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SOME VEGETABLE PLANT DISEASE DETECTION FROM LEAF IMAGES USING RESNET-9

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Abstract: The very initial phase to alleviating losses in the quality and productivity of agricultural products is recognizing plant diseases. Utilizing these modern innovations is a key objective of this effort, which focuses on plant disease detection specifically. The system will use state-of-the-art image processing algorithms to evaluate plant pictures in order to accurately detect diseases and provide suggestions. for the necessary nutrient supplements and pesticides. The suggested technique will not only detect the presence of diseases but will additionally pinpoint specific nutrient deficiencies that have caused issues with crop health. In the end, this will support prompt and effective management of crop diseases, increase agricultural productivity, and lessen financial losses. Equipped with 13505 photos of crop leaves from an available dataset, a Residual Network (ResNet-9) was trained to deal with this classification operation. The postulated ResNet-9 model showcased its viability by achieving 99.20% accuracy on a test set. All in all, employing an open-picture dataset to train ResNet models proposes a reliable path toward crop disease detection.

I. INTRODUCTION

In India, which is a developed nation, 70% of the population contributes to agriculture. Farmers have an extensive amount of alternatives when it comes to deciding upon different kinds of crops as well as discovering plant-safe insecticides. Harm to the crops would subsequently result in a major decrease in productivity, which would thereby have consequences on the economy. initially leaves are indeed the most tender element of a plant, indicators of illness appear initially on leaves. The crops dire need to have their health regularly checked from the initial stage of their life cycle till they are suitable to be harvested. Early on, the traditional naked-eye method of analyzing plants for illnesses was implemented. That approach needs time and needed proficient to meticulously inspect the field of crops [1].

Numerous approaches have been deployed in recent years to construct automatic and semi-automated disease identification systems. It is currently simpler and more affordable to identify diseases automatically by just gazing for signs and symptoms on the plant leaves. At present, these technologies have shown to be speedy, convenient & better comprehensive in contrast to inspections carried out by farmers, regarded as the conventional approach. Disease symptoms tend to arise on the fruit, stems, and leaves [2]. The plant leaf that showcases the signs of the disease is taken taken into account for disease detection. There are many instances where farmers lack comprehensive knowledge about the crops and diseases that may damage them. Rather than going to the expert and asking for a helping hand, farmers may maximize yield simply by employing this material or paper data efficiently. Enough water, sunlight, and plant nutrition intake are the essential elements of the agricultural system. Different plants require varying concentrations of nutrients, which fall into two groups as macro- and micronutrients. Given that macronutrients serve as vital for the proper growth of plant cells and tissues, they are present in higher concentrations than micronutrients. Ferrum (Fe), Potassium (K), Calcium (Ca), Zinc (Zn), Cuprum (Cu), Manganese (Mn), Phosphorus (P), Sulfur (S) & Magnesium (Mg) are the constituent elements of macronutrients. Leaf growth interferes with food generation, resulting in a macronutrient shortage. Growth problems including dwarf plants and poor flowering and fruiting are associated with inadequate food formation [4]. A lack of nutrients will instantly show up in the color and growth of the foliage; Table 1 lists the specific symptoms.

Macronutrients	Symptoms
Nitrogen (N)	Greening of upper leaves & lower leaves becomes green.
Potassium (K)	Leaves becomes yellow and purple and at leaves edges it becomes brown & poor flower & fruits.
Phosporus (P)	Yellow folliage and slow growth notice in plants.

Table 1. Macronutrients deficiency symptoms

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During this entire time frame, deficiency surveillance carried out by personally observed observation. cultivators frequently verify the health of their plants to see if they are receiving adequate nutrition. The method's drawback, though, is if the agricultural field is quite big. To comprehensively analyze the whole field, greater effort would be needed. Prior research has stated numerous of methods for figuring out nutritional deficiencies. A machine vision process is utilized to confirm the emergence of a calcium deficit in lettuce via examining the plants' morphological, color, and temporal alterations. When compared to human eyesight, this approach proved successful in spotting calcium insufficiency early. Based on information gathered through optical sensors, potato yield and sulphur insufficiency are projected for various types of crops. Image processing is not something that is novel in the realm of agriculture. Several ML and DL approach have been implemented to assist farmer to assist with, manage, or oversee agricultural procedures. So here the introduce system help to give the suggention on nutrient deficiency for greater quality of yield.

II. RELATED WORK

Following are the related work done by the researchers on plant disease detection.

1. Turkey D, Singh KK, et al. proclaimed that DL-based approaches have been proposed for genuine detection & identification of insect in soybean fields. The efficacy of several transfer learning (TL) approaches have been examined in order to figure out the method's dependability in terms of insect detection accuracy. The recommended method's effectiveness was 97% with InceptionV3, 97% with YoloV5, and 98.75% with CNN. The YoloV5 method, which operates in dynamic detection at 53 frames per second, noticed to be excellent among these. Additionally, a number of imaging technologies were utilized in order assemble and annotate a database of agricultural diseases. The technique provided better results, eased the study's burden on the producers & reduced costs associated with production.

2. Employing the "PlantVillage" dataset, Ahmed I., et al. (2023) demonstrate two virus, two mold diseases, four bacterial infections one & ailment associated to mites. There were also images of leaves from a dozen crop varieties that were untouched. GLCM, CNN, and SVM, among other machine learning techniques, were utilized to build prediction models. An extension of the study used ML techniques along with KNN to identify illnesses in real-time leaf pictures. It was shown that the overall efficacy of rice and apple plants was 98% and 98%, respectively, and that of tomato plants was 96%, 94%, 95%, and 97%. Utilizing a dataset containing one symptom pool per class, multi-layer classification has been assessed using Precision, F-measure & Recall metrics.

3. An adaptable DL method for disease diagnosis and bifurcation called ACO-CNN (Ant colony optimization with Convolutional neural network) was introduced by Algani YMA, Caro OJM, et al. in 2022. While CNN classifiers have been utilized to eradicate texture, geometric plant placement, color, and texture from the given pictures, ACO was implemented to assess illness diagnosis in plant leaves. This type of approach performs consistently better than previous attempts, judging by a number of effectiveness measures. These evaluations are used to analyze the data and propose a course of action. All of these approaches were put into practice with tangible actions.

4. Multi-level attention system, dilated convolution, & gap layers are characteristics of DL model PPLCNet, which was introduced by Dai G, Fan J, et al. in 2023. By broadening the sample size and strengthening feature extraction resilience & generalization, creative meteorological data supplementation was utilized. By utilizing saw-tooth dlated convolution with adjustable expanding rates that broaden the field of convolutional domains, the system outperforms insufficient data information extraction. A light-weight CBAM approache in a central layer facilitates information representation. The GAP layer decreased overfitting by lessening the no. & complexity of parameters. On the test dataset that was preserved for validation, the PPLC-Net model achieved an F1-score of 98.442% and a recognition accuracy of 99.702%. The model meets the requirements for precise and quick recognition with 15.486 million parameters and 5.338 billion FLOPs.

5. P. Nayar, et al. (2022) presented a technique for developing disease detection models by using deep convolutional networks (DCN) for leaf categorization. New possibilities for precision agriculture applications are being generated by the expanding field of computers, which provides the ability to improve and expand the usage of precise crop protection approaches. This process makes it potential to implement the system rapidly and directly. The research made use of seventy seven thousand pictures of both in good health and damaged leaves in the data set. A CNN was trained to categorize plant diseases and identify their presence, while YOLOv7 was used to train a second model to identify diseases. The advanced classification model accomplished a precision and recall rate of 65, 59, and 65 percent, whereas the training model obtained an efficacy of 99.5%.

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6. Kukadiya H. & Meva D. stipulated a CNN strategy based on DL regarding the diagnosis and differentiation of cotton leaf diseases. Plenty of studies have been done to investigate common leaf diseases associated with various plants; yet, the current research has presented a dependable and efficient method for diagnosing leaf diseases in cotton. The proposed approach adequately classified and identified three cotton leaf diseases that hadn't previously been found. The recommended model for identifying and classifying cotton leaf diseases is CNN, which has 100% and 90% testing and training efficacy, respectively.

7. In an attempt to boost information extraction from processed photos, Adesh V. Panchal, et al. (2023) recommend treating crop diseases as diseases that can probably be identified by labeling afflicted leaves based on disease patterns. Then, leveraging a CNN that depends on patterns discovered, feature extraction, image segmentation, and crop disease classification are executed out. This has been demonstrated via a publicly available dataset of over 87,000 RGB-type images, comprising a combination of healthy and sick leaves.

8. A technique based on image processing was demonstrated by Sami Ur, et al. (2023) for automated identification and preventive treatment for the diseases occur on leaf of tomato plants. Their strategy incorporates the gray level co-occurrence matrix (GLCM) technique of 13 statistical factors from tomato leaves, which are subsequently categorized using support vector machines (SVM) into various diseases. The outcomes of the experiment indicates that the approach is highly beneficial: for healthy leaves (100%), late blight (85%), early blight (95%) & for septoria leaf spots (90%). For implementation used Mobile application.

9. A DL system for tomato disease diagnosis based on image segmentation has been offered by Gangwar A, Rani G, and Dhaka VPS in 2023. Their approach utilizes of a convolution network for disease classification, a novel U-Net model for picture segmentation, and the VIA instrument for creating leaf masks. This sort of technology possesses the potential for enhancing yield and lessen crop loss in tomato disease detection seamlessly, with an accuracy rate of 98.12%.

10. B. Paulos & M. M. Woldeyohannis (2022) generated a novel method for categorizing & diagnosing coffee plant diseases, highlighting that it is crucial for yield improvement. In this scenario, pictures (1120) obtained from center of agriculture which is wolaita sodo .had been employed to train the DL model. Data overfitting has been tackled through the utilization of an augmentation strategy. Overall 3360 pictures seemed implemented. In order accomplish highly favorable outcomes in noticing these disorders, they analyzed training through scratch leveraging TL tactics. Resulting efficacy rates for transfer-based learning (97.01 & 99.89) utilising resnet50 & mobilenet, accuracy for training through scratch (98.5%). The pre-trained Resnet50 model performed better at categorizing photographs than other methods.

11. Shoaib M., et al. (2022) offers a InceptionNet & CNN model as an element of a DL based technique to diagnose tomato plant illnesses. They implemented an approach of supervised learning to train the CNN with upto 18,000 non segmented & segmented pictures of tomato leaves.They received better outcomes utilizing the modified U-Net model, gaining IoU score of 98.66% & 98.73% on the dice, via the U-Net & Modified U-Net segmentation algorithms.

12. Utilising three compact CNNs, Attallah O. (2023) demonstrates an approach for intelligently predicting tomato plant illnesses. By utilizing elements from all three architectures and grabbing deep feature signals through the CNNs' final connected layer, the team obtain high accuracy with KNN of 99.92% & with SVM of 99.90% respectively.

13. Ayadi M., et al, (2022) develop a DFC (deep feature concatenation) mechanism that fabricates the MobiResNet neural network utilizing the MobileNet & ResNet50 models. MobiResNet gained an overall accuracy for classification of 97.08%, Here dataset containing 5400 pictures of olive leaf obtained by an agricultural UAV.

14. An effective strategy to categorizing plant diseases deploying a Custom CenterNet architecture alongside DenseNet77 is put forth by Albattah W., et al. in 2022. Their strategy outperforms more current methods for identifying plant illnesses in terms of accuracy as well as effectiveness since it takes benefit of the Plant Village Kaggle database and enhances key point extraction.

15. Seventy research works on DL applications in agricultural disease detection & control are thoroughly analyzed by Dharmendra S., Ahmad, Aanis, et al. in 2023. Their review, which covers on whatever from DL approaches to dataset requirements, attempts to direct the creation of new tools and serve farmers in successfully regulating plant diseases.

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16. Shang F., et al. convey an approach integrating feature signal concatenation & transfer learning for the diagnosis of tomato plant illnesses. utilizing kernel principal component analysis, features are subsequently retrieved & concatenated from pre-trained NASNetMobile & MobileNetV2 kernels. Upon being put together, the results get fed into a standard learning system, where logistic regression outperforms other tested classifiers, obtaining an accuracy of 97%.

17. Amritha Haridasan, et al. (2023) offer a computer vision-based procedure that employs image processing, machine learning, and DL tool tactics for discovering disease in rice plants. implementing this strategy, the need for on conventional techniques to safeguard paddy crops against major illnesses is drastically decreased. The approach suggested, that utilizes a support vector machine SVM classifier and convolutional neural networks CNN, exhibits a validation accuracy of 91.45%, facilitating in swift diagnosis and treatment proposals.

18. The ‘VGG-ICNN’, an agile CNN for crop diagnosing diseases exploiting plant-leaf pictures, was demonstrated by Poornima thakur in 2023. VGG-ICNN outperforms other top-performing deep learning models by utilizing over 6 million parameters & embraces a broad range of crop varieties across diverse datasets. The research results reveal consistent performance for various crop datasets & great accuracy attaining 99.16% via the PlantVillage dataset.

19. Shoaib et al. (2022) demonstrate how CNN models might be utilized for categorizing diseases of plants with higher precision by improving detection accuracy via imaging data. Having accuracy rates varying from 99% to 99.2%, CNNs beat other ML & DL algorithms in the field of feature extraction and classification.

20. Rice plant diseases can be effectively assessed & categorized via an innovative approach designed by Upadhyay SK, et al. that takes onto account the shape, color & size size of lesions in leaf pictures. The recommended strategy, employing a completely CNN trained of 4000 picture samples, surpasses current techniques for plant disease detection and categorization with a high efficacy rate of 99.7%.

III. PROPOSED SYSTEM

The proposed system employs Convolutional Neural Network (CNN) algorithms for plant disease detection through image processing in Python, accompanied by a user-friendly graphical interface (GUI). Users can upload images of plant leaves affected by diseases, which undergo preprocessing before CNN-based classification. Upon identification of the disease, the system provides tailored recommendations for pesticides or treatments and necessary nutrient supplements. 4 plants i.e Orange, potato, tomato, corn studied here in this proposed system. Here for orange plant take only one disease & for potato, tomato, corn taken two diseases for each. This unified solution aims to empower users in agricultural decision-making, facilitating timely disease management and crop preservation.

IV. METHODOLOGY

1. Data Acquisition – The dataset consists of 13505 pictures of 4 crop leaves both healthy and damage. Overall dataset consist of 7 diseases. These photos have been split into 32 classes, which likely correspond to different diseases. This data is taken from Kaggle.

2. Data Preprocessing – Data preparation is the process of transforming the data into a format that makes the feature extraction method and other processes work precisely. In this step, data augmentation and normalization are executed out.

- Normalization: Neural networks execute most effectively with normalized data, thereby after loading the data, each image's pixel values (0–255) must be switched to 0–1. The torch tensor is utilized to the whole array of pixel values, and its output is divided by 255. To verify that the mean and standard deviation of each pixel value are the same, normalization is executed. In addition to promoting convergence, this phase stabilizes the training process. Mathematically, for each pixel p in the image:

$$p \text{ normalized} = p \,/\, 255$$

Where 255 is the maximum pixel value in the image.

- Data Augmentation: data augmentation is crucial for improving model generalization. Various transformations can be applied to the images, such as rotation, flipping, or random cropping. These transformations introduce diversity into the training data.

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3. Feature Extraction – In order to cope with the current classification matter, relevant features are initially extracted. Color, layout, and texture are examples of features in pictures [17]. Systems that use leaf Pictures emphasize the textural element more. The GLCM, auto-correlation, Gabor transformation methods are a few examples of techniques which can used[17]. GLCM stands for Gray-Level Co-occurrence Matrix. It's widely used texture analysis technique in image processing and computer vision. GLCM calculates the frequency of co-occurring pixel intensity values within an image or a region of interest. Auto-correlation analyze spatial patterns in images of plants to pinpoint areas with unusual pixel intensity distributions, aiding in the early and accurate identification of diseased regions.Gabor transformation is a method used to analyze the frequency content of signals or images. It's particularly useful for extracting texture features from images. In the context of plant disease detection, Gabor transformation can be applied to plant images to highlight textural characteristics associated with different diseases. Its capacity to automatically extract features has been proven to be one of the key advantages of employing DL models, in addition to their high accuracy. ResNet-9 is a DL model that directs automatic feature extraction in addition to classification. Therefore, our proposed approach doesn't need the deployment of an additional feature extraction method.

4. Classification – There are several options for classification. Logistic Regression, Radial Basis Function, CNN, Classification Trees, SVM, K-NN, Linear Vector Quantization and other classifiers are some of the methods that can be employed in this step [17]. ResNet-9 used for classification in this proposed work.

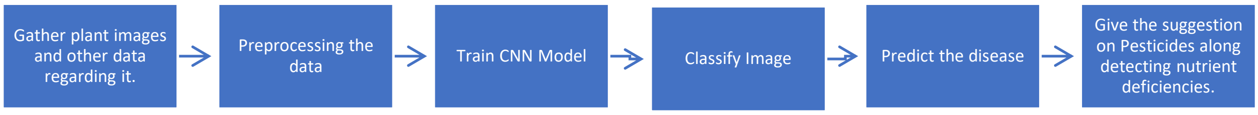

Fig. 2 : Execution process of model.

CNN : A DL method called a convolutional neural network leverages convolution operations in place of straightforward matrix multiplication [21]. CNN tackles pictures exceptionally well when it comes to DL methods. Three core layers make up the CNN architecture: a fully connected (FC) layer, pooling layers, and convolutional layers.

1. Convolution Layer - The convolutional layers are the core part of the network and where the bulk of the computations are being carried out. The information that is given is filtered with the aim to identify features. This filter, which is regarded as a feature detector, explores the picture input's receptive fields for specific feature. Convolution is the name given to this procedure. A particular section of the source image gets passed to the filter, which estimates the dot product within the pixels & delivers it into an output array. subsequently then, the filter slides & keeps on until every part of the picture is surrounded [22]. The feature map is a final of the outcome of all the filter execution.

2. Pooling Layer – A downsampling or pooling layer brings down the input's dimensionality. Pooling operations, though do not employ weights, leverage a filter to sweep the whole input picture, exactly as convolutional operations execute. Rather than utilizing the receptive field for completing the output array with information, the filter incorporates an aggregation function.

3. Fully connected Layer – A CNN's fully connected layer is its last layer. The features that were successfully extracted by preceding layers and filters get utilized by the FC layer to carry out classification tasks. Typically, the FC layer analyzes inputs more appropriately by using a softmax function in contrast to ReLu (Rectified Linear Unit) functions. So, CNN has been utilized for gaining spatial information from images. So as to strengthen image recognition execution, prior researchers recommended a number of CNN architectures. Based on plant photos, this research relies on the Inception Resnet algorithm to identify plant diseases and nutrient deficiencies. A smartphone camera has been employed to take pics of plants, including their good health and deficiency conditions which are subsequently processed as input inforamation. This input information is fed into the CNN algorithm in order to decide if the plant is healthy or deficient.

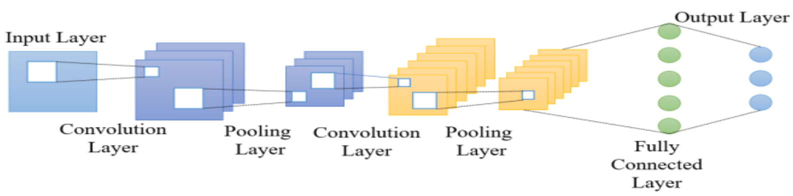

Fig 3 : Basic Architecture Of CNN [23]

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ResNet : Application builders use a DL model called Residual Network (ResNet) for computer vision tasks. It is a CNN conception which accommodates hundreds or even thousands of convolutional layers. The principal objective of the RESNET design is to try to solve the neural network degradation issue, which is the rising training error rate associated with deeper neural networks [24]. As a solution to residual structure came into picture. due to the fact that ResNet utilises "residual blocks," which enabling gradients to circulate effectively everywhere the network, it is competent to train highly deep networks. In a residual block, the original input is added straight to the output of the convolutional layers immediately thereafter the activation function, totally omitting the convolution layer. An activation function and two or more convolutional layers are followed by this shortcut link. The main element of a residual network, or ResNet, is a residual block, which is a CNN architecture [25]. A residual block can be found in Fig. 3.

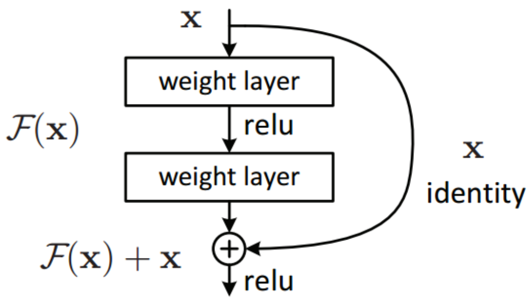

Fig. 4: A residual Block [25]

Skip connections is utilized by a residual block to rectify the degradation issue [21]. A typical residual block is depicted in the image above. The phrase output = F(x) + x, where x is an input to the residual block & an output from the preceding layer, and F(x) is a component of a CNN made up of multiple convolutional blocks, can be utilized to define this in Python code. Through utilizing this tactic, the gradient flow during backpropagation is smoothed out, ensuring the the network to grow to new layers. The network does not see any rise in computing load when a connection is skipped.

ResNet-9 - ResNet-9 is a variant of the ResNet architecture, which is a type of CNN commonly used for image classification tasks. ResNet-9 specifically refers to a ResNet architecture with 9 layers. It makes utilized residual connections, which circumvent the issue of vanishing gradients & permit the training of exceedingly deep networks. In ResNet-9, the basic building blocks are residual blocks, typically consisting of 2 convolutional layers in addition Batch Normalization & ReLU activation functions, plus avoid the connection that integrates the input to the second convolutional layer's results. Such a skip connection makes it capable of allowing gradients to pass right through the network, which facilitates the optimum training of deeper models.ResNet-9 architecture has been designed to balance model complexity and performance, making it suitable for various image classification tasks while being more lightweight compared to deeper ResNet variants like ResNet-18, ResNet-34, etc.

V. EXPERIMENTAL RESULT & ANALYSIS

A. Dataset : The ResNet 9 model is trained and evaluated on a dataset sourced from Kaggle, which comprises 13,505 images categorized into 32 distinct classes. The table 2 shows the plants taken for the study.

Plant Name	**No. of Images**
Orange(Huanglongbing)-citrus Greening	1907
Potato (Early Bright)	1949
Tomato (Early Bright)	1980
Tomato (Bacterial Spot)	1716
Potato (Late Bright)	1997
Corn-(Common Rust)	1918
Northern (Leaf Blight)	2038

Table 2 : Shows The Data Set Information

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B. Training : During the training phase, the model is initially trained using the images from the training set. Subsequently, classification tasks are carried out on the test set images utilizing the trained model. In total, the training process involves 13,505 images.

Parameter	Values
Total Parameter size(MB)	369.77
Training Set Size(MB)	188
Test Set Size(MB)	47.2
Learning Rate	0.008

Table 3: Parameters of the trained ResNet 9 model

C. Graphs -

1. Accuracy and epoch graph -

In the first epoch of model training, the validation accuracy reached 0.9321 that is 93.21%, indicating that the model correctly classified 93.21% of the validation data samples. This initial validation accuracy provides an early insight into the model's performance, suggesting that it has learned some patterns from the training data but may still require further optimization.

Upon completing the second epoch, the validation accuracy significantly improved to 0.992 that is 99.2%. This substantial increase suggests that the model has made considerable progress in learning the underlying patterns in the data and has become more adept at generalizing to unseen examples. Achieving a validation accuracy of 99.2% after only two epochs is promising, indicating that the model is learning effectively and demonstrating strong predictive capabilities. The notable improvement in validation accuracy between the first and second epochs indicates that the model is learning from the training data and making adjustments to better capture the underlying patterns. This progress underscores the importance of iterative training and highlights the potential for continued improvement with additional epochs.

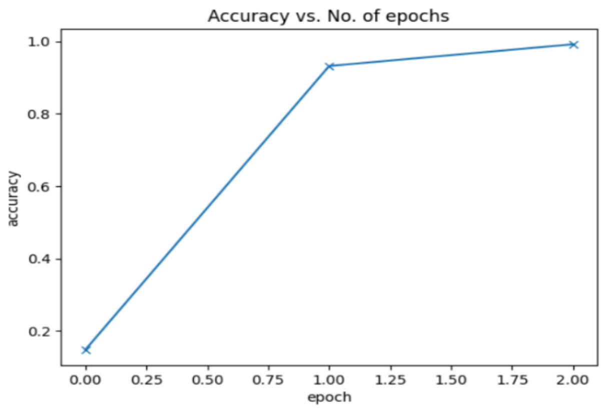

Fig.5: Accuracy and epoch graph

2. Valid loss and train loss graph –

The graph depicts the loss values of a DL model against the number of epochs, with separate curves for training and validation losses. The x-axis represents the number of epochs, ranging from 0 to 2, and the y-axis represents the loss, ranging from 0 to 3.5.

At epoch 0, the training loss starts just above 1.0, and the validation loss starts significantly higher at approximately 3.5. This indicates that the model initially performs poorly on the validation set compared to the training set.

After the first epoch, both training and validation losses drop significantly. The training loss decreases to about 0.5406, while the validation loss drops more drastically to about 0.326. This suggests substantial improvement in the model's performance for both training and validation data during the first epoch.

From the first to the second epoch, both training and validation losses continue to decrease but at a slower rate. By epoch 2, the training loss approaches 0.0867, and the validation loss falls slightly below 0.0223, indicating continued improvement and convergence of the model.

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The closeness of the training and validation loss curves after the first epoch suggests that the model generalizes well to unseen data, avoiding overfitting. The steep decline in both curves during the initial epoch indicates rapid learning, with subsequent epochs contributing to fine-tuning the model's performance. Overall, the graph illustrates the model's ability to reduce both training and validation losses effectively, showcasing significant improvements in early epochs and continued refinement in later epochs. The decreasing trend in loss values signifies enhanced model accuracy and reduced prediction errors over the training period.

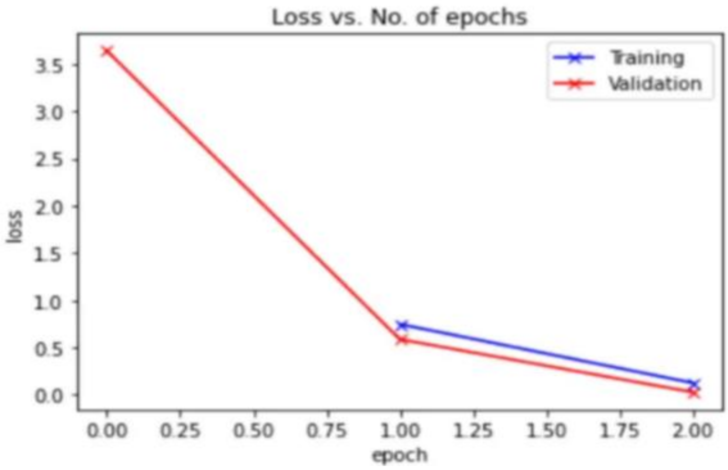

Fig. 6: Valid loss and train loss graph

3. learning rate and batch number graph -
The graph illustrates the relationship between the learning rate and batch number during the training of a DL model. The x-axis represents the batch number, ranging from 0 to 800, while the y-axis represents the learning rate, ranging from 0 to 0.01. Initially, the learning rate increases, starting from nearly 0, and peaks around a batch number of 200, reaching a maximum value 0.01. After reaching this peak, the learning rate gradually decreases, returning to nearly 0 by the batch number of 800.

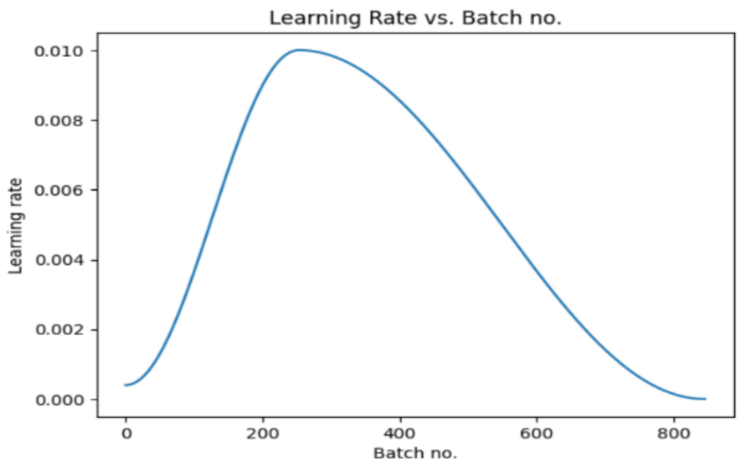

Fig. 7: learning rate and batch number graph

This pattern suggests a learning rate schedule where the rate is increased to encourage exploration and rapid learning initially, then decreased to fine-tune the model's performance and ensure convergence. The curve indicates an adaptive learning strategy to balance between fast learning and stable convergence throughout the training process.

The overall shape of the graph, rising and then falling, suggests a learning rate schedule designed to optimize the training process. Initially, a higher learning rate encourages quick learning, then as training progresses, the rate is reduced to refine the model's parameters and enhance performance stability. This approach helps in balancing exploration and convergence during the training process.

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D. Performance evolution -

1. Accuracy: The ratio of the number of correct predictions to the total no of predictions made is known as accuracy

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

True positives are the number of examples where the actual label is true and the model correctly predicts this. False negatives are the number of examples where the actual label is true, but the model incorrectly predicts it. True negatives refer to the number of examples where the actual label is false and the model correctly identifies this. False positives are the number of examples where the actual label is false, but the model incorrectly predicts it as

The accuracy of the proposed model comes out to be 99.2%.

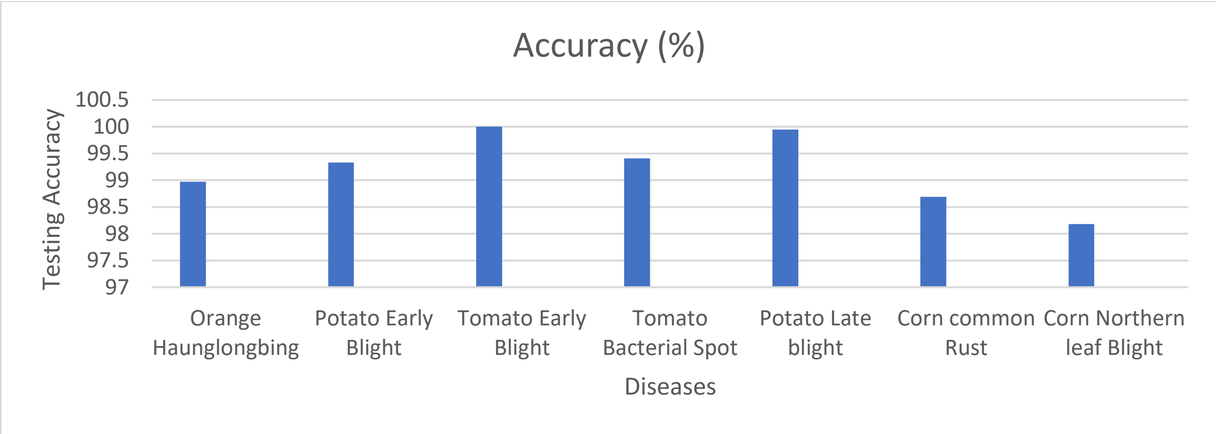

Fig. 8: Accuracy (%) for each disease

The figure 8 shows accuracies range from 98% to 100%, showing high effectiveness in disease classification. Tomato Early Blight have the highest accuracie (100%), indicating near-perfect detection. Corn Northern Leaf Blight has the lowest accuracy (98.18%), suggesting it is the most challenging disease to detect accurately among the listed diseases. Overall, the system demonstrates strong performance across various plant diseases.

The performance comparison of ResNet-9 against SVM, decision trees, logistic regression, and K-NN is conducted using accuracy metric. The values for the accuracy other models were sourced from [26, 27, 28, 29]. The information regarding it shown in figure 9 below.

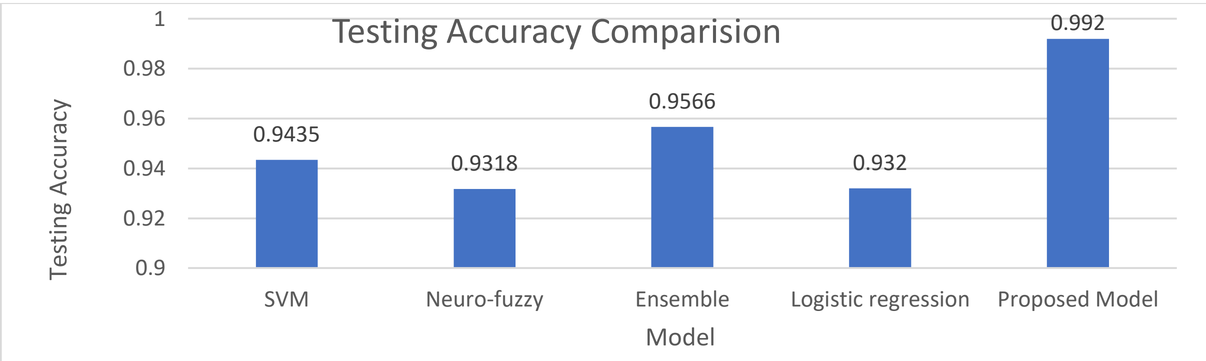

Fig. 9 : Comparison among accuracies of various models

2. Recall - Recall is crucial in plant disease detection as it measures the model's ability to correctly identify diseased plants. High recall ensures that most instances of disease are detected, facilitating timely intervention and preventing the spread of disease. The formula for recall is:

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$$Recall = \frac{TP}{TP + FN}$$

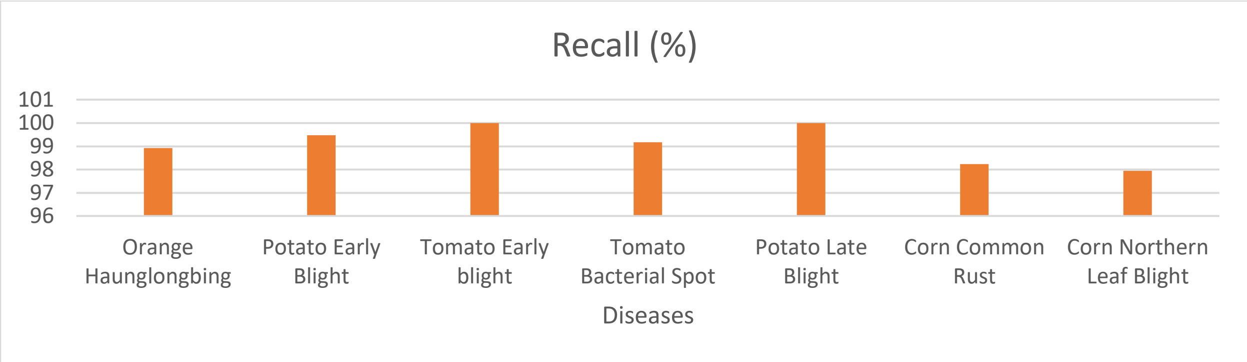

Fig. 10 : Recall (%) for each disease

Figure 10 shows recall values range from 97.94% to 100%, indicating a high ability of the model to detect actual cases of diseases. Tomato Early Blight and Potato Late Blight have the highest recall values (100%), showing nearly perfect detection. Corn Northern Leaf Blight has the lowest recall (98.24%), indicating more difficulty in identifying all actual cases. Overall, the recall percentages reflect strong model performance in identifying true cases of various plant diseases.

3. Specificity - The main goal of specificity in plant disease detection is to accurately identify healthy plants, minimizing false positives to avoid unnecessary treatments and resource wastage, thus ensuring efficient crop management and reducing costs. The formula for specificity is:

$$Specificity = \frac{TN}{TN + FP}$$

Figure 11 shows the specificity percentages for different plant diseases, which measure the model's ability to correctly identify non-diseased instances (true negatives). Specificity ranges from 98.42% to 100%, showing the model's strong ability to correctly identify non-diseased cases across various diseases. Tomato Early Blight achieve the highest specificity at 100%. Corn Northern Blight Leaf has the lowest specificity at 98.42%. Overall, the model demonstrates robust capability in distinguishing non-diseased cases across various plant diseases.

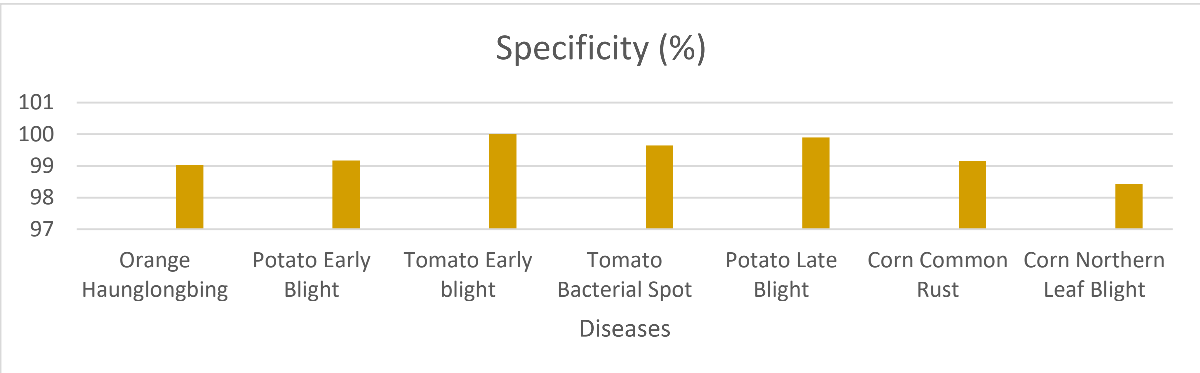

Fig. 11 : Specificity (%) for each disease

4. Precision – The aim of precision in plant disease detection is to accurately identify diseased plants, minimizing false positives. This ensures reliable diagnoses and optimizes the use of treatments and resources. The formula for precision is :

$$Precision = \frac{TP}{TP + FP}$$

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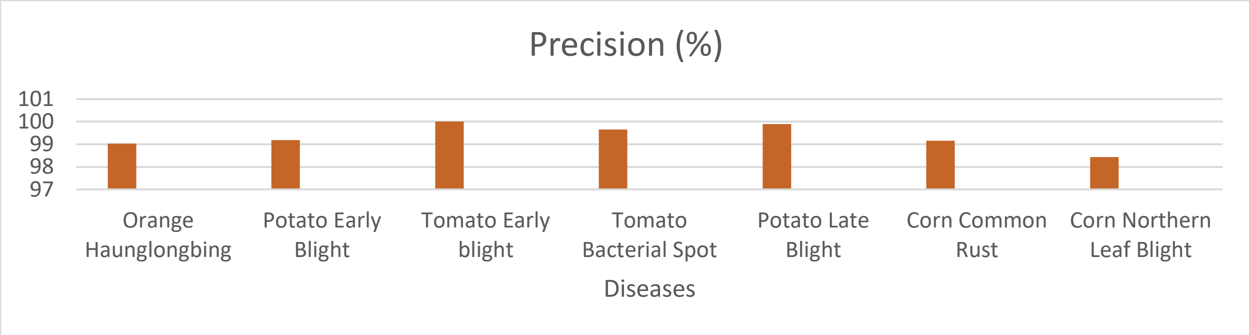

Fig. 12 : Precision (%) for each disease

The figure 12 shows high accuracy in correctly identifying true positives across various plant diseases, with values ranging from 98.44% to 100%. Tomato Early Blight achieve perfect precision at 100%, indicating near-perfect detection. Corn Common Rust has a precision of approximately 99.16%, while Corn Northern Leaf Blight has the lowest at 98.44%. Overall, the model is highly precise, effectively minimizing false positives for most diseases.

5. F1-Score – It provides a single metric that balances both precision (accuracy of positive predictions) and recall (ability to detect all positive instances). F1 scores indicate a model's effectiveness in correctly identifying diseased plants while minimizing false positives and false negatives. The formula for F1 score is :

$$F1\ Score = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

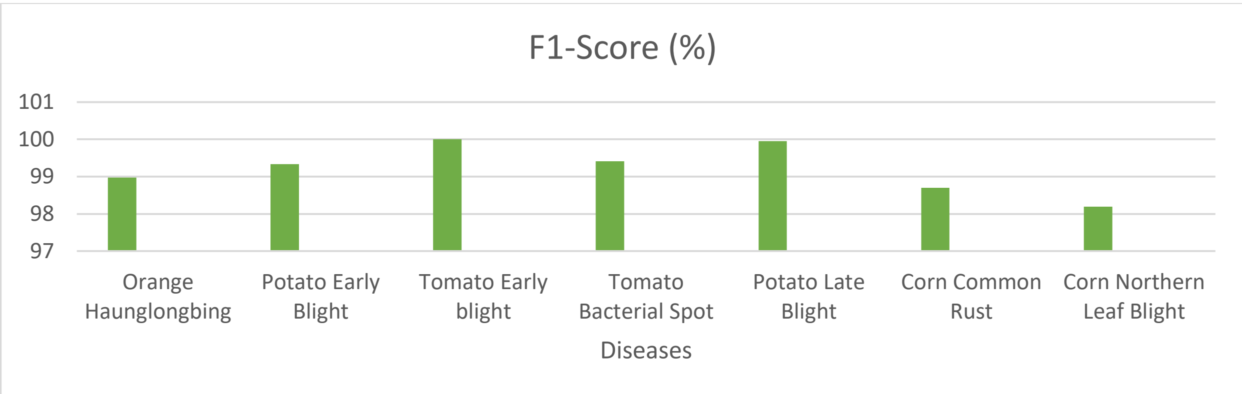

Fig.13 : F1-Score (%) for each disease

The figure 13 shows high F1 score for Tomato Early Blight (100%) while the lower percentage of 98.18% for Corn Northern Leaf Blight.

6. FDR - In plant disease detection, FDR (False Discovery Rate) measures the proportion of false positive predictions among all positive predictions made by a model. The formula to calculate FDR is:

$$FDR = \frac{FP}{FP+TP}$$

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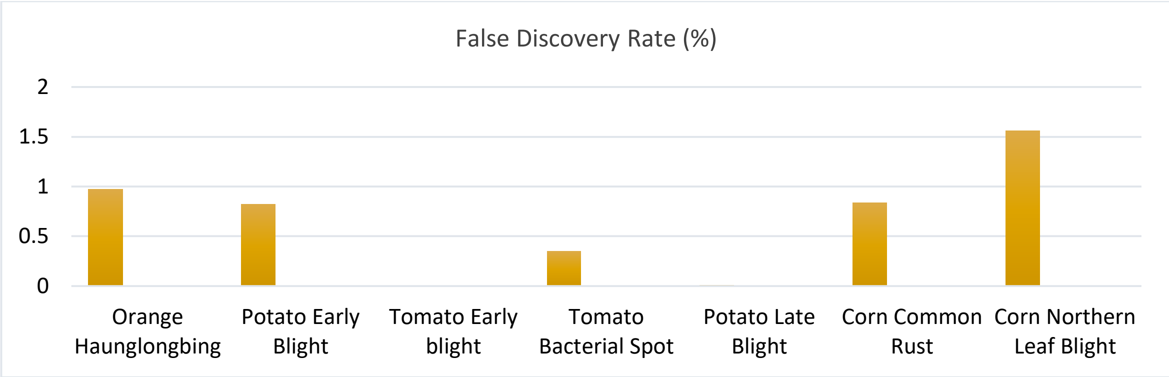

Fig.14 : FDR (%) for each disease

The FDR is a critical metric in evaluating the reliability of plant disease detection models, as it helps quantify the rate of false alarms, aiding in model optimization and performance assessment. The FDR percentage for different diseases in given in figure. In figure 14 highest FDR is for Corn Northern Leaf Blight (1.56%) while lowest FDR is of Tomato Early Blight is 0% & Potato Late Blight is 0.01%.

7. NPV - In plant disease detection, NPV (Negative Predictive Value) assesses the proportion of true negative predictions among all negative predictions made by a model. The formula to calculate NPV is:

$$NPV = \frac{TN}{TN + FN}$$

NPV is a crucial metric as it quantifies the ability of a model to accurately identify healthy plants, aiding in the assessment of its reliability for disease exclusion. The NPV percentage for different diseases in given in figure 15. Highest NPV is for Tomato Early Blight & Potato Late Blight (100%) while lowest FDR is of Corn Northern Leaf Blight is 98.21%.

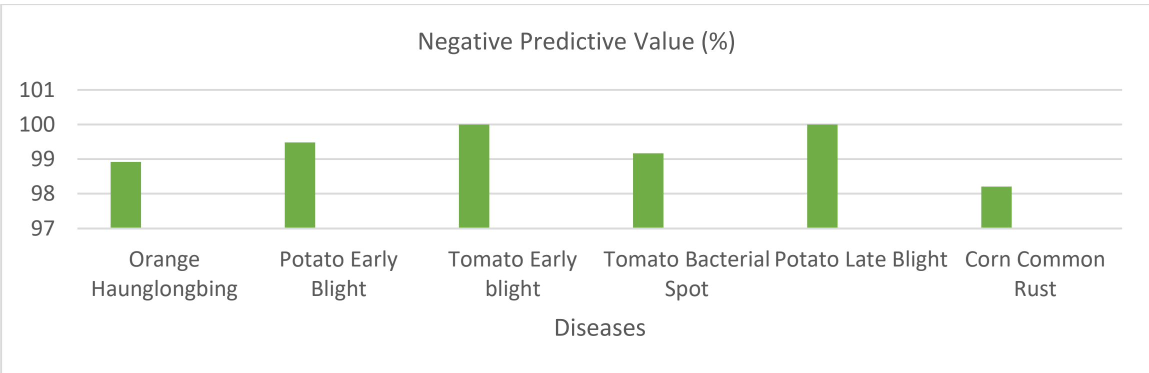

Fig.15 : NPV (%) for each disease

Overall model performance of model is shown in figure 16. where model shows accuracy of 99.2%, Precision is 99.11%, Recall is 99.32%, F1-Score is 99.19%, Specificity is 99.11%.

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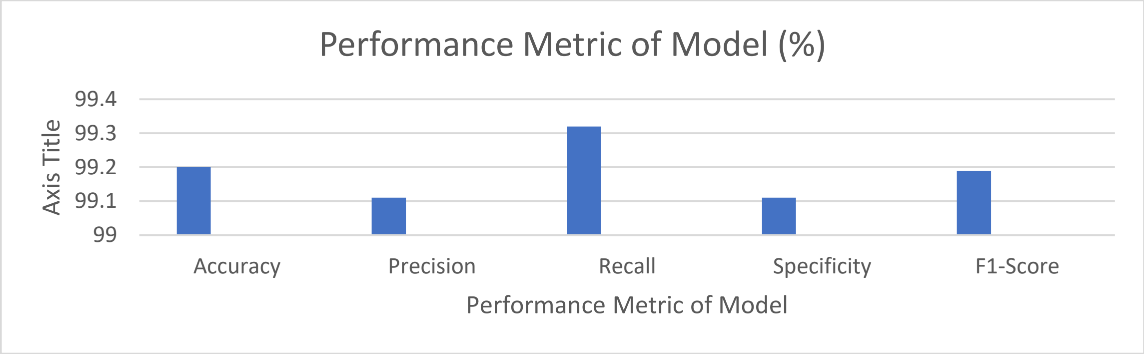

Fig.16 : Performance Metric of overall model

E. Result image –

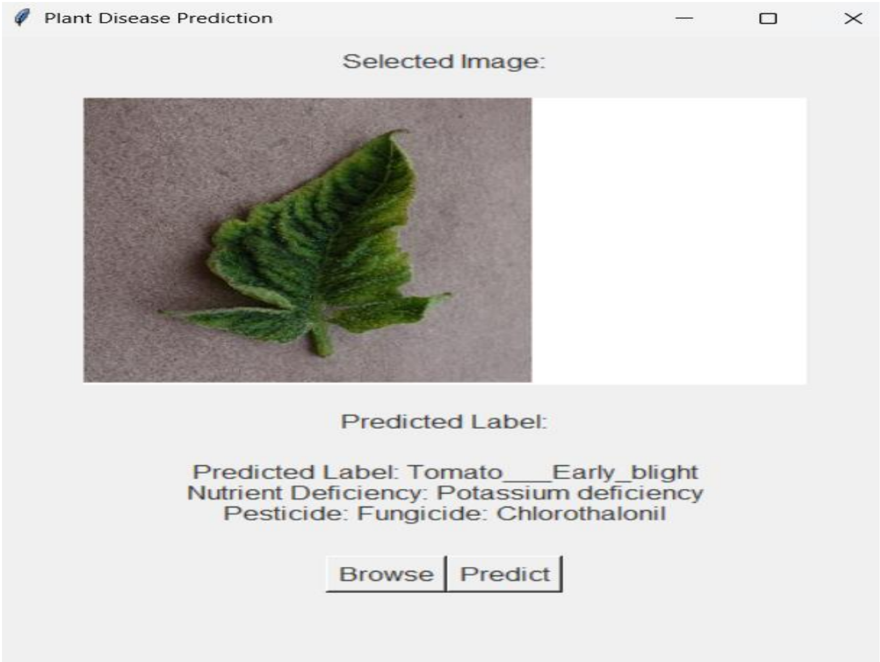

Fig 17: Result image

VI. CONCLUSION

The proposed integrated agricultural monitoring and management system presents a comprehensive and technology-driven solution for precision farming. The study demonstrated that the Residual Network model (ResNet9) is highly effective in detecting and classifying diseases from images of leaves. Utilizing the 'Kaggle Dataset,' which comprises images from 32 different classes, the model achieved a remarkable weighted precision of 99.11% and an accuracy of 99.2%. The proposed system showcases promising results in revolutionizing agricultural practices through its integrated approach to plant disease detection. Through advanced image processing algorithm the system demonstrates its efficacy in accurately identifying plant diseases, detecting nutrient deficiencies. By providing intelligent recommendations for pest control measures & giving suggestion o nutrient deficiency present in plant. Enabling them to make informed decisions for optimizing resource utilization and enhancing crop productivity. This holistic approach fosters sustainable farming practices, ultimately contributing to the resilience and prosperity of agricultural communities.

VII. FUTURE WORK

Future advancements for this project involve incorporating drones or satellite imagery for remote sensing and monitoring could provide real-time data at larger scales, enabling more precise and timely interventions.

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Furthermore, the development of predictive analytics models based on historical data and environmental factors could enable proactive decision-making and risk mitigation strategies, ultimately contributing to even greater yield optimization and sustainability in agriculture. Also in future going to form the App where user can easily upload the image and also try to develop the website using some web application and try to make the website easily available on the computers and mobile to install.

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