

PLANT LEAF DISEASE DETECTION

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ABSTRACT

During the growth season, several illnesses can affect plants. One of the most significant issues in agriculture is the early diagnosis of plant diseases. Diseases can diminish total yields and farmers' income if they are not identified early enough. Reducing plant diseases and enhancing the quality and yield of food crops can both benefit from early and accurate analysis and identification of plant diseases. Use CNN devised a methodology. This work makes use of 2560 original image dataset and 82,592 augmented images. CNN models have a classification accuracy of 90.07% to 95.3% and can automatically learn features from raw photos. Convolutional neural networks (CNN) and other deep learning techniques can be used to detect plant illnesses.

Keywords: Convolutional Neural Networks (CNNs), Confusion Matrix, Deep Learning, Machine Learning, Disease Prediction, Data Augmentation, Model Comparison.

I. INTRODUCTION

Detecting plant leaf diseases is essential for maintaining healthy crops and ensuring high agricultural productivity. This process involves capturing and enhancing images of leaves to highlight disease symptoms. Advanced techniques like deep learning, particularly Convolutional Neural Networks (CNNs) and Transformer-based architectures, have been employed to analyse leaf images effectively. Data augmentation, which includes transformations like rotation and flipping, enhances the robustness of the models.

Several traditional machine learning algorithms already used to classify leaf disease. This study for combining segmentation techniques and deep learning algorithms together to improve classification results. Image segmentation to mask the images of the potato leaves can produce a better image dataset. Computerized pictures are transformed into different picture sections using the method of image segmentation. This technique is ordinarily utilized to find objects and boundaries in pictures. It is the method of relegating a name to each pixel in a photo such that pixels with the same name share specific characteristics. However, several algorithms for image segmentation are Otsu's Binary threshold algorithm, Contour Detection, and K-means clustering Algorithm.



Fig 1: Tomato-plant-leaf



Fig 2: Pepper bell -plant-leaf



Fig 3: Potato -plant-leaf

We use tomato, potato and pepper bell plant to show common diseases then predict the disease by using CNNs method.

Tomato, potato, and bell pepper plants are all susceptible to a variety of diseases that can significantly impact their health and yield. In tomatoes, common diseases include early blight, which presents as dark spots with rings on lower leaves; fusarium wilt, causing wilting and yellowing leaves; powdery mildew, characterized by dusty white patches; bacterial speck, showing as brown or black leaf spots; and late blight, which creates greasy brown blotches with white mold. Potato plants can suffer from early and late blight as well, with similar symptoms to those in tomatoes, along with verticillium wilt, which causes leaves to wilt and yellow, and black scurf, which manifests as black spots on tubers. Bell pepper plants are prone to mosaic virus, which results in

mottled leaves with yellow and green spots; bacterial spots, causing brown leaf spots and holes; powdery mildew, with white powdery spots; and anthracnose, which appears as sunken, water-soaked spots on the fruit. Effective management of these diseases involves regular monitoring, practicing crop rotation, using resistant varieties, and applying appropriate treatments promptly to maintain plant health and productivity.

II. METHODOLOGY

1. Problem Definition

Objective: Develop a CNN-based system to detect and classify potato leaf diseases.

Scope: Focus on common diseases like Early Blight, Late Blight, and Black Scurf.

2. Data Collection

Image Dataset: Collect a large dataset of potato leaf images, including healthy and diseased leaves.

Sources: Use publicly available datasets, agricultural research institutions, and field data collection.

3. Data Preprocessing

Image Augmentation: Apply techniques like rotation, flipping, and scaling to increase dataset size and variability.

Normalization: Normalize pixel values to improve model performance.

Labeling: Ensure all images are accurately labelled with the correct disease category.

4. Model Selection

CNN Architecture: Choose a suitable CNN architecture (e.g., VGG16, ResNet50) based on complexity and performance.

Transfer Learning: Utilize pre-trained models to leverage existing knowledge and improve accuracy.

5. Model Training

Training Setup: Split the dataset into training, validation, and test sets.

Hyperparameter Tuning: Optimize parameters like learning rate, batch size, and number of epochs.

Loss Function: Use appropriate loss functions (e.g., categorical cross-entropy) and optimization algorithms (e.g., Adam).

6. Testing and Validation

Field Testing: Test the system in real-world conditions to validate its effectiveness.

User Feedback: Collect feedback from farmers and agricultural experts to refine the system.

7. Maintenance and Updates

Continuous Learning: Update the model with new data to improve accuracy over time.

Bug Fixes: Regularly maintain the system to fix any issues and ensure smooth operation.

8. Documentation and Reporting

Documentation: Maintain comprehensive documentation of the development process, model architecture, and usage guidelines.

Reporting: Prepare reports on system performance, including detailed analysis and visualizations

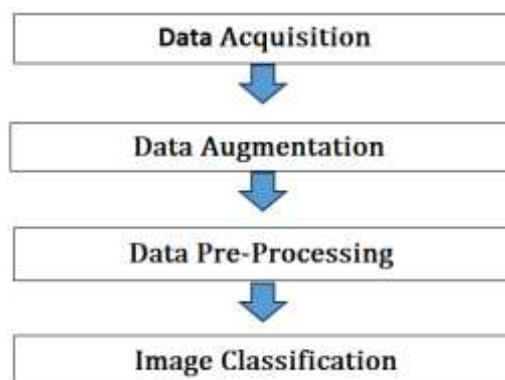


Figure 4: Proposed Methodology

III. MODELING AND ANALYSIS

The process of using a Convolutional Neural Network (CNN) to predict potato leaf diseases. Here's a breakdown of the steps:

1. **Collect Leaf Image:** Images of leaves are collected.
2. **Data Cleaning:** The collected images undergo a cleaning process to ensure quality and accuracy.
3. **Image Segmentation:** The cleaned images are segmented to highlight the areas of interest, such as the leaves.
4. **Split Segmented Dataset:** The segmented dataset is split into a test set (20%) and a train set (80%) to ensure a robust evaluation of the model.
5. **Convolutional Neural Network:** The training set is used to train the CNN model. This step involves learning the features of the leaf images to identify diseases accurately.
6. **Validation:** The model is validated using the test set to check its performance and accuracy.
7. **Evaluate Performance:** The performance of the model is evaluated based on metrics like accuracy and loss.
8. **Disease Prediction:** The trained model is then used to predict diseases in new potato leaf images.

This systematic approach highlights the integration of machine learning into agricultural practices, facilitating early disease detection and effective crop management. By employing advanced techniques like CNNs, farmers can more accurately diagnose and address plant health issues, leading to better yield and productivity.

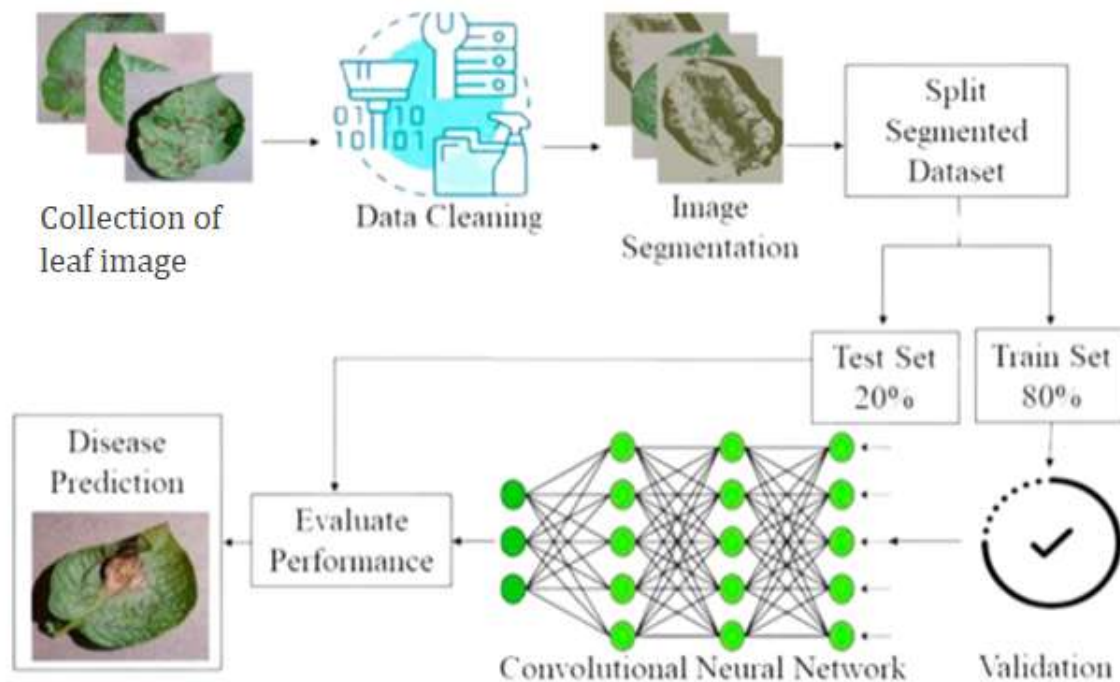


Figure 5: Model Building

IV. RESULTS AND DISCUSSION

The provided image illustrates the performance of a model over 50 epochs, showing both the accuracy and loss during training and validation phases. The training accuracy quickly reaches near-perfect levels, close to 1.0, indicating the model performs exceptionally well on the training data. However, the validation accuracy fluctuates around 0.4 to 0.5, suggesting the model does not generalize well to unseen data, a clear sign of overfitting. The training loss starts very high but rapidly drops to near zero, showing the model effectively minimizes errors on the training set. Conversely, the validation loss remains relatively low and stable, reinforcing the notion that despite the model's excellent performance on the training data, it struggles to accurately predict on the validation set. This discrepancy highlights the need for better regularization or more data to improve the model's generalization capability.

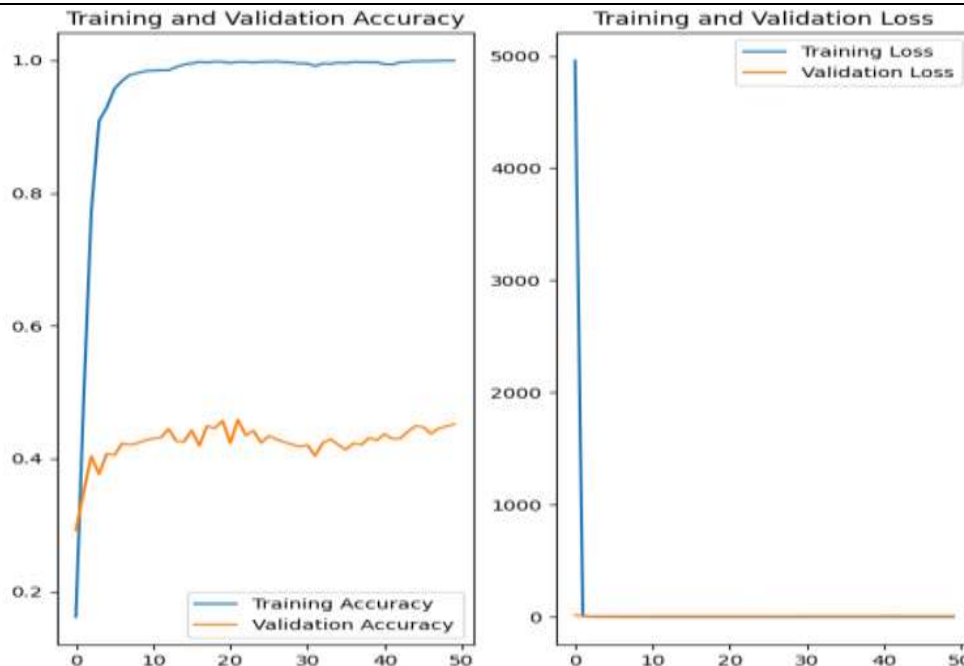


Figure 6: Accuracy and loss count

The image provided shows a leaf suffering from the Tomato Yellow Leaf Curl Virus. The leaf displays characteristic symptoms of this disease, such as curling and yellowing. According to the accompanying text, the model predicted this disease with 100% confidence, matching both the actual and predicted labels as "Tomato_Tomato_YellowLeaf_Curl_Virus." The prediction process took 520 milliseconds per step. This example demonstrates the effectiveness of machine learning models in accurately diagnosing plant diseases, which is crucial for timely intervention and management in agriculture. By identifying the disease early, farmers can take.

Appropriate actions to protect their crops and minimize yield loss

Actual: Potato_Late_blight,
Predicted: Pepper_bell_Bacterial_spot
Confidence: 94.43%



Actual: Tomato_Tomato_YellowLeaf_Curl_Virus,
Predicted: Tomato_Tomato_YellowLeaf_Curl_Virus.
Confidence: 100.0%



Figure 7: Accuracy count and prediction

V. CONCLUSION

Intercropping tomatoes, potatoes, and bell peppers can greatly benefit your garden, enhancing productivity and maintaining plant health. By leveraging the complementary growth patterns of tomatoes and bell peppers, along with the beneficial interactions of potatoes, you can optimize space utilization and reduce pest and disease pressures. Careful planning is essential, including appropriate spacing to prevent resource competition and ensuring support structures for tomatoes. Modern techniques such as statistical modelling, computer simulations, and machine learning can be used to analyse and optimize intercropping strategies, leading to improved crop management. With thoughtful implementation, intercropping these plants can lead to healthier and more productive gardens, benefiting both home gardeners and larger-scale agricultural practices.

VI. REFERENCES

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