal is to utilize image processing to identify and diagnose silkworm diseases, offering insights into their origins and effective preventive measures. This initiative is aimed at enhancing silkworm health, ensuring not only robust silk production but also elevated product quality.

Expanding our focus to mulberry plant health, we apply the same image processing techniques to detect diseases, identify their causes, and suggest prevention strategies. This holistic approach strengthens the entire sericulture ecosystem, safeguarding the well-being of both silkworms and their primary food source.

Silkworms are susceptible to various diseases, including Flacheria, Grasseria, Muscardine, and Pebrine [1]. Flacheria exhibits symptoms such as sluggish movement, loss of appetite, abdominal shrinkage, thorax swelling, fluid vomiting, reduced clasping power, body softening, and thorax blackening. Grasseria symptoms include sluggish movement, restlessness, shiny skin, hanging upside down, intersegmental swelling, loss of clasping power, rectal protrusion, and anal region soiling. Muscardine is characterized by swelling, and upon death, the bodies harden, becoming stiff, chalky, and mummified within 24 hours.

Pebrine manifests symptoms like slow growth, undersized bodies, reduced appetite, pale, flaccid bodies with tiny black spots on the integument, and infected larvae remain rubbery without putrefaction after death.

Mulberry plants are also susceptible to diseases, including Powdery Mildew, indicated by the appearance of white powdery patches on the lower surface of the leaves. Leaf Rust Disease presents circular pinhead- sized light brown spots that become darkish brown as the disease advances [2]. Additionally, Rolled or Folded Leaves are symptoms of another condition where leaf rollers typically roll or fold leaves around themselves for shelter while they feed. Our article's holistic approach addresses these diseases through advanced image processing and machine learning, aiming to fortify disease management, optimize cocoon production, and ensure sustainable growth in the sericulture industry[3].

Beyond disease identification, our solution offers resources upon detection, providing literature on the identified disease and preventive measures. It facilitates direct contact with relevant experts, supplying specific details to assist sericulture practitioners in implementing preventive measures effectively.

Silkworms (Bombyx mori) and mulberry plants are integral components of the sericulture industry, contributing significantly to the global silk trade [4]. The industry, however, faces several challenges related to diseases that affect both silkworms and mulberry plants. Understanding these diseases and implementing effective control measures is crucial for sustaining silk production. Here is more information on silkworm and mulberry plant diseases:

Silkworm Diseases:

i. Pebrine Disease:

Caused by: Microsporidia Nosema bombycis.
Symptoms: Reduced silk production, slow growth, and discoloration.
Transmission: Vertical transmission (from infected silkworm to its offspring) and horizontal transmission (through contaminated food).

ii. Flacherie:

Caused by: Bacterial infection (Bacillus bombysepticus).
Symptoms: Softening and liquefaction of silkworm tissues, leading to larval death.
Transmission: Contaminated rearing conditions and poor hygiene.

iii. Nuclear Polyhedrosis Virus (NPV): Caused by: Baculovirus.

Symptoms: Darkening of body color, sluggish behavior, and eventual death.
Transmission: Viral particles spread through feces and other contaminated materials.

Mulberry Plant Diseases:

i. Leaf Spot Disease:

Caused by: Fungi (e.g., Cercospora spp., Myrothecium spp.).
Symptoms: Circular spots on leaves, leading to defoliation.
Transmission: Airborne spores and contaminated plant material.

ii. Powdery Mildew:

Caused by: Fungi (e.g., Phyllactinia spp.).
Symptoms: White powdery growth on leaves, affecting photosynthesis.
Transmission: Airborne spores.

iii. Root Rot:

Caused by: Soil-borne pathogens (e.g., Fusarium spp.).
Symptoms: Wilting, yellowing, and eventual death of plants.
Transmission: Contaminated soil and water.

Detecting plant diseases, such as those affecting mulberry plants, and providing smart prevention recommendations involve the integration of technology, data analysis, and agricultural expertise. The paper gives a detailed overview of the components involved in mulberry plant disease detection and prevention.

II. LITERATURE REVIEW

This literature review provides a comprehensive overview of the recent advancements in deep learning technology and image processing. The integration of these methods and components from the following literature review has the potential to transform traditional way of silkworm and mulberry plant disease detection to a new improved smart way of detection and recommendations.

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S. No.	Author	Title and Year	Findings
01	Manjunath B, B Lakshith Reddy.	Smart Sericulture System using Image Processing 2022	Seasonal environmental variations affect silkworm health, causing genetic alterations and reducing silk quality and quantity. Arduino-controlled system monitors environment, detects diseased silkworms through image processing, and administers automated treatment for enhanced health.
02	Sunil H, Ayesha Siddiqa, R Pramodhini	Plant leaf disease detection using computer vision and machine learning algorithms 2022	Machine learning and image processing detect early symptoms of tomato leaf diseases, aiding farmers in timely intervention. With accuracy in SVM (88%), K-NN (97%), and CNN (99.6%).
03	Santosh M N, Sharanagouda Biradar, Srinidhi D D.	Detection of Disease in Bomby Mori Silkworm by Using Image Analysis Approach 2019	Employing image classification and deep learning, a model distinguishes healthy and diseased silkworms, aiding early intervention.

03	Santosh M N, Sharanagouda Biradar, Srinidhi D D.	Detection of Disease in Bomby Mori Silkworm by Using Image Analysis Approach 2019	Employing image classification and deep learning, a model distinguishes healthy and diseased silkworms, aiding early intervention.
04	Shrutika Sarda, Sonali Sormare, Usha Rahinj.	A Novel Approach for Plant Disease Detection 2018	A software solution uses image analysis and cloud processing to detect and classify plant diseases, aiding early intervention in agriculture.
05	Mr. V Suresh, D Gopinath, M Hemavarthini,	Plant Disease Detection using Image Processing 2020	Automated plant disease identification with image processing streamlines monitoring, reducing manual efforts and time.
06	Puneet Chopade, C.G. Raghavendra , Mohan K S	Assessment of Diseases in Bombyx Mori Silkworm – A Survey 2021	The survey covers varieties, disease dynamics, influencing factors, treatments, and image processing applications.
07	Vitthalrao B. Khyade and Brij Kishor Tyagi	Detection of Grasserie Virus, BmNPVin the Fifth Instar Larvae of Silkworm, Bombyx mori Through Polymerase Chain Reaction 2017	Using PCR with specific primers, this study detects BmNPV in Bombyx mori larval midgut tissue, addressing its vulnerability to viral diseases.
08	Shyam Kumar V, Xing M Lu, Neetha, Mallikarjun,	Rapid detection of infectious flacherie virus of the silkworm, Bombyx mori, using RT-PCR and nested PCR 2013	PCR confirms BmIFV in Karnataka silkworms, simplifying detection. Nested PCR affirms BmIFV in Karnataka's silkworms. Infected midgut tissues simplify detection, aiding early identification

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III. METHODOLOGY

In the realm of leaf disease detection utilizing Convolutional Neural Networks (CNNs), the existing body of work follows a structured approach involving several key steps:

Image Acquisition:

The initial step involves loading the image in digital picture processing. This encompasses capturing the image through a digital camera and storing it in digital media, laying the foundation for subsequent MATLAB operations.

Image Preprocessing:

Image preprocessing plays a crucial role, aiming to enhance image information by eliminating unwanted distortions or reinforcing specific features. This phase employs various techniques, including dynamic image resizing, noise filtering, image conversion, and morphological operations.

Image Segmentation:

The process of image segmentation is adopted, utilizing the K-means cluster technique. This technique partitions pictures into clusters, ensuring that at least one part of the cluster contains images with a significant portion of unhealthy areas. The K-means cluster algorithm is employed to categorize objects into a specific number of clusters based on sets of features.

Feature Extraction:

Following the formation of clusters, texture features are extracted using the Gray-Level Co-occurrence Matrix (GLCM). This technique enables the extraction of meaningful texture information for further analysis and classification.

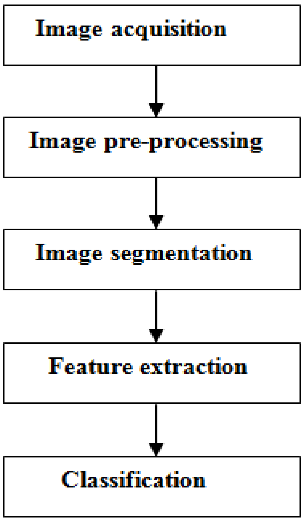

Fig. 1: General Block Diagram of Feature Based Approach

Classification:

The final stage involves classification for testing leaf diseases. In this context, the Random Forest classifier is employed to categorize and differentiate between healthy and diseased leaves. This classification step aids in the identification and labelling of specific diseases within the dataset.

This structured methodology underscores the importance of image preprocessing, segmentation, feature extraction, and classification in the successful detection and categorization of leaf diseases using CNNs. The utilization of advanced techniques such as K-means clustering and GLCM highlights the sophistication of the approach, contributing to accurate and reliable disease identification.

IV. IMPLEMENTATION

Silkworm and Mulberry plant leaves which are categorized total 10 types of labels. Silkworm label namely: Grasserie, Flacherie, Pebrine, Muscardine and healthy silkworm. Mulberry plant leaves label namely: Mulberry leaf roller, Powdery mildew, Leaf rust and Healthy leaf [6].

The dataset consists of 340 images of Silkworm and mulberry out of 340 images 300 images are used. all Images are resized into 256 x 256, that images divided into two parts training and testing dataset, the whole range of the train test split using 80-20 (80% of the whole dataset used for the training and 20% for the testing). Then train CNN model.

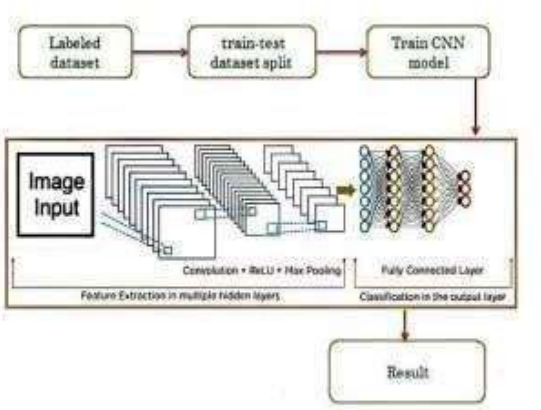

Fig 2: Proposed workflow

Convolutional neural can be used for the computational model creation that works on the unstructured image inputs and converts to output labels of corresponding classification. They belong to the category of multi-layer neural networks which can be trained to learn the required features for classification purposes [5].

The convolutional layer is a fundamental building block in Convolutional Neural Networks (CNNs), and its purpose is to apply convolution operations for feature extraction from input data, such as images.

Convolution Operation:

Kernel (Filter): A small matrix (typically 3x3 or 5x5) that slides or convolves over the input data.

Feature Map (Convolved Feature): The output obtained by applying the convolution operation to the input using the kernel. It highlights patterns or features present in the input

Convolution Process:

The kernel is systematically moved across the input, and at each position, it performs element-wise multiplication with the overlapping region of the input.

The results of these multiplications are summed up to produce a single value, which becomes the corresponding element in the feature map.

Local Receptive Fields:

Convolutional layers work with local receptive fields, focusing on small, overlapping regions of the input. This helps capture local patterns and spatial hierarchies.

Stride and Padding:

Stride: The step size at which the kernel moves across the input. A larger stride reduces the spatial dimensions of the feature map.

Padding: Zero-padding can be added to the input to maintain spatial dimensions and avoid edge information loss during convolution.

Multiple Channels:

For color images, which typically have three channels (RGB), each channel is convolved independently with its set of filters. The results are then combined to form the final feature map.

Activation Function:

After convolution, an activation function (commonly ReLU - Rectified Linear Unit) is applied element-wise to introduce non-linearity to the model.

Multiple Convolutional Layers:

CNNs often consist of multiple convolutional layers stacked together. Each layer can learn increasingly complex and abstract features from the input data.

Pooling Layers:

After convolution, pooling layers (e.g., max pooling or average pooling) are often used to downsample the spatial dimensions of the feature map. Pooling helps reduce computation and makes the network more robust to variations in input.

Parameters and Training:

The convolutional layer has parameters (weights and biases) that are learned during the training process. These parameters are adjusted through backpropagation and optimization algorithms to minimize the difference between the predicted output and the true labels [8].

Less pre-processing is required in comparison to traditional approaches and automatic feature extraction is performed for better performance. For the purpose of leaf disease and silkworm disease detection, the best results could be seen with the use of a variation of the LeNet architecture. LeNet consists of convolutional, activation, max-pooling and fully connected layer also LeNet is simple CNN model.

This architecture used for the classification of the leaf diseases in LeNet model. It consists of an additional block of convolution, activation and pooling layers in comparison to the original LeNet architecture. The model used in this paper been shown in Fig. 2. Each block consists of a convolution, activation and a max pooling layer. Three such blocks followed by fully connected layers and soft-max activation are used in this architecture. Convolution and pooling layers are used for feature extraction whereas the fully connected layers are used for classification [7]. Activation layers are used for introducing non-linearity into the network.

Convolution layer applies convolution operation for extraction of features. With the increase in depth, the complexity of the extracted features increases. The size of the filter is fixed to 5 × 5 whereas number of filters is increased progressively as we move from one block to another. The number of filters is 20 in the first convolution block while it is increased to 50 in the second and 80 in the third. This increase in the number of filters is necessary to compensate for the reduction in the size of the feature maps caused by the use of pooling layers in each of the blocks. After the application of the convolution operation feature maps are zero padded, in order to preserve the size of the image. The max pooling layer is used for reduction in size of the feature maps, speeding up the training process, and making the model less variant to minor changes in input. The kernel size for max pooling is 2×2. Re-LU activation layer is used in each of the blocks for the introduction of non-linearity. Also, Dropout regularization technique has been used with a keep probability of 0.5 to avoid over-fitting the train set [9].

Dropout regularization randomly drops neurons in the network during iteration of training in order to reduce the variance of the model and simplify the network which aids in prevention of over fitting. Finally, the classification block consists of two sets fully connected neural network layers each with 500 and 10 neurons respectively [10]. The second dense layer is followed by a soft max activation function to compute the probability scores for the ten classes.

Further, in every experiment, the overall accuracy over the whole period of training and testing regular intervals (for every epoch) will be computed. The overall accuracy score will be used for performance evaluation

V. CONCLUSION

Beyond disease identification, our solution provides valuable resources upon detection, including literature on the identified disease and recommended preventive measures. Our integrated approach not only tackles the immediate challenges of disease control in the sericulture industry but also establishes a foundation for sustainable growth, quality improvement, and enhanced collaboration among industry stakeholders. Through the fusion of technology and agricultural practices, we envision a future where sericulture thrives with minimized disease impact and optimized

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