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Automated Plant Disease Detection and Recognition Using Convolutional Neural Network

Ayesha Rehan[1], Avanish Verma[2], and Chitransh Nigam[3]

[1, 2, 3] B. Tech Scholar, Department of Computer Science & Engineering, Khwaja Moinuddin Chishti Language University, Lucknow, India

Correspondence should be addressed to Ayesha Rehan; ayesharehan680@gmail.com

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ABSTRACT- Sustainable Agriculture has reduced environmental harms, aids and expands natural resources for productive purpose. It allows the production of crops to ensures global food security. Plant Diseases leading to considerable crop losses and economic challenges for farmers. In the era of Modern technology there is a need of fast and accurate detection is essential for effective intervention and management. Modern innovation and research developments in machine learning and deep learning enabled automated plant disease detection that are providing fast scalable, and highly accurate solutions. While previous models are implemented for single type plant to get higher accuracy and therefore, they need high resolution images. Convolutional Neural Network provide excellent performance in classifying and identifying diseases from datasets of plant leaves images with low resolutions. The usage of pre trained models and focus on the fine tuning of the hyperparameters leads the highest accuracy in detecting plant disease. However, there is need of strategy, adaptability and robustness to achieve goals.

KEYWORDS- Plant Disease Detection, Convolutional Neural Network, Accuracy

I. INTRODUCTION

Agriculture is the primary sector of most of countries across globe. It is the major source of their economic growth. Plant Diseases spread in crops affect the quality of plant and production that can lead a major threat to global food chain supply. Therefore, advanced and precise AI based technology solutions can prevent threat by early detection of disease and provide end to end solutions. Convolutional Neural Network is a deep learning model that leveraged power of pre trained models in detecting different plant image classes. In such model there are different critical factors for image analysis and pattern recognition, there are many models to initialize the process. To learn a robust distance metric, we need abundant side information which is usually unavailable in practice due to the high labelling cost. A process like a matrix factorization, distance metric learning, and clustering method finds similar pixels to classify into clusters or classes, yet these distance metric problems in unsupervised or weakly supervised clustering tasks, especially for unified theoretic schemes and optimization algorithms. There is no proper image recognition using a huge number of images trained into a model which can be achieved by a Convolution neural network. Basically, in the existing system there is no such feature by which we can detect the affected leaf, for which there is huge cause of damage of different types of crops and plants. In recent times due to bad weather and less soil farmers are facing huge losses. In crops different types of substances are present like diseases, pests, etc., The impact of these dangerous factors on crops has an appearance, morphology, and other characteristics of the leaves. By using the older existing system, it is impossible to find an affected leaf and cure it.In this used system, any user who wants to find the disease formed in their crops are benefited. When the user uploads images of the affected crop by fungus and bacteria, the user can conclude what caused it and what should be used to mitigate the problem in near future. It has a trained model which contains a huge number of images by matrix conversion using CNN then admin compares the user given images with the trained model. So, initial images are converted into an input layer which is a grayscale image. The output layer is a binary or multi-class label. Hidden layers consist of convolution layers, ReLU (rectified linear unit) layers, the pooling layers, and a fully connected Neural Network. The above process takes care of image conversion matrix to segregate each block according to the density of greyscale, compare it with the same kind of format and recognize disease using the trained model.

II. RELATED WORKS

Here we will discuss the progress and research work done in the field of Plant disease detection.

S. K. Noon, M. Amjad, M. A. Qureshi, and A. Mannan, et .al [6] describes various approaches for detecting the disease in plant leaf using various image processing techniques Several studies on Machine Learning and Deep Learning approaches used in agriculture have been evaluated, leaving a gap to comprehensively examine image-centered plant disease detection. Most recently, a review was made of the imperativeness of existing Plant Disease Detection methods and included segmentation, classification, localization, and disease techniques.

R. Manavalan, et .al [7] study concentrated on the performance of the CNN method in Plant Disease Detection, primarily on various plants. The authors compared the performance of various approaches based on feature extraction, classification, segmentation, and

preprocessing using IP. They noticed that the segmentation strategy known as "k-means" was frequently used to identify plant diseases

A. Abade, P. A. Ferreira, and F. de Barros Vidal, et .al [8] experiment is generally focused on the CNN model as it is used in the PDD and concluded by showing that there is still a gap to fill in improving the methods when considering identical visual environments, respectively. There is a need to assess the in-situ application potential of various techniques. Since datasets are a vital part of making artificial intelligence applications, it is not impractical to ignore data collection techniques and the fact that there are public data sources.

M. Nagaraju and P. Chawla, et .al [9] analyze different techniques and interview also discusses the various kinds of openly accessible datasets that in the field use. In addition, this review examines the influence of current trends in DL, localization, TF, and attention processes, together with lightweight approaches in PDD. In addition to the necessity for additional research on TF strategies, the impact of lightweight models in real- time applications must also be investigated.

Mohit Agarwala, at all [10] The Plant Village dataset was used to create a CNN-based algorithm for identifying sickness in tomato plants. Three convolution and max pooling layers, each with a different number of filters, are included in the proposed CNN-based design. There are nine disease categories in the collection, as well as a healthy image category. Because the photographs in the class were uneven, data augmentation techniques were used to equalize them. The model's average testing accuracy is 91.2 percent, according to experiments. The suggested model uses only 1.5 MB of storage space, compared to roughly 100 MB for pre-trained algorithms, demonstrating its superiority to pre-trained algorithms.

Liaghat, S. Mansor, R. Ehsani, H. Z. M. Shafri, S. Meon, and S. Sankaran, et .al [11] model attained an accuracy of 97% when applied to the dataset consisting of sugar beetroot leaves. The authors utilized KNN and NB classifiers to identify oil palm leaf diseases. On the validation DSS, the proposed method attained an accuracy of 92%. To construct a disease classification model utilizing hyperspectral images, we first performed several image preprocessing approaches, and then we used a super vector machine classifier.

A. Abbas, S. Jain, M. Gour, and S. Vankudothu, et .al [12] In this study researchers extracted features from the first two VGG16 to minimize the model size. SVM and random forest methods are classified. A variance of plant symptoms and diseases as a time function developed a CNN model that could capture variations. Their approach was tested on plant images from the Plant Doc Dataset collection, and a little model showed 93% accuracy. A classification model that was a modified version of DenseNet .

S. Jadhav, et .al [13] ReLu nonlinearity and overlapping pooling have become a prevalent feature in modern architecture. Such developments have helped to reduce training time and error rate. Above all, the evolution of architecture has been a necessary demand of large and complex datasets.

Kumari, Ch. Usha, et .al [14] In her experiment she proposed a two-step approach for leaf disease detection, involving feature extraction using K-means clustering and disease classification using an artificial neural network. The study demonstrated the effectiveness of this method in accurately identifying leaf diseases, contributing to improved accuracy and efficiency in disease detection systems.

P. Manoj, Kumar, C. M. Surya, and Varun P. Gopi, et .al [15] A system that investigates feature vectors from both the front and back sides of the green leaf, as well as morphological traits, to find a unique ideal combination that maximize the identification rate. Using a classifier or matching algorithm the performance analysis is executed and displays the name of the medicinal plant with its accuracy.

Bhimte, Namrata R., and V. R. Thool, et .al [16] Their proposed technique has been devised for detecting cotton illnesses at an early stage of diagnosis. The classification and image preprocessing of cotton leaves are done in the following steps. RGB Image Acquisition, Image acquisition and preprocessing Segmentation of images, Segmented Image Feature Extraction and Categorization. The composed classifier functions give the accuracy of 98.46%.

Kulkarni, Pranesh, et al. [17] the built system employs computer vision and machine learning techniques to identify crop disease in a smart and effective manner. With a 93 percent accuracy, their suggested method can detect 20 distinct diseases in five popular plants to increase the efficiency of system. As a result, the technology can be used to detect unhealthy plants in an agricultural setting in real time. It has a 93 percent accuracy rate and a 0.93 F1 score.

Singh et al. [18] presented disease detection and classification of potato plant leaves using machine learning methodologies. Utilizing machine learning techniques, the proposed model was used to identify and categorize potato leaves that were damaged and those that weren't. The entire procedure involved several processes, including image collecting, image preprocessing, image segmentation, feature extraction, evaluation of the impacted region.

Shah, Nikhil and Jain, et .al [19] conducted research on disease detection in cotton leaves using an artificial neural network (ANN). Their study aimed to develop an efficient system for identifying diseases in cotton crops based on leaf images. By training an ANN using features extracted from the images, the authors achieved satisfactory accuracy in disease detection.

Tejaswini et al. [20] The Grey Level Co-occurrence Matrix was utilized for feature extraction, the K-means approach employed image segmentation, and a multi-class support vector machine algorithm with a linear kernel function was used to classify potato leaves. There is different framework was used to check criteria, such as precision, recall, F1-score, and accuracy. The model F1-score, precision and recall found approximately 96.16%,96.12% & 96.25% respectively. Its total accuracy is approximately 95.99%.

Mamta Gahlot et al. [21] with minimum resources, uses five different CNN models to classify tomato leaf diseases into ten different classifications. The models are AlexNet, VGG16, GoogleNet, ResNet-101, and DenseNet-121 and of the five models, this is the tiniest, DenseNet-121, has the greatest precision (99.694%) as well as the finest size (113.28MB). Plant Villages pictures were utilized in the recommended system, which totaled 14529. Data Generator was used to reduce memory use because loading 14529 photographs with 256 256 sizes was difficult.

Krishnaswamy Rangarajan Arvind, Purushothaman Raja & et al. [22][34] found the biotic stress of agricultural crops is

major concern across the globe. Its major effects are felt in economically poor countries where advanced facilities for diagnosing a disease are limited as well as lack of awareness among the farmers. In this study images acquired through smartphones are transmitted to a personal computer via wireless LAN for classification of ten different diseases using transfer learning in four major agricultural crops which are least explored. Six pre-trained Convolutional Neural Networks have been used namely Alex Net, Visual Geometry Group16(VGG16), VGG19, Google Net, ResNet101 and DenseNet201 with its corresponding results explored. Google Net resulted in the best validation accuracy of 97.3%. The misclassification was mainly due to TMV and two-spotted spider mite. In test conditions, images were classified in real-time and prediction scores have been evaluated for each disease class. It depicted a reduction in accuracy in all models with VGG16 resulting in the best accuracy of 90%.

Table 1: Comparison among various existing techniques from different research papers

Crop Focus	Dataset	Classes	Model	Limitations	Results
Soybean leaves [23]	Self-generated Database	3	AlexNet and GoogleNet CNNs	The model slipped in Classification diversity. Many current models focus on defining a single class of plants disease instead of building a model to classify different plant diseases.	98.75% and 96.25%
Tomato [24]	Conditional, Generative, Adversarial Network for generation	10	DenseNet121 model	Reliance on synthetic data may hinder model's real-world performance.	97.11%
Tomato [24][25][26]	Plant village and Taiwan tomato leaves,	13	CNN model	Benchmark studies lacked realism, affecting model performance in practical scenarios.	95.98%
Several[27]	Plant Village	39	VGG16	Solely emphasizes tomato crop disease identification, limiting broader applicability.	94.9%
Tomato plant [28]	Self-generated Database	9	Faster Region based CNN and Region based Fully Convolutional Network	Limited realism hampers model's efficacy in real-time disease recognition.	85.98%
Apple [30]	AI-Challenger plant disease recognition	6	DenseNet-121	Insufficient exploration of apple leaf disease recognition challenges and solutions.	93.71%
Several [31]	Plant Village	38	MobileNetV3	Limited assessment of deep learning models' real-world performance on edge devices	96.58%
Several [32]	Public Database	7	Pre-trained models	Limited analysis of deep transfer learning for plant disease identification.	91.83%
Paddy [33]	Self-generated Database	4	Pre-trained CNN with SVM classifier	Focused on color features, potentially overlooking other relevant disease indicators.	94.65%

III. METHODOLOGY

This section explained how we collected the plant leaf image dataset and any preprocessing techniques that were used to prepare the data for modeling. It also describes the models that are implemented and evaluation metrics that are used to measure performance. It is important to explain how you optimized hyperparameters of your models, such as the learning rate and batch size, and how you validated your models to prevent overfitting. In this project, we implement several deep learning technologies in order to classify the diseases in crops. Among machine learning techniques, deep learning is an interesting area since it can easily recognize patterns and perform complicated procedures, which makes it suitable for the disease classification task. In deep learning, deep neural networks are created, among which is the CNN, short for Convolutional Neural Networks, that can easily analyze images upon training. In our project, VGG-16 was selected to be the CNN classifier of different plant disease.

A. Dataset Collection

The chosen dataset for our study is the Plant Doc dataset consisting of 13500 images of various plant leaves, with approximately 70% of the images being Healthy and 30% being different kinds of disease.

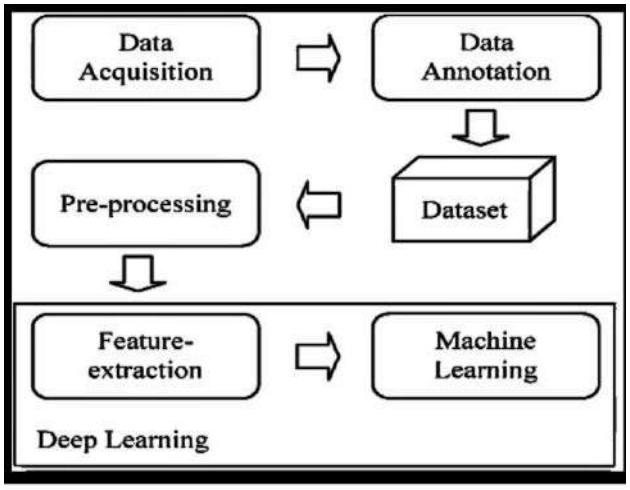

Figure 1: Steps in the Implementation of Deep Learning Models in Plant Disease Detection and Recognition

Our dataset images are selected from different flora regions where the diseases were spread. There are 20% relative distribution of the total dataset. The fifteen classes include tomato, grape, apple, tomato, and corn diseases as well as healthy classes. In the above Figure 1 demonstrates in detail the different classes and to which crop they belong. The number of images per class varies between the classes. After the data had been selected, they are collected in a csv file, where each image is labeled with a path that indicates the health conditions of the crop within the image. In order for the data to be convenient for our chosen model, all the text value had to be converted into numeric values that are suitable for the model. Moreover, the majority of the dataset's images (80%) were utilized in the training procedure, and the rest 20% were kept for testing.

B. Used Model Architecture

VGGNet is the CNN architecture that was developed by Karen Simonyan, Andrew Zisserman et al. at Oxford University. VGGNet is a 16-layer CNN with up to 95 million parameters and trained on over one billion images (1000 classes). It can take large input images of 224 x 224-pixel size for which it has 4096 convolutional features. CNNs with such large filters are expensive to train and require a lot of data, which is the main reason why CNN architectures like GoogleNet (AlexNet architecture) work better than VGGNet for most image classification tasks where input images have a size between 100 x 100-pixel and 350 x 350 pixels. Real-world applications/examples of VGGNet CNN architecture include the ILSVRC 2014 classification task, which was also won by GoogleNet CNN architecture. The VGG CNN model is computationally efficient and serves as a strong baseline for many applications in computer vision due to its applicability for numerous tasks including object detection. Its deep feature representations are used across multiple neural network architectures like YOLO, SSD, etc. The diagram below represents the standard VGG16 network architecture diagram. In fact, “V” means Visual,” G” Geometry while “G” stands for the research group who contributed to the development of this Convolutional Neural Network model, whereas the number 16 refers to the neural network layer’s number. ImageNet is so large that it contains more than fourteen million images distributed over thousand classes. This architecture is one of the top 5 models in terms of performance achievement in the ImageNet dataset, where its accuracy reached 92.7%. As an approach for the AlexNet enhancement, this architecture was submitted to ImageNet.Large Scale Visual Recognition Challenge (ILSVRC), where this model has replaced the large kernel-sized filters

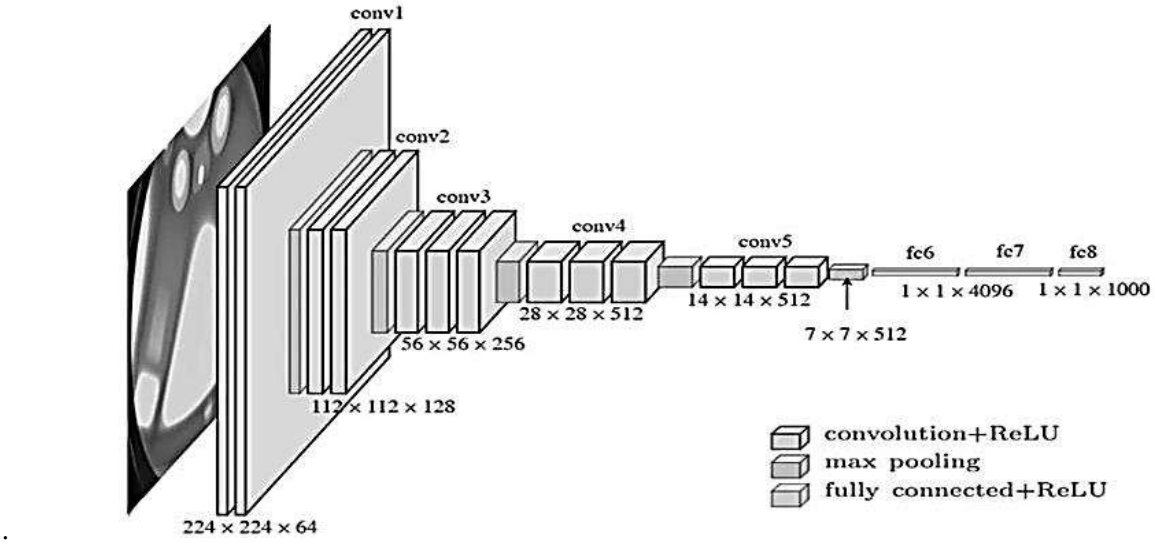

Figure 2: Representations of VGG16 Architecture

C. Preprocessing

Total 13500 images of various plant leaves of Plant doc dataset are selected causing different cameras, lighting conditions and orientations. We preprocess the images to ensure that are fit to consistent format and size. we first resize all images to 256 x 256 pixels using bilinear interpolation and normalized the pixel values of the images to have zero mean and unit variance. Finally, we applied both random horizontal and vertical flips, as well as random rotations and zooms, to each image to increase the size of dataset

D. Labelling

Labelling is the process of label each image in our dataset with the correct class label to trained our supervised

learning model Each image label with one of three labels: Late Blight, Early Blight or Healthy. We randomly sampled a subset of images and had two annotators independently label the same images to increase accuracy and used Cohen's kappa to measure the agreement between the two annotators with kappa score of 0.92, indicating almost perfect agreement between the annotators.

E. Data Augmentation

Data augmentation techniques such as random cropping, flipping, rotation, and zooming are used to provide diversity and variability of dataset. This will help prevent overfitting and improve the generalization ability of our CNN model. Flipped each image horizontally and vertically with a probability of 0.5and randomly rotated each image within a range of -10 to 10 degrees and zoomed each image by a factor of 0.8 to 1.2. We used the Keras Image Data Generator class to perform data augmentation during training. This allowed us to generate new images on-the-fly during training without having to store them on disk. There is a batch size of 32 images during training, and generated 10 augmented images for each original image in dataset.

F. Feature Extraction

This process extracts high-level features from plant leaf images to effectively classify them into different disease classes. To obtain, we use a pre-trained CNN model (VGG16) to extract features from the images and then fine-tune the model on our specific task. Before training our CNN model, we performed feature extraction on our dataset of plant leaf images. Figure 2 shows that VGG16 is a widely-used pre-trained model that has been trained on the ImageNet dataset and has achieved state-of-the-art performance on various computer vision tasks. Final classification layer of the VGG16 model removed and used the resulting convolutional layers to extract features, flattened the output of the last convolutional layer and used it as input to our own fully connected layers. By using the pre-trained VGG16 model for feature extraction, we were able to leverage the model's ability to extract high-level features from images and improve the performance of CNN model.

G. Neural Network Training

Convolutional Neural Network (CNN) to classify various plant leaves into different classes: Late Blight, Early Blight, and Healthy. Our CNN model consisted of four convolutional layers, followed by two fully connected layers, and a final output layer with a SoftMax activation function. Model have a total of 33,248,707 parameters and trained using the Adam optimizer with a learning rate of 0.0001 and a batch size of 32. We used categorical cross-entropy as the loss function and accuracy as the evaluation metric. We trained model on a GPU for 50 epochs, and we monitored its performance on a validation set of 20% of the dataset. We found that our CNN model achieved a validation accuracy of 95%, shows that able to classify images. We found that the use of dropout regularization and data augmentation significantly improved the model. Model is trained on the extracted features and evaluated its performance on the validation and testing sets. We used appropriate loss and evaluation metrics such as categorical cross-entropy and accuracy to measure the model's performance. Once we have developed a CNN model that meets our accuracy and performance requirements, we can deploy it in a real-world scenario for practical use. This involves integrating the model into an application or system that can automatically detect and classify plant diseases based on input images. The model can handle different types of input images and produce reliable and consistent results. Performance of our model and helped to reduce overfitting.

H.Activation Function Used

Two activation Functions were used for our model training where the Softmax activation and the ReLU function. The ReLU function was used at the fully connected layers, where the ReLU or “Rectified Linear Unit” is one of the popular activation functions used in Neural Networks and specifically in Convolutional Neural Networks and is defined as in $y = \max(0,x)$.Moreover, the Softmax activation function is used for the output layers and this activation function is a type of logistic regression that is able to normalize the inputted vector to a new vector where its probability distribution is equal to 1 and it is defined.

I. Loss Functions used

In the machine learning domain, the cost functions tend to optimize the model in the training procedure and the aim of the training procedure is to minimize the loss function and the model obtained is better as much as we tend to minimize this loss function. Therefore, one of the most important loss functions is the Cross Entropy Loss Function where it is used for Classification model optimization and the complete understanding of this loss function depends on the Softmax activation function understanding. Moreover, in our project, the Sparse Categorical Cross Entropy is used for training our model where it has the same loss function as that of the cross entropy. However, the truth labelling procedure is what differs between the two loss functions, where in the case of a one hot encoded true labels ([1,0,0], [0,1,0] and [0,0,1] in classification problem) the categorical cross entropy is used, while the cross entropy is used in the case of an integer truth labels coding ([1],[2],[3]).

J. Accuracy Calculation

The accuracy of the model is calculated as

$$Accuracy = \frac{\text{Total Positive}}{\text{Total Positive} + \text{Total Negative}} \times 100$$

IV.RESULT AND DISCUSSION

Our trained Model detecting and classifying different types of plant diseases. We obtained an accuracy of 98% on average, with the accuracy ranging between 95% to 100%. Specifically, the accuracy for identifying early blight was 98%. We used confusion matrices, precision, recall, and F1-score techniques to check performance of the model. The model's performance on the test set, which was separate from the training and validation sets, showed that it was highly effective in real-world situations. Figure 3 shows the comparative analysis of our model accuracy with training and validation set on a GPU of 50 Epochs. The accuracy always ranges between 95 % to 99%. Figure 4 shows the loss with training and testing sets on a GPU of 50 Epochs. Loss Function always lies minimum means no data loss.

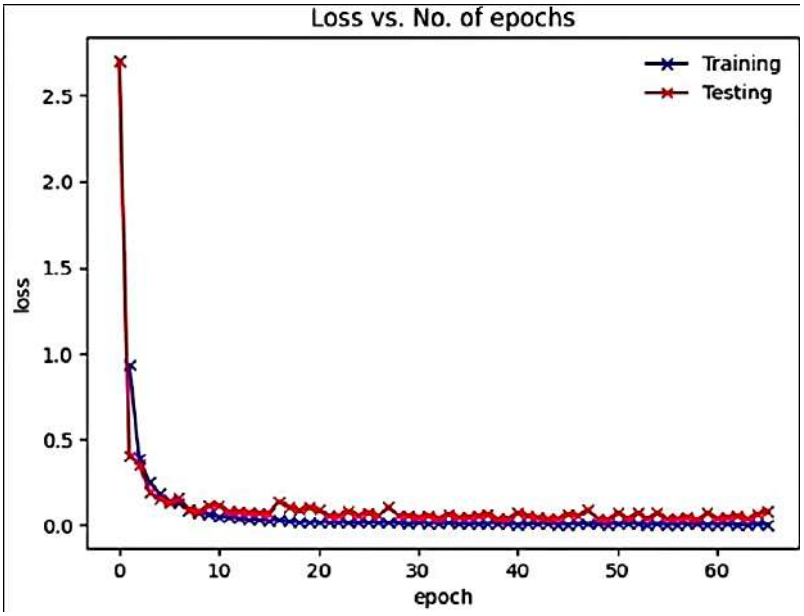

Figure 3: Accuracy vs No. of Epochs for CNN

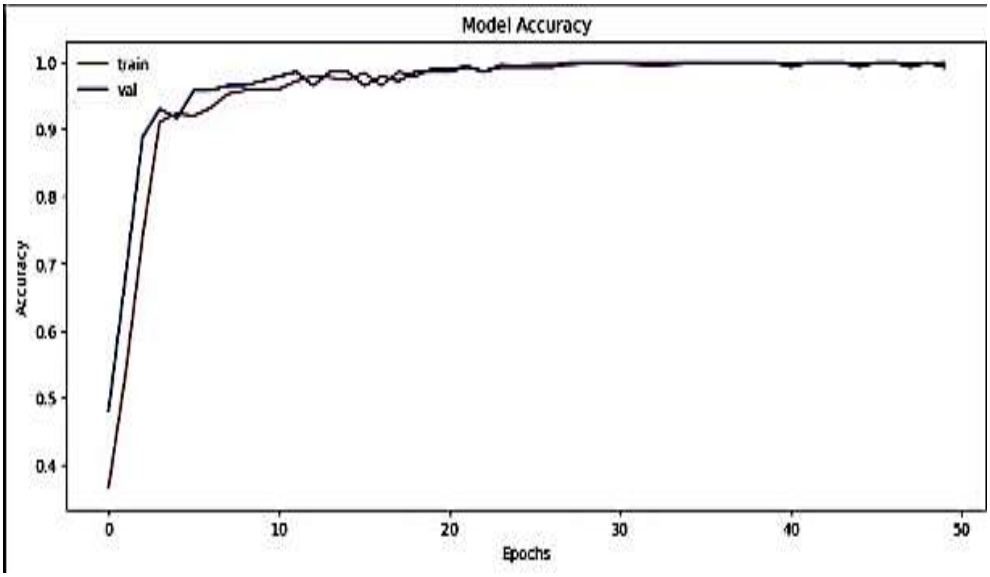

Figure 4: Loss vs No. of Epochs for CNN

V. FUTURE SCOPE

In future there are different tool and techniques to improve the computational time and accuracy of Transfer Learning model. It can be done by fine-tuning their parameters and updating the final layers. Reducing complexity, such as model compression or pruning, can further enhance efficiency. Accurate disease detection is challenging task. Dataset plays a major role and will be working on this issue in future. FLOPs (Floating Point Operations) can optimize the models for better efficiency can optimizing accuracy to reduce costs. Vision transformers and attention system can improve detection efficiency under different environmental conditions. Smartphones, drones, and IoT sensors can used for on ground diseases diagnosis with lightweight model. We can integrate the multi-dimensional data such as climatic data, environmental dataset to early detection of disease and for better cure. We can improve model interpretability using explainable AI methods to make decision-making transparent for farmers and agricultural experts. User-friendly mobile and cloud-based applications with real-time alerts boosts the farmers to facilitate cure timely. We can collaborate with agricultural stakeholders for field trials in varied ecological settings to validate and refine the system's practical utility.

VI. CONCLUSION

Plant Disease Detection and Recognition are crucial and challenging in sustainable agriculture. The research shows how Convolutional Neural Network of Deep learning and pre trained model like VGG16 has accomplish remarkable potential in automating plant disease detection. It offers scalable and accurate solutions that benefit agriculture across globe. It helps research in data collection, model robustness, and interpretability will further enhance the adoption and impact of these technologies. There is always improvement to focus on the accessibility and usability of deep learning enabled techniques and tools. To providing the stock of technologies available to smallholder farmers,

who represent a significant portion of the global agricultural food security and rural economies. Users and stakeholders will depend on the ability to explain model predictions, safeguard sensitive data, and create frameworks that promote fair and equitable benefits from this advancement. However, research continues and multidisciplinary approach will be essential for maximizing the positive impact of deep learning in plant disease detection.

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CONFLICTS OF INTEREST

The authors declare that they have no conflicts of interest.

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