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A comparative analysis of different CNN models for plant disease detection and classification

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Abstract: Global agriculture is greatly impacted by plant diseases, since different infections cause 20% to 40% of agricultural production to be lost each year. These losses are caused by bacteria, viruses, fungi, and other microorganisms that affect both economic stability and food security. For example, in the United States alone, the fungal infection Fusarium oxysporum causes losses of up to $1 billion yearly. Furthermore, academics and farmers alike are also concerned about the development of diseases like citrus greening and wheat rust. To mitigate these consequences and ensure long-lasting crop production, integrated approaches to disease control, like resistance breeding, cultural practices, and the prudent use of fungicide are crucial. Convolutional Neural Networks (CNNs), particularly those pre-trained on large datasets like ImageNet, have revolutionized identification of plant diseases by providing excellent accuracy and effectiveness in diagnosing various plant illnesses from images. This approach, which includes optimizing already trained models on plant disease datasets, reduces the requirement for big annotated datasets and computational resources, making it highly applicable for agricultural use. Google's Inception v3 model, known for its efficient architecture and use of inception modules, is widely used in plant disease diagnosis. It can precisely identify plant diseases through transfer learning by being pre-trained on ImageNet and fine-tuned on specific plant disease datasets. The Inception-ResNet v2 model, combining Inception architecture with residual networks, also excels in identification of plant diseases. Its deep structure captures detailed features from plant images, enabling accurate disease diagnosis. Like Inception v3, it uses transfer learning to generalize across various plant species and disease types, aiding in precision agriculture by facilitating early illness detection and timely intervention. This project aims to deploy and Compare the results of three models—Xception, Inception v3, and Inception-ResNet v2—in detecting fungal diseases in fruit plant

Keywords: Plant disease detection, CNN, Xception model, Inception V3 model, Inception ResNet V2 model

I. INTRODUCTION

As plant diseases result in significant financial losses and decreased agricultural productivity, they pose a substantial threat to global food security. Automated and efficient solutions must be developed because classical methods of disease identification and classification are frequently labor- and time-intensive. Due to their ability to extract complex patterns and attributes from massive image datasets, machine learning (ML) techniques—in particular, deep learning models—have become more viable tools for the identification and classification of plant diseases in recent years. For the purpose of detecting plant diseases, this research study compares three cutting-edge machine learning models: Inception-ResNet v2, Xception, and Inception v3.

To put things in perspective, earlier research on machine learning techniques for plant disease detection has shown promise for deep learning models to provide high levels of accuracy and dependability. For example, Kc et al. [1] suggested depthwise separable convolution structures for the categorization of plant diseases, and Saleem et al. [2] looked into deep learning methods for the identification and classification of plant diseases. Furthermore, Kerkech et al. [3] demonstrated the effectiveness of deep learning segmentation techniques by focusing on vine disease identification using UAV multispectral pictures. Other research has looked into residual CNNs, attention mechanisms, and traditional machine learning approaches for plant disease identification. These papers include Karthik et al. [4], Behera et al. [5], and Khan et al. [6].

Furthermore, models especially designed for plant disease identification have been developed as a result of developments in deep learning architectures. Awais et al. [8] used deep CNNs and multispectral imaging for rice plant disease identification, whereas Jasiński et al. [7] suggested a five convolutional layer deep CNN for plant leaf disease detection. Additionally, for early disease detection in plant leaves, researchers have investigated novel strategies as leaky ReLU-ResNet [9], enhanced DenseNet with attention mechanisms [10], and U-Net segmentation in conjunction with transfer learning [11].

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Even with these developments, thorough comparative analysis is still required to assess the efficacy and performance of various machine learning models for the identification of plant diseases. This study fills in this void by thoroughly examining the Xception, Inception v3, and Inception-ResNet v2 models while taking generalizability, accuracy, and computing efficiency into account. This research attempts to provide important insights for the development of reliable and scalable plant disease detection systems by combining findings from earlier studies and doing empirical evaluations.

II. LITERATURE REVIEW

Kc et al.[1] investigated the application of depthwise separable convolutions in CNN architectures for the classification of plant illnesses. This technique decreases the number of parameters and computational cost, making the model more efficient while maintaining high accuracy. The study evaluates the performance of these architectures on various datasets, showing that depthwise separable convolutions can significantly enhance the speed and efficiency of the classification process without compromising accuracy. This method is particularly beneficial for deploying models on resource-constrained devices like smartphones.

M. Saleem, et al [2] explored the use of deep learning techniques, particularly CNNs, for the identification and classification of plant diseases. Saleem et al. compared the different deep learning models and highlight their advantages and disadvantages according to their accuracy, computational cost, and ease of implementation. The study provides a detailed analysis of various pre-processing techniques, data augmentation strategies, and model architectures. The results indicate that deep learning models are able to achieve high accuracy in classifying plant diseases, making them suitable for practical applications in agriculture.

The use of unmanned aerial vehicles (UAVs) fitted with multispectral cameras for the identification of vine diseases was the main emphasis of M. Kerkech, et al.'s study [3].. The study employs advanced image registration techniques to align multispectral images accurately, followed by deep learning-based segmentation to identify diseased regions. The methodology includes optimizing the image registration process to enhance the quality of the input data for the CNN model. The outcomes show how well the suggested method can identify and pinpoint vine diseases, which makes it a useful instrument for precision farming.

A. Karthik, et al [4] explored an advanced CNN architecture that integrates attention mechanisms within residual networks to enhance the identification and classification of tomato leaf diseases. The attention mechanism helps the model focus on relevant parts of the image, improving the accuracy and robustness of disease identification. The study compares various CNN architectures and demonstrates significant improvements in classification performance because of the inclusion of attention layers. The results suggest that the proposed model can effectively differentiate between healthy and diseased tomato leaves, achieving high accuracy rates.

Behera et al. [5] present a study on the application of machine learning models, specifically deep learning, for plant disease identification and classification. The paper evaluates the performance of various CNN architectures on different plant disease datasets, demonstrating their effectiveness in identifying and classifying diseases. The authors discuss the importance of image pre-processing, data augmentation, and model selection to attain a high degree of classification accuracy. The study's results highlight the potential of machine learning models in improving agricultural disease management.

Khan et al. [6] give a thorough analysis of the evolution of plant disease identification techniques, highlighting the change from classical machine learning methods to modern deep learning approaches. The study covers a range of datasets, evaluation measures, and algorithms that are used in the field., highlighting the deeper learning models' superior performance. The review covers CNNs, RNNs, and other advanced architectures, illustrating their effectiveness in handling complex image data. The authors also address the issues and future directions in the field, like the need for big annotated datasets and real-time deployment.

Jasiński et al. [7] propose a deep CNN with 5 convolutional layers designed for plant leaf disease identification. The model leverages data augmentation and hyperparameter optimization to enhance its performance. The authors conduct extensive experiments on a big dataset of plant leaf images, demonstrating that their model has an average classification accuracy of 98.41%. The paper highlights the importance of network depth and optimization techniques in improving the model's generalization capability and robustness.

In 2023, N. A. Awais et al. [8] discusses using ResNet18 architecture combined with multispectral imaging to identify and classify illnesses in rice plants. The study emphasizes addressing the vanishing gradient problem with residual networks and demonstrates high accuracy in classifying rice diseases using RGB and R-G-NIR image pairs.

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Smitha Padshetty and Ambika [9] introduced a novel Leaky Rectilinear Residual Network (LRRN) for detecting plant leaf diseases. The model integrates ResNet architecture with the Leaky ReLU activation function and shows superior accuracy and other performance metrics when tested on the Plant Village dataset.

Y. Zhao et al. [10] proposed an improved DenseNet model with an attention mechanism for detecting plant diseases. The attention mechanism helps the network focus on important features, enhancing its accuracy and robustness in identifying various plant diseases.

R. Thomas et al. [11] utilized U-Net for segmenting diseased regions in plant leaves and employs transfer learning to improve detection accuracy. The approach is particularly effective for early disease detection, which is crucial for timely intervention.

M. Nguyen et al. [12] explored the application of ensemble learning techniques integrating a number of deep learning models for robust plant disease detection. The ensemble approach improves overall performance by leveraging the strengths of various models.

III. METHODOLOGY

Data Acquisition: Gather relevant dataset containing images of leaves of plants, both healthy and with fungal diseases from Kaggle. The data should be representative and properly labeled . The dataset has 54,305 images. It is divided into training set (43,444) and testing set (10,861 images). It has a ratio of 80% to 20%. Fig. 3.1 shows the class distribution of the dataset.

Dataset Preprocessing: Preprocess the dataset by resizing the images, format conversion, labelling, etc, in order to enhance the performance of the models.

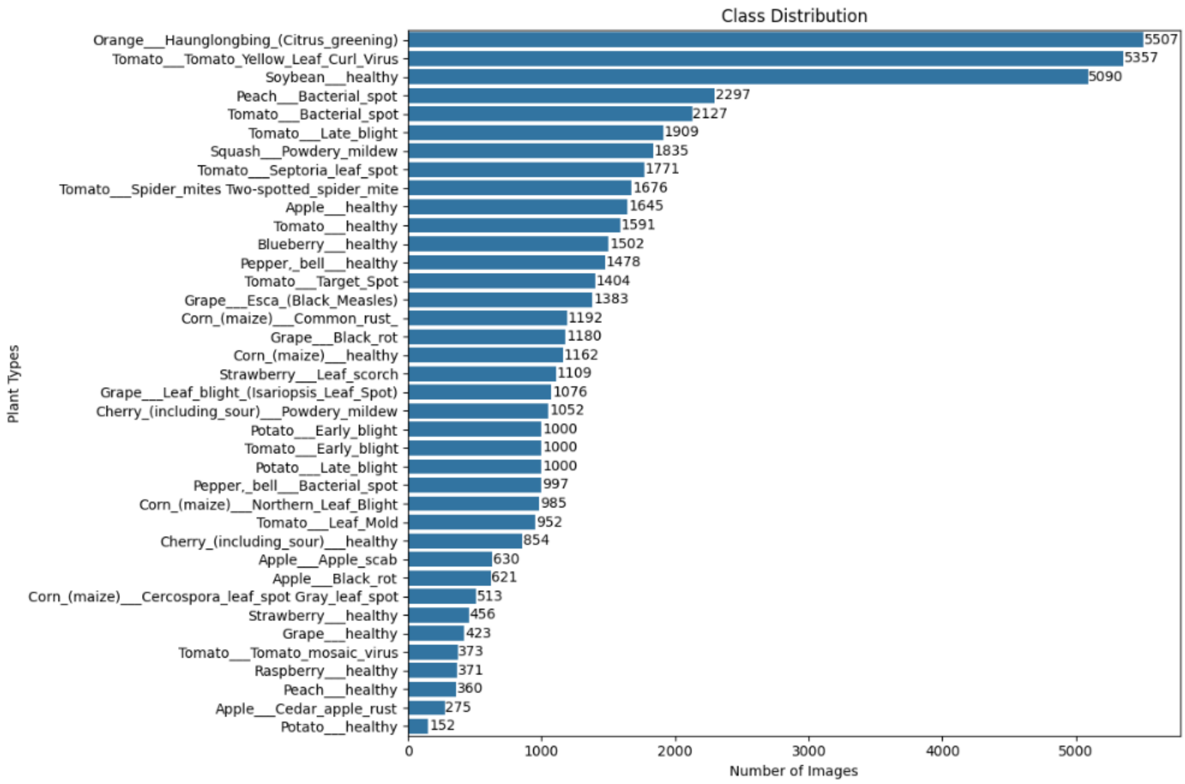

Fig. 3.1 Class distribution of the dataset

Model training, Model Evaluation and Testing: Train the models using the training dataset, optimizing hyperparameters like batch size, learning rate, and number of epochs. Validate the trained model using the validation dataset, monitoring metrics such as accuracy, value loss, precision, etc.

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Fig. 3.2 below shows the process involved in implementing the project and the analysis

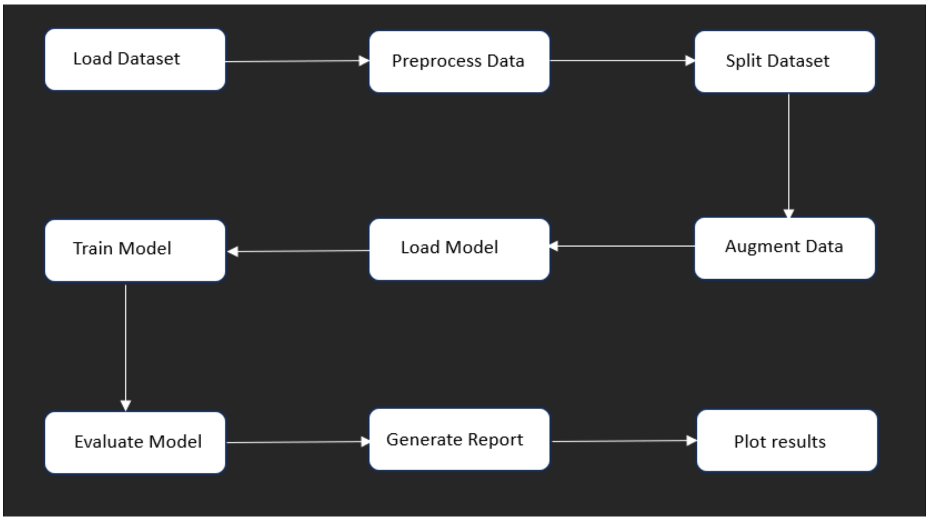

Fig. 3.2 Methodology

IV. RESULTS

The findings of the comparison study of 3 machine learning models for plant disease detection: Xception, Inception V3, and Inception-ResNet V2 are as follows:

Training Accuracy and Loss: With a training loss of 0.0356, the Xception model had the best training accuracy of 98.98%. With a training loss of 0.0486 and a training accuracy of 98.37%, Inception V3 likewise showed excellent performance. The Inception-ResNet v2 model had a larger training loss of 0.2732 and a somewhat lower training accuracy of 91.14%. Test Accuracy: The Xception model demonstrated its superiority when evaluated on the test dataset, attaining the maximum test accuracy of 99.34%. With a test accuracy of 95.43%, Inception V3 trailed closely behind, while Inception-ResNet v2 performed worse, with a test accuracy of 92.75%.

Extra Measures for Inception V3 and Inception-ResNet v2:
Additional measures, like recall and precision, were calculated for Inception-ResNet v2 and Inception V3 for additional study. With a precision of 0.949 and a recall of 0.908, Inception-ResNet v2 demonstrated its capacity to accurately identify sick plants while reducing false positives. In contrast, Inception V3 showed marginally better recall (0.9508) and precision (0.9587), indicating its strong competence in correctly detecting both healthy and ill plants.

Metric	Value for Xception Model	Value for Inception V3 Model	Value for Inception ResNet V2 Model
Training Accuracy	98.98%	98.37%	91.14%
Validation Accuracy	99.57%	98.09%	93.26%
Testing Accuracy	99.34%	95.43%	92.75%
Training Loss	0.0356	0.0486	0.2732
Validation Loss	0.0197	0.0578	0.2117
Precision	0.99	0.9587	0.949
Recall	0.99	0.9501	0.908
F1-score	0.99	0.95	0.928

Table 4.1 Metrics for different models

V. CONCLUSION

It is clear from the comparative study of 3 machine learning models for plant disease detection—Xception, Inception V3, and Inception-ResNet v2—that each model has their own advantages and disadvantages. With the greatest accuracy scores of 98.98% and 99.34% in training and testing, respectively, the Xception model performs quite well.

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Furthermore, it demonstrates strong learning capabilities with the lowest training loss of 0.0356. The Inception V3 model also exhibits commendable performance, however, with a lower accuracy scores while retaining high recall and precision rates. While the Inception-ResNet v2 model shows reasonable precision and recall values, it notably lags behind in terms of training and test accuracy. The Inception-ResNet v2 model may still be useful in situations where computing efficiency is a top concern, even with its lower accuracy results. In summary, the selection of a machine learning model for the identification of plant diseases ought to be customized to individual needs, taking into account, elements like precision, processing capacity and use.

VI. FUTURE SCOPE

Future developments and advances in the domain of machine learning-based plant disease identification have enormous potential. Future work should focus on improving the scalability, accuracy, and efficiency of current machine learning models through optimization and refining. To enhance model performance and generalization across a variety of plant species and disease types, researchers can investigate alternative designs, optimization algorithms, and training techniques.

Furthermore, new paths for the detection of plant diseases are made possible by the integration of cutting-edge sensing technologies such as unmanned aerial vehicles (UAVs), hyperspectral imaging, and multispectral imaging. Through the integration of machine learning algorithms with these technologies, scientists may create remote sensing systems which have the ability to detect diseases in their early stages, track crop health in real-time, and enable focused actions for disease control. Moreover, the employment of machine learning in precision agriculture presents encouraging opportunities for maximizing resource efficiency, mitigating ecological consequences, and elevating agricultural yield. Farmers may make educated judgments about planting, irrigation, fertilizer, and pest control with the help of machine learning models for crop monitoring, decision support, and predictive analytics. This results in more sustainable and effective farming operations.

The creation of approachable and user-friendly solutions for plant disease identification is also receiving more attention in order to help stakeholders, agronomists, and farmers make good use of machine learning technologies. Subsequent investigations may concentrate on the development and execution of mobile applications, web-based systems, and portable gadgets furnished with machine learning algorithms to facilitate prompt disease diagnosis and field judgment.
All things considered, the field's future potential is vast and includes developments in machine learning models, sensor technology, precision agriculture methods, and user-centered solutions. To address global difficulties in crop protection and food security, researchers may help construct resilient, sustainable, and technologically advanced agricultural systems by keeping up their innovative work and collaboration across interdisciplinary areas.

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