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Tomato Leaf Disease Detection

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Abstract :Plants are a major source of food for the world population. Plant diseases contribute to production loss, which can be tackled with continuous monitoring. Manual plant disease monitoring is both laborious and error-prone. Early detection of plant diseases using computer vision and artificial intelligence (AI) can help to reduce the adverse effects of diseases and also helps to overcome the shortcomings of continuous human monitoring. In this study, we have extensively studied the performance of the different state-of-the-art convolutional neural networks (CNNs) classification network architectures i.e. ResNet18, MobileNet, DenseNet201, and InceptionV3 on plain tomato leaf images to classify tomato diseases. The comparative performance of the models for the binary classification (healthy and unhealthy leaves), six-class classification (healthy and various groups of diseased leaves), and ten-class classification (healthy and various types of unhealthy leaves) are also reported. InceptionV3 showed superior performance for the binary classification using plain leaf images with an accuracy of 99.2.

***IndexTerms*– CNN, Image processing, Disease Detection,Raspberry pi.**

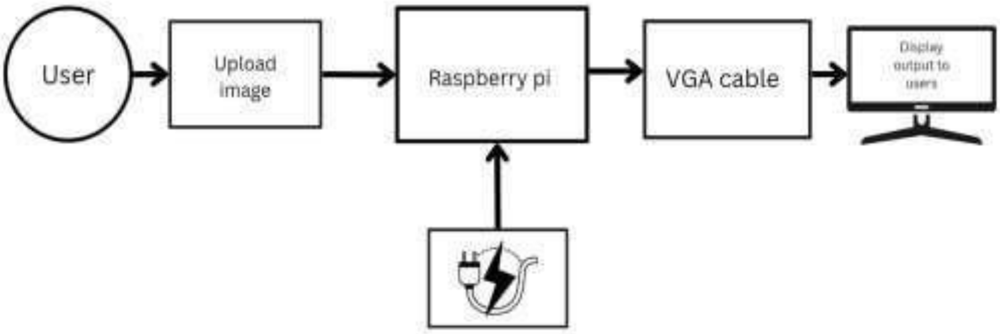
I. INTRODUCTION

For a long time, the agriculture industry has used modern science to meet the food demands of 7 billion people. However, there are numerous threats that people working in the agriculture industry face that threaten the food security of the human society.With the dawn of machine learning models, the early identification of plant diseases has been made much easier, less time consuming and cheaper in comparison to the traditional visual identification of plant diseases.It will help farmers to detect and predict the disease, which will technically benefit in cure and improving production .

II. LITERATURE REVIEW

Machine learning algorithms are applied in various fields, but feature engineering remains the main problem. With the emergence of deep neural network, the promising results are available for plant pathology without laborious feature engineering. Deep neural networks significantly increase the image classification accuracy. This section provides a various deep learning technique used by researchers in plant disease identification. We used AlexNet to train classify plant diseases that were not seen before. Model accuracy was substantially reduced while testing image conditions are different than training image. Sometimes, disease appears on upper sides of the leaves sometime, lower sides of the leaves. Rangarajan et. al., trained both AlexNet and VGG16net with minimum batch size, weight and bias learning rate as hyper-parameters. Accuracy is negatively correlated with minimum batch size in case of VGG16net. Convolution and pooling layers together stacked in a module and applied to GoogleNet architecture as Inception V4 for dimension reduction. Too et al. applied weights that are pre-trained on ImageNet to this architecture average pooling layer of 8×8 for fine tuning. In addition to that DenseNets with 122 layers is also fined tuned for plant disease recognition. Caffe framework is used to develop a CNN with local response normalization for eight class classification. A CNN with local contrast normalization layer is designed for binary classification with ReLu as activation function . AlexNet and GoogleNet are trained and fine-tuned for classification disease regions and symptoms. DeChant et al proposed 3 stage training CNN. In first stage, it learns the presence of lesions while in second stage it produces heat map to identify infection. Finally, features learned from previous stages are classified based on heat maps. Brahimi et al introduced saliency map method for localization of infected regions. This type of visualization improves classification accuracy. Wang et al identified the impact of depth of network on classification accuracy. Even with transfer learning, high classification accuracy is achieved with low number of convolutional layers. Tan et al employed variable momentum rule to CNN for parameter learning from lesions images; that results in quick convergence with comparative good accuracy. Yamamoto et al retrieved detailed images by applying super resolution method over low-resolution method and thus achieved better classification accuracy. Performance of various CNN for plant disease identification depends on various factors: availability of limited number of annotated; poor representation of disease symptoms, image background and capturing conditions; limited variations in disease symptoms.

III. RESEARCH METHODOLOGY



3.1 SYSTEM ARCHITECTURE

The project focuses on tomato leaf disease detection using a Convolutional Neural Network (CNN) implemented on a Raspberry Pi. The process begins with a dataset of tomato leaf disease images, which are fed into the Raspberry Pi. The Raspberry Pi reads each pixel value and converts the images to RGB format for further processing. User feds input image to model trained on raspberry pi which is powered by charger and the output whether the stage is normal, benign or malignant is displayed on users mobile device.

3.2 METHODOLOGY

- **Image processing:**

Image preprocessing techniques are applied to enhance the quality, analyze, and extract information from digital images. Several libraries and frameworks in Python provide comprehensive support for image processing tasks. Some commonly used libraries are PIL(python image library), OpenCV(Open Computer vision), Scikit images , numpy.

Images undergo preprocessing to improve their quality by correcting distortions, reducing noise, and adjusting color balance.

Image enhancement techniques are then applied to improve the visual appearance by adjusting contrast, brightness, and sharpness

.• **Segmentation**:

The tomato leaf images are subjected to segmentation technique. This step involves identifying and separating the infected leaf area from healthy tomato leaf. The result is a segmented image that contains only infected region of tomato leaf.

- **Feature extraction:**

Once the infected region or leaves are segmented, feature extraction is performed on the segmented image. Various techniques and algorithms are used to extract meaningful features from the segmented region. These features capture relevant information about the shape, texture, intensity,color or other characteristics of the leaves.

- **Model training and CNN :**

Model is trained using a machine learning model, CNN a classification algorithm, such as a convolutional neural network (CNN), is applied to classify the tomato leaf into healthy and infected leaves. The CNN model is trained using libraries like TensorFlow and Keras, leveraging the power of deep learning algorithms to learn patterns and identify infected regions in the leaf images.CNNs consist of multiple layers, including convolutional layers, pooling layers, and fully connected layers. . CNNs excel at capturing spatial hierarchies and local patterns in images, making them well-suited for image classification tasks. The network learns to recognize and discriminate between different image features at different levels of abstraction. While training the model we provided a total of 1000+ leaf images where we landed up with 90% model ouput accuracy during training process.

- **Model Output :**

The extracted features are used as inputs to the classification model, which has been trained on a labeled dataset to learn the patterns and characteristics associated with each class. The classification model assigns a probability or confidence score to each class, indicating the likelihood of the image belonging to that category. The model learns the patterns and relationships between the extracted features and the corresponding classes during the training process. The architecture is designed to automatically learn and extract relevant features from input images through the application of convolutional filters. The learned features are then fed into fully connected layers, followed by a final classification layer that outputs the predicted class probabilities.
In the context of Leaf Disease detection using CNN, the CNN model is trained to classify leaf images into healthy and infected leaves.

- **Model Testing :**

Testing the model involves evaluating its performance on a separate set of images that were not used during the training phase. The testing phase helps assess the model's ability to generalize and make accurate predictions on unseen data. The model is used to predict the classes of the test images, and performance metrics such as accuracy, precision is calculated. The results provide insights into the model's ability to classify infected leaf images accurately.

IV. RESULTS

4.1 HARDWARE IMPLEMENTATION

4.2 IMAGE PROCESSING RESULT

V. CONCLUSION

An image processing-based solution is proposed and evaluated in this project for the detection and classification of Leaf Disease.The proposed approach is composed of steps which include image preprocessing, image segmentation, performed features extracted and training and classification.It would also promote Indians farmers to do smart farming which helps to take a timely decisions which also saves time and reduce the loss of fruit due to the diseases to leading objective of our project is to enhance the value of Tomato leaf disease detection.

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