JOURNAL OF SCIENCE, SOCIETY AND LANGUAGE
A Peer-Reviewed, Multidisciplinary Journal

Vol. 2 · Issue 1 · June 2026
e-ISSN: 3108-0359

REVIEW ARTICLE

OPEN ACCESS

The Use of Machine Learning for Rubber Disease Prediction: A Review

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DOI: https://doi.org/10.67060/JSSL.2026.2108

Pages 87–97

ABSTRACT

Rubber (Hevea brasiliensis) is an important agricultural product that makes significant contributions to the world economy, especially in tropical areas like Malaysia, Thailand, and India. However, rubber plantations face high susceptibility to a range of leaf diseases, including Abnormal Leaf Fall, Powdery Mildew, and Corynespora Leaf Fall, which can cause large production decreases. Traditional methods for identifying diseases can be difficult and mostly depend on expert visual inspection. Machine learning (ML) and deep learning (DL) techniques have shown good results in the automated process of plant disease detection and prediction in the past few years. This research paper presents a comprehensive review of ML-based techniques for disease prediction and detection in rubber plantations. This research paper discussed various image processing techniques, machine learning algorithms, datasets, and performance.

Keywords: *Rubber tree, Machine Learning, Disease Prediction, Image Processing, Leaf Disease Detection, Abnormal Leaf Fall*

1.Introduction:

A large portion of Tripura's economy is derived from rubber trees, which give many farmers work and cash. However, the production of rubber can be negatively impact by diseases such powdery mildew, leaf fall, and root rot. Traditional methods for detecting diseases depend on manual observation and expert help, which can be time-consuming.

The development of artificial intelligence, in particular neural networks, has opened up new opportunities for improving and automating disease prediction. Large datasets can teach complex patterns to neural networks, which makes them useful for applications like image-based disease detection. The purpose of this project is to use neural network models to predict diseases in rubber plants in order to give a reliable tool for early detection and monitoring.

The rubber plant is a significant export of natural resources to a number of nations, including Malaysia, Indonesia, India, and others. One of the industries in Indonesia that generates foreign exchange earnings is the agricultural sector. Rubber plantations can generate employment and serve as the primary source of income for households. However, The difficulties faced are troubling particularly in regard to rubber diseases. Using more advanced technologies can help start the process of detecting rubber diseases.

1.2 Diseases in Rubber Trees

Rubber trees are susceptible to a variety of diseases that can significantly impact yield. Powdery mildew, caused by the fungus Odium heave, is one of the most common diseases affecting rubber trees. Leaf fall disease, caused by Phytophthora spp., and root rot, caused by Rigidoporus lignose, are other significant diseases (Jacob & Mathew, 2007).

South American Leaf Blight (SALB): A devastating fungal disease mainly affecting rubber plantations in South America. It spreads through spores and thrives in humid conditions.

Symptoms: Small brown or black spots on young leaves. Leaf curling and premature defoliation. Twigs and young shoots die back.

Impact: Leads to defoliation, reducing photosynthesis and latex production. Can destroy entire rubber plantations if not controlled. (Sterling & Di Rienzo, 2022)

Powdery Mildew: A fungal disease affecting young leaves, especially in dry weather with high humidity.

Symptoms: White powdery fungal growth on young leaves and shoots. Leaves become distorted and drop prematurely. Delayed tree growth.

Impact: Reduces tree vigour and delays tapping maturity. Can cause severe leaf loss in nurseries and young plantations. (Liyanage et al., 2016)

White Root: A deadly root disease affecting rubber plantations, commonly found in older trees.

Symptoms: Yellowing and wilting of leaves. Decay of feeder roots, leading to tree instability. White fungal mycelium on the root surface.

Impact: Causes tree death if untreated. Weakens the root system, reducing latex yield.

Pink Disease: A fungal disease affecting young branches, often in high humidity.

Symptoms: Pinkish fungal growth on the bark. Branch dieback and drying of leaves.

Impact: Weakens tree branches, reducing growth and latex yield. Severe cases cause branch breakage.

Corynespora Leaf Fall Disease (CLFD): CLFD is one of the most serious and widespread fungal diseases affecting rubber trees, particularly in tropical regions like India, including Tripura

Symptoms: Brown or grayish circular to irregular spots. Spots grow larger and coalesce (merge), causing leaf tissue to die. Leaf becomes necrotic and drops prematurely. Yellow halo around the spots.

Impact: Reduces photosynthesis, Reduced latex yield. Poor tree health and growth.

Oidium Leaf Disease (Powdery Mildew – Early Stage): Oidium leaf disease is a fungal infection of rubber trees, commonly seen in nurseries and young plantations. It primarily affects young leaves, especially during dry or transitional weather conditions.

Symptoms: Fine white or greyish powder appears on the upper surface of young leaves. Often starts as small patches, then spreads across the leaf.

Impact: Reduces leaf area and photosynthetic capacity. Delays growth in young plants. In nurseries, can cause high seedling mortality. Leads to poor canopy development, affecting future latex yield.

2. Machine learning:

Machine learning (ML) is a subset of artificial intelligence (AI) that focuses on developing algorithms and statistical models that enable computers to perform specific tasks without being explicitly programmed to do so. Instead, these systems learn from data by identifying patterns and making decisions or predictions based on that data.

Machine learning is a type of technology that allows computers to learn and make decisions from data without being explicitly programmed. Think of it as teaching a computer to recognize patterns and make predictions based on examples, just like how humans learn from experience.

Supervised learning is a type of machine learning where the model is trained on a labelled dataset. This means that each training example includes input data and the corresponding correct output. The goal of supervised learning is for the model to learn the mapping between inputs and outputs so that it can predict the output for new, unseen data. Consider a spam email classifier. The training data consists of emails (input) and labels indicating whether each email is spam or not (output). The model learns to identify patterns associated with spam emails and can then predict whether new emails are spam. Common algorithms are Linear regression, logistic regression, support vector machines (SVM), and neural networks.

Unsupervised learning is a type of machine learning where the model is trained on unlabelled data. The goal is to identify hidden patterns or structures within the input data without prior knowledge of the correct outputs. Consider a customer segmentation task. The data consists of customer purchase histories without any predefined categories. The model groups customers with similar behaviour, which can then be used for targeted marketing. Common algorithms are K-means clustering, hierarchical clustering, and principal component analysis (PCA). (Mitchell, 1997)

2.1 Artificial Neural Network (ANN)

Artificial neural networks (ANNs) are being evaluated as a way to predict rubber tree diseases. On the other hand, it is generally known that artificial neural networks (ANNs) may be used for nonlinear analysis of complex data. The purpose of this study is to evaluate the usefulness of ANNs applied to rubber tree for diseases detection. The ANNs used in the present study were based on a feed forward layered model with input, hidden, and output layers, on which a back-propagation learning model was implemented. An artificial neural network (ANN) is a system based on the operation of biological neural networks, in other words, is an emulation of biological neural system.

Input Layer: Receives the initial data.

Hidden Layers: Perform intermediate computations and feature extraction.

Output Layer: Produces the final output. (Haykin, 1998)

Artificial Neuron

An artificial neuron is the basic unit of an ANN. It mimics the function of a biological neuron. Each artificial neuron receives one or more inputs, processes them (often using a weighted sum), and passes the result through an activation function to produce an output.

A biological neuron: A biological neuron is a specialized cell in the nervous system responsible for receiving, processing, and transmitting information through electrical and chemical signals. It is the fundamental unit of the brain and nervous system, allowing organisms to perceive, think, move, and respond to their environment.

2.2 Feed forward Neural Network (FNN): The simplest type of Artificial neural networks (ANN) where the information moves in one direction—from the input nodes, through the hidden nodes (if any), and to the output nodes. There are no cycles or loops. Used this classification and regression tasks.

Example: A network that takes features of a house (e.g., size, number of rooms) as input and predicts its price.

2.3 Convolutional Neural Network (CNN): A type of ANN specifically designed to process structured grid data like images. It uses convolutional layers that apply filters to the input to detect patterns such as edges, textures, and shapes. Image and video recognition, image classification, medical image analysis, and computer vision tasks. Example: A network that classifies images of animals into categories like dogs, cats, and birds.

2.4 Recurrent Neural Network (RNN): An ANN where connections between nodes form directed cycles. This allows the network to maintain a 'memory' of previous inputs, making it well-suited for sequential data. Time series prediction, Natural language processing (NLP) and speech recognition.

Example: A network that predicts the next word in a sentence. (Haykin, 1998).

3. Literature Review:

(Nayak et al., 2024) With the help of CNN-based models, Rubber tree leaf diseases may be efficiently identified and categorized, allowing for better disease management and early intervention.

The suggested CNN-based approach offers an accurate and cutting-edge disease identification method, which can potentially transform disease management in rubber plantations completely.

In addition to developing an understandable application to encourage broader use of the technology, the study attempts to optimize and further refine the CNN model to increase its robustness and adaptability in real-world circumstances.

(Balaga and Patayon, 2024) The accuracy of the DenseNet, Inception, and MobileNet architectures for diagnosing powdery mildew and anthracnose (leaf blight) in rubber plants was greatly increased by the application of a background segmentation technique.

While the MobileNet design attained 98% accuracy for powdery mildew and 90% accuracy for anthracnose, the DenseNet architecture earned the maximum accuracy of 97% for powdery mildew identification. According to the study, rubber tree plant disease detection accuracy may be improved by applying background segmentation algorithms, which could lead to a rise

in rubber exports from the Philippines.

(Cheng et al., 2024) Powdery mildew infection in rubber trees leads to de creases in chlorophyll content and increases in anthocyanin content. Models using wavelet features (WFs) demonstrated the best performance, with the SVM model achieving a 92.5 detection accuracy. The model combining WFs and physicochemical parameter features (PFs) showed the highest overall accuracy (94.3) and F1-score (0.952) among all the models tested.

(Hidayah and Samurai, 2023) The suggested machine learning approach utilizing ANFIS may reduce losses, enhance plant number and quality, and facilitate the early identification of illnesses affecting rubber leaves.

When it came to rubber leaf disease detection, the ANFIS algorithm using the Gbellmf membership function had the best accuracy; This study achieved a 99 per cent accuracy rate for training data and 93% for testing data, with a Root Mean Square Error (RMSE) value of 0.113263. This approach shows significant potential for early disease detection, helping to minimize agricultural losses, improve plant quality and quantity, and provide timely interventions for better disease management

(Kaewboonma et al., 2023) The YOLOv8n-cls model emerged as the optimal choice for Thai rubber leaf disease classification, demonstrating exceptional efficiency, accuracy (98.68), and F1-score (0.98).

A comparative analysis of YOLOv8 classify models identified YoloV8s as the most favourable option, characterized by the lowest validation loss. The study employed a diverse set of CNN models, including VGG16, ResNet50, Ef f icientNet, and YOLOv8, to classify Thai rubber leaf diseases using leaf images.

(Cheng et al., 2023) The model that combined random forest classification with PCA-WFs performed the best, showing that continuous wavelet transform is a feasible method for identifying powdery mildew on rubber trees. Its overall accuracy was 92.0%, and its kappa coefficient was 0.90. The degree of powdery mildew on rubber trees could be determined using all three wavelet feature types, with PCA-WF-based models showing the best accuracy and stability.

The severity of the disease increased with the spectral reflectance of rubber tree leaves in the visible and near-infrared wavelength ranges.

(Zeng et al., 2023) The blue, green, red-edge, and near-infrared bands were the most sensitive spectral bands for tracking powdery mildew (PM) on rubber tree leaves. Vegetation indices (CCCI, NormRRE, PSRI, BNDVI), texture features (Mean, Homogeneity), and colour features (RGBVI, ExB, GLA, ExG) were the most sensitive feature combinations.

When compared to employing single feature types, the combination of spectral, texture, and colour characteristics (SF + TF + CF) yielded the highest overall accuracy (95.88) % and kappa coefficient (0.94) for recognizing different stages of PM infection.

For early monitoring and control, the fusion of all features produced the highest accuracy (93.2) % in identifying PM infection at an early stage. The BPNN model was beaten by the SVM and RF models, with the SVM model exhibiting the best performance when combining all features.

(Zeng et al.,2022) The suggested GMA-Net model outperformed other cutting edge methods, achieving an accuracy of 98.06% on the rubber leaf disease dataset.

Compared to other lightweight models, the GMA-Net model has a substantially smaller model size and fewer parameters, but it still improves recognition accuracy by 3.86–6.1 Surpassing previous state-of-the-art methods, the GMA-Net model obtained a 99.43 % recognition accuracy on the Plant Village public dataset.

(Sulaiman and Saad, 2020) Reliability has been demonstrated by the established model that uses electrical properties (relative permittivity and capacitance) to distinguish between healthy rubber trees and those that have white root disease. Based on parameters like lowest hidden layer size, best sensitivity and specificity, optimal accuracy, and highest area under the curve (AUC), the most optimized models were ANN1IPHS27neu for single input relative permittivity measurement and ANN2IPHS7neu for single input capacitance measurement.

Rubber trees with white root disease and healthy trees could be distinguished from one another by the classification models that used these optimized models.

(Lazim et al., 2023) White root disease (WRD) is a common infection problem in rubber plantations that can cause the death of rubber trees with varying degrees of white root disease severity, the ANN model distinguished between healthy and diseased rubber leaves with the highest classification accuracy of 90 %. The ANN classifier in conjunction with spectroscopic technology is a potential method for the early, non-destructive, and quick identification of white root disease in rubber plantations.

(Sterling and Di Rienzo 2022) Random forest(RF), boosted regression tree (BRT), bagged classification and regression trees (BCART), artificial neural network (ANN), and support vector machine (SVM) were the five machine learning (ML) techniques that were evaluated. On the training dataset, RF, ANN, and BCART performed the best for classifying SALB levels, with accuracies ranging from 98.0 to 99.8 %, and on the test dataset, with accuracies ranging from 97.1 to 100 %.

(Abdullah et al. 2007) Nearly 100% classification accuracy was attained by both the Ezan1 and Ezan2 models, with 96.5% being the highest accuracy. Over 90% sensitivity and specificity were also attained by both models. With greater accuracy and a smaller network size than the Ezan1 model, the Ezan2 model which employed PCA to minimize the input data size—was determined to be the best model

(Liyanage et al., 2016) Rubber tree powdery mildew disease can cause a 45 17 % reduction in rubber latex yields. Though the exact cause of the illness is yet unknown, Golovinomyces or Podosphaera are the most plausible candidates. The disease mostly affects young rubber leaves, buds, and inflorescences and is spread by dry spores.

(Sulaiman & Saad, 2020) The study developed a classification system to detect white root disease in rubber trees using relative permittivity and capacitance, with accuracy greater than 70%. Two optimized models, ANN1IP(SCG) and ANN2IP(SCG), were identified as reliable for classifying healthy and infected trees based on performance evaluation parameters.

Lertkrai et al., 2025) The YOLOv8 model achieved an overall mAP50 of 57.9% and mAP50-95 of 42.8%, with strong performance in detecting healthy leaves (mAP50: 98.3%) but lower accuracy in identifying Powdery Mildew (mAP50: 22.4%).

User testing with 50 beta testers resulted in a detection accuracy of 72.4%, a misclassification rate of 5.4%, and an average response time of 2.5 seconds.

Table: REVIEW TABLE

Author and Year	Method	Dataset	Disease Types	Finding
(Nayak et al.,2024)	CNN	Images of diseased rubber leaves were collected in various weather scenarios. Mangalore, India.	Powdery mildew leaf Disease.	The study success fully utilized Convolutional Neural Networks (CNN) to detect diseases in rubber leaves.
(Hidayah and Samuri, 2023)	Machine Learning Adaptive Neuro-Fuzzy Inference System (AN FIS)	The dataset for this paper was collected from rubber plantations in Tanjung, Tabalong, South Kalimantan, Indonesia	Powdery Mildew leaf Disease.	A Machine Learning strategy that has been proposed may decrease losses, improve plant quantity and quality, and enable the early detection of diseases that impact rubber leaves.
(Cheng et al.,2023)	Continuous Wavelet Transform and Machine Learning	Hyper spectral reflectance data from 1250 rubber tree leaves at five distinct severity levels of powdery mildew disease comprise the dataset used in this investigation.	Powdery Mildew leaf disease	The model that combined random forest classification with PCAWFs performed the best, showing that continuous wavelet transform is a feasible method for identifying powdery mildew on rubber trees
(Zeng et al.,2023)	Random Forest (RF), Back Propagation Neural Network (BPNN), and Support Vector Machine (SVM)	The study was conducted in Danzhou City, Hainan Province, China, in the China Academy of Tropical Agriculture's rubber forest research area.	Powdery Mildew Disease	The maximum accuracy (93.2) per cent was achieved in early PM infection identification when all features were combined.
(Lazim et al.,2023)	ANN	The dataset collected from infected rubber plant from Malaysia	White root Disease	the ANN model distinguished between healthy and diseased rubber leaves with the highest classification accuracy of 90%
(Zeng et al.,2022)	CNN	The dataset includes 2,788 rubber leaf samples collected from the rubber tree cultivation farm of the Rubber Research Institute, Chinese Academy of	Rubber leaf Disease	Using the rubber leaf disease dataset, the proposed GMA-Net model achieved an accuracy of 98.06% out performing previous

Author and Year	Method	Dataset	Disease Types	Finding
		Tropical Agricultural Sciences in Danzhou City, Hainan Province, China		state-of-the-art techniques
(Abdullah etal. 2007)	Neural Network	The dataset consisted of 700 images of rubber tree leaves affected by three different diseases The neural Network	Rubber Leaf Diseases	developed for classification showed approximately 70% diagnostic accuracy.
(Sterling and Di Rienzo, 2022)	Machine Learning	The dataset used in this study consists of leaf hyper spectral reflectance data and photosynthetic trait measurements from 120 rubber tree leaf samples across 5 different South American Leaf Blight (SALB) severity classes.	South American Leaf Blight	The RF, ANN, and BCART models achieved the best performance for classifying the SALB levels on the training dataset (accuracies of 98.0 to 99.8) and test dataset (accuracies of 97.1to100)
(Cheng et al., 2024	Machine Learning	Hyper spectral reflectance data collected from 263 rubber tree leaf samples, including 152 healthy leaves and 111 leaves with early-stage powdery mildew lesions covering less than one-eighth of the total leaf area. Yunnan Province, China	Powdery mildew infection	Models using wavelet features (WFs) demonstrated the best performance, with the SVM model achieving a 92.5 detection accuracy. The model combining WFs and physicochemical parameter features (PFs) showed the highest overall accuracy (94.3) and F1-score (0.952) among all the models tested.
(Kaewboonma etal.,2023)	CNN	The dataset used in the study is the "Rubber Leaf Disease Dataset", which consists of 734 rubber leaf images categorized into three classes: new diseases, powdery mildew	Thai rubber leaf disease	The YOLO v8n-clsmodel emerged as the optimal choice for Thai rubber leaf disease classification, demonstrating exceptional efficiency, ac curacy (98.68), andF1 score (0.98).

Author and Year	Method	Dataset	Disease Types	Finding
		disease, and healthy leaves.		
(Sulaiman & Saad, 2020)	ANN	A dataset consisting of 600 samples of latex from rubber trees, with 300 samples from healthy trees and 300 samples from trees infected with white root disease. The dataset was collected from the RRIM station in Kota Tinggi, Johor, and was used for input measurements.	white root disease	The study developed a classification system to detect white root disease in rubber trees using relative permittivity and capacitance, with accuracy greater than 70%. Two optimized models, ANN1IP(SCG) and ANN2IP(SCG), were identified as reliable for classifying healthy and infected trees based on performance evaluation parameters.
Lertkrai et al., 2025)	Deep Learning	The dataset used in the study is called the "Rubber Leaf Disease Dataset." It consists of 734 rubber leaf samples collected from various sources, divided into three categories: 205 images of powdery mildew disease, 259 images of a newly identified disease, and 270 images of healthy leaves. The dataset was annotated by experts and enhanced through data augmentation to increase its size to 1536 images.	Rubber leaf disease	The YOLOv8 model achieved an overall mAP50 of 57.9% and mAP50-95 of 42.8%, with strong performance in detecting healthy leaves (mAP50: 98.3%) but lower accuracy in identifying Powdery Mildew (mAP50: 22.4%). User testing with 50 beta testers resulted in a detection accuracy of 72.4%, a misclassification rate of 5.4%, and an average response time of 2.5 seconds.
(Liyanage et al., 2016)		The dataset includes genetic sequence data such as rDNA and ITS sequences from rubber powdery mildew fungus isolates from different geographical locations (Brazil, Malaysia, Thailand)	powdery mildew disease	The paper reviews the classification conflicts and main causes of powdery mildew disease in rubber trees, highlighting the confusion between Oidium heveae and Erysiphe quercicola. Environmental

Author and Year	Method	Dataset	Disease Types	Finding
				conditions, particularly temperature and humidity, are critical for the germination and spread of the disease. Climate change is identified as a significant factor that can exacerbate the disease by creating favorable conditions for its spread.

Conclusion: Rubber disease prediction has been significantly improved by machine learning, particularly deep learning. High accuracy is provided by CNNs and Vision Transformers, which can automate diseases identification. However, there are still issues with multi-disease prediction, real-time deployment, and dataset availability. This review discusses that machine learning has become an effective method for accurate and on time prediction of diseases in rubber trees.

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