Tomato Leaf Disease Detection Using Deep Learning

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Abstract: The recognition of crop diseases is essential to increase the yield and reduce quantity losses in agricultural by products. Plant diseases pose a significant threat to global food security, yet early detection remains challenging in many parts of the world due to the absence of essential infrastructure. Almost 60 percent of the population is related to any kind of agriculture. The combination of expanding smartphone usage and the breakthrough in computer vision and Image classification driven by deep learning has prepared the path for smartphone or cellphone assisted-illness detection. This research presents a deep learning framework identifying the disease on tomato leaves. By utilizing convolutional neural networks (CNNs), the system extracts distinguishing features from input images and classifies them into one of the multiple classes of diseases. The dataset used for training and evaluation consists of diverse images of different tomato plant leaves with various diseases, collected from different sources. Experimental results demonstrate the model's capability to achieve a 99.38% accuracy on test data, outperforming existing approaches. The proposed approach has the potential to assist farmers and researchers in monitoring the health of plants, enabling them to take timely action to prevent or minimize yield losses due to diseases.

1 INTRODUCTION

India has huge amount of population depending on agriculture. Farmers have different options for picking various acceptable crops and finding appropriate insecticides for plants. Plant disease reduces quality and quantity of farm products significantly which may also lead to damage to the consumers food health. Crop disease research is mainly focused on the examination of visually seen patterns on plants. Monitoring plant diseases is critical for an effective crop production in the farm or for an agriculture industry. In the previous times both plant monitoring, and analysis of it was done manually by a knowledgeable person in agriculture. It requires a significant lot of labour as well as a lengthy processing time. However, to identify plant diseases we can use Image processing technique. This study supports more in focusing on the visibly intended crop quality.

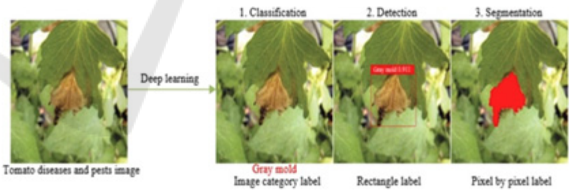

Figure 1: Sample of Tomato disease identification and it's process in deep learning for the identification of the disease.

In most situations, illness signs may be found on the leaves, stems, and fruit. The plant leaf is recommended for disease detection since it displays disease signs. Traditionally recognizing plant leaves disease is a costly process as everything is done by an expert, and hence inadequate for precision agriculture since they need manual examination. To replace these untrustworthy methods of disease diagnosis, research has looked at image processing techniques on plant photos. This study provides an outline of image processing techniques used for plant disease identification. Several conventional machine learning

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methods can be employed for detecting diseases in plant leaves, including Support vector machines known as SVM, random forests. To diagnose the condition and determine its severity, machine learning techniques were also applied.

Traditional machine learning approaches, on the other hand, still depended on extracting crucial characteristics from inputs for training models will be a time- consuming process. Moreover, classical image processing and machine learning were only effective under certain situations. As a result, research in the recent decade began to combine deep learning algorithms that automatically perform feature extraction and produce greater accuracy than previous approaches with less time.

Deep learning can automatically extract characteristics from photographs, it is one of its advantages. Neural networks acquire a knowledge of how to extract characteristics in the preparation time. Convolutional Neural Networks, a type of multi-layer feedforward neural network, are the most well-known deep learning models. CNNs perform clustering by grouping a vast number of image pixels into a smaller number of clusters. However, determining the optimal number of clusters can be challenging, as different cluster sizes can lead to varying types of image segmentation.

For the validation and classification of various plant diseases from leaf images, several partitioning and machine learning techniques have been proposed. These methods have helped address existing challenges, but the next step is to effectively communicate the findings. Enhancing yield efficiency in this sector remains a key objective.

2 LITERATURE SURVEY

Many researchers have focused on developing detection of plant leaf disease. The highest accuracy generated till now for plant leaf disease detection is 99.35%. Plant is one of the most widely used crops the world by providing good nutrition and proteins to our health. plants are affected by various diseases like fungal, viral, and bacterial diseases which in turn affect the plant growth and yield. The disease caused by plants is harming our health. For good health, yield, and plant growth we need to minimize plant disease. To do that we have to predict the detection of plant disease early.

Tiwari, 2020 explores the detection of potato leaf diseases using deep learning models. The study employs a Convolutional Neural Network on a dataset of both healthy leaves and leaves affected by four diseases. VGG16 architecture was utilized for feature extraction, and classification is performed with the use of Support Vector Machine.

Jiang, 2019 is about detection of apple leaf diseases improved Convolutional Neural Networks (CNN) in real-time. The authors proposed an improved version of the CNN for disease detection in apple leaves.

H. F, 2021 is about plant disease detection mobile application development using deep learning. In this study, the author utilized the Faster R-CNN with an Inception-v2 backbone network for the application, achieving an accuracy of 97.9%.

A. Lakshmanarao, 2021 is about plant disease prediction and classification using deep learning ConvNets. ConvNets were applied to three separate datasets, achieving accuracies of 98.3% for potato plants, 98.5% for pepper plants, and 95% for tomato plants in disease detection.

S. Veni, 2021 the use of content-based image retrieval for identifying plant leaves and detecting diseases. They have used various image processing techniques on images of leaves for recognising the leaf plant type and for detecting the disease. Also, the authors utilized two different classification techniques. They are SVM, KNN and compared their performance.

M. Kirola, 2022 presents a plant disease prediction framework: an image-based system utilizing deep learning. The authors employed various machine learning (ML) and deep learning (DL) algorithms, including Convolutional Neural Networks (CNN) for disease prediction in plants. They compared the performance of ML and DL techniques, achieving a 97.12% accuracy with the Random Forest classifier.

P. B, 2021 focuses on classifying plant diseases using deep learning models. The authors utilized a Convolutional Neural Network (CNN) based on the AlexNet architecture. This model was compared to other CNN models based on VGG-18 and LeNet-5 architectures. The study achieved accuracy of 96.76 with CNN model.

S. N, 2022 uses Convolutional Neural Network (CNN) algorithm and linear regression analysis to evaluate model performance. discovered that increasing the number of images leads to higher model accuracy, especially when images have clearer visibility, compared to fewer images.

P. Sudharshan, 2022 utilizes a Support Vector Machine (SVM) classifier to identify specific disease affecting rice plants. The authors identified disorders from their texture, shape and the colour of the rice.

R. G, 2018 employs the Faster R-CNN (F-RCNN) detection model, achieving a confidence level of 80 and an overall accuracy of 95.75%. Also, the authors evaluated the model's accuracy for tomato leaf disease detection using automatic image capturing, resulting in an accuracy of 91.67%.

P. K, 2022 presents a multi-layer deep learning model for detecting potato leaf diseases. The model achieved an impressive accuracy of 99.76%.

Shruthi, 2019 provides a review of machine learning classification techniques for plant disease detection. The authors highlight the use of Convolutional Neural Networks (CNNs), noting their high accuracy and ability to identify multiple diseases in leaves.

K. Aparna, 2018 focuses on weed detection by employing shape and size analysis. For detection of the leaves that are affected they have used thresholding methods.

T. Postadjian, 2018 discusses the effectiveness of Convolutional Neural Network (CNN) architectures in capturing disease-specific patterns from leaf images. Additionally, the paper covers feature extraction techniques such as transfer learning and highlights evaluation metrics used to assess model performance.

S. Ghosal, 2018 encompasses a wide range of Convolutional Neural Network (CNN) architectures, discussing their effectiveness in accurately identifying plant diseases. The paper also explores preprocessing techniques designed to enhance image quality and discusses data augmentation strategies for generating diverse training instances.

Y. Guo, 2020 explores various network architectures, feature extraction methods, and image augmentation techniques used for precise disease classification. The paper discusses the efficacy of these techniques in capturing and extracting relevant features from leaf images.

D. Pujari, 2013 covers various architectures, datasets, preprocessing techniques, and challenges in the plant disease detection. It also discusses popular models like Convolutional Neural Network (CNN) and Recurrent Neural Network (RNN) and their effectiveness in capturing relevant features. It highlights the importance of diverse datasets and explores preprocessing techniques for improving image quality. The review also addresses challenges such as class imbalance, limited labelled data, and interpretability of model predictions.

H. Park, 2017 focuses specifically on deep learning techniques for plant disease recognition. The study provides a complete examination of different network architectures, transfer learning methods, and datasets. The survey highlights the importance of datasets for training and evaluating models in the field of plant disease recognition.

V. Pooja, 2017 employs digital image processing techniques for detecting and classifying plants disease using different classifier and different Convolutional Neural Network (CNN) techniques which improved the accuracy of the model overall.

N. K. E, 2020 utilizes ResNet-50 for pretraining their model, with the implementation developed in PyTorch. The study focuses on six types of diseases and achieved an accuracy of 97%.

Below are the few literature survey questions by that we will review the current state of research on plant leaf disease detection.

I. What are the factors that are affecting the growth of plant leaves and their yield?
   - Soil quality
   - Temperature and light exposure
   - Pesticides
   - Watering technique

II. What are the most common and important pests that are causing damage to the tomato leaves and should be identified early?
   - Early and late blight are most common diseases which are affecting tomatoes.
   - Spider mites, budworm, two-spotted mite, thrips, and caterpillars are the most common pests affecting tomatoes.

III. What is the nutritional content of tomatoes when consumed by humans?
   - The healthy tomato consists of vitamin C, potassium and calcium and many other needful nutrients for the body.
   - Over consumption of tomatoes may result in heartburn and acid reflux which can get even worse if consumed over the limit.

The novelty of this deep learning work is used in search of different self-operated detection techniques of tomato diseases and provide a user-friendly interface and accurate detections rate to the farmers to find the disease in field. The inspection of studies shows the historic progress made in evolution of detection systems based on deep learning, machine learning, hyperspectral imaging, smartphone-based technologies, and cost efficiency detection systems. These systems provide several advantages, including high precision, real-time detection, feasible, and cost efficient. Moreover, these systems have the capability to decrease the spread of diseases, and enlarge crop yields, which gives a better output in improved food security and prosperity.

The use of automated detection for tomato leaf diseases detection aligns with several UN SDGs. By detecting diseases early and accurately, these systems can minimize crop damage and increase yields, thus contributing to SDG 2. The early detection and management of diseases also promotes plant health, ensuring healthy crops and contributing to SDG 3.

3 DATASET DESCRIPTION

The dataset we used have 11600 images of 5 different classes which are Early Blight leaves, Healthy leaves, Late Blight leaves, Leaf Mold leaves and Bacterial Spot leaves. The dimension of every images is 256x256 pixels.

4 PROPOSED SYSTEM

4.1 Preprocessing & Data Augmentation

The collected information known as images may have outlier and unclear images, so we must preprocess them or clean them to build up a model. Comparatively preprocessed or cleaned data will give better accuracy than uncleaned data. Resizing should be done to constant size as the images come from various locations, we must resize the images to maintain consistency. Normalizing the pixel value will make the neural network to learn easily. Data augmentation can also be done it does flip, shifting and changing the brightness on the images. Blurring of image is done to reduce the noise of the image.

4.2 Study of MLP

Disease classification using CNNs was compared to classifications using SVM and MLP algorithms to determine the best method for diagnosing tea leaf illnesses from photos. The latter two classifiers' image features were derived by utilizing the bag of visual words (BOVW) model, which is based on the dense scale-invariant feature transform (DSIFT).

Disease Dataset: Using a Cannon camera, pictures of tea leaf diseases were all taken in Yichang, Hubei province, China, in their natural settings. The photographs had a resolution of 4000 3000 pixels and were taken in auto-focus at around 20cm above the leaves.

The symptoms of seven different diseases, as determined by phytopathologists, were depicted on a total of 3810 photographs. Every image included in the current manuscript was reduced in size to 256 x 256 pixels. We increased the dataset size, which is better for the network's training, to enhance the classifier's generalization capabilities.

4.3 Network Architecture of MLP

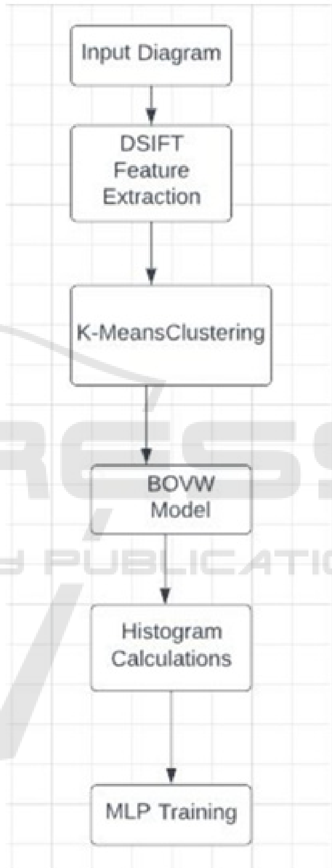

Figure 2: Network architecture of MLP.

The whole dataset is trained and tested using the Multi-Layer Perceptron (MLP) Classifier. The network architecture has six stages as shown below. Classification using MLP network is a common technique used in leaf disease detection. The basic idea is to train a neural network on a set of labelled leaf images (i.e. images with known disease labels) to learn to recognize patterns that distinguish between healthy leaves and with different diseases.

4.4 Study of Convolutional Neural Networks

Convolutional Neural Networks (CNNs) have become widely adopted for detecting leaf diseases, representing a significant application of machine learning and deep learning in agriculture. CNNs possess the inherent capability to autonomously extract relevant features from images through their layered convolutional filters.

Firstly, we gathered high-resolution images of tomato leaves, capturing both healthy specimens and those exhibiting signs of disease. The collected images effectively depict various diseases that impact tomato plants. The images underwent resizing and preprocessing to optimize them for CNN analysis. The CNN model was trained using this prepared dataset, incorporating convolutional, pooling, and fully connected layers. Once trained, the model was tested on a distinct validation dataset to determine its effectiveness in recognizing diseases in plant leaves.

After development and testing, the model is ready for practical use in detecting diseases in plant leaves and it has been highly effective. We have used because it can learn and extract relevant features from images has led to improved accuracy in disease detection compared to traditional methods. Moreover, it can help farmers to identify diseased plants early, preventing the spread of disease and minimizing crop loss.

4.4.1 Architecture of Convolutional Neural Network

The proposed Convolutional Neural Network (CNN) architecture is tailored for accurate detection and classification of tomato diseases. We normalized input images of size 256 × 256 pixels for efficient training. In our model first convolutional layer uses 24 filters with an 11 × 11 pixel kernel and a stride of 2, producing 24 feature maps of size 55 × 55 pixels. ReLU activation introduces non-linearity, followed by a 3 × 3 pooling layer and Local Response Normalization (LRN), reducing the feature map size to 24 × 27 × 27 pixels. The second convolutional layer, with 64 filters and a 5 × 5 kernel, outputs 64 feature maps of size 27 × 27 pixels. Batch Normalization and pooling layers further reduce the size to 64 × 13 × 13 pixels. Subsequent layers utilize 96 filters with 3 × 3 kernels, producing 96 feature maps of size 13 × 13 pixels. The final convolutional layer uses 64 filters with the same kernel size.

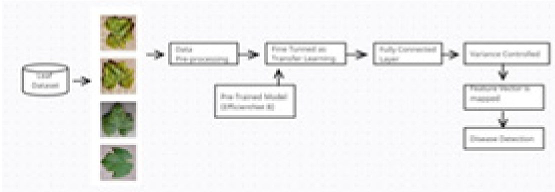

Figure 3: Architecture of Convolutional Neural Network.

Flattened feature maps are passed to a fully connected layer that maps feature to five disease categories: Early Blight, Healthy, Late Blight, Leaf Mold, and Bacterial Spot. A SoftMax layer performs classification. Regularization techniques, including dropout and the Adam optimizer, ensure robust training and prevent overfitting, enabling the model to achieve high classification accuracy.

4.4.2 Training and Validation Plots

The model has been trained on the training dataset of plant leaf images and training accuracy is calculated for it. As the number of training epochs increases, the training accuracy increased as well, as the model become more familiar with the training data and better at predicting its class labels. During the validation phase, we evaluated the model on a separate dataset called the validation dataset. This validation accuracy is calculated and plotted against the training accuracy.

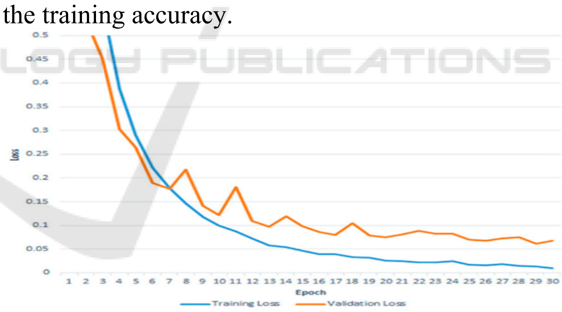

Figure 4: Validation Loss.

By analyzing the training and validation accuracy plot, you can get a better understanding of how well deep learning model is performing and adjust as necessary. By analyzing the training and validation loss plot, you can get a better understanding of how well your deep learning model is performing and adjust as necessary. For example, if the training loss is decreasing but the validation loss is increasing, it may indicate that the model is overfitting, and you may need to apply techniques such as regularization or early stopping to prevent overfitting.

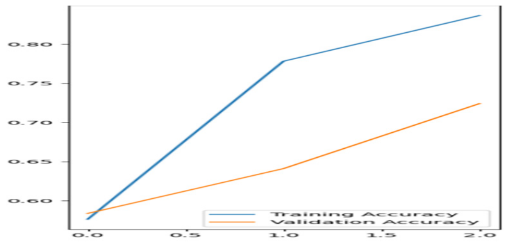

Figure 5: Validation Accuracy.

4.4.3 Classifiers

The classifiers we used are MLP, Support Vector Machine also known as SVM, Random Forest, XGBoost and CNN. In all we got CNN with highest accuracy compared to other classifier models.

4.4.4 Regularization Study

Regularization techniques are used in deep learning to prevent overfitting of the model, which occurs whenever you have an issue like your model is performing well on test data but not on the training data. Then we will use regularization techniques. In deep learning models, overfitting can be a common issue, especially when the model is complex and contains a lot of parameters.

A penalty term is added to the loss function using L1 and L2 regularization approaches, which compels the model to have light weights. As a result, the model's complexity is decreased, which give lower overfitting. Another method, called dropout regularization, reduces the dependency of neurons during training to reduce overfitting by randomly removing certain neurons. Early stopping is applied to terminate training when the model's performance on the validation set ceases to improve, either after a model set number of epochs or when additional epochs yield no further gains.

The study demonstrates that incorporating L1 and L2 regularization enhances the CNN model's performance by mitigating overfitting. Dropout regularization lessens overfitting, which enhances the performance of the model. Similarly, we have used early stopping to prevent overfitting and to end the training process before the model begins to overfit.

Overall, the regularization methods we have used in the study have improved the CNN model's performance on the dataset with encouraging findings. To get the best results, it is advised to combine various strategies, as some of them might be more effective for models and datasets. For deep learning practitioners, regularization techniques are a crucial tool to avoid overfitting and boost model performance.

4.4.5 Optimizers

By using optimization, the loss will be reduced. It is done by adjusting our weights and bias of the trained model. Our training model is trained with image samples similarly it is tested with testing image samples it is done to compare the performance of both the models. We used two optimization techniques as they gave the better results, they are Adam's optimization technique and stochastic gradient technique with k iterations and momentum. By using optimization, the loss will be reduced. It is done by adjusting our weights and bias of the trained model.

As we have many neural networks in this deep learning model optimization techniques are needed to use. The benefit we get by using optimization techniques is that we get a good performance by decreasing the loss function of the training model. In our project all optimizers have achieved almost the same validation and testing accuracy, which is 0.8 so that is a good score for our training techniques. The all-different optimization techniques which we used are stochastic gradient descent technique and Adam. We got the best results for them but there are few other optimization techniques we used which are AdaDelta, RSMProp, SGD, and Adagrad.

Adam's and Stochastic gradient descent optimization techniques stood out for our training model as they gave better results. Adam's optimization technique is the mix of two optimization techniques which are SGD and RMSprop with momentum. In the optimization technique to fit the model to the best weight for the neural network it is updated using backpropagation algorithm.

5 RESULTS

The dataset we used in this study includes leaf images from various plants such as tomato, potato, pepper, and weed. To ensure uniformity, the images underwent preprocessing techniques like resizing and normalization. Both CNN and MLP models were tested, with CNN delivering the highest accuracy of 99.38%, significantly outperforming MLP, which achieved 78%. This superior performance of our model can be attributed to its ability to efficiently capture spatial and visual patterns in images.

Regularization methods such as L1 (48% accuracy), L2 (52% accuracy), and Dropout (45% accuracy) were applied to reduce overfitting and improve generalization. Additionally, several optimizers were tested to enhance model training, yielding the following accuracies: Adam (93.25%), RMSProp (91.34%), SGD (87.45%), Adagrad (89.32%), and Adadelta (74.25%). These optimization techniques we used played a crucial role in improving model convergence and stability.

In conclusion, We have created a user-friendly interface with TKinter GUI which can be easily used by farmers to capture images and the CNN model proved to be the most effective for detecting plant leaf diseases, achieving remarkable accuracy. By integrating advanced regularization techniques and optimizers, the study highlights the potential of deep learning in agricultural applications.

6 FUTURE WORK

In the future, we aim to expand the dataset with more diverse plant species and environmental conditions to improve model robustness. Additionally, integrating multi-disease detection capabilities and severity classification will enhance its utility. Field testing with feedback from agricultural experts will validate the model, paving the way for practical implementation in precision farming.

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