PLANT DISEASES DETECTION USING DEEP LEARNING AND MACHINE VISION

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***Abstract*— This research delves into deep learning and machine vision applications for plant leaf disease detection in agricultural settings, focusing on farm village datasets. Utilizing a blend of authentic farm village data and synthetic data from Generative Adversarial Networks (GANs), three advanced convolutional neural network (CNN) models VGG16, ResNet50, and InceptionNet V3 are employed with transfer learning. Leveraging transfer learning enhances model performance through fine-tuning pre-trained networks. The study systematically evaluates models based on key metrics like accuracy, precision, recall, and F1 score. Results showcase the methodology's robustness, with ResNet50 emerging as the leading performer at 83.23%, contributing to precision agriculture's advancements with promising implications for sustainable farming and crop yield optimization.**

Keywords— Plant leaf diseases, Convolutional neural networks, Transfer learning, Generative Adversarial Networks, Machine Vision

I. INTRODUCTION

In the realm of modern agriculture, timely and accurate diagnosis of plant diseases is crucial for crop health and yield optimization. Plant leaf diseases pose a significant threat to global food security, necessitating innovative methods for early identification and control. This study addresses these challenges by exploring the combined application of deep learning and machine vision for automated plant leaf disease identification in the intricate context of agricultural communities, particularly farm villages. Leveraging state-of-the-art convolutional neural network (CNN) architectures VGG16 with transfer learning, ResNet50 with transfer learning, and InceptionNet V3 the study aims to enhance the accuracy and efficiency of disease detection. Traditional methods relying on manual inspection by agronomists are subjective and limited in scalability, making the adoption of deep learning and machine vision imperative for automated, rapid, and precise diagnosis. The study acknowledges the complexities of farm village environments, encompassing diverse crop varieties, environmental factors, and agricultural practices, requiring a flexible and robust approach. Transfer learning is employed to adapt pre-trained models to the unique features of farm village datasets, addressing the scarcity of labelled data specific to these settings. Additionally, the study introduces the use of Generative Adversarial Networks (GANs) to generate synthetic data, augmenting the training set and enhancing the models' generalization capabilities in practical agricultural scenarios. The research aims to advance the understanding of plant leaf disease detection in rural communities, with a focus on developing, testing, and assessing deep learning models that contribute to precision agriculture. The evaluation of ResNet50, InceptionNet V3, and VGG16 within the context of farm villages, utilizing transfer learning and GAN-generated data, aims to provide valuable insights into addressing the unique challenges of agricultural disease identification and foster sustainable farming practices.

II. LITERATURE REVIEW

In the study by Pranesh Kulkarni et al. on "Plant Disease Detection Using Image Processing and Machine Learning," despite achieving a commendable 93% accuracy, limitations such as challenges in generalizing results to new datasets and varying environmental conditions must be acknowledged [1]. The dynamic nature of plant diseases and computational demands in large-scale agriculture may impact the model's effectiveness, and reliance on image-based detection may overlook other influential factors like weather conditions or soil variations.

Yan Guo et al. research, "Plant Disease Identification Based on Deep Learning Algorithm in Smart Farming," introduces a mathematical model utilizing deep learning for efficient plant disease detection [2]. While exhibiting an accuracy of 83.57% and effectiveness against certain diseases, challenges include the iterative nature of the Chan–Vese algorithm, suggesting potential improvements for faster identification in future research.

Andrew J. et al.'s study on "Deep Learning-Based Leaf Disease Detection in Crops Using Images for Agricultural Applications" emphasizes the critical role of the agricultural sector and explores the application of CNN-based pre-trained models [3]. DenseNet-121 achieves a remarkable 99.81% classification accuracy, highlighting the potential of deep learning in enhancing early diagnosis of plant diseases. Future work aims to address real-time data collection challenges and develop a multi-object deep learning model.

Sharada P. Mohanty et al.'s study on deep learning-based plant disease detection achieves an impressive accuracy of 99.35% [4]. However, limitations include reduced accuracy under varied testing conditions and constraints in classifying single leaves on homogeneous backgrounds. Ongoing research aims to address these drawbacks for practical real-world applications in agriculture.

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Riyao Chen et al.'s study introduces CACPNET as a promising model for plant disease identification, achieving high accuracy but acknowledging limitations in the attention mechanism and the trade-off between accuracy and real-time deployment demands [5]. Despite limitations, CACPNET demonstrates notable advantages, emphasizing its potential for lightweight deployment in precision agriculture.

The literature survey by Kowshik B et al. on "Plant Disease Detection Using Deep Learning" underscores the significance of agriculture and the potential of deep learning for improved accuracy in disease detection [6]. While highlighting positive impacts on early disease detection, the review acknowledges the need for further research to address existing gaps in disease detection transparency and proposes future expansions for additional features like pesticide price lists and market information. Specific drawbacks or limitations are not explicitly outlined.

In summary, these studies collectively contribute to the advancement of plant disease detection through deep learning and machine vision. While showcasing impressive accuracies and potential applications, each study recognizes specific limitations, highlighting the ongoing need for research and improvement in this critical domain of precision agriculture.

III. MATERIALS AND METHODS

A. Data Acquisition

The study uses the PlantVillage dataset, which consists of 19,458 photos that have been hand-picked to improve plant disease identification through computer vision and deep learning. Data augmentation methods and a Generative Adversarial Network (GAN) model provide an extra 9,973 augmented photos in order to improve dataset variety. 29,928 photos in all, divided into 20 different classifications that correspond to various plant health and disease categories, make up the full dataset. The dataset provides a rich depiction of plant conditions and spans a variety of crops, including blueberries, apples, cherries, corn, grapes, peppers, potatoes, and strawberries.

TABLE I. Dataset Details

No.	Class Names	Images count
0	Blueberry___healthy	2002
1	Apple___Cedar_apple_rust	777
2	Apple___healthy	2146
3	Cherry_(including_sour)___healthy	1363
4	Cherry_(including_sour)___Powdery_mildew	1564
5	Corn_(maize)___Cercospora_leaf_spot Gray_leaf_spot	1015
6	Corn_(maize)___Common_rust_	1707
7	Corn_(maize)___healthy	1662
8	Corn_(maize)___Northern_Leaf_Blight	1485
9	Grape___Black_rot	1681
10	Grape___Esca_(Black_Measles)	1884
11	Grape___healthy	916
12	Grape___Leaf_blight_(Isariopsis_Leaf_Spot)	1577
13	Pepper,_bell___Bacterial_spot	1487
14	Pepper,_bell___healthy	1976
15	Potato___Early_blight	1476
16	Potato___healthy	552
17	Potato___Late_blight	1496
18	Strawberry___healthy	956
19	Strawberry___Leaf_scorch	1609

B. Data Preparation

In this part, the dataset containing 29,928 images of leafs are splitted into 65 and 35percent as training dataset and test dataset. The training set comprises 19,458 plant leaf images, categorized into 20 classes, representing diverse plant species and health or disease conditions. This dataset is strategically divided, with 85% (16,545 images) allocated for training and 15% (2,911 images) for validation, ensuring robust model development and evaluation.The testing set of the dataset comprises a subset of 9,973 images distributed across 20 different classes, with each class representing a specific category of plant health or disease. The distribution of images per class is as follows:

C. Image preprocessing and Data Augmentation

In the model training process, a batch size of 64 images per iteration is specified, aiming to efficiently process and optimize the deep learning model. Two distinct image data generators are defined: one for training and validation (train_generator) and another for testing (test_generator). The training and validation data generator incorporates diverse transformations, including a rotation range of 90 degrees, varied brightness between 0.1 and 0.7, horizontal and vertical shifts within a range of 0.5, as well as horizontal and vertical flips. A validation split of 15% is employed to allocate a portion of the training data for validation purposes. The VGG16 preprocessing function is applied to enhance data compatibility. Utilizing flow_from_directory, batches of training and validation data are created from the original and enhanced datasets, specified by the directories train_data_dir and test_data_dir. The class_subset, containing the list of class names, is retrieved from the original dataset. For testing data, the test_generator employs the VGG16 preprocessing function, pulls batches from the upgraded dataset directory, and resizes images to (299, 299). With a batch size of 1, images are processed independently, ensuring consistent evaluation without data scrambling, and reproducibility is maintained through the use of a seed. These generators collectively contribute to the model's ability to generalize effectively and recognize diverse patterns, thereby enhancing its performance across different datasets.

IV. EXPERIMENTAL PROCEDURE

The development of a deep learning model for image classification entails a meticulously orchestrated series of steps to ensure both robust performance and interpretability. Commencing with the loading and segregation of the dataset into test, validation, and training sets, the process integrates diversity through data augmentation techniques applied specifically to the training set. Efficient batch processing is facilitated by a data loader, optimizing the training process by feeding the model with batches of augmented data. Subsequent image preparation involves essential steps such as pixel value normalization and scaling to standardize input data, ensuring consistency and aiding in model convergence. Leveraging the power of transfer learning, pre-trained models like VGG16, ResNet50, or InceptionV3 form the

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backbone of the architecture, with the feature extraction phase initiated by removing the classification head of the pre-trained model. The model is then fine-tuned for task-specific classification by adding a custom classification head. Post this; the entire model is compiled, specifying the optimizer, loss function, and metrics for training. The training strategy includes freezing convolutional layers initially, gradually unfreezing them, and monitoring performance on the validation set. Techniques such as early stopping and learning rate schedules are implemented to optimize the training process and prevent overfitting. Post-training, fine-tuning options are explored to create a versatile model deployable for inference or storage. In-depth information on hyperparameter choices, such as learning rates and batch sizes, becomes imperative for understanding the model's sensitivity. Moreover, the incorporation of regularization techniques, like dropout rates or weight decay, not only mitigates overfitting but also enhances model interpretability. The systematic approach outlined ensures the adaptability of image classification models to diverse datasets and task requirements, fostering transparency and reproducibility crucial for guiding practitioners. This framework is particularly valuable in the realm of plant disease detection. The transparency in model configuration not only elevates the reproducibility of the study but also offers invaluable guidance for practitioners aiming to implement or extend analogous approaches in this domain. With a focus on adaptability, this systematic methodology addresses the nuanced challenges posed by different datasets and specific classification tasks in image analysis. It serves as a reliable guide for practitioners in the intricate field of plant disease detection, aiding in the effective implementation or extension of similar approaches. The commitment to transparency in model configuration enhances the reliability of results and encourages a standardized approach for future research and applications in image classification, especially in the context of agricultural and plant health monitoring.

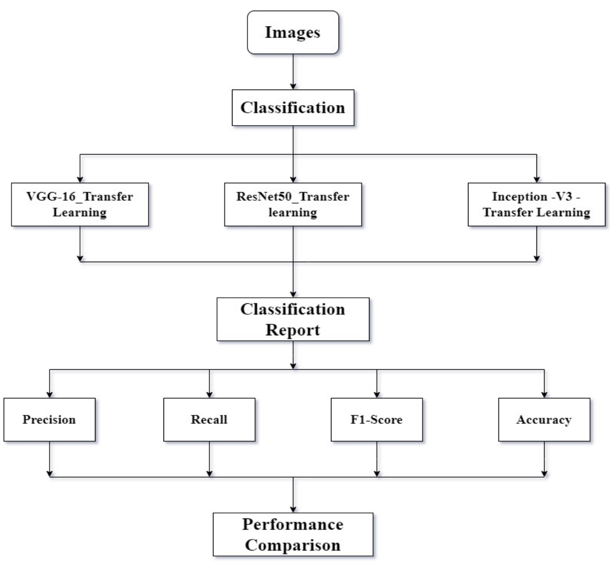

Fig. I Proposed Architecture

A. The ResNet50 Transfer Learning model

The model architecture utilizes the ResNet50 convolutional neural network, pre-trained on ImageNet, for plant disease detection. The top layers are excluded, repurposing ResNet50 as a feature extractor. A Global Average Pooling layer condenses features, and a Dense layer with Softmax activation enables multi-class classification. ResNet50 base weights remain non-trainable, leveraging prior knowledge from ImageNet for enhanced performance. Stochastic Gradient Descent optimizes the model with carefully adjusted parameters. Categorical crossentropy serves as the loss function for multi-class classification, with relevant evaluation metrics. Training occurs iteratively using generators, and critical callbacks ensure optimal model weights and early termination if needed. The preserved model offers a robust solution for accurate image categorization.

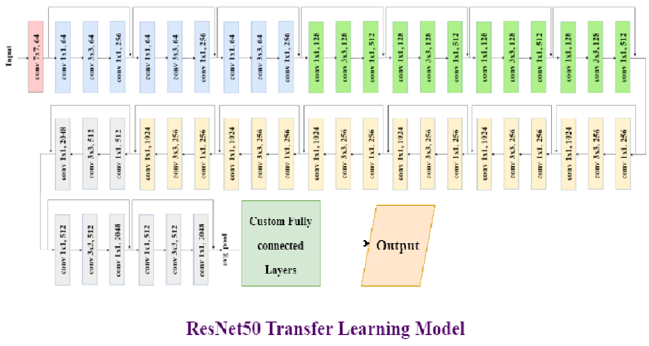

Fig. II The ResNet50 Transfer Learning Model

B. The VggNet16 Transfer Learning model

The model architecture for plant disease classification is built upon the VGG16 convolutional neural network, utilizing transfer learning with ImageNet weights. The modified model includes a custom classification head and fine-tuning options for selective training. Two densely connected layers, a dropout layer, and a softmax output layer form the classification head. The model is assembled with categorical crossentropy loss, an optimizer (initially 'rmsprop'), and accuracy metric, employing early halting and learning rate adjustments for enhanced training convergence.

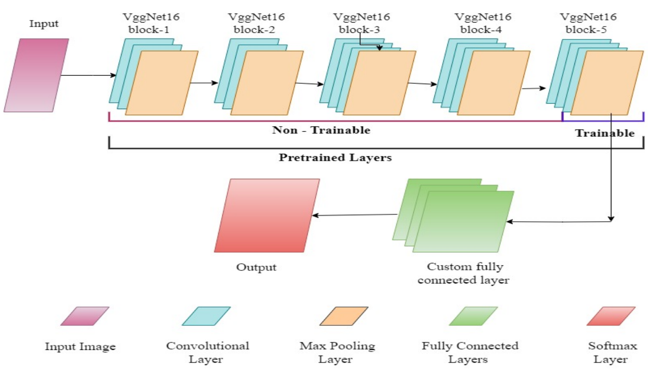

Fig. III The VggNat16 Transfer Learning Model

C. The InceptionNet V3 Transfer Learning model

Utilizing InceptionV3 architecture with pre-trained weights from ImageNet, a plant disease identification model is crafted. Customizable fine-tuning, specifying trainable layers, strikes a balance between adapting to plant disease datasets and leveraging pre-trained knowledge. The model includes global average pooling, a densely linked layer, and a dropout layer to mitigate overfitting. The output layer, employing softmax activation, classifies outputs into probability distributions across plant disease classes. Assembled with Adam optimizer, categorical crossentropy loss, and accuracy metric, the model is configured for training.

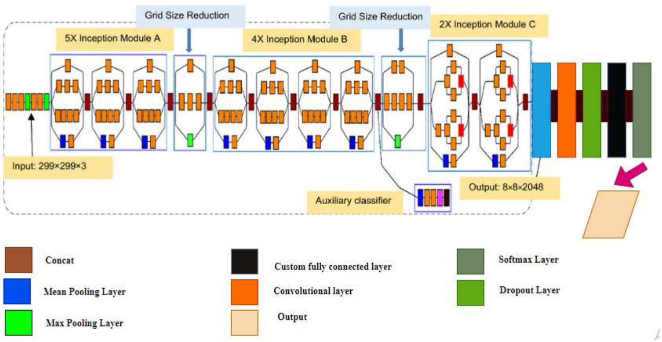

Fig. IV The InceptionNet V3 Transfer Learning Model

V. RESULTS AND CONCLUSION

The experimental findings show that the assessed pre-trained models applying transfer learning for image classification have different performance traits. ResNet50 was the most impressive performer, with the best accuracy of 83.23%. This conclusion is consistent with the literature's general trend, which highlights the effectiveness of deeper architectures especially those that incorporate residual learning for better feature representation and classification accuracy. The accuracy of the VGG16 model was improved to a notable 79.27% after fine-tuning. This result emphasizes how flexible VGG16 is when task-specific modifications are implemented, corroborating earlier studies that promote fine-tuning as an effective method for improving trained models.

InceptionV3 showed competitive performance with and without fine-tuning. With an accuracy of 76.43%, the untuned InceptionV3 demonstrated a trade-off between computing efficiency and accuracy. A further indication of the refined InceptionV3's adaptability in attaining a trade-off between model complexity and performance is its accuracy of 74.82%. These findings give practitioners practical advice on how to choose a model depending on the demands of a given activity and the computational resources at hand. ResNet50 performs well in situations where high accuracy is critical, while VGG16 is a strong option for task-specific optimization due to its fine-tuning-capable flexibility. Efficiency-wise, InceptionV3 shows itself to be a reasonable choice because of its well-balanced performance. All things considered, this thorough research adds significant knowledge to the larger field of pre-trained models, helping practitioners make judgments that are appropriate for their practical image classification applications.

The comparison study on transfer learning-based pre-trained models for plant disease detection—ResNet50, VGG16, and InceptionV3—revealed distinct performance characteristics. ResNet50 outperformed others with an accuracy of 83.23%, highlighting the efficacy of deep residual learning. VGG16 demonstrated flexibility through fine-tuning, achieving a notable accuracy boost to 79.27%. InceptionV3, with and without fine-tuning, showcased a balance between computing efficiency and accuracy (76.43% and 74.82%, respectively). These findings guide practitioners in selecting models based on task demands and computational resources. The research contributes valuable insights to the field, informing decisions for practical image classification applications, and suggests future directions for enhancing model flexibility, fine-tuning strategies, and generalization skills.

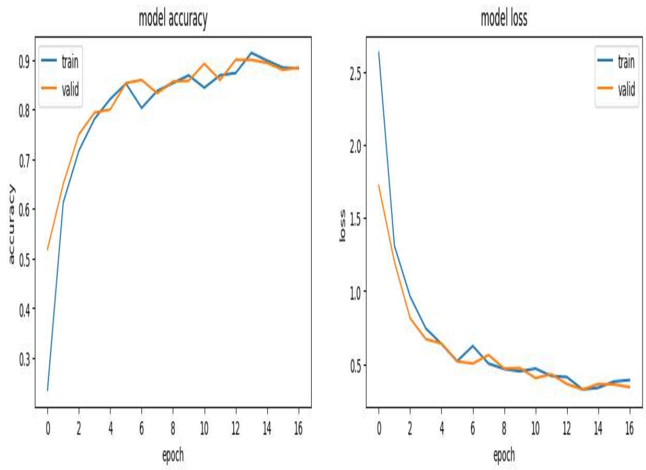

Fig. V Accuracy and loss plot diagram of ResNet50

TABLE 2. Accuracy and loss result of ResNet50 model

Parameter name	Accuracy (%)	Loss
Training	88.28	0.3898
Validation	88.44	0.3409
Test	83.23	--------

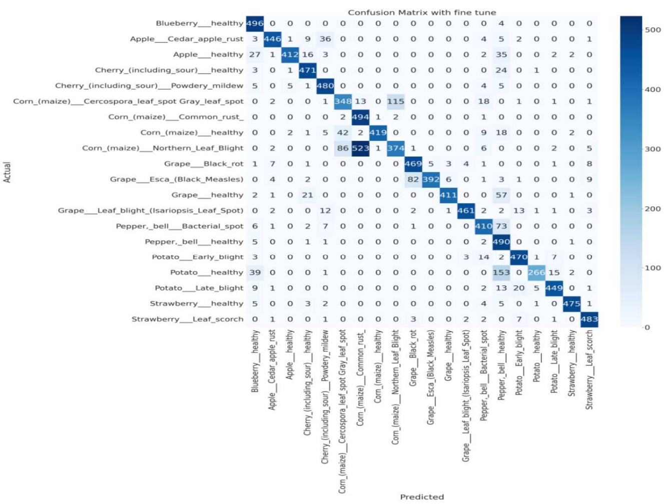

Fig. VI Confusion Matrix of ResNet50

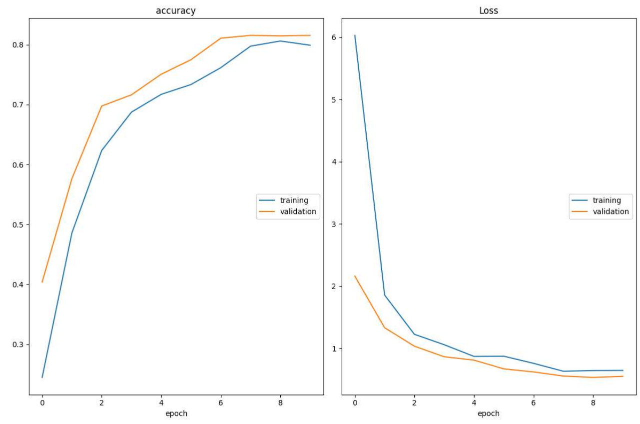

FIG. VII VGGNET16 TRAINING AND VALIDATION ACCURACY AND LOSS OVER EPOCHS

TABLE 3. Accuracy and loss result of VggNet16 model

Parameter name	Accuracy (%)	Loss
Training	79.92	64.67
Validation	81.56	55.14
Test	79.27	-

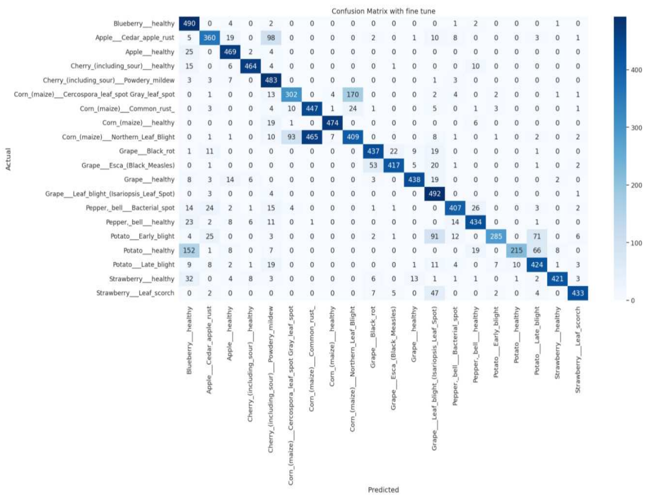

Fig. VIII VggNet16 Confusion Matrix

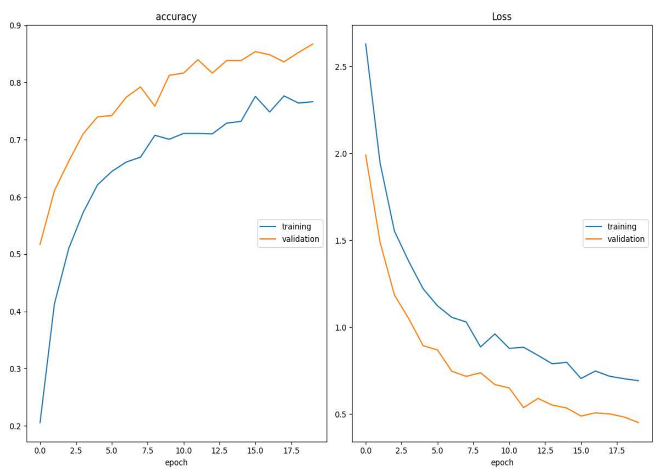

FIG.. IX INCEPTIONNET V3 TRAINING AND VALIDATION ACCURACY AND LOSS OVER EPOCHS

TABLE 4. Accuracy and loss result of InceptionNet V3 model

Parameter name	Accuracy (%)	Loss
Training	73.12	0.7790
Validation	88.13	0.3089
Test	76.43	---------

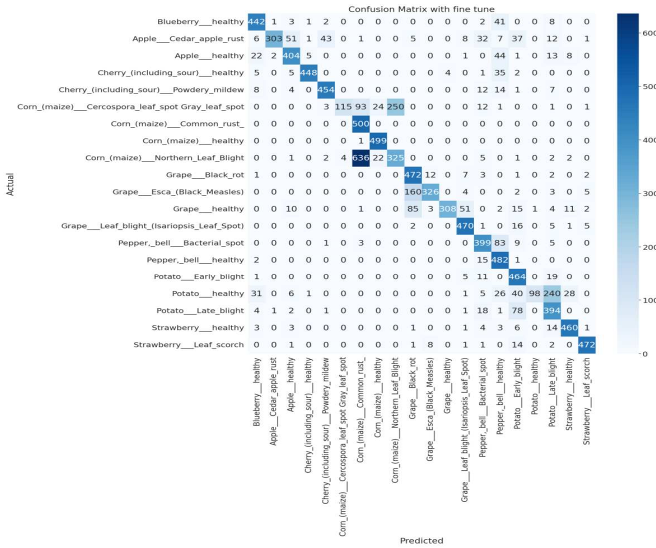

Fig. X InceptionNet V3 Confusion Matrix

VI. LIMITATION AND FUTURE SCOPE

The systematic approach delineated for developing adaptable image classification models in the context of plant disease detection presents a comprehensive framework, yet it is crucial to acknowledge certain limitations and outline future directions for continued improvement. Limitations include potential biases within the training data, raising concerns about the model's ability to generalize effectively to unseen environmental conditions or emerging plant diseases. Furthermore, the computational demands of training deep learning models, particularly those with intricate architectures, may pose accessibility challenges for researchers with limited computational resources. The interpretability of the model remains an ongoing challenge, given the inherent complexity of deep learning systems. Looking forward, the future scope entails exploring multi-modal fusion techniques, incorporating data from diverse sources such as spectral and textual information, to enhance the model's robustness across varied agricultural scenarios. Refining transfer learning strategies, especially through domain adaptation tailored to agricultural contexts, represents a key avenue for improving model performance. The prospect of real-time deployment in agricultural settings, while considering computational constraints, emerges as a critical area for practical implementation. Future work should focus on the integration of explainable AI techniques to enhance model interpretability, conducting longitudinal studies to assess model performance over time in dynamic agricultural environments, addressing privacy and ethical considerations, collaborating closely with domain experts to integrate valuable domain-specific insights, benchmarking across different crops for broader applicability, and promoting open-source initiatives to facilitate collaboration and accelerate advancements in the field. Additionally, the integration of edge computing capabilities stands out as a promising avenue to enable on-device processing, reducing dependency on centralized infrastructure and facilitating real-time decision-making in the field. These collective efforts aim to propel the refinement and extension of deep learning models in plant disease detection, addressing technical challenges while ensuring ethical and responsible deployment in agricultural settings.

ACKNOWLEDGMENT

With immense pleasure and a deep sense of gratitude, I wish to express my sincere thanks to my supervisor **RAJKUMAR S**, Associate Professor Sr., School of Computer science and Engineering(SCOPE), Vellore Institute of Technology (VIT), Vellore without his/her motivation and continuous encouragement, this research would not have been successfully completed.

CONFLICT OF INTEREST

The author states that there is no conflict of interest.

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