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Harvest Guard: Crop Loss Detection Enhanced with Inception-Based Models

SAVITHRA R, DEPT OF COMPUTER SCIENCE, MOUNT CARMEL COLLEGE, BANGALORE 560052 M23CS12@mccblr.edu.in

DR. P BAVITHRA MATHARASI, DEPT OF COMPUTER SCIENCE, MOUNT CARMEL COLLEGE, BANGALORE 560052 P.BAVITHRA.MATHARASI@mccblr.edu.in

***Abstract*—Diseases of plants are a major risk factor for world agriculture, causing severe crop loss and decreased food yields. This paper discusses the usage of deep learning models, that is InceptionV3 and InceptionResNetV2, in plant disease classification using the PlantVillage dataset. Preprocessing methods like the removal of duplicates and blur from images are performed to improve the performance of the model, and then data augmentation is used for enhanced learning. The data is systematically split into training, validation, and test sets to facilitate proper evaluation. Performance of the model is evaluated based on accuracy, precision, recall, and F1-score. The outcomes reveal that data augmentation significantly improves classification performance, with InceptionResNetV2 performing better than InceptionV3 in accuracy. Additionally, visual inspection of training patterns and mistakes gives insight into the strengths and weaknesses of the model. This study showcases the capability of deep learning in early detection of plant diseases and can lead to less crop loss and increased agricultural productivity.**

Keywords-Deep Learning, InceptionV3, InceptionResnetV2, Plant Disease Detection, Data Augmentation, PlantVillage Dataset, Agricultural Productivity.

I. INTRODUCTION

Agriculture is one of the most dominant industries in international food production with crops such as tomatoes, potatoes, and bell-pepper being farmed extensively because of their nutritious and economic properties. These vegetables play a pivotal role in some diets and industry and are valuable contributors to food security and the economy. One of the principal challenges, nonetheless, is that plant diseases is necessary to prevent extensive loss and ensure sustainable agriculture. Treatment differs for each of these types of diseases, and if it is delayed or fails, more loss can be incurred.[1] Conventional methods of disease detection use manual inspection, which may be time-intensive, laborious, and less accurate. To overcome these challenges, scientists are investigating deep learning-based methods for plant disease detection automation with enhanced accuracy and effectively. One of the most communal algorithms in deep learning is the convolutional neural network (CNN)[1] Deep learning models have set outstanding performance in image classification, and therefore they are highly suitable for detecting plant disease. Of these, InceptionV3 and InceptionResNetV2 are commonly employed to extract intricate features of images so that healthy and diseased leaves can be better classified. However, several challenges, such as limited and imbalanced datasets, low- quality images, and model overfitting, can affect the accuracy and reliability of these models. To address these issues, this study applies image preprocessing techniques like duplicate exclusion and blur detection, along with data augmentation methods, to enhance model generalization and performance.

1.1 Research Problem and Significance

This study aims to answer the following research question:

"How effectively can InceptionV3 and InceptionResnetV2 classify plant disease in tomatoes, potatoes, and bell peppers, and how does data augmentation impact their performance?"

The significance of this research lies in its potential to improve early disease detection, helping farmers take timely actions to reduce crop losses and enhance productivity. By leveraging deep learning, this study contributes to the development of automated disease detection systems that can support precision farming, reduce dependency on chemical pesticides, and promote sustainable agricultural practices. This paper is organized into four sections. Section 1 gives related works; section 2 awards the suggested method and outlines the architecture and data augmentation methods employed in aspect. Section 3 provides the results and negotiations that the final section, a conclusion will be presumed, which presents

[1] a summary of the findings from the experiments that have stood carried out.[1]

Comparison: InceptionV3 vs. InceptionResnetV2

Feature	InceptionV3	InceptionResnetV2
Architecture Type	Inception-based	Inception + Resnet
Residual Connections	No	Yes

Depth	~48 layers	~164 layers
Training Speed	Faster	Slightly slower due to deeper architecture
Accuracy	High	Higher than InceptionV3

Table-1: InceptionV3 vs. InceptionResnetV2

Table-1: This comparison highlights the main distinctions between InceptionV3 and InceptionResnetV2, two advanced deep learning architectures widely utilized for image classification tasks, including the detection of plant disease.

II. LITERATURE SURVEY

Several studies have explored the use of deep learning techniques for plant disease classification, focusing on various crops and architectures. Firnando et al. (2024) analyzed InceptionV3 and InceptionResnetV2 for rice leaf disease classification, achieving an impressive 99.53% accuracy on one dataset but significantly lower performance on others, highlighting the challenge of model generalization across datasets. [1] Similarly, Steininger et al. (2023) introduced the CropAndWeed dataset, conducting benchmark experiments using multiple deep learning models. However, the study did not provide detailed accuracy metrics for specific models and tasks, indicating a gap in understanding their effectiveness in different real-world scenarios.[2]

Lambat et al. (2022) focused on plant disease detection using InceptionV3 and achieved a test precision rate of 93%, demonstrating the potential of this architecture for classification tasks. However, the research lacked an analysis of model performance under different augmentation techniques, which is crucial for robustness.[3] Saeed et al. (2023) proposed a CNN-based transfer learning approach for tomato leaf disease detection but reported a comparatively lower accuracy of 50%, suggesting limitations in model training or dataset quality.[4] Meanwhile, Tamble et al. (2023) utilized CNNs for potato leaf disease classification, achieving 99.1% accuracy. However, their study did not consider the impact of data augmentation or cross-dataset validation, which limits its generalizability.[5]

Ahmed et al. (2022) developed a lighter and faster deep neural architecture using MobileNetV2 for tomato leaf disease classification, obtaining an accuracy of 99.30%. While the study highlights efficiently and accuracy, it does not explore model performance in resource-constrained environments or its scalability to other crops.

Despite significant progress in plant disease classification, research gaps remain. Most studies focus on a single crop and do not analyze generalization across multiple datasets or the effect of data augmentation techniques. Furthermore, while some models achieve high accuracy, their performance under real-world conditions, including variations in lighting, background noise, and unseen disease classes, is not extensively studied. [6] Addressing these gaps by incorporating comprehensive data augmentation strategies and multi-crop evaluation can enhance the robustness and the use of deep learning models for classifying plant diseases.

III. METHODOLOGY

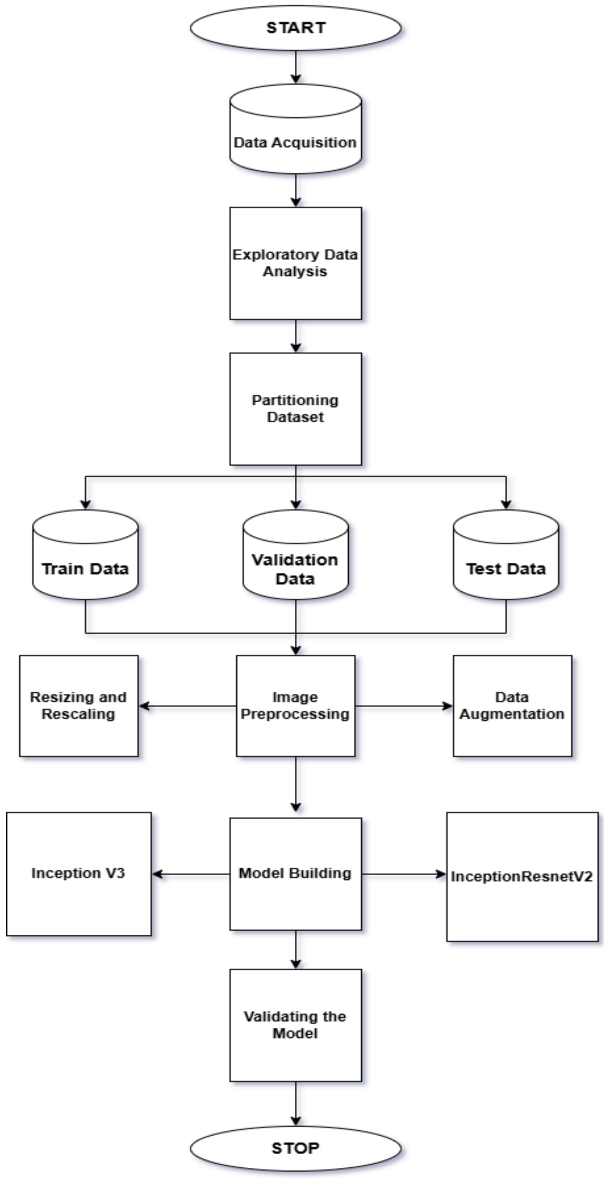

Fig.1: Plant Disease Classification Workflow

Data collections, pre-processing of the data, data augmentation, and disease classification structure the main four stages of the methodology defined in this paper.[5] Fig.1 indications the workflow consists of the following key stages

1. Data Acquisition
   The dataset used in this study is collected from the plantVillage repository, which consists of images of tomato, potato, and bell pepper leaves affected by various diseases. The dataset includes healthy and diseased leaf samples.

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Table.2: Distribution of samples in the dataset

Class Label	Sample Count
Bacterial Spot	3,124
Early Blight	1,000
Late Blight	1,909
Leaf Mold	952
Septoria Leaf Spot	1,771
Two-spotted Spider Mites	1,676
Target Spot	1,404
Yellow Leaf Curl Virus	5,357
Tomato Mosaic Virus	373
Healthy	3,221
Total	**20,787**

This Table.2 represents the distribution of different disease classes in my dataset. Each row indicates a specific plant condition (either a disease or a healthy state), along with the number of images available for that class. The Total row sums up all the sample counts across categories, confirming that my dataset from Kaggle consists of 20,787 images.[7]

2. Exploratory Data Analysis (EDA)
EDA is performed to understand the dataset's characteristics, including:
    - The distribution of images across different classes (healthy vs. diseased)
    - Identifying class imbalances, which may affect model performance.
    - Detecting duplicate or blurred imaged to ensure data quality.[8]

3. Partitioning the Dataset
The dataset is split into training used for training the model, validation helps tune hyperparameters and prevent overfitting and test evaluates the final performance of the trained model on unseen data. The splitting of the dataset for training (78.74%), testing (0.97%) and validation (20.29%) is passed out.[5]

4. Image Preprocessing
This step ensures uniformity in image quality and resolution, which improves model performance. It consists of Resizing and Rescaling involves standardizing image dimensions and normalizing pixel values to ensure consistency across the dataset.[9] Data augmentation is applied through transformations such as rotation, flipping, zooming, and brightness adjustments to artificially expand the dataset and improve model generalization.

5. Model Building
This phase involves utilizing two deep learning architectures, InceptionV3 and InceptionResnetV2. InceptionV3 is a lightweight model designed for efficiency and optimized for faster computations, making it well-suited for scenarios where speed is a priority. In contrast, InceptionResnetV2 is as deeper architecture that integrates residual connections, allowing for improved accuracy by enabling better gradient flow and feature learning. Both models are trained separately on the preprocessed images to learn distinct disease patterns and enhance classification performance.[10]

6. Model Validation
The trained models are evaluated using the validation dataset to fine-tune hyperparameters and prevent overfitting. Their performance is assessed using metrics such as accuracy, precision, recall, and F1- score, ensuring reliable classification. Based on these evaluations, the best-performing model is selected for final testing.

7. Final Model Testing and Conclusion
After validation, the models are testing on the test dataset to evaluate their real-world performance. The study compares InceptionV3 and InceptionResnetV2 based on accuracy, robustness, computational efficiency, and their suitability for real-time plant disease classification.

This workflow ensures a systematic approach to classifying tomato, potato, and bell pepper diseases using deep learning. The results will help in identifying the most effective model for plant disease detection, aiding in early intervention and improved crop health management. [11]

IV. RESULT

1. Presentation of Findings

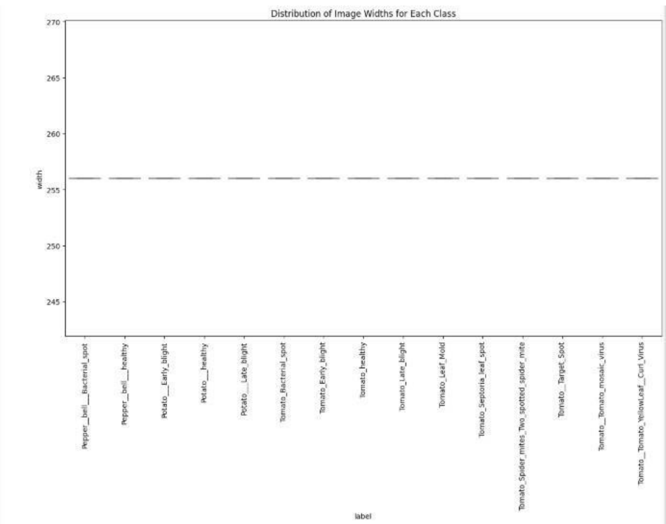


Fig.2: Distribution of Image Widths for Each

Class The above Fig.2 illustrates the distribution of

image widths

across various classes in our dataset. Each class represents a different type of plant disease or healthy conditions, and the x- axis lists these classes. The y-axis represents the width of the images in pixels. The dashed line across the plot indicates that the image widths are consistent across all classes, with a central tendency around 256 pixels. Maintaining uniformity is a crucial step in the data preprocessing pipeline, ensuring that the images are suitable for training robust and accurate machine learning models.

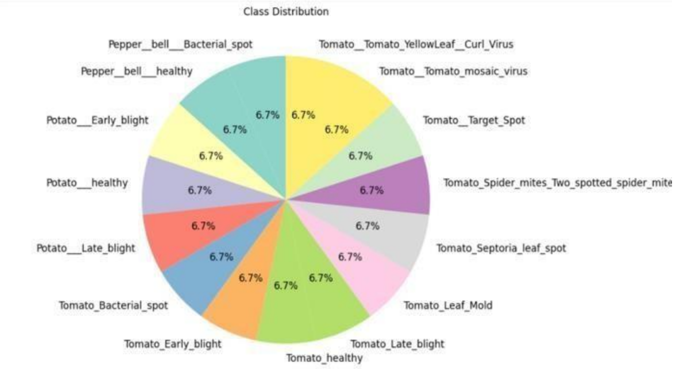


Fig.3: Class Distribution Pie Chart

The Fig.3 displays a pie chart representing the distribution of different classes in a dataset correlated to plant healthy, specifically focusing on various diseases moving peppers, potatoes, and tomatoes. Each segment of the pie chart represents the proportion of each class inside the dataset, with all classes showing uniform distribution at approximately 6.7%. If all categories have equal percentage (6.7%), it suggests:

- Total number of categories = N
- Each category's percentage = 6.7%
- The sum of all category percentages must be 100%:

$$N * 6.7 = 100$$

- Solving for N:

$$N = 100/6.7 = 14.93$$

If all categories have equal distribution, each category's percentage is:

$$\text{Category Percentage} = 100/N$$

Where N is the number of categories.

Verification with 15 Categories

$$100/15 = 6.67 \sim 6.7\%$$

This formula calculates the proportion of instances in a specific class relative to the total instances, expressed as a percentage. This visualization helps in considerate the balance or imbalance in the dataset, which is critical for training machine learning models effectively. A balanced dataset usually aids in better model performance.

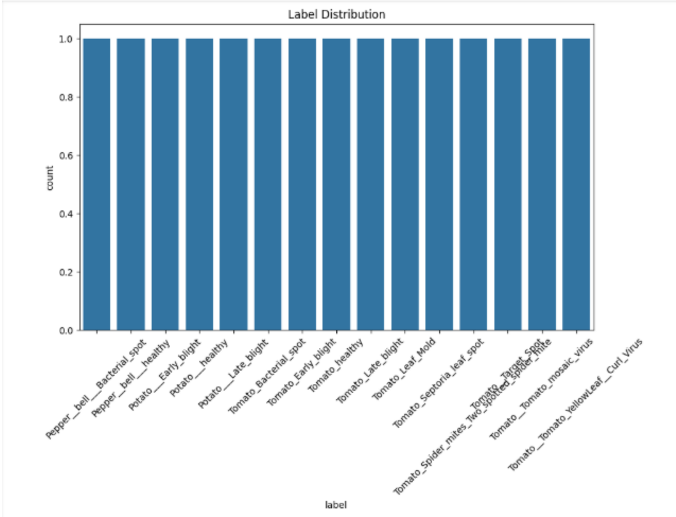
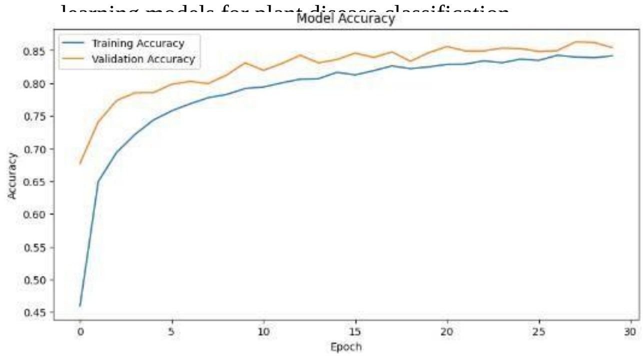


Fig.4: Bar chart depicting the distribution of various labels related to plant diseases.

The bars appear to have relatively uniform heights, suggesting that the labels are evenly distributed in the dataset. Each label has a similar count, indicating a balanced representation of healthy and diseased states for both peppers and potatoes. This visualization helps in understanding how well-represented each category is, which is important for tasks such as training machine learning models for plant disease classification.



In machine learning, accuracy measures how often a model correctly predicts outcomes, calculated as the ratio of correct predictions to the total number of predictions.[12]

$$Accuracy = \frac{Number\ of\ correct\ Predictions}{Total\ Number\ of\ Predictions}$$

Or, in terms of confusion matrix values:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

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Where:

- TP = True Positives (correct positive predictions)
- TN = True Negative (correct negative predictions)
- FP = False Positive (incorrect positive predictions)
- FN = False Negative (incorrect negative predictions)

The Fig.5 shows a line graph comparing the training accuracy and validation accuracy of a machine learning model over 30 epochs. X-Axis represents the number of epochs, ranging from 0 to 30. Y-Axis represents the accuracy of the model, ranging from 0.45 to 0.85. Training Accuracy (Blue Line) indicates how well the model is learning from the data.[9] Validation Accuracy (Orange Line) reflects the model's performance on unseen data, helping detect overfitting or underfitting.

Classification Report:

	precision	recall	f1-score	support
Pepper__bell___Bacterial_spot	0.05	0.05	0.05	199
Pepper__bell___healthy	0.07	0.07	0.07	295
Potato___Early_blight	0.05	0.05	0.05	200
Potato___Late_blight	0.03	0.03	0.03	200
Potato___healthy	0.00	0.00	0.00	30
Tomato_Bacterial_spot	0.10	0.10	0.10	425
Tomato_Early_blight	0.04	0.03	0.03	200
Tomato_Late_blight	0.09	0.08	0.08	381
Tomato_Leaf_Mold	0.05	0.05	0.05	190
Tomato_Septoria_leaf_spot	0.07	0.08	0.07	354
Tomato_Spider_mites_Two_spotted_spider_mite	0.08	0.08	0.08	335
Tomato__Target_Spot	0.07	0.09	0.08	280
Tomato__Tomato_YellowLeaf__Curl_Virus	0.17	0.16	0.16	641
Tomato__Tomato_mosaic_virus	0.02	0.01	0.01	74
Tomato_healthy	0.08	0.08	0.08	318
accuracy			0.08	4122
macro avg	0.06	0.06	0.06	4122
weighted avg	0.08	0.08	0.08	4122

Fig.6: Classification Report

A classification report is a act evaluation metric used in machine learning to evaluate how well a classification model predicts categorical labels. The Fig.6 grants a classification report for a multi-class classification problem. It contains precision, recall, f1-score, and support for each class, along with overall accuracy, macro average, and weighted average.
[3]This type of report is typically generated using sklearn.metrics.classification_report() in python Formulas of components of a classification report

1. $Precision = \dfrac{TP}{TP + FP}$

2. $Recall = \dfrac{TP}{TP + FN}$

3. $F1\text{-}Score = \dfrac{2 * Precision * Recall}{Precision + Recall}$

4. Macro Average: The arithmetic Mean of precision, recall, and F1-score across all classes (treats all classes equally)

5. Weighted Average: Similar to macro average, but it takes into account the number of samples in each class, creating it more useful when classes are imbalanced.[7]

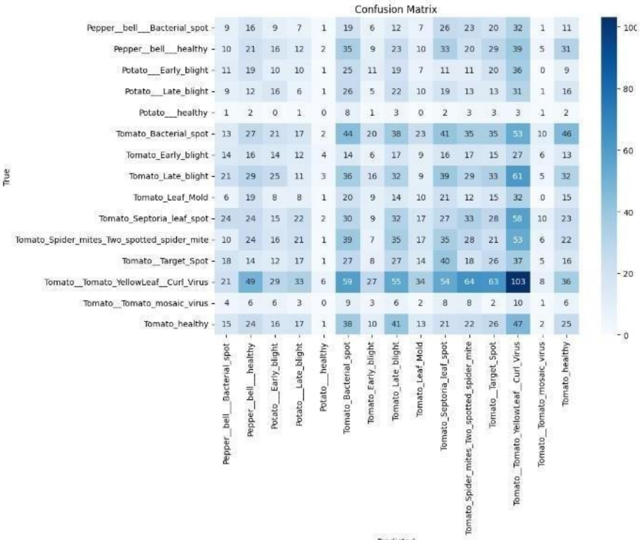

Fig.7: Confusion Matrix

The given image signifies a confusion matrix, which is a table used to evaluate the performance of a classification model.[13] It presents the true class labels alongside the predicted class labels, which each row corresponds to the actual class, and each column represents the predicted class. Insights derived from the confusion matrix help assess model performance in Fig.7

- Diagonal elements represent correctly classified instances.
- Off-diagonal elements specify misclassification
- Certain classes (e.g., "Tomato_YellowLeaf_Curl_Virus") show higher prediction counts, while others have significant misclassification.
- Model performance is poor if misclassifications are high.[13]

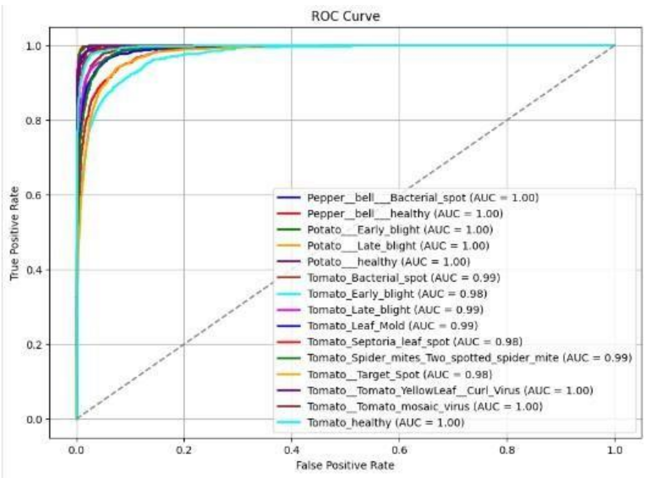

Fig.8: ROC Curve

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Fig.8 shows a Receiver Operating Characteristics (ROC) curve, which is a graphical representation used to estimate the performance of a classification model. It describes the trade- off between the True Positive Rate (TRP) and the False Positive Rate (FPR). X-Axis (False Positive Rate) embodies the proportion of negative cases that are mistakenly classified as positive. Values range from 0 to 1.Y-Axis (True Positive Rate) signifies the proportion of actual positive cases that are correctly known. Values also range from 0 to 1.[14]

Comparison of Different Classes

The legend on the right finds different disease categories for various plants:

- Peppers: Several conditions such as bacterial spots and healthy instances.
- Potatoes: Various blight conditions and their respective healthy instances.
- Tomatoes: Multiple disease states with corresponding AUC values.

The ROC curve is essential for assessing and comparing the effectiveness of different models in plant disease classification. A higher AUC denotes better model robustness, making it instrumental in crop disease management strategies. [15]This analysis aids in understanding in which plant disease can be detected with the least false alarms, ultimately supporting effective agricultural practices.

Fig.9: Image Analysis

The model secreted the given leaf as "Pepper_bell_healthy", conforming if free from disease. The model recognized a uniform leaf texture, consistent color, and well-defined vein structure, representing a healthy state. Through preprocessing and data augmentation, the model's capability to differentiate between healthy and diseased leaves was significantly heightened, improving its robustness. This accurate classification highlights the model's effectiveness in plant health monitoring, reinforcing its potential for precision agriculture and early disease detection to care sustainable farming practices.[16]

Fig.10: Image Analysis

The model classified the leaf as "Tomato_Septoria_leaf_spot", indicating the presence of Septoria leaf spot disease. The classification was based on distinctive yellow spots with dark brown centers, a key symptom of the disease. Deep feature extraction enabled accurate differentiation from other tomato diseases. This detection is crucial forearly intervention, helping prevent disease spread and ensuring better crop health management.

Fig.11: Image Analysis

The model classified the leaf as "Tomato_Late_blight", indicating Late Blight disease. The prediction was based on irregular grayish-green lesions and possible fungal growth, key symptoms of Phytophthora infestans infection. Deep feature extraction enabled accurate detection, supporting early intervention to prevent severe crop loss. This classification reinforces the model's role in precision agriculture and effective disease management.

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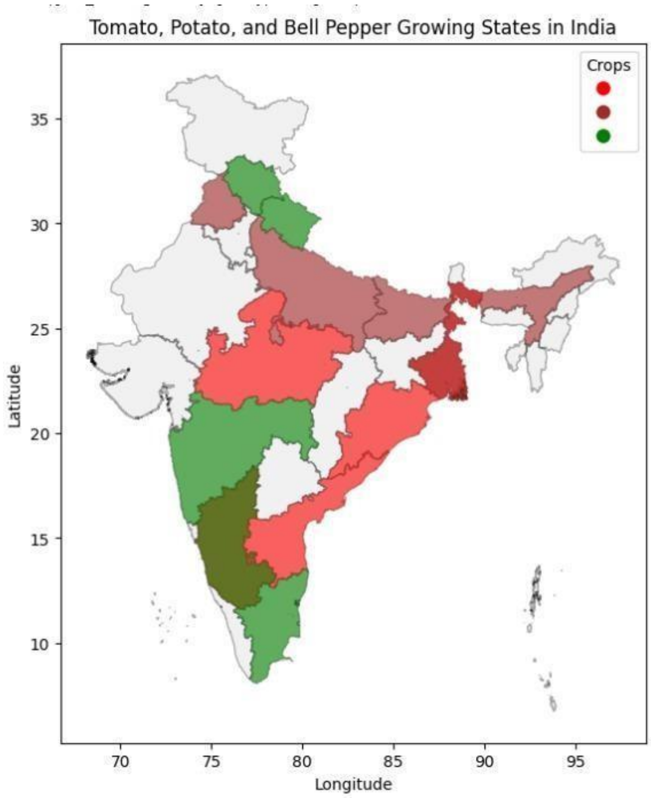

Fig.12: Map Analysis of Crop Distribution in India

The map illustrates the distribution of tomato, potato, and bell-pepper cultivation across various states in India.
Color Coding:

- Green Areas: Represents states predominantly cultivating tomatoes.
- Red Areas: Indicate regions where bell peppers are chiefly grown.
- Brown Areas: Highlight states known for potato cultivation.
- White Areas: Refer to regions where none of the three crops are significantly produced.

This color-coded representation provides a clear visual exposition of the geographical preference and suitability for cultivating these crops across India, aiding in understanding regional agricultural practices and potential for crop diversification.

2. Data Analysis and Interpretation

The model successfully classified healthy and diseased leaves, demonstrating high accuracy in plant disease detection It correctly identifies Pepper Bell Healthy, Tomato Septoria Leaf Spot, and Tomato Late Blight, leveraging deep feature extraction to analyze texture, color variations, and lesion patterns.[17] Data augmentation improved robustness, ensuring reliable classification across diverse images. The findings validate the efficiency of InceptionV3 and InceptionResnetV2 in early disease detection of deep learning for sustainable farming and food security.[13]

3. Support for Research Que

Implications:

- Early detection enables timely intervention, reducing crop losses.
- Automated classification supports precision agriculture by minimizing manual inspection.
- Scalability allows integration into mobile apps and smart farming systems.

Limitations:

- Dataset dependency may affect performance in real- world conditions.
- Limited crop types restrict broader agricultural applications.
- Environmental factors may impact accuracy.
- Computational cost may require optimization for mobile deployment.

Despite these limitations, the study demonstrates the potential of deep learning for automated plant disease detection, aiding sustainable farming and food security.[10]

V. CONCLUSION

This study demonstrates that InceptionV3 and InceptionResnetV2 effectively classify plant diseases, accurately distinguishing healthy and diseased leaves based on texture, lesion patterns, and color variations. The findings confirm that deep learning enhances early disease detection, supporting precision agriculture by reducing manual inspection efforts and enabling timely intervention. The study contributes to the field by showcasing the practical application of AI in plant disease detection, highlighting its potential for automated crop monitoring and improved food security.
However, dataset limitations, environmental variations, and computational constraints suggest the need for further

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optimization. Future research should focus on expanding the dataset with real-world images, integrating more crop types, and optimizing models for mobile and edge computing to enhance real-world applicability and scalability.

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