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AI driven Mango Plant Disease Preduction and Management System

S. Girinath [1*], N. Divya [2]

[1*] Department of CA, Mohan Babu University ,Tirupati, Andhra Pradesh , India
[2] PG Student, Department of CA, Mohan Babu University, Tirupati, Andhra Pradesh , India; divyareddy7990@gmail.com

* *Corresponding Author:* divyareddy7990@gmail.com

Abstract: The Mango leaf diseases significantly restrain mango output as they affect yield and tree health. Mango leaf sooty mould disease is one of the diseases which affects the tree's photosynthesis and general vigor quite severely. This research study looks into the use of deep learning models like the Residual Network with 50 stacks and ResNext50 for assessing that severity classification of mango leaf sooty mould disease. The model evaluates severity based on the dataset of 25,000 images obtained from different mango fields, as per the study. The overall accuracy achieved is 94.61% for the ResNext50 architecture through layer-wise parameter analysis, performance metrics, and confusion matrices. Model comparisons in the field reveal advantages across and between models. This research not only proves the use of DL in disease management but also paves the way for more applications in farming use. Automated mango leaf disease assessment is always bright white.

Keywords: Machine Learning, Precision Agriculture, Image Recognition, Crop Management, Environmental Data,.

1. Introduction

Mango is one of the maximum essential tropical culmination, identified for its sweetness and nutrients, as well as its economic significance. However, mango plantation cultivations have a slew of issues, including preeminent plant diseases affecting crop fitness, yield potential, and quality. While common diseases such as Anthracnose, Powdery Mildew, Bacterial Blight, and Cercospora Spot may go unrecognized and uncontained, they nonetheless embody treasured resources in terms of possibly ruining considerable amounts of crops. The time-consuming, inaccurate [1], and low-value traditional inspection-disease detection-and-control approaches require much time and are usually limited by factors such as the skill of the person performing them. Overuse of chemicals, environmental injury, and any further unnecessary costs are due to traditional pesticide application and disease-control measures, which usually lack the accuracy necessary to target infection in time.

However, the increasing boom of artificial intelligence (AI) and system mastering offers an excellent opportunity for modernizing plant sickness analysis and management. Using imaging, data analytics [2], and pattern reputation, artificial intelligence technology provides accurate and efficient solutions for finding out disease signs and symptoms and predicting their future outbreak. Machine-learning models use large datasets of plant pictures and environmental data for training to look for visual and environmental cues to decree diseases in their early development through proactive control, which may cut down on extensive-spectrum pesticide programming and advocacy for more sustainable agricultural activities.

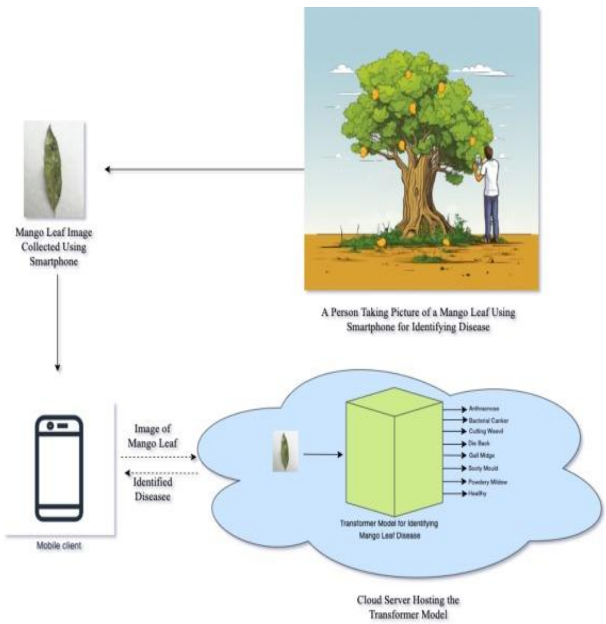

Fig.1 Identifying Leaf Disease

AI-Driven Mango Plant Disease Prediction and Management Systems are right set to handle those

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challenges in giving farmers a trusted real-time platform for early detection, forecasting, and management advice. Identifying possible threats to the crop through high-resolution images of mango leaves combined with environmental data such as temperature, humidity, and soil conditions [3]. This makes it possible for farmers to take targeted, timely actions to halt the spread of pathogens with minimal crop losses but low ecological impacts of farming activities. The system is considered a giant leap in applying AI in agriculture, bringing a scalable solution for mango growers and enhancing productivity while addressing issues related to the overall health and sustainability of mango farming worldwide.

Their AI-based mango plant disease prediction and management system applies novel machine learning approaches like convolutional neural networks to identify and classify the categories of diseases present in mango crops. Most traditional diagnoses typically require many tedious and error-prone manual inspections. Once AI is put into practice by this device, the entire block is covered: quick, accurate, real-time predictions are made from the images of the leaves of the mango plant [4]. The CNN model is trained on a dataset of healthy and diseased leaves so that it can identify these patterns that correlate with diseases. By blending photo processing with deep learning, this device automatically extracts some key features such as colour variations, texture differences, and lesions shapes to efficiently classify the diseases. The identification of a disease in the system automatically provides actionable advice on what to treat, which helps support farmers in being able to act preventively and correctly in a timely way.

2. Literature Survey

Before, Earlier, mango leaf diseases were identified using manual observations and classical machine learning techniques such as SVM, k-NN, and Random Forest which required handcrafted feature extraction. Deep learning, specifically Convolutional Neural Network (CNN), has shown good improvement [5], yet classical interpretation methods remain warranted.in terms of performance, it still tends to struggle in capturing long-range dependencies in images. Emerging from the NLP field, Vision Transformers (ViTs) were introduced as viable replacements by taking an image, splitting it into patches, and then applying self-attention to them for learned feature extraction. Recent studies have shown that ViTs outperform ConvNets in their ability to classify disease-infected plant materials, showcasing their high qualities in the ability to generalize over variances in illumination, angles [6], and background noise. The very recent works have integrated CNNs with ViT architectures, where CNNs are used for initial feature extraction followed by ViTs in the classification phase, worth noting very high accuracy reported for the modern-day applications. Despite that, ViTs are very computably intensive and necessitate significant datasets for optimal performance. Advances are now driven by self-supervised learning and lightweight ViTs such as MobileViT in a bid to defeat this limitation. Comparisons indicated that ViTs certainly excel CNNs in terms of accuracy, particularly in very complicated disease patterns. Future affirmation of ViT work must encode optimization studies for real-time use in smart agriculture [7].

Conclusively, ViTs give a great chance to mango leaf disease identification for enhancements in precision and detailed capabilities in pathogen detection. In agriculture, the impact of Artificial Intelligence on disease epidemiology has vastly improved, especially through deep learning methods such as CNN. Several studies have proposed the development of CNN-based systems for plant disease classification on image datasets. Works done by Mohanty et al. revealed that deep learning learnable machines trained through the Plant Village dataset should realize high accuracies as high as 99% in the detection of plant diseases [8]. Likewise, Shrivastava et al. focused on mango leaf disease classification, achieving 95% accuracy in recognizing anthracnose, powdery mildew, and bacterial black spot. Another study, Tanwar et al. n 2021, numerous advantages of transfer learning were witnessed through pre-trained models, including VGG16 and ResNet, which lead to improved model performance with decreased computational times.

Apart from the above work, Patel et al. reviewed IoT and AI for real-time disease monitoring with smart cameras and cloud computing (2022). Kumar et al. introduced an AI-based disease management system the following year, which anticipates diseases and suggests treatments (2023). Both studies endorse that CNNs are efficient in plant disease identification, the accuracy of which largely relies on the quality of the dataset, preprocessing, and some optimization parameters of the model. Such an IoT interface could enlarge the prospects of wide-scale disease forecasting whilst relieving manual labor. This will minimize human intervention for active plant disease management and effective use of the AI model which can optimally allocate control measures including microbial and chemical options to control plant disease. Also, cloud systems could enable real-time scouting of plant diseases and help put an alarm system in place [9].

Based on targeted weather predictions, such models would be highly effective in promoting preventive measures against diseases. Simultaneously, AI-enabled interventions alongside various other methods drastically limit crop losses, bringing the opportunity for enhancing agricultural production. Further studies would need to explore live mapping, pre-emptive detection

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automation, and decision-making aligned with precision agriculture [10]. AI, IoT, and Cloud Computing Interface paves the way for ushering in a new-lead perspective of smart agronomy towards betterment in plant health and productivity.

3. Methodology and Related Work

This AI-based mango plant disease prediction and management systems deals with a systematic methodology for guaranteeing proper disease detection and the right kind of management actions to be set in. The first step is data collection, where high-resolution leaf images from mango trees have been collected from farms, research institutes [11], and online image datasets, containing both healthy and diseased samples affected by different diseases such as anthracnose, powdery mildew, and bacterial black spot. Further, the image quality enhancement using resizing, normalization, and augmentation techniques [12], say rotating and flipping, confers good diversity to the processed data set, besides enhancing the model accuracies in the downstream tasks.

A CNN model trained on the data serves as a classifier for the diseases. Its model construction consists of convolution layers which act as feature extractors, pooling layers which act to decrease the computational complexity while retaining the most important information, coupled with fully connected dense layers which perform the classification through a softmax activation function. The model is trained on labelled images via Adam optimizer with categorical cross-entropy loss function [13]. The resulting model is evaluated through accuracy metrics, loss function, and confusion matrix to ensure precision. The model once trained is deployed for disease prediction in which new mango leaf images will be used to classify any type of disease along with confidence score. After detection of the disease [14], the system emphasizes management of the disease through chemical treatments, organic solutions, and agronomic best practices for the control of diseases. Finally, the trained model is incorporated into a simple mobile or web application which allows farmers and agriculturalists to append background images and get analysis results and management alternatives in a timely fashion. This structured methodology ensures that mango plant disease detection is a reliable and efficient process that saves farmers losses and augments his/her productivity [15]. But ShuffleNet was to artwork on cell gadgets so it has very restricted computing strength. It does the computation three instances as speedy over AlexNet for ARM devices with out compromising on massive quantity of accuracy. ShuffleNet convolves inside its very personal input channel agencies. These organizations stand out for their numerous computation fee effectiveness. Together, this and the channel shuffle operation do now not allow the depthwise stacking into more than one-organization convolutions. These make up the shufflenet block altogether. Then follows the 3x3 common pooling wherein the connection turned into defined as taking the channel concatenation and substituting it by way of manner of detail sensible addition. With this, the channel may also moreover little by little move up stage thru degree which improves schooling performance [16].

EfficientNets are a family of 8 baselines networks, engineered mo-cellular based totally and res internet. Scaled uniformly to increase its depth, width and determination with a compound coefficient known as compound scaling And in the end, we come to EfficientNet-B7, which acquired a top-1 accuracy of ImageNet of eighty four.1% with a reduction in duration by way of eight.Four times and an stepped forward 6.1 times for inference tempo [17]. DenseNet Creative Passing Direct Connections Drops It builds as many direct connections between all layers and all next layers improving the reuse of all available features. This structure modifies the sparse connections.

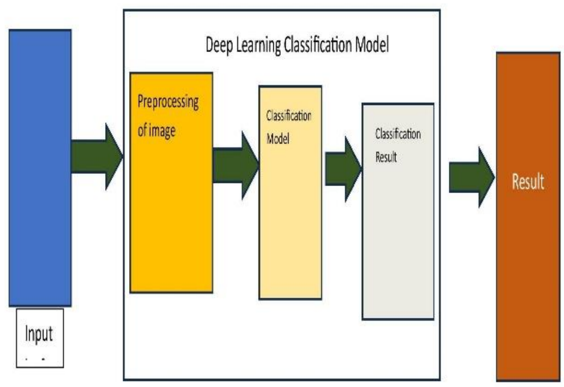

Fig.2 Processing of the dataset along with the ML models

Algorithm

Input: Advanced Detection of Mango plant Disease
Output:

- Step-1: Start
- Step-2: Advanced Detection Mango Plant Disease Detection Dataset (Data Collection)
- Step-3: Perform Data Preprocessing.
- Step-4: Data Cleaning for missing values.
- Step-5: Feature Engineering, derivation of features based on raw input features
- Step-6: Design an Efficient Model in terms of using Machine Learning and CNN

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Step-7: 7.End

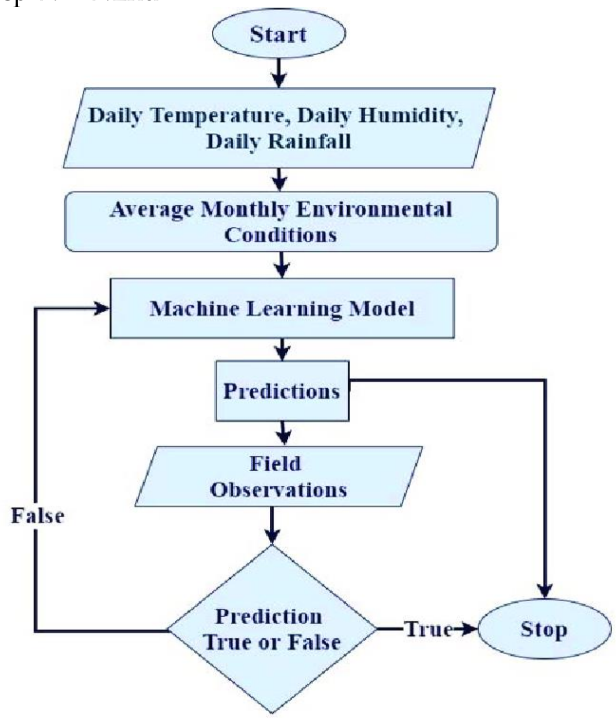

Fig.3 Flowchart of a machine learning-based environmental prediction and validation system.

This flowchart Fig3 represents a system getting to know-based totally environmental prediction device. It starts with collecting each day temperature, humidity, and rainfall data, that's then used to compute commonplace monthly environmental situations. These conditions are fed proper into a device gaining knowledge of model to generate predictions. The predictions are then in comparison with challenge observations to validate their accuracy [19]. If the prediction is correct, the system stops; in any other case, it loops returned for in addition evaluation and refinement.

4. Data Description

This dataset has 4000 mango leaf images used as plant disease recognition for the MangoLeafBD dataset. They are all in the JPG format and measure 240 by 320 pixels." This dataset consists of eight classes: seven for diseases and one for healthy mango plants. Thus, each of the classes has been assigned equally into a total number of 500 images for each class, that is, 1800 by camera angle, and other images were zoomed and rotated for variation. Those diseases observed during that period of data collection in the dataset are Anthracnose, Bacterial canker, Cutting Weevil, Die Back, Gall Midge, Powdery Mildew, and Sooty mould + Data were collected from four mango orchards at one of the following locations in Bangladesh, Sher-e-Bangla Agricultural University orchard, Jahangir Nagar University orchard, Udaypur village orchard and Itakhola village orchard [20]. The data is useful for both binary classification (healthy versus diseased) and multi-class classification (specifying the particular dataset was collected from the Mango orchards that fit the characteristics include - Self-Eating Agricultural University Orchard, Jahangir Nagar University, and Mango Orchard, Udaypur Village and Itakhola Village Mango Orchard. The data is useful for both binary classification (healthy versus diseased) and multi-class classification (specifying the particular disease) because it has applications in machine learning and deep learning pertaining to plant disease recognition.

5. Result

A CNN-clouded completely and purely AI-powered mango plant infection prediction-and-control system endeavors to distinguish and classify mango plant diseases using deep learning techniques. The The system is built according to a Convolutional Neural Network (CNN) architecture that analyzes pictures of mango leaves to form a pattern regarding diseases like anthracnose, powdery mildew, and bacterial black spot. The model is trained using a dataset composed of healthy leaves and leaves afflicted by diseases by looking at different characteristic features such as color, texture, and structure.

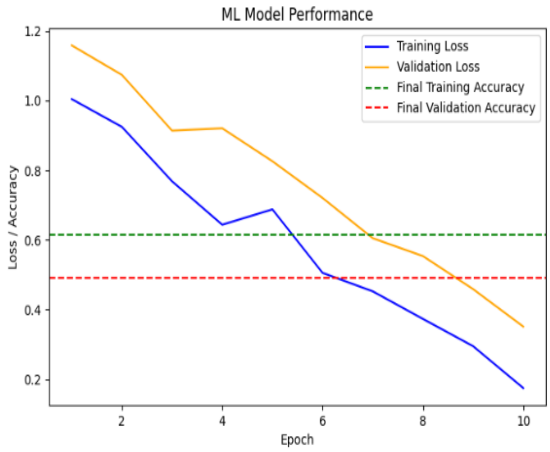

Fig.4: Post-Processing of the dataset along with the output ML models

When predicting, CNN through the convolutional layer extracts hierarchical features which are selected for pooling and subsequently classified through layers. The tool maximizes its accuracy by fine-tuning its hyperparameters to allow generalization and enhancing this generalization through data augmentation and transfer learning techniques. The trained model allows real-time detection of infections and hence a proactive intervention for farmers. The automated system also comprises a control module that suggests the right remedy, i.e . natural remedies, fungicides, or irrigation techniques. With this AI solution launched on the mobile app or web platform, farmers can upload pictures and receive instant contamination diagnosis and treatment plans. This leads to

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enhanced crop yield, reduced losses, and sustenance for agriculture through early intervention and information-driven decision-making.

6. Conclusion

Coconut diseases of mango based on AI technology for precision and management have evolved a new concept for diagnosis in the plant-detection system. This system employs a deep learning mechanism for accurate classifying diseases based on leaf images ensuring early diagnosis towards intervention. This reduces the dependency on manual inspection, which is more time-consuming and computerized types of error by using *Convolutional Neural Networks (CNNs)* for precision feature extraction, improving overall classification accuracy. To further enhance the model robustness to the real-world agricultural environment, techniques like data augmentation and transfer learning have been used. The system can provide farmers with actionable insights they can use to take preventive and corrective measures before spread disease. Also, the integration of disease management strategies provides farmers with effective treatment recommendations, such as using both organic solutions and chemical interventions. The system is accessible via mobile apps or web platforms, making it easily usable for farmers in remote areas. Hence, this would finally be an AI model to increase crop productivity, minimize losses, and promote sustainable practices. Further advancements can easily extend this model to other crops, revolutionizing disease management in agriculture.

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