RECOGNITION OF LEAF ILLNESS DETECTION

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ABSTRACT

Plant disease early detection has a major impact on crop quality and financial stability, making it essential for India's agriculture. The precision of current detection techniques is lacking, which puts yields at risk. In order to identify cotton leaf illnesses and classify leaves as healthy, unhealthy, or sick, this study suggests a prediction method. This focused strategy enables focused therapies and aids in the prevention of disease spread. The framework can also be modified to identify diseases that affect tomato plants with the goal of increasing agricultural yields, lowering costs, and promoting environmentally friendly farming methods.

Keyword: Leaf, Diseases, Support Vector Machine (SVM), Convolutional Neural Networks(CNN).

I. INTRODUCTION

India is a shining example of gastronomic diversity and cultural richness, supported by a booming agricultural industry that employs close to 70% of its workforce. In this context, identifying and controlling plant diseases become crucial issues that impact crop yield and financial stability. The goal of this study is to increase the precision of disease detection, with a focus on leaf-based diseases as opposed to overall plant size. Diseases such as russet are major dangers to cotton leaves. On the other hand, disease prevention is critical in tomato agriculture since it affects output, quality, and production costs.

Artificial intelligence (AI) and image processing technologies are being used more and more in agricultural research, taking use of tools like the Support Vector Machine (SVM) that can quickly, non- invasively, and accurately diagnose problems. Novel methods utilizing trained convolutional neural networks (CNNs), including Inception ResNet V2 and Inception V3, have demonstrated application in both laboratory and field settings by exhibiting encouraging results in differentiating between healthy and diseased tomato leaves. These technologies not only improve disease diagnosis but also set the stage for integrated systems that can fully address a variety of plant health issues. This paper suggests an intelligent plant leaf recognition model based on the ResNet50 model and Keras neural network architecture to address these complications. With the help of this model, users can input photos of leaves for automatic disease identification, giving them instantaneous feedback on the health of their plants. The system's objective is to facilitate well- informed decision-making in agricultural management by means of user-friendly interfaces and unique prediction methods for tomato and cotton diseases. Administrative features include safe administration of user interactions, feedback aggregation, and dataset access, promoting a cooperative environment for ongoing agricultural practice improvement and advancement. With this integrated strategy, food production in India and abroad may be made more sustainable, agricultural resilience will be strengthened, and economic losses would be reduced.

II. LITERATURE SURVEY

A "Classification of Pomegranate Diseases Based on Back Propagation Neural Network" was proposed by S. S. Sannakki and V. S. Rajpurohit. It primarily operates on the color and texture are employed as features in the process of segmenting the defective area. For the classification in this case, they employed a neural network classifier. The primary benefit is that the image's chromaticity layers can be extracted by converting to L*a*b, and 97.30% of the images are correctly classified. The primary drawback is that it can only be applied to a restricted number of crops[1].

The "Cotton Leaf Disease Identification using Pattern Recognition Techniques" presented by P. R. Rothe and R. V. Kshirsagar uses snake segmentation; here's Hu's Moments serve as a distinguishing feature. Using an active contour model to restrict the amount of energy within the infected area, the BPNN classifier addresses a variety of class issues. It is discovered that the average categorization is 85.52% [2].

"Leaf Disease Detection and Grading using Computer Vision Technology & Fuzzy Logic," by Aakanksha Rastogi, Ritika Arora, and Shanu Sharma. Using K-means clustering divide the affected area; fuzzy logic is used to grade the illness; GLCM is utilized to extract textural information. Artificial neural networks (ANNs) were employed as a classifier, primarily to assess the extent of the sick leaf[3].

Automated Vision-Based Diagnosis of Banana Bacterial Wilt Disease and Black Mold" was proposed by Godliver Owomugisha, John A. Quinn, Ernest Mwebaze, and James Lwasa. Sigatoka Illness Color histograms are taken out and converted from RGB to L*a*b and HSV.Five shape attributes are used, peak components are used to form a max tree, and area under the curve analysis is done for classification. They employed Naïve Bayes, SV classifier, Decision tree, random forest, nearest neighbors, and extremely randomized tree. Randomized trees give very good scores in seven classifiers, offer real-time information, and give the application flexibility [4].

SVM-based Multiple Classifier System for Recognition of Wheat Leaf Diseases," uan Tian, Chunjiang Zhao, Shenglian Lu, and Xinyu Guo. Color features are represented in RGB Seven invariant moments are taken as the form parameter to HIS utilizing GLCM. They employed an offline SVM classifier with MCS to identify illness in wheat plants[5].

talked about a way to identify infections that manifest in cucumber plant leaves. Division of well-being into is achieved by using a statistical pattern identification method to diseased areas. Features such as color, shape, and texture will be taken from within that. The SVM receives those features and conducts the most thorough classification. In his conclusion, he said that the SVM's findings were far superior to those of neural networks. A unique approach for illness identification was proposed by Latha S. et al.[6].

He talked on the K-means and Ottsu Threshold algorithms for the division of the pictures into segments. For the feature extraction, the Color co-occurrence approach and Leaf color extraction utilizing H and B components are covered. And in order to categorize the disorders, he contrasted ANN and BPNN classifiers. According to Abirami Devaraj [7].

the image is segmented using a K-means clustering technique that divides the image into k clusters. That particular cluster member includes a picture that mostly shows the unhealthy portion. He used the laborious and intricate Random Forest Classifier to categorize illnesses. SujaRadha[8].

suggested a technique to determine the leaf's damaged area. K-means clustering is the technique used for segmentation. She employed Support Vector Machine (SVM) for disease classification, as it has a higher dimensional input space than the other classifiers. S. Yun [9] .

A feature descriptor for object detection is HoG . The object's look and the image's contour are described in this feature descriptor as defined by the gradients of its intensity. The fact that HoG feature extraction works with the generated cells isone of its benefits [10].

III. METHODOLOGY

This the endeavor's technique combines machine learning, image processing, and UI design to provide a complete system for the identification of illnesses in cotton and tomato leaves. This multimodal method creates a workable solution for early disease diagnosis in agricultural settings by fusing cutting-edge technologies in machine learning and image processing with the concepts of user-centric design.

figure1 describes the architecture for illness image detection.

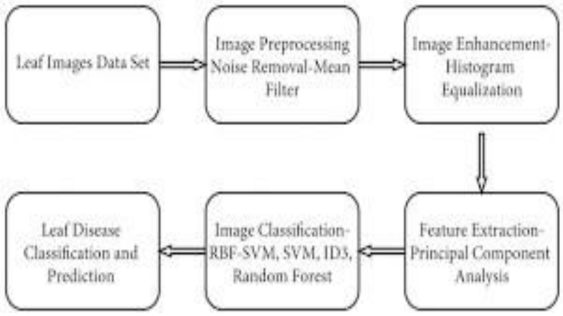

Figure 3.1: Architecture Diagram

The system seeks to equip farmers and agricultural practitioners with tools that optimize crop management and boost overall agricultural productivity by utilizing cutting-edge CNN models with anintuitive interface.

1. Data Collection:

To start the study, a variety of datasets with pictures of cotton and tomato leaves in both healthy and diseased states are gathered. These datasets provide the basic information needed to train and assess the machine learning models.

2. Pre-Processing:

To standardize size, improve contrast, and lower noise, preprocessing techniques are applied to the gathered leaf images. Through this preprocessing stage, the uniformity, consistency, and optimization of the input data fed into the machine learning models are ensured for subsequentanalysis.

3. ML Model Development:

Leaf images are classified into healthy and ill categories using two pre-trained convolutional neural networks (CNNs), Inception V3 and Inception ResNet V2. These models are refined with the use of the pre-processed datasets, which help them identify the distinct traits connected to various leaf situations.

4. User Interface Design:

To make it easier for users to engage with the system, an intuitive user interface (UI) is created. Through the interface, which has buttons to start the prediction process, users can upload photographs of leaves. Furthermore, the interface offers the ability to differentiate between cotton and tomato leaf diseases, guaranteeing customized disease detection capabilities.

5. Integration and Testing:

To facilitate the smooth processing of uploaded leaf photos, the machine learning models are seamlessly incorporated into the user interface. Based on the integrated models, users obtain estimates regarding the health status of their leaves. To ensure strong performance across all scenarios and datasets, extensive testing is carried out to verify the precision and dependability of the prediction results.

3.1 DATASET USED

Images of both healthy and sick tomato and cotton leaves are the main datasets used for training and testing intelligent plant leaf disease detection systems. These datasets provide the basic knowledge needed to train machine learning models to distinguish between various leaf states. These datasets are frequently obtained from publicly accessible sites like PlantVillage and Stanford, which provide substantial collections of plant photos labeled with disease information. Specialized datasets that may concentrate on certain crop types or the incidence of diseases in a given areaare also contributed by research institutions and agricultural research programs. To ensure applicability to actual agricultural circumstances, researchers frequently work with farmers or conduct field surveys to collect bespoke datasets. These datasets go through a thorough preparation procedure to improve clarity, standardize image formats, and eliminate discrepancies.

3.2 DATA PRE PROCESSING

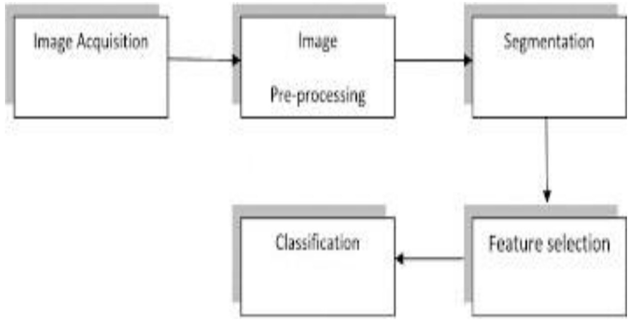

Figure 3.2: Flow chart for data preprocessing

1. **Getting an Image:** Leaf photos are obtained from a number of sources, such as publically accessible databases, controlled conditions, and field studies.
2. **Standardization of Images:** To guarantee consistency across the collection, resize photos to a standard size (256 × 256 pixels, for example). This stage guarantees compliance with model specifications and streamlinesworkflow.
3. **Normalization:** To promote quicker convergence during model training, normalize pixel values to a similar scale (e.g., [0, 1] or [-1, 1]). Normalization improves model stability and lowers computingcomplexity.
4. **Improvement in Visual Clarity:** Utilize methods like noise reduction, contrast enhancement, and sharpening to enhance image clarity and draw attention to important details. By taking this step, the model's capacity to distinguish minute variations between

healthy and diseased leaves is improved.

5. **Annotation and Labelling:** Based on professional diagnosis or annotation from datasets, assign labels to each image that represent its appropriate class (healthy or diseased). To effectively train supervised learning models, accurate labeling is essential.
6. **Dividing the Sets into Training and Validation:** To evaluate model performance during training and avoid overfitting, split the dataset into training and validation sets. Usually, 20% of the data is used for validation and 80% is used for training.

3.3 ALGORITHM USED

A particular kind of deep learning algorithm called a Convolutional Neural Network (CNN) is made especially for processing and evaluating visual data, including photos. Multiple layers make up CNNs, which use input images to automatically and adaptively learn the spatial hierarchies of various attributes. The main parts of CNNs are pooling layers, which shrink the spatial dimensions of the feature maps while preserving crucial information, activation functions like ReLU, which introduce non-linearity by converting negative values to zero while keeping positive values, and convolutional layers, which apply filters to the input image to detect features like edges and textures. The final feature maps are flattened into a single vector following multiple rounds of convolution, activation, and pooling. This vector is then fed through fully connected layers in order to identify high-level patterns and generate predictions. Typically, a softmax activation function is used in the final output layer to generate probabilities for various classifications, such as healthy or diseased leaves. Using labeled datasets, CNNs are trained, and the network's parameters are changed using optimization algorithms to reduce prediction errors. With proper training, CNNs can reliably identify novel images, which makes them ideal for applications such as diagnosing illnesses in plants.

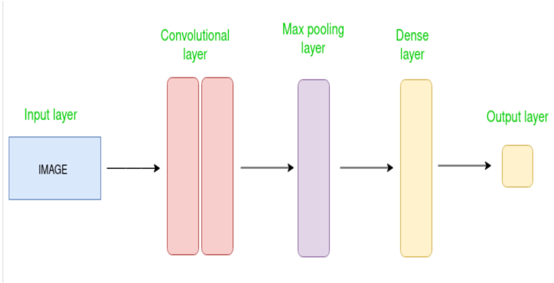

Figure 3.3:Simple CNN Architecture

Algorithm for Using a Convolutional Neural Network (CNN) To Detect Leaf Diseases:

1. **Image input:** Begin with a picture of a leaf.
2. **Convolution:** To scan the image and find essential elements, apply filters.
3. **ReLU Initiation:** To make all negative numbers equal to zero, use ReLU.
4. **Combining:** Minimize the feature map's dimensions while preserving crucial data (e.g., by taking the maximum value in each small region).
5. **Again:** To understand more complicated features, repeat steps 2 through 4 more times.
6. **Flatten:** Create a single 1D vector from the completed collection of feature maps.
7. **Completely Networked Layer:** Using a fully linked layer, run the vector across to identify patterns and arrive at a conclusion.
8. **Training:** To reduce errors, use labeled images to change the network's

settings. To increase the accuracy of the model, iterate over a large number of photos.

9. **Prediction:** To obtain a forecast, feed a fresh image of a leaf into the trained model (e.g., whether the leaf is healthy or diseased).

3.4 TECHNIQUES USED

Through the analysis and interpretation of visual data, machine learning techniques are essential for the detection and categorization of leaf diseases. The Support Vector Machine (SVM), a supervised learning model that can identify images based on extracted characteristics, is one well-known technique. In order to maximize the margin between data points of distinct classes, SVM finds the best hyperplane in a high-dimensional feature space to divide classes. Because of this, SVM is very useful for binary classification jobs and can be easily adjusted to multi-class problems using techniques like one-vs-all or one-vs-one. K-Nearest Neighbors (K-NN), a straightforward yet effective classifier that assigns a class to a given data point based on the majority class of its nearest neighbors in the feature space, is another often used approach.

3.5 MECHANISM USED

1. **SVM(Support Vector Machine):**
   In order to classify images, SVM, a supervised learning model, determines the optimal boundary (hyperplane) between various classes. It can handle both binary and multi-class classification and performs best when there are distinct boundaries between classes.

2. **K-NN(K-Nearest Neighbors):**
   K-NN is a basic classifier that determines a new data point's class by looking at the most prevalent class among its 'k' nearest neighbors. It is based on the notion that comparable data points are probably members of the same class and is simple to apply.

IV. RESULT AND DISCUSSION

4.1 GRAPHS

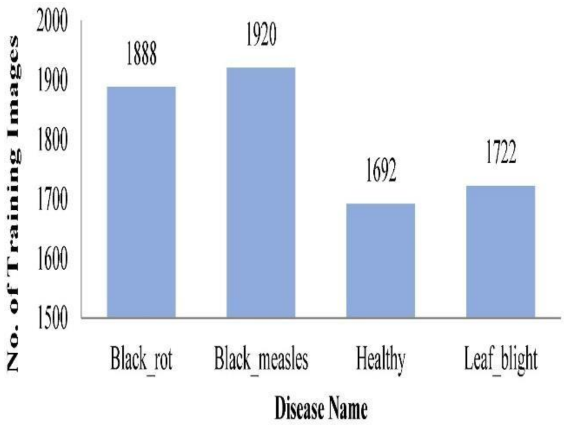

Figure 4.1:Diseases of Leaf illness

4.2 RESULT

The identification and categorization of tomato and cotton leaf diseases produced encouraging results with the use of the intelligent plant disease detection system. By using pre-trained convolutional neural networks (CNNs) like Inception ResNet V2 and Inception V3, the system was able to identify between healthy and diseased leaves with a high degree of accuracy. Early testing on a variety of datasets showed that the models performed well, accurately identifying common diseases such as russet in cotton and a variety of fungal infections in tomatoes.

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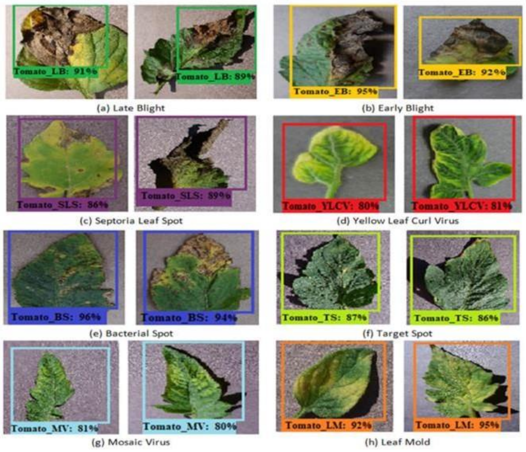

Figure 4.2.1: Detected image of single class in multiple position

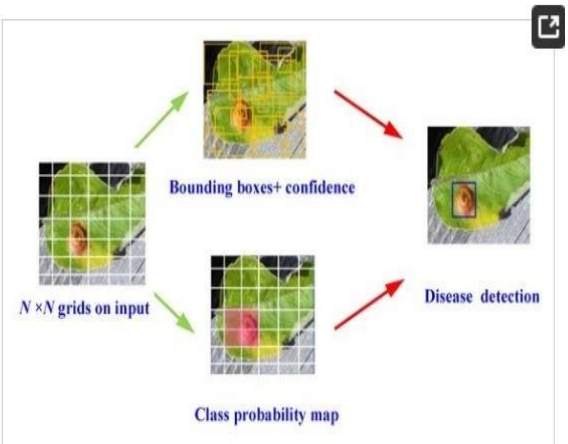

Figure 4.2.2: Leaf illness Detection

Farmers and other agricultural professionals might input leaf photos and get real-time disease predictions with this user-friendly interface. Early user testing feedback emphasized how user-friendly the system is and how useful its diagnostic features are in real-world situations. Farmers valued the quick report on the health of their leaves, which allowed for prompt interventions to stop the spread of illness and improve treatment plans. The system's potential to transform disease management techniques was also highlighted in conversations with agricultural specialists. The approach encourages sustainable agriculture practices while simultaneously improving crop output and quality through the incorporation of cutting-edge technologies into routine farming activities. The system is being updated and refined continuously to increase its accuracy and broaden its disease detection capabilities in a wider range of agricultural contexts. These updates and improvements are based on user input and current research. In general, the intelligent plant leaf disease detection system is an important advance in agricultural technology, providing a scalable response to manage crop yield, prevent disease outbreaks, and assist food security programs in India and beyond. It will be essential for researchers, farmers, and software developers to keep working together to optimize the system and make sure it works well in a variety of agriculturalenvironments.

V. CONCLUSION

In summary, India's agricultural sector has advanced significantly with the introduction of the intelligent plant leaf disease detection system. The system efficiently identifies illnesses in crops like cotton and tomatoes at an early stage through the use of cutting-edge technologies like machine learning and intuitive interfaces. High accuracy in distinguishing between healthy and diseased leaves has been demonstrated by the incorporation of CNN models such as Inception V3 and Inception ResNet V2, giving farmers timely knowledge to safeguard their crops and increase yields. Positive user feedback has emphasized the system's usability and useful advantages in actual farming situations. Experts believe it has the ability to completely change the way diseases are treated, promoting environmentally friendly farming methods and guaranteeing food security. Future updates will concentrate on enhancing user interfaces and adding additional crop varieties to the system's repertoire of features. The system works with researchers and farmers to continue improving the resilience and efficiency of agriculture in India and abroad.

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