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Tomato Leaf Disease Detection

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Abstract: Agriculture is the backbone of nations, and safeguarding crops from diseases is vital for food security. This research focuses on tomato, a quintessential crop present in various culinary forms, emphasizing the importance of disease prevention for maintaining quality. This article presents an innovative approach utilizing Machine Learning algorithms for early prediction and detection of tomato plant leaf diseases. A curated datasets was prepared, and operations such as feature extraction and rigorous testing were performed on it using eight diverse machine learning algorithms

Keywords: machine learning algorithm, disease prevention, feature extraction

I. INTRODUCTION

Due to serious tomato leaf diseases that could affect tomato production, India's tomato output has been steadily declining over time. Many tomato growers experience a sharp decline in their yield and revenue as a result. Farmers will be able to use pesticides and other medical equipment to sprinkling medicines over plants and protect their crops from diseases in the early stages of production if they are aware of the plants that are diseased and infected at an early stage of growth. By submitting images of tomato leaves, this project will assist farmers in differentiating between fresh and diseased tomato leaves. We have applied machine learning ideas in this project.

II. LITERATURE SURVEY

A. Nadra Ben Romdhane, Hazar Mliki, Mohamed Hammami (2016), "Improved signature authentication and tracking methods for driver assistance", IEEE/ACIS 15th International Conference on Computer and Infor mationSciences(ICIS).

Multilayer deep neural network (DNN) improves driver assistance's ability to recognize traffic signs. To achieve this goal, the method proposed in this study uses the robust DNN. Deep learning techniques are often used in computer programming because they can eliminate complex pattens. The system is divided into two phases: analysis and discovery; Among them, colour recombination is used in the detection phase.

B. Hassan, S.M.; Maji, A.K.; Jasinski, M.; Leonowicz, Z.; Jasińska, E. Identification of Plant-Leaf Diseases Using CNN and Transfer Learning Approach. *Electronics* 2021, *10*, 1388.

Timely detection and prevention of crop diseases is important for increasing crop yield. This paper uses a counterrevolutionary neural network (CNN) model to detect leaf lesions and leverages the success of CNNs in machine vision. Depth separation convolutions replace standard convolutions to reduce parameters and computational costs. Using data from 14 plants sand 38 organisms, the study model achieved greater accuracy than traditional methods. Optimized testing parameters such as batch size and throughput. The accuracy of InceptionV3, InceptionResNetV2, MobileNetV2, and EfficientNetB0 is 98.42%, 9.11%, 97.02%, and 99.56%, respectively, outperforming other models with short training time. MobileNetV2's compatibility with mobile devices is obvious. These results show that deep CNN models have great potential, especially in identifying these kind of disease in real time.

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C. Early Disease Classification of Mango Leaves Using Feed-Forward Neural Network and Hybrid Metaheuristic Feature Selection Pham, T.N.; Tran, L.V.; Dao, S.V.T.

Plant diseases pose a major threat to food security worldwide and impact agriculture by affecting crop quality. Traditional diagnostic methods based on visual inspection are unreliable and defective. Our research focuses on early detection of leaf disease using artificial neural networks (ANN), focusing on minor disease that require solutions. After processioning using contrast, infected areas are segmented and their representatives are selected using a wrapper based algorithm. When we compare our ANN method with CNN models such as Alex Net, VGG16 and ResNet50 developed with adaptive learning, our method outperforms simple network models (89.41% vs 89.41%, 78.64%, 79.92% and 84.88% respectively). This shows that our method is suitable for low-end devices such as smartphones, which will benefit farmers in the field.

III. EXISTING SYSTEM

Tomato leaf disease detection systems typically involve manual inspection by farmers or agriculture Tomato leaf disease detection systems typically involve manual inspection by farmers or agricultural experts, which can be time-consuming and prone to errors. Some existing systems may utilize basic image processing techniques or simple machine learning algorithms to automate the process to some extent. However, these systems often lack accuracy and efficiency due to limited computational power and reliance on simplistic algorithms.

DISADVANTAGE

- Limited accuracy
- Lack of real time monitoring Inefficient resource allocation

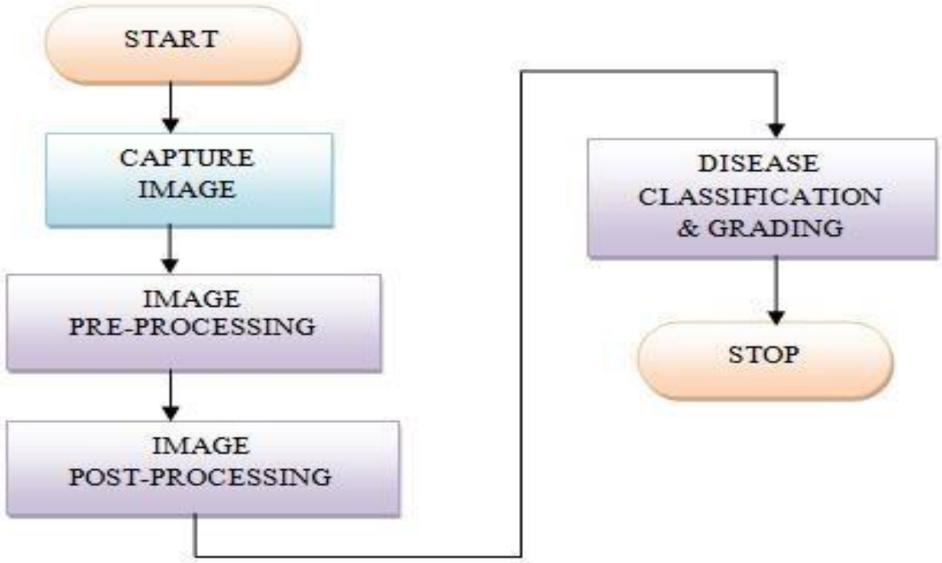
IV. PROPOSED SYSTEM

A proposed system for tomato leaf disease detection could leverage advanced machine learning techniques, such as deep learning, and incorporate technologies like computer vision and IoT (Internet of Things) for improved accuracy and efficiency. By employing convolutional neural networks(CNNs) and other DL techniques, the system can analyze large volumes of tomato leaf images rapidly and accurately.

ADVANTAGES

- Early detection
- Enhanced accuracy
- Resource optimization

V. METHODOLOGY



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VI. DATASET

There are fourteen different kinds of crops in the Plant Village dataset, which may be accessed by the public and was obtained from Kaggle. The tomato leaf was our choice for this project. This tomato crop dataset consists of ten distinct classes. One of them is a healthy class, while the other nine are disease classes.

VII. IMAGE PREPROCESSING

Before training the model, Image pre-processing was used to alter or improve the raw images that the CNN classifier needs to process before training the model. An effective model must be constructed by examining both the network's architecture and the input data's format. In order for the suggested model to extract the relevant features from the image, we pre-processed our dataset. The image was initially resized to 256 × 256 pixels and its size was normalized. The pictures were then converted to grayscale. For the explicit learning of the training data feature, a significant amount of training data is needed at this pre-processing stage

VIII. DATASET SPLIT

The dataset is split into three sections for the purpose of assessing the CNN model's performance: training, validation, and testing data. Testing data is used to assess the model's performance on unidentified data, reference data is used to adjust hyperparameters, and training data is used to train the model. Three groups comprise the data: 80% of the photos are in the training data, 10% are in the application data, and 10% are in the testing data.

IX. CONVOLUTIONAL NEURAL NETWORK

A convolutional neural network (CNN) is a type of neural network widely used for image and video analysis, recognition, and processing. It is designed to extract important details from the raw pixel data of images, enabling it to recognize objects, faces, shapes and patterns. Inspired by facial recognition, CNNs consist of layers that perform calculations on input data. Master elements include layers, and outer layers. Convolutional layers use filters to detect patterns in the input image and create an image. The combination method subsamples the specification map to check the matching and is usually followed by ReLU to detect irregularities. Finally the layer all performs some preprocessing to classify the image, making CNNs crucial for image recognition.

X. ALGORITHM

Step 1: Bring in the required libraries.
Step 2: Configure the input settings, including the batch size, image size, and class number.
Step 3: Preprocess the photos and load the dataset
Step 4: Describe the architecture of the CNN model.
Step 5: Use several epochs to train the CNN model.
Step 6: Assess the model's performance and save it using.h5 layout
Step 7: Reload the model and forecast the pictures of tomato leaves.

XI. RESULT

Initially, the model was trained with various input image sizes, ultimately settling on a size of 128 × 128 for optimal performance. Despite differing image ratios in the dataset, efforts were made to balance it by ensuring 300 photographs per class. Training was done using a split ratio of 70:30 for training and testing. The CNN model underwent training for 100, 200, and 300 epochs, with the highest accuracy and lowest loss observed at 300 epochs, as depicted in Figure 5.1. Overall, the model demonstrated superior accuracy and minimal loss during both training and validation at 300 epochs.

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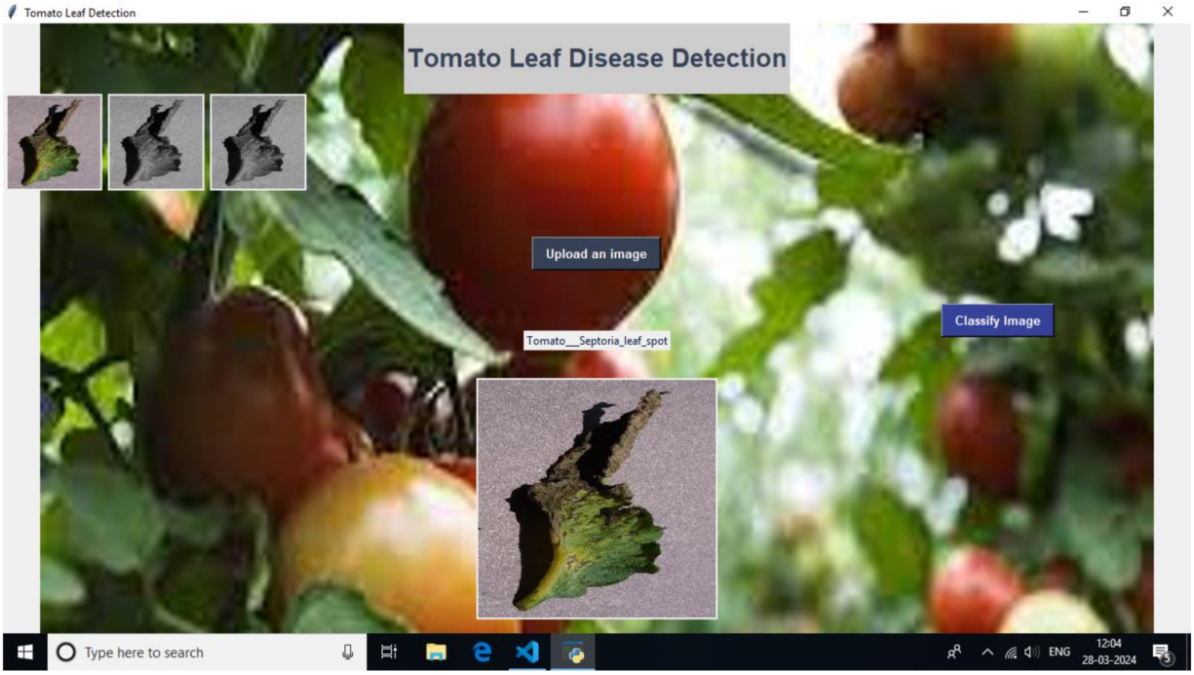

XII. CONCLUSION

The study focuses on deep learning for detecting and categorizing tomato leaf diseases, comparing it with transfer learning techniques like ResNet152, VGG19, and InceptionV3. The CNN model achieved impressive results, boasting a training accuracy of 98% and a testing accuracy of 88.17%. This accuracy aids farmers in effectively managing tomato plant diseases, potentially increasing crop yields and profits. The authors aim to expand the model to detect diseases in other crops, demonstrating a commitment to ongoing research and improvement in plant disease detection.

XIII. FUTURE ENHANCEMENT

Real-time disease detection: The current project used per-captured images of tomato leaves for disease detection. In the future, the system can be designed to detect diseases in real-time using a camera attached to a robotic arm that moves around the tomato plants. This would enable early detection and treatment of diseases, thus improving crop yields and reducing losses.

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