International Journal Of Advance Research, Ideas And Innovations In Technology

IJARIIT

ISSN: 2454-132X
Impact Factor: 6.078

(Volume 10, Issue 4 - V10I4-1182)
Available online at: https://www.ijariit.com

Plant Afflict Perception using Deep Learning

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ABSTRACT

Plant disease detection is a critical task in agriculture to prevent significant losses due to disease spread. The manual examination process used in traditional disease detection methods takes a lot of time and labour. This research presents a plant disease detection system using deep learning, specifically leveraging the InceptionV3 architecture, a type of Convolutional Neural Network (CNN). Our approach demonstrates improved accuracy and speed in identifying plant diseases, contributing to more efficient agricultural practices. The model achieved a validation accuracy of 96%.

Keywords*: Plant Disease Detection, Convolutional Neural Network (CNN), Inception v3*

1. INTRODUCTION

Plant diseases pose a significant threat to agriculture, affecting crop yields and leading to substantial economic losses. Traditional methods of detecting plant diseases, which rely on manual inspection, are often time-consuming and prone to error. In recent years, advancements in artificial intelligence, particularly in deep learning, have shown promise in automating and improving the accuracy of disease detection. This study presents a plant disease detection system using Convolutional Neural Networks (CNNs), specifically the InceptionV3 architecture. Leveraging a dataset from Kaggle, which includes 38 classes of healthy and diseased plant images, the system employs data pre-processing and augmentation techniques to enhance model performance. The proposed InceptionV3-based model achieves a validation accuracy of 96%, demonstrating its potential for effective plant disease detection in agricultural applications.

2. FRAMEWORK

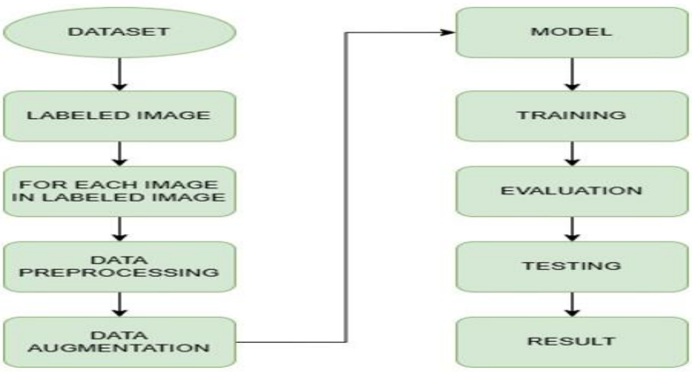


Fig 1: Flowchart of Disease Detection

3. METHODOLOGY

3.1 DATASET

The dataset used in this project was “plantvillage”, which was obtained from Kaggle. It consists of 54,300 images categorized into 38 classes, representing various plant species and their disease conditions, including both healthy and diseased plants. This extensive dataset provides a rich variety of examples, essential for training a robust model capable of accurately detecting plant diseases.

3.2 DATA PREPROCESSING AND DATA AUGMENTATION

Data pre-processing is a crucial step in preparing the dataset for training a neural network. For this project, rescaling was employed to normalize pixel values to the range [0, 1]. This normalization helps in speeding up the training process and improving the model's convergence. Additionally, the dataset was split into training (80%) and validation (20%) sets to evaluate the model's performance effectively. Data augmentation techniques were applied to increase the diversity of the training data and help the model generalize better. The augmentations included rotation (up to 20 degrees), width and height shifts (up to 20%), and horizontal flipping. These transformations create new variations of the training images, allowing the model to learn more robust features and reducing the risk of overfitting.

3.4 INCEPTIONV3

The plant disease detection system utilizes the InceptionV3 architecture, a sophisticated convolutional neural network (CNN) that has been pre-trained on the ImageNet dataset. For the specific purpose of plant disease classification, the top layers of the pre-trained InceptionV3 model are removed and replaced with custom layers. The input images are resized to 299x299 pixels with three color channels to align with the model's input specifications. New layers are integrated into the base model, including a Global Average Pooling (GAP) layer to compress feature maps into scalar values, a dense layer with 128 neurons utilizing ReLU activation, and a final dense layer with softmax activation to categorize plant diseases into three distinct groups. The model is trained using the Adam optimizer and categorical cross-entropy loss, demonstrating significant accuracy and reliability in identifying various plant diseases.

The diagram illustrates the architecture of the InceptionV3 model employed in this study. This architecture integrates a series of convolutional layers, inception modules, and pooling layers. The model concludes with a global average pooling layer followed by dense layers specifically designed for the plant disease detection application.

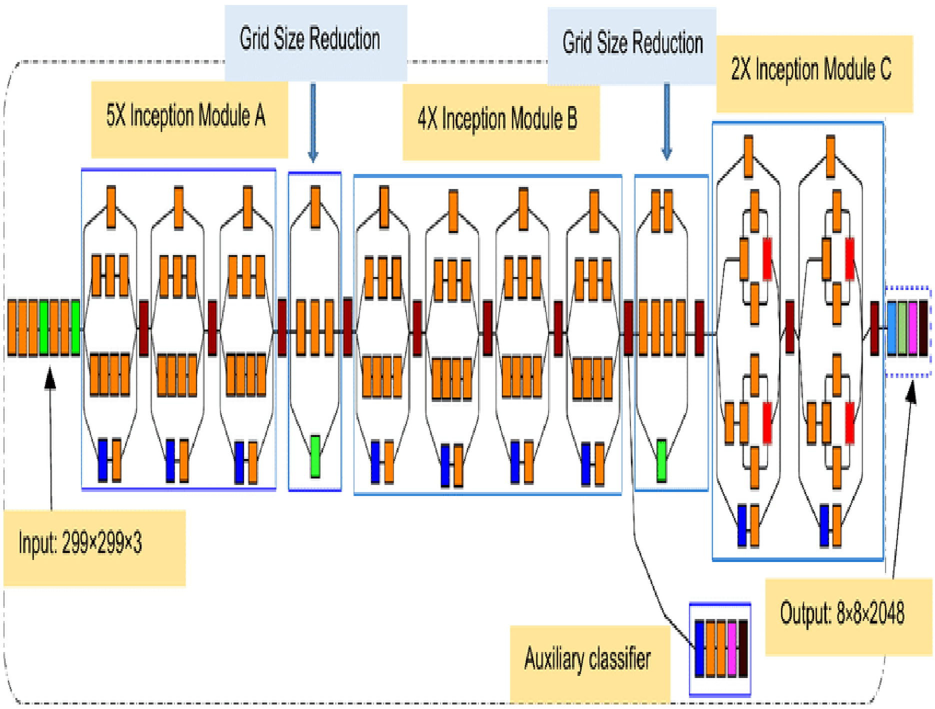


Fig 3: InceptionV3

3.5 TRAINING AND VALIDATION

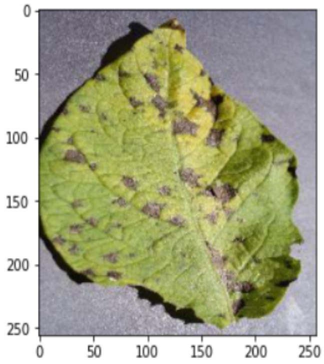
The model was compiled and trained using the Adam optimizer with a learning rate of 1e-4, and the categorical cross-entropy loss function. Accuracy was used as the performance metric. The model was trained for 20 epochs using the augmented training data. The model's performance was validated on the validation set. In this project, 54,300 images with 38 classes were used to ensure robust training and accurate validation.

4. RESULTS

The results of this study demonstrate the efficacy of the InceptionV3 model in detecting plant diseases. Trained on a dataset comprising 54,300 images across 38 classes, the model achieved a peak validation accuracy of 96% after 20 epochs. Pre-processing and augmentation techniques contributed significantly to this performance. The evaluation of the test set yielded a test accuracy of 96.4% and a test loss of 0.11, indicating the model's robustness and generalization capability. The classification report and confusion matrix further confirmed high precision, recall, and F1 scores across all classes, highlighting the model's effectiveness in real-world scenarios.

```
predict_disease('/content/PlantVillage/val/Potato___Early_blight/03b0d3c1-b5b0-48f4-98aa-f8904670290f___RS_Early.B 7051.JPG')
```

Potato___Early_blight

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predict_disease('/content/PlantVillage/val/Tomato___Target_Spot/1006b3dd-22d8-41b8-b83d-08bf189fcdaa___Com.G_TgS_FL 8118.JPG')
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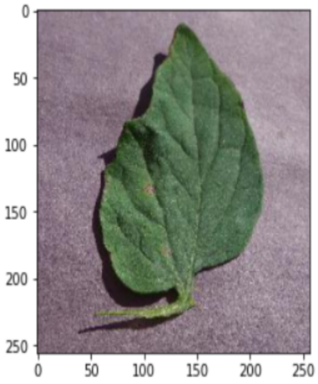
Tomato___Target_Spot




```
predict_disease('/content/PlantVillage/val/Blueberry___healthy/008c85d0-a954-4127-bd26-861dc8a1e6ff___RS_HL 2431.JPG')
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Blueberry___healthy

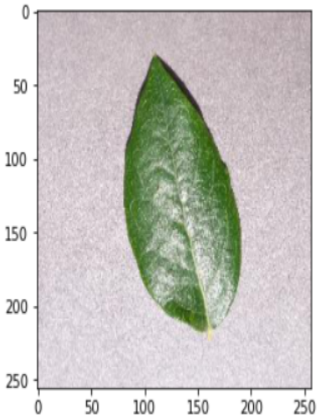

Fig 4.2: Output Screenshot

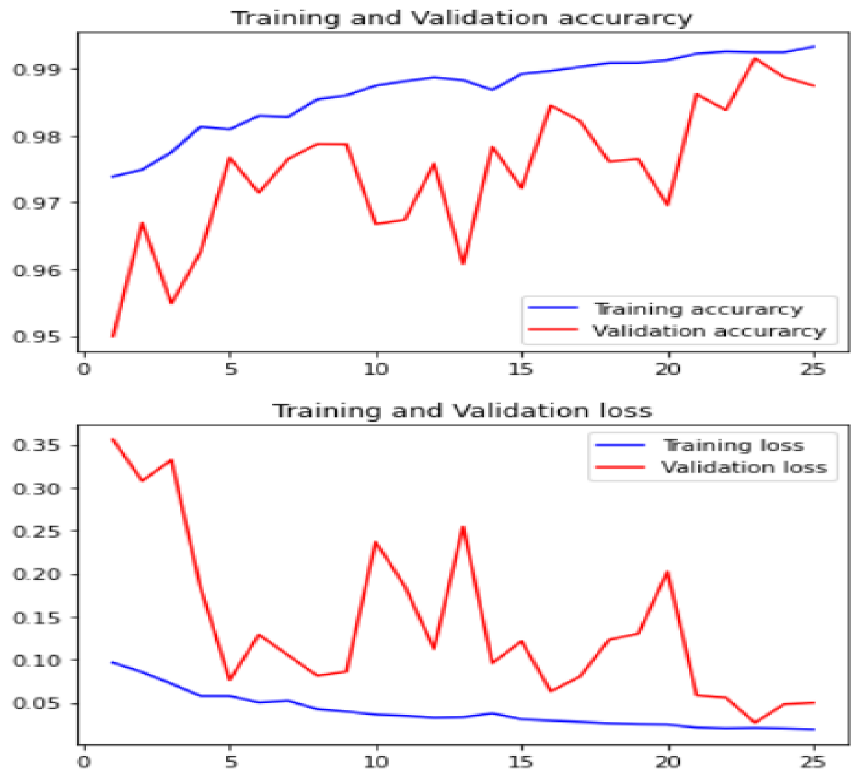

Fig 4.3: Training and Validation Accuracy

5. DISCUSSION AND CONCLUSION

In this project, the implementation of the InceptionV3 model for plant disease detection showcased its robustness and high performance. The pre-processing steps, including rescaling, data augmentation, and validation splitting, played a crucial role in enhancing the model's ability to generalize from the training data. The application of data augmentation techniques, such as random rotations, width and height shifts, and horizontal flips, increased the diversity of the training dataset, which is essential for improving the model's ability to handle real-world variability in plant images.

The InceptionV3 architecture, with its inception modules and auxiliary classifiers, effectively captured multi-scale features and mitigated the vanishing gradient problem, leading to faster convergence and improved accuracy. The transfer learning approach, utilizing a pre-trained model on ImageNet, significantly boosted the model's performance by leveraging learned features from a vast and diverse dataset. This approach proved to be effective, as evidenced by the high validation accuracy of 96%.

The evaluation of the test set demonstrated the model's capability to generalize well to unseen data, achieving a test accuracy of 96.38%. The confusion matrix and classification report provided insights into the model's precision, recall, and F1 score for each class, indicating strong performance across different plant diseases. The slight variations in accuracy for different classes highlight the challenges in distinguishing between visually similar diseases, suggesting areas for further improvement.

6. CONCLUSION & FUTURE WORK

In conclusion, the application of the InceptionV3 model for plant disease detection in this project has proven to be highly effective. The combination of advanced data pre-processing techniques, the robust architecture of InceptionV3, and the transfer learning approach resulted in a model capable of accurately identifying plant diseases with high precision. The high accuracy achieved in both validation and test sets underscores the potential of deep learning models in revolutionizing agricultural practices by providing timely and accurate disease detection.

Future work could explore several avenues to further enhance the effectiveness and applicability of the plant disease detection system. One area of improvement could involve expanding the dataset to include a wider variety of plants and disease types, which would help in making the model more comprehensive and versatile. Additionally, integrating the model into a mobile application could provide farmers with real-time disease detection capabilities in the field. Another potential enhancement could involve using advanced techniques such as transfer learning with more specialized models or incorporating attention mechanisms to further improve the model's accuracy and interpretability. Finally, testing the model in real-world conditions and gathering feedback from users can provide valuable insights for refining the system and ensuring its practical utility in agricultural settings.

REFERENCES

[1]. Chong Sun, Yong AI, Jun Tie & Xiantao Cai "Research on Recognition Model of Crop Diseases and Insect Pests Based on Deep Learning in Harsh Environments" https://ieeexplore.ieee.org/document/9201298

[2]. Qingmao Zeng, Xinhui Ma, Baoping Cheng, Erxun Zhou & Wei Pang "GANs-Based Data Augmentation for Citrus Disease Severity Detection Using Deep Learning" https://ieeexplore.ieee.org/document/9200543

[3]. Basvaraj Tigadi, Bhavana Sharma "Banana Plant Disease Detection and Grading Using ImageProcessing"https://www.researchgate.net/publication/346902943_GANs Based_Data_Augmentation_for_Citrus_Disease_Severity_Detection_Using_Deep_Learning

[4]. Shima Ramesh Maniyath and Hebbar Ram "Plant disease detection using machine learning" https://www.researchgate.net/publication/327065422_Plant_Disease_Detection_Using_Machine_Learning

[5]. Debasish Das, Mahinderpal Singh, Sarthak Swaroop Mohanty & S Chakravarty "Plant Disease Detection Using Support Vector Machine" https://ieeexplore.ieee.org/document/9182128

[6]. S. Datir and S. Wagh, "Monitoring and detection of agricultural disease using wireless sensor network," Int. J. Comput. Appl., vol. 87, no. 4, pp. 1–5, Feb. 2014

[7]. L. Deng, O. Abdel-Hamid, and D. Yu, "A deep convolutional neural network using heterogeneous pooling for trading acoustic invariance with phonetic confusion," in Proc. IEEE Int. Conf. Acoust., Speech Signal Process., May 2013, pp. 6669–6673.

[8]. N. Srivastav, G. Chopra, P. Jain, and B. Khatter, "Pest Monitor and control system using WSN with special reference to the acoustic device," in Proc. 27th ICEEE, Jan. 2013, pp. 92–99.

[9]. G. Athanikar and M. P. Badar, "Potato leaf diseases detection and classification system," Int. J. Comput. Sci. Mobile Comput., vol. 5, no. 2, pp. 76–88, 2016

[10]. H. Wang, G. Li, Z. Ma, and X. Li, "Application of neural networks to image recognition of plant diseases," in Proc. Int. Conf. Syst. Informat. (ICSAI), May 2012, pp. 2159–2164.