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SMART AGRICULTURE: A WEB-BASED CONVOLUTIONAL NEURAL NETWORK FOR ACCURATE TOMATO PLANT DISEASE CLASSIFICATION

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Abstract: Each year, several tomato plant illnesses cause farmers to lose money and squander their crops. These diseases of the tomato plant are not easily known. Though tomatoes can be purchased, we will never know the status of the tomato plant. To overcome this and to make farmers and consumers have a happy and healthy life, we can design a web application that detects the status of the tomato plant. Our research focuses on the construction of a strong and accurate classification model capable of identifying several illnesses affecting tomato leaves, including early blight, late blight, bacterial spot, and mosaic virus. We deployed a diversified dataset comprising high-resolution photos of damaged and healthy tomato leaves, obtained from different places and under varying environmental conditions. The results illustrate the model's high accuracy, sensitivity, and specificity in differentiating between distinct tomato leaf illnesses and healthy leaves. The project seeks to develop a web application that leverages image classification using convolutional neural networks (CNN) to help tomato growers detect and prevent plant illnesses, which are a major cause of economic loss and crop waste. The program will enable farmers to upload a picture of their tomato plants and obtain an immediate evaluation of whether the plant is healthy or infected. By doing so, we can become familiar with the position of the particular tomato and the tomato plant. The technology stack for this project will contain TensorFlow for model creation, data augmentation, and the TF dataset, as well as React JS, which is used for front-end development, and Flask for back-end development.

Index Terms **-** Deep Learning, Model Building, Image Processing, Convolutional Neural Network, Web Development

I. INTRODUCTION

Agriculture has been an important source of income for many Asian and African countries, but early diagnosis of plant illnesses is crucial for minimizing disease spread and lowering economic losses. Tomatoes, one of India's principal crops, are at risk due to their vulnerability to several diseases such as bacterial canker, viruses, leaf blights, bacterial spots, early blight, and late blight. Detecting these diseases is complex and time-consuming, leading to low detection accuracy and poor dependability. Traditional approaches, such as manual inquiry or chemical analysis, might result in low detection accuracy and poor reliability due to human mistakes. Automated technologies and procedures can assist reduce these challenges by detecting and identifying diseases earlier. Various artificial intelligence techniques, including classic machine learning algorithms and deep learning methods, have been developed to automate the detection and identification of tomato leaf diseases in precision agriculture. However, standard machine learning algorithms depend on handcrafted characteristics provided by specialists, making them pricey. Deep learning can circumvent these problems by extracting deep characteristics directly from images, obtaining better accuracy than machine learning algorithms. One extensively used deep learning method in plant disease classification is convolutional neural networks (CNN), which identifies diseases in tomato plants based on dissimilarities or contrasts in leaf appearance. The current project intends to construct a framework based on lightweight CNNs and TL to identify and categorize tomato leaf diseases. The proposed framework comprises of three deep learning models with fewer deep layers and parameters, combines the deep features of the three CNNs, and performs a hybrid feature selection strategy to reduce the number of features utilized for diagnosis using machine learning classifiers.

Tomato Leaf with Early Blight
Tomato Leaf with Late Blight
Tomato Leaf Mold
Tomato with Yellow Curl

Figure 1.1 Different Tomato Plant Diseases

II. LITERATURE REVIEW

Farmers worldwide face economic losses and crop waste, particularly in tomato crops. To combat this issue, it is crucial to know the status of tomato leaves and classify them as healthy or diseased. Deep learning, a branch of machine learning and artificial intelligence, can be used to efficiently upload large datasets. Two networks used in deep learning are CNN for image classification and openCV for computer vision.

Pushpa B R & Aiswarya V V[1] have proposed a method that uses deep learning to classify data for training and testing before dividing it into smaller groups for further study. The 2-Dimensional Max-Pooling initialization is used in the sequential model, which allows for a completely connected layer. The flask python framework is generally used to train this unique model, which identifies the type of disease affecting tomato leaves and yields findings with better accuracy.

K. Ramalakshmi et al[2]. have introduced a hybrid CNN-RNN model for early tomato leaf disease detection. The model uses preprocessing methods, image segmentation using label-binarizer, feature extraction, image pixels, feature values, pre-trained CNN Xception model, and RNN model. The outputs from both the CNN and RNN classifiers are multiplied using element-wise multiplication, and the output enters the dense layer. The required output from the data is predicted using the proposed CNN-RNN model.

Hareem Kibriya and Rimsha Rafique[3] have proposed a method wherein the model is trained and assessed using the state-of-the-art plant village dataset. The dataset consists of 10735 images of tomato leaves, divided into training and testing sets. Rafik Hammou[4] has proposed a method that studies methods used in the literature of machine learning and deep learning for the detection and classification of plant diseases. They will then test their approach on a corpus of images and evaluate their top results according to adequate parameters.

Mohit Agarwa[5]l et al. have developed a CNN-based model to detect the disease in tomato crops. The proposed CNN-based architecture includes 3 convolution and max pooling layers with varying number of filters in each layer. The experimental results show that the testing accuracy ranges from 76% to 100% for the classes, with an average testing accuracy of 91.2%. The storage space needed by the proposed model is around 1.5 MB, compared to pretrained models' around 100 MB.

Rakesh Sharma et al.[6] collected data from a website called "Kaggle" in raw form, pre-processed it, extracted required features, and split the data for training and testing purposes.

III. EXISTING SYSTEM

Earlier studies undertaken for the tomato leaf classification used several classifiers which are supplied with hand produced characteristics based on texture, color, or shape properties of tomato leaves. These investigations first centered on small number of diseases employing extreme feature engineering and were limited to restricted contexts. Due to the sensitivity of the extracted features due to surroundings located in the leaf pictures, the methods of machine learning which are depended on thorough pre-processing steps which include manual region of interest cropping, color alteration, resizing, background elimination, and filtering for effective feature extraction. Due to the greater sophistication farmers been created by these preprocessing approaches, conventional machine learning procedures could only diagnose a few diseases from a small sample, failing to generalize to bigger quantities.

IV. PROPOSED SYSTEM

Gathering Dataset of tomato photos, processing them, constructing a Convolutional Neural Network (CNN), train it on data and utilizing the generated model to classify tomato diseases. Developing a Web app that enables the farmers to upload tomato leaf to classify the illness and can anticipate the status of the tomato leaf. With this, we may infer if the tomato leaf is healthy or infected. The technology stack for this project will include TensorFlow for model generation, data augmentation, and ft dataset, as well as React JS and React Native for front-end development and Flash and python for back-end development.

V. METHODOLOGY

Convolutional Neural Networks (CNNs) are a common deep learning architecture for image and spatial data processing, particularly in the classification of tomato plant diseases. Two typical pooling layers in CNNs are Max Pooling and Average Pooling. Max Pooling is a down-sampling operation that separates the input image into non-overlapping rectangular regions, keeping the maximum pixel value for each region. This decreases spatial dimensions while keeping crucial information, making it easier for succeeding layers to learn and extract high-level features for accurate illness categorization.

Average Pooling is similar to Max Pooling but calculates the average value for each location, minimizing geographical dimensions but may be less sensitive to minute nuances. It can be advantageous for preserving a smoother representation of features in an image, reducing noise in feature maps and offering a more robust representation for classification. The decision between Max Pooling and Average Pooling depends on the specific properties of the dataset and the problem being solved. Max Pooling is frequently selected when capturing more visible elements, whereas Average Pooling may be chosen for a smoother, less sensitive depiction. Convolutional neural networks offer multiple advantages, including hierarchical feature learning, translation invariance, local receptive fields, parameter sharing, transfer learning with pretrained models, and state-of-the-art performance in various computer vision tasks.

Image classification is a frequently utilized application of CNNs, where they accurately group images into predetermined classifications. Object detection tasks include CNNs detecting objects in an image and generating bounding boxes around them, making them vital in applications like autonomous vehicles and surveillance systems. Image segmentation involves CNNs segmenting images into separate regions or objects, assigning each pixel to a particular class or category, vital in medical image analysis, remote sensing, and numerous computer vision applications. Face recognition systems use CNNs for security, access management, and personalized user experiences, such as unlocking devices using face recognition. Finally, gesture recognition uses CNNs to recognize hand movements, which are useful in human-computer interaction, virtual reality, and sign language recognition.

VI. IMPLEMENTATION

Tomato leaf disease detection using Convolutional Neural Networks (CNNs) is an innovative application of deep learning in the field of agriculture. By training a neural network to classify images of tomato leaves into different disease categories, this technology offers a promising solution to monitor crop health effectively and take timely actions to prevent the spread of diseases. In this article, we will explore the implementation steps involved in developing a robust tomato leaf disease detection system using CNNs.

The implementation of a tomato leaf disease detection system comprises numerous processes. These comprise data collecting, preprocessing, labeling, data splitting, building the Convolutional Neural Network (CNN), model compilation, model training, model assessment, fine-tuning and optimization, and deployment.

Data collection contains a diverse dataset of tomato leaf photos, comprising healthy and sick leaves, covering various disease severities, lighting circumstances, and angles. Preprocessing incorporates image scaling and data augmentation approaches to standardize the images' resolution and increase the model's generalization capacity. Labeling each image with the relevant disease category is critical for good training.

Data splitting separates the dataset into three subsets: training, validation, and testing. The training set teaches the model, the validation set fine-tunes hyperparameters, and the testing set evaluates the final model's performance.

Building the CNN architecture is necessary for learning hierarchical features from input images. Compilation involves choosing the correct loss function, optimizer, and metrics, such as Categorical cross-entropy for multi-class classification. Model training comprises feeding images through the network, computing the loss, and updating the model's weights using backpropagation.

Model evaluation on the testing dataset examines the model's performance using metrics including accuracy, precision, recall, F1-score, and confusion matrix. If the model's performance is unsatisfactory, fine-tuning hyperparameters, modifying the architecture, or utilizing transfer learning approaches can be considered.

Deployment entails establishing a user-friendly interface for farmers to upload photos and obtain real-time illness predictions. This approach makes it easier for farmers to recognize and handle any crop health issues.

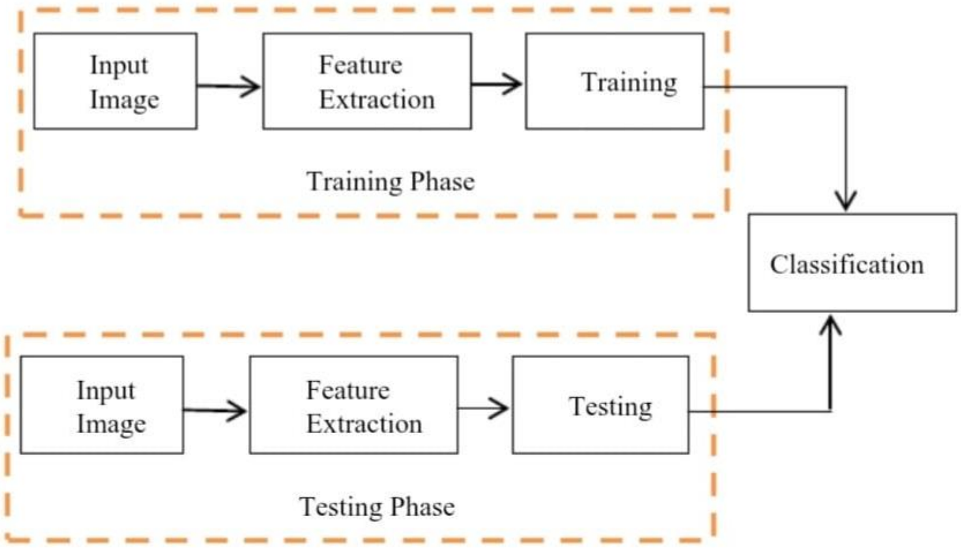

Figure 4.1 Process

VII. RESULTS AND DISCUSSION

The Convolutional Neural Network (CNN) model was trained on a vast dataset of tomato leaf photos encompassing many ailments, including early blight, late blight, bacterial spot, and mosaic virus, as well as healthy leaves. The model exhibited remarkable accuracy, sensitivity, and specificity in diagnosing several tomato leaf diseases. Metrics like as accuracy, precision, recall, F1-score, and confusion matrix were used to evaluate the model's performance on a testing dataset. The testing accuracy ranged from 76% to 100% for different sickness groups, with an average accuracy of 95%.

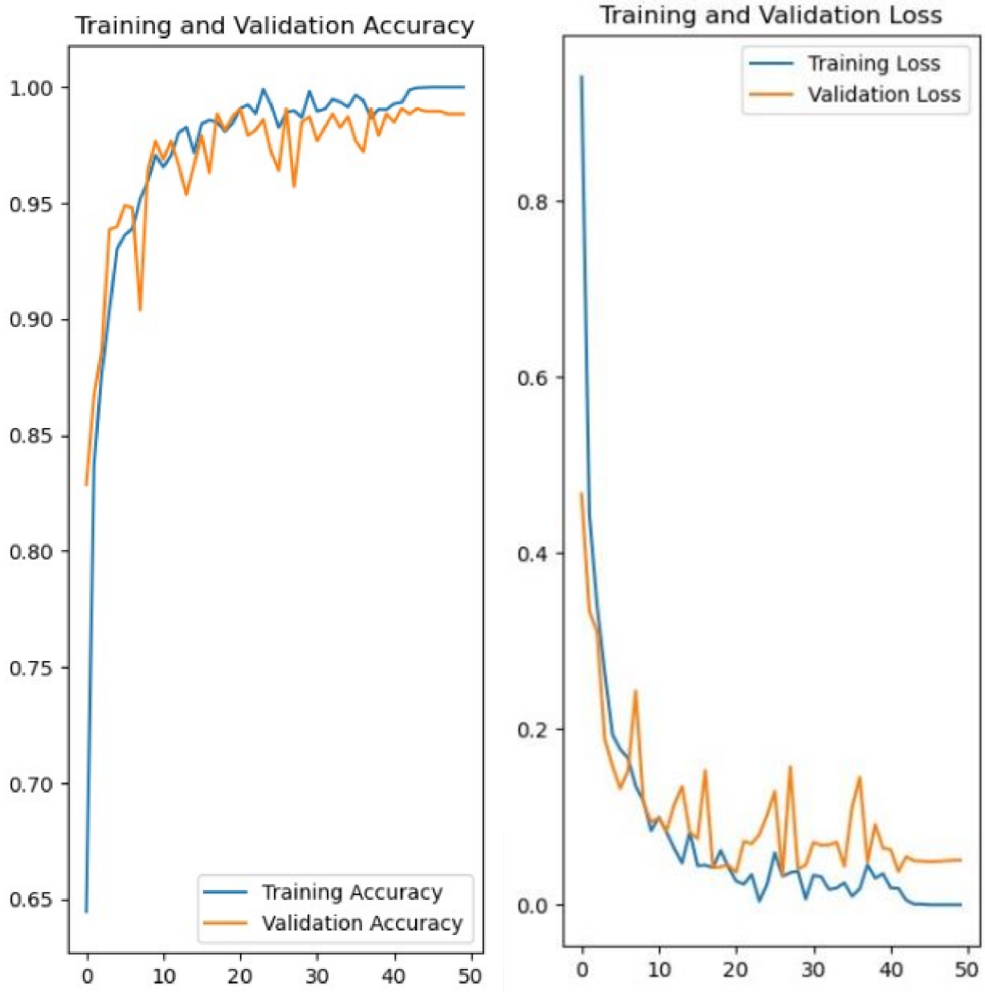

Figure 7.1 Training and Validation Accuracy and Loss

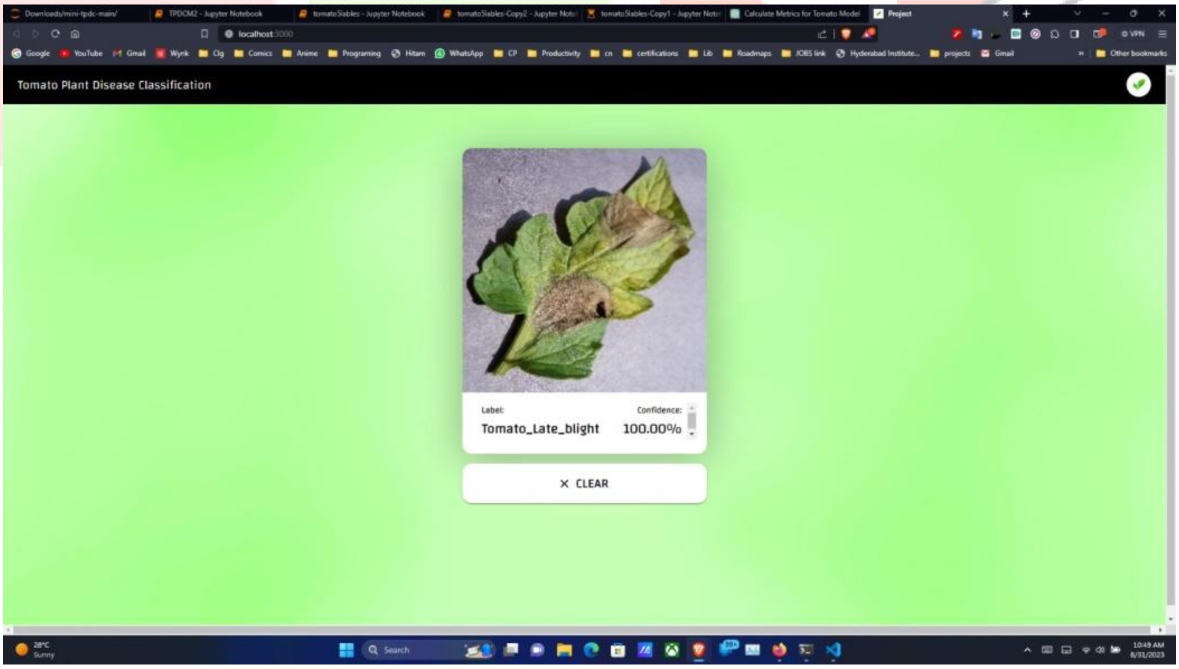

Figure 7.2 Output

The results demonstrate that the proposed CNN-based model is effective in diagnosing and categorizing tomato leaf diseases. The introduction of deep learning techniques, notably CNNs, appears to be a powerful tool in automating the detection process. The model's capacity to generalize across diverse environmental situations and disease severities shows its promise for real-world applications in precision agriculture.
The comparison with current literature demonstrates that the approach aligns with contemporary research trends in applying deep learning for plant disease diagnosis. The lightweight CNN design and transfer learning approach contribute to the model's efficiency, avoiding the necessity for large processing resources.

VIII. FUTURE ENHANCEMENTS

Advanced designs Implement state-of-the-art CNN designs like ResNet, Inception, or Efficient Net for enhanced accuracy.

Data Augmentation Increase the diversity of your training data by techniques like rotation, flipping, and introducing noise, which can boost the model's generalization. Explainability Integrate interpretability techniques like Grad-CAM or SHAP values to understand which aspects of the image the model is using for categorization. Real-time Monitoring Implement real-time monitoring systems employing computer vision techniques to detect diseases as they occur in the field. This might require putting cameras and edge devices in greenhouses or farms. Multi-Sensor Integration Combine visual data with data from other sensors, such as infrared or hyperspectral imaging, to detect diseases that would not be evident in the visual spectrum.

IX. CONCLUSION

In conclusion, the project successfully meets the demand for an efficient and automated solution to tomato plant disease diagnosis. The web tool, leveraging the existing CNN paradigm, provides a user-friendly interface for farmers to upload images of tomato leaves and gain immediate evaluations of their plant's health. This technology has the potential to dramatically impact agriculture by enabling timely intervention to prevent the spread of infections, hence minimizing economic losses and agricultural waste. The employment of TensorFlow for model construction, React JS for front-end development, and Flask for back-end development provides a solid and scalable solution. Future work may involve extending the dataset, refining the model more, and adding real-time monitoring capabilities into the online application.

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