Android Application for Plant Diseases Management (Cotton Plant)

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Abstract--- Cotton is the most important cash crop in India. It is also known as "White Gold" or "The King of fibres" among all cash crops in the country. About 80-90% of the diseases which occur on the leaves of cotton are Alternaria leaf spot, Cercospora leaf spot, Bacterial blight, and Red Spot. This paper presents a survey of the detection and classification of cotton leaf diseases. It is difficult for human eyes to identify the exact type of leaf disease which occurs on the leaf of the plant. Thus, in order to identify cotton leaf diseases accurately, the use of image processing and machine learning techniques can be helpful. Different segmented images will be used for extracting the features such as colour, shape, and texture from the images. At last, these extracted features will be used as inputs for the classifier.

Keywords: Machine learning, CNN, Python

I. INTRODUCTION

Cotton is a significant cash crop in India, commonly known as "White Gold" or "The King of Fibres". However, the growth of the plant in fields is often obstructed by numerous diseases, such as Alternaria leaf spot, Cercospora leaf spot, Bacterial blight, and Red Spot. The identification and diagnosis of cotton leaf diseases are essential to take timely measures to prevent further crop damage. The use of image processing and machine learning techniques can be helpful in accurately identifying cotton leaf diseases. These techniques can extract features such as color, shape, and texture from segmented images, which are then used as inputs for classification. In this regard, different machine learning algorithms, such as Convolutional Neural Networks (CNN) and Support Vector Machines (SVM), can be employed to classify and identify diseases like bacterial blight, Alternaria, and others.

In India, agriculture is a valuable source of economic development, and agriculture industries are continually searching for efficient methods to protect crops from damage. The identification of diseases in crops is crucial to ensure high productivity and prevent economic losses for farmers and agricultural industries. The proposed work aims to develop an efficient diagnosis system that focuses on leaf disease identification by processing acquired digital images of leaves of the plant. The study seeks to measure the extent to which diseases affect plants, specifically plant leaves, and aims to detect and identify diseases on a plant leaf, quantify them, and provide necessary measures for curing them. The study utilizes image processing techniques, pre-processing methods for image enhancement, and feature extraction from the region of interest to accurately detect and identify diseases on the plant leaf. The paper is organized into five sections, which discuss the introduction, literature survey, methodologies, results, and conclusion and future scope of the study

A. Present theory and practices

Artificial Intelligence is revolutionizing the field of agriculture, providing a boost to crop production and improving real-time monitoring, harvesting, processing, and marketing. One practical application of AI in agriculture is image-based insight generation, where drone-based images assist in crop monitoring and field scanning, and can be combined with PC vision innovation and IoT for quicker actions. This technology can produce ongoing climate alarms for farmers [22]. Another application is disease detection, where image sensing and analysis ensure that plant leaf images are segmented into surface areas like background, diseased area, and non-diseased area of the leaf [11]. The infected or diseased area can then be harvested and sent to the laboratory for further diagnosis.

Field management is another area where AI is making a significant impact in agriculture. High-resolution images from drone and copter systems enable real-time estimations during cultivation by creating a field map and identifying areas where crops require water, fertilizer, and pesticides. Additionally, crop health monitoring using remote sensing techniques, including hyperspectral imaging and 3D laser scanning, is essential in constructing crop metrics over thousands of acres of cultivable land [2].

B. NEED

The proposed plant disease diagnosis system serves the farming community to improve their crop productivity by correctly classifying the disease type being occurred. The system is developed to detect plant disease. This project is meant to detect diseases on a leaf. Plant disease not only reduces their products but also deteriorates their variety and their withdrawal from cultivation. The use of pesticides and fungicides in excess for the treatment of such diseases increases the danger of toxic residue levels on agricultural products and has been identified as a major contributor to groundwater contamination [14]. Again, farmers incur much loss due to the cost of these pesticides as applied on plant.

C. Problem statement

Plant diseases have turned into a dilemma as it can cause significant reduction in both quality and quantity of agricultural products. Automatic detection of plant diseases is an essential research topic as it may prove benefits in monitoring large fields of crops, and thus automatically detect the symptoms of diseases as soon as they appear on plant leaves. The proposed system is a software solution for automatic detection and classification of plant leaf diseases. The application is made to detect the disease of the plant and then provide the preventive measures to cure it

II. PROJECT METHODOLOGY

This project aims at designing an application which is capable of detecting the pests/diseases from the medicinal plants and gives the user the analysis or percentage of damage occurred to the plants using deep learning and the preferred data. I. To enhance the given input image by Image acquisition and Image pre-processing. ii. Identify the affected part through texture analysis and Segmentation. iii. Classify the healthy and affected leaf part by feature extraction and classification. iv. Train the model by using testing data for accurate results. A. Deep Learning Convolutional neural network (CNN) Model: CNN may be a prevalent demonstration within the field of profound learning. The convolutional neural network model is composed of an input layer, convolution layer, pooling layer, full connection layer and output layer. CNN is more productive since it diminishes the number of parameters which makes it distinctive from other profound learning model

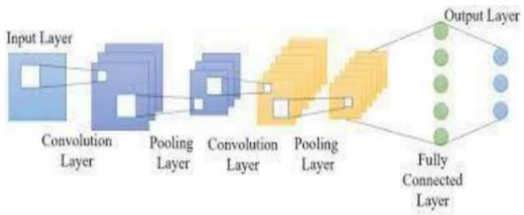

Figure 1: CNN Layers

Proposed System:

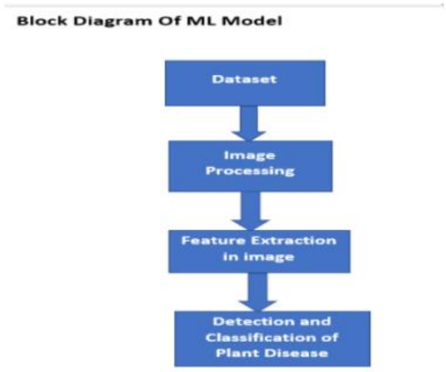

Figure 2: Block Diagram of ML Model

III. DESIGN APPROACH

A. Model preparation

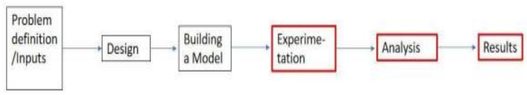

Figure 3 : Process Layout

1.Design:

1. System Architecture: The system architecture of the Android application involves three main components: the user interface, the image processing module, and the backend server. λ User: The user has to upload the picture or can click the picture from phone's camera for disease detection. λ Image processing: For image processing we have used machine learning method. Inception V3 is used that is one of the types of CNN that is used in the model. λ Back end: The picture that is uploaded is then processed by the model and then the required action is taken place. The result will be shown on the screen detecting the disease. λ Data Collection: For data collection we have done a field visit and have collected real life pictures from the field for training of the model. λ Data Pre-processing: The collected data must be pre-processed to prepare it for use in the model. As the data was not sufficient, we have used data augmentation for it. We have used CNN for processing of data. λ Feature Extraction: The next step is to extract relevant features from the pre-processed images. For this we have used Inception V3 algorithm.

2. Building Model:

λ Model Training: After selecting an algorithm, the model must be trained using the pre-processed and feature-extracted datasets. This involves splitting the datasets into training and validation sets, and then iteratively adjusting the model parameters until the validation accuracy reaches a satisfactory level. λ Model Evaluation: Once the model is trained, it must be evaluated on a separate test set to assess its performance on unseen data. This involves calculating metrics such as accuracy, precision, recall, and F1 score, and comparing them to the results of other models or benchmarks. 2. Experimentation: We have used real life data. As the data is not that much sufficient, we have used data augmentation method. We have spilted each picture in different angles and positions to increase the data. And also, with the help of the expert we have segregated the data into each disease and then we have trained the model.

1. Analysis:

Analysis in the cotton plant disease detection android application project involves evaluating the performance of the developed model, interpreting the results of the experimentation, and identifying areas where the model needs improvement. The results of the analysis can help to refine the model and improve its effectiveness in detecting cotton plant diseases. As we are using Resnet50 Transfer Learning Algorithm, because Resnet50 has over 23 million trainable parameters. To be more accurate for disease prediction we tried applying Resnet50 along with InceptionV3 and Resnet152v2 Transfer Learning Algorithms. Comparing the accuracy of the 3 algorithms, Resnet152v2 has the highest accuracy. But due to high time complexity we will be using Inception V3. Inception V3 gives accurate time complexity as it is required for our project

5. RESULT AND DISCUSSION

5.1 Confusion matrix A confusion matrix is used to evaluate the performance of our artificial intelligence (AI) model in detecting cotton plant diseases. In our case, the AI model is typically trained on a dataset of images of healthy and diseased cotton plants and is then used to classify new images as healthy or diseased. However, the rows and columns have been labelled as "Actual Healthy" and "Actual Diseased", and the entries would be the number of images classified as healthy or diseased by the model.

	Predicted Healthy	Predicted Diseased
Actual Healthy	Number of correctly classified healthy images	Number of healthy images incorrectly classified as diseased
Actual Diseased	Number of diseased images incorrectly classified as healthy	Number of correctly classified diseased images

The performance of the model is evaluated using several metrics derived from the confusion matrix, such as accuracy, precision, recall, and F1 score. Accuracy is the proportion of correctly classified images (TP + TN) out of the total number of images. Precision is the proportion of correctly classified diseased images (TP) out of all images classified as diseased (TP + FP). Recall, also known as sensitivity, is the proportion of correctly classified diseased images (TP) out of all actual diseased images (TP + FN). The F1 score is the harmonic mean of precision and recall.

By analysing the confusion matrix and the associated metrics, we have identified areas where the model needed improvement, such as reducing the number of false positives or false negatives, which can be achieved by fine-tuning the model using additional training data or adjusting the model's parameters.

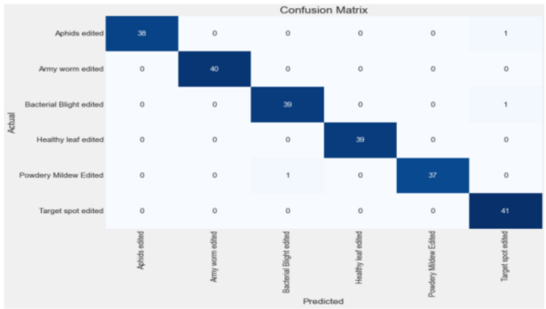

Fig 4: confusion matrix

In summary, a confusion matrix is a useful tool for evaluating the performance of an AI model in detecting cotton plant diseases. It provided a detail breakdown of the model's performance, which is used to improve the accuracy and effectiveness of the model 5.2 Training and validation analysis Training and validation analysis is an important part of developing an artificial intelligence (AI) model for cotton plant disease detection. It involved training the model on a dataset of labelled images, and then evaluating the model's performance on a separate validation dataset

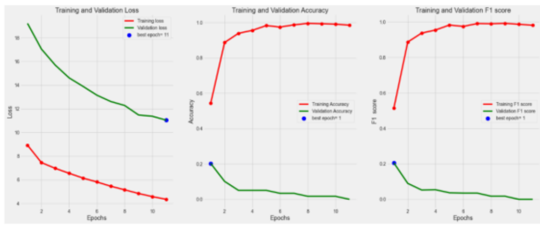

Fig 5 : Traning VS validation graph

The training dataset was used to train the model to recognize patterns in the images and make accurate predictions about whether the cotton plant was healthy or diseased. During training, the model was presented with a set of input images, and the corresponding output labels were used to adjust the model's internal parameters. This process was repeated multiple times until the model's accuracy on the training dataset reached a satisfactory level. After training, the model was evaluated on a separate validation dataset to assess its generalization ability. The validation dataset was separate from the training dataset and contained images that the model had not seen before. The performance of the model was evaluated using metrics such as accuracy, precision, recall, and F1 score. If the model's performance on the validation dataset was not satisfactory, it was necessary to adjust the model's architecture, hyper parameters, or training process. This could involve tweaking the number and size of the layers in the model, adjusting the learning rate, or adding regularization techniques such as dropout or weight decay. Once the model's performance on the validation dataset reached a satisfactory level, it could be used to make predictions on new, unseen images of cotton plants. However, it was important to continue to monitor the model's performance over time and retrain the model as needed to maintain its accuracy.

IV. RESULT AND DISCUSSION

1. Diseases predicted by CNN and remedial action are suggested.

2. The suggestion of pesticides and insecticides for the diseases predicted using model is done by CNN.

3. The best fit CNN algorithm for better prediction is Inception V3 as its time complexity is low and has good precision.

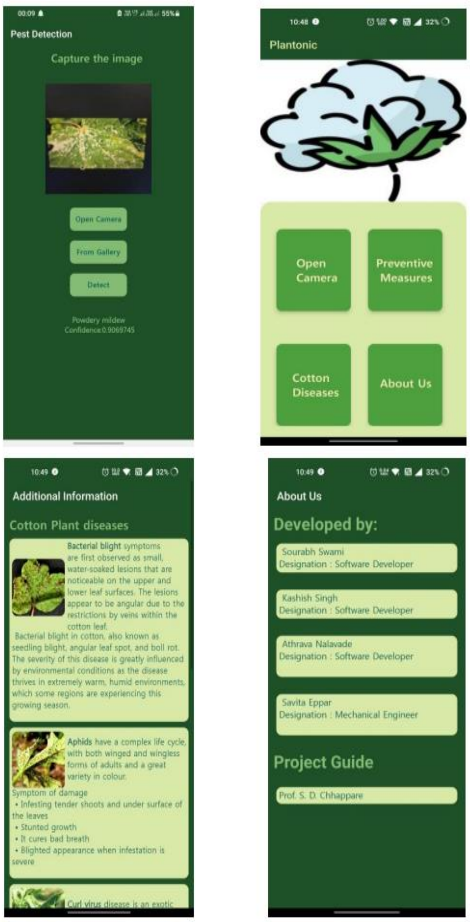

Figure 6 : App Images

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