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Potato Plant Disease Detection using CNN

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Abstract: Agriculture sustains nearly 70% of the population, yet crop diseases pose a significant threat to its productivity. Traditional manual methods for disease monitoring are time-consuming and labour-intensive. This research focuses on leveraging image processing techniques to provide effective, precise, and widely accessible solutions for plant disease diagnosis. By exploring visually discernible patterns on plant leaves, this study addresses the urgent need for innovative approaches to disease identification in Indian agriculture.

Keywords*:* Agriculture, Crop diseases, Image processing, Diagnosis

I. INTRODUCTION

Agriculture sustains nearly 70% of India's population, yet crop diseases threaten its productivity and food security. Traditional manual disease monitoring methods are labour-intensive and time-consuming. Our research aims to address this pressing challenge by leveraging image processing techniques to develop efficient, precise, and accessible solutions for plant disease diagnosis. By analysing visual patterns on plant leaves, we seek to revolutionize disease identification in Indian agriculture. Our goal is to empower farmers with timely and accurate information to effectively combat crop diseases. Through scalable and accessible tools, we envision improved crop management practices and reduced agricultural losses, ultimately contributing to the resilience and sustainability of India's agricultural sector.

II. LITERATURE REVIEW

The focus of this literature review is plant leaf disease prediction algorithms that use machine learning and deep learning. Among the studies found are as follows:

Sachin B. Jadhav et al. [1] conducted a study using CNN transfer learning to identify three common soybean plant diseases from leaf photos. They compared the accuracy of pre-trained CNN models with traditional methods. Their dataset included 649 damaged and 550 healthy soybean leaf pictures, divided into disease and non-disease classes for testing. More research is needed to fully understand the effectiveness of CNN transfer learning in agricultural disease detection.

Jun Liu et al. [2] aimed to explore deep-learning approaches for detecting plant diseases and pests. They compared these methods with traditional techniques, emphasizing the importance of organized datasets. Their study focused on classification, detection, and segmentation networks, providing insights into their strengths and weaknesses. They stressed the need for further research to develop deep-learning methods suitable for real-world plant disease identification.

Defu Zhang et al. [3] used deep transfer learning to enhance rice disease detection. Their model, DENS-INCEP, outperformed existing techniques with high accuracy. They used two datasets: one with 120 images from the UCI repository and another with 515 images from various sources. Despite their success, they highlighted the need for more research in rice disease diagnosis.

Arti N. Rathod et al. [4] explored methods for automatically identifying leaf diseases, crucial for monitoring agricultural fields. They examined various image processing techniques, emphasizing the need for efficient and objective methods. They used digital cameras to capture leaf patches and applied image growing algorithms for easier classification. They stressed the need for scalable image processing methods suitable for practical agricultural contexts.

Ms. Rashmi N et al. [5] aimed to develop a machine learning tool for accurately classifying plant diseases, focusing on those affecting leaves. They analyzed several algorithms and image processing methods, particularly using Support Vector Machine (SVM) techniques. They trained their model using a dataset containing images of diseased and healthy leaves, highlighting the importance of feature extraction for effective classification.

Punam Bedi et al. [6] conducted a comprehensive analysis of machine learning algorithms and image processing methods for automating plant disease identification. They used SVM techniques for preprocessing and feature extraction, training their model on a dataset of diseased and healthy leaf images. They emphasized the significance of preprocessing for accurate classification.

Ms. Sumita Mishra et al. [7] aimed to improve deep neural network performance for real-time maize leaf disease identification. They achieved high accuracy using a CNN model on a dataset containing images from corn plantations and the PlantVillage Disease Classification Challenge. Their study demonstrated the practicality of using deep learning for disease identification on smart devices.

Vempaty Prashanthi et al. [8] focused on employing image processing techniques for identifying various plant diseases to minimize harvest losses. They investigated different stages of image processing, including acquisition, segmentation, and feature extraction, using support vector machines and neural networks for classification. They highlighted the importance of dataset quality and accuracy for training their model.

J. Arun Pandian et al. [9] introduced a novel deep learning model for plant leaf disease identification, creating a new dataset called PlantDisease59. They used data augmentation techniques to ensure balanced class sizes and achieved a large image collection with healthy and diseased plants. Their study emphasized the importance of data augmentation for training deep learning models effectively.

Surender Kumar et al. [10] conducted a comprehensive study on plant leaf diseases using image processing techniques. They explored various methods, including Principal Component Analysis (PCA) and Support Vector Machines (SVM), for preprocessing, segmentation, and classification. Their study highlighted the need for accurate and timely disease analysis in agriculture.

These studies collectively contribute to advancing the field of plant disease prediction, offering insights into challenges and suggesting directions for future research.

The below table1.1 summarizes research efforts in plant disease detection and diagnosis. It includes details such as researchers' names, study years, methods/models used, research purposes, datasets, and outcomes, offering a concise overview of advancements in the field.

Researcher Name+ Year	**Model Used**	**Purpose**	**Dataset**	**Result**
Priyanka Kulkarni et al.2024	Data analysis methodologies	To examine the objectivity of qualitative datasets and assess their suitability for research purposes	Qualitative information collected through research endeavors	Image processing techniques 85% to 90%
J. Arun Pandian et al.2022	14-layered deep convolutional neural network (14-DCNN)	To detect plant leaf diseases using leaf images	Comprising 147,500 images spanning across 58 different healthy and diseased plant leaf classes	Prediction accuracy of 90.63%
Jun Liu et al. 2021	Deep learning	Detecting plant diseases and pests using deep learning	PlantVillage and other self-collected or publicly available	Accuracies ranging from 80% to 95%
Punam Bedi et al.2021	Convolutional utoencoder (CAE) and Convolutional Neural Network (CNN) hybrid model	Specifically Bacterial Spot disease in peach plants,	Containing 4457 leaf images of peach plants	99.35% training accuracy and 98.38% testing accuracy
Ms. Rashmi N et al.2021	SVM	Equip farmers with a tool to mitigate losses and enhance crop yield	Dataset comprising images of plant leaves afflicted with various diseases	Accuracies ranging from 80% to 95%

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Sachin B.Jadhav et al.2020	CNN AlexNet GoogleNet	Support the Plant Pathologist in diagnosing disease.	Comprises 649 and 550 image of diseased and healthy leaves	Accuracy across both AlexNet and GoogleNet models would be approximately 88%
Defu Zhang et al.2020	DENS-INCEP	Detecting rice plant diseases.	515 images of rice affected by 13 different diseases	Prediction accuracy of 98.63% for classifying rice disease images
Vempaty Prashanthi et al.2020	Neural networks and Support Vector Machines (SVM)	Plant infections to mitigate harvest losses and sustain farming productivity.	600 images of maize leaves captured manually against a white background using a 13MP camera.	Deep SVM model achieves an impressive accuracy of 85.76%
Sumita Mishra et al.2019	Deep Convolutional Neural Network (CNN)	Introduce a real-time approach for recognizing corn leaf diseases.	Images obtained from corn plantations and the Plant Village Disease Classification	The implemented deep CNN model achieves an impressive accuracy of 88.46%
Surender Kumar et al.2015	Support Vector Machines (SVM), Neural Networks	To conduct a comprehensive survey of plant leaf diseases classification utilizing image processing techniques	Images of plant leaves afflicted with various diseases	Approximately 88% to 90%
Arti N. Rathod et al.2013	SVM	Automatically detecting leaf diseases	Images of diverse leaf spots captured through digital cameras or mobile devices.	Image processing techniques 70% to 90%

Table 1.1 summarizes the researchers' work.

III. PROPOSED METHODOLOGY

Our proposed methodology begins with a supervised machine learning approach to train our model for potato plant disease detection. We pre-process the acquired images using Python library (TensorFlow) to enhance their suitability for analysis, followed by feature extraction using convolutional layers to extract essential features from input images.

Utilizing Convolutional Neural Networks (CNNs), we classify the images into three categories: early blight, healthy, and late blight. Once trained, the model is deployed into an application interface, facilitating easy diagnosis for farmers and plant enthusiasts by scanning the image of the plant in real-time or uploading the image and the farmer can get the optimum solution by finding the correct disease.

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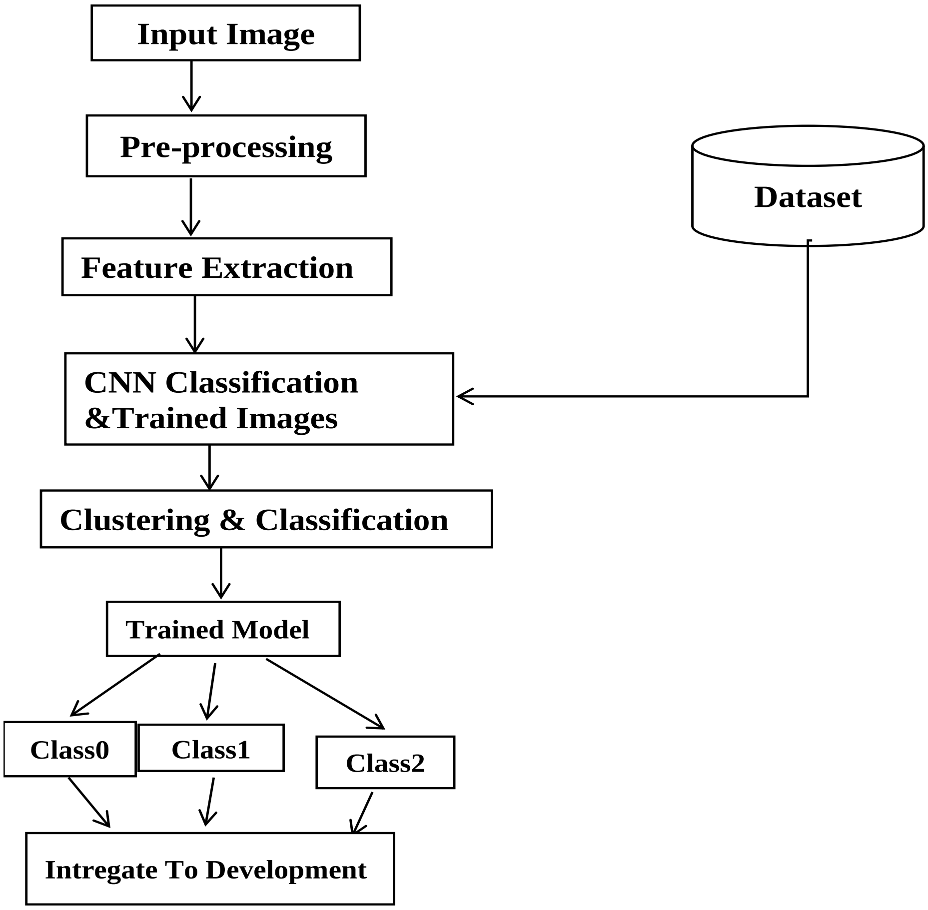

Figure 1:-Flowchart of Proposed System

The major programming language for the study article on detecting illnesses was Python, and Anaconda Navigator was used to create a specific environment for the project. This environment included important tools and libraries including NumPy, Matplotlib, Keras, TensorFlow, and PIL.

These tools enabled data manipulation, visualization, the creation of deep learning models, and efficient image processing. Anaconda Navigator ensured smooth operation by consolidating all important tools in one location. The setup of the environment is detailed to begin are following -

(1) **Environment: -** The Disease Detection System is made using Python as the main programming language. To handle all the additional tools and libraries that Python needs, we use a software called Anaconda Navigator. This software helps create a special environment for our project and installs everything we need, like NumPy for number crunching, Matplotlib for making graphs, Keras and TensorFlow for building deep learning models, and PIL (Python Imaging Library) for working with images. These tools are important for our system because they help us manipulate data, visualize information, develop advanced models for disease detection, and process images effectively. Using Anaconda Navigator makes sure that everything runs smoothly and we have all the tools we need in one place, which is super helpful for our project.

(2) **Processing: -** The captured images from the camera to the Disease Detection System looks like the images in the Figure1.1.

The dataset = Plant_Village.jpg The built-in TensorFlow function image_dataset_from_directory is used to load an image dataset from the directory "Plant Village".

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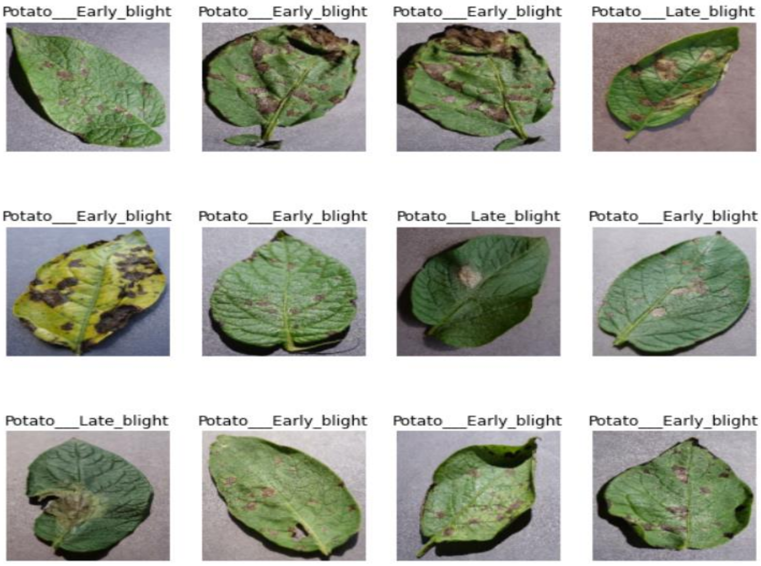
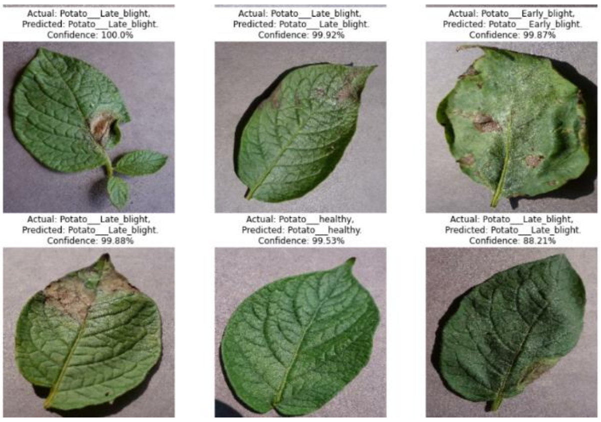


Figure 2: Distribution of Disease Cases by Region

These cropped images are fitted into a graph of size 256 X 256 i.e., the images are divided into blocks that can be used in training the model. But for understanding purpose, the images as shown in the Figure 4 are labelled as labelled images are as shown in the Figure 3. The final output for the processing images is the labelled images of the leaves of dimensions 256X 256. These dimensions fit exactly as the input dimensions for the neural network.



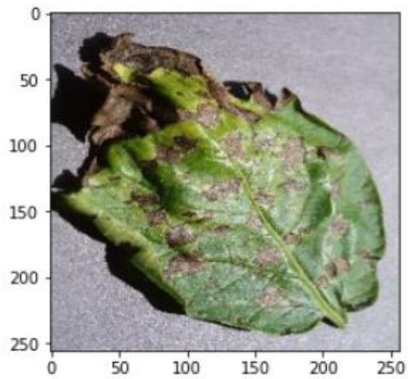


Figure 3 **Figure 4** : PROCESSED IMAGES AFTER LABELLING

(3) **Model Development: -** To address this issue, the early detection of plant diseases is necessary. Manual disease detection in plants is done either by farmers or by agricultural scientists. The aim of this project is early prediction of crop disease with greater accuracy and prevention of further damage done to the crops. The area of the disease affected is also found so that fertilizers application can be optimized. However, this is a very challenging and time-consuming task. To address this problem, many researchers across the globe presented different state-of-the-art systems for automatic plant disease detection with the help of various Machine Learning. Deep learning techniques draw inspiration from the structure of neurons present in the human brain. These methods involve using Convolutional Neural Networks (CNNs), Support Vector Machines (SVM), Artificial Neural Networks (ANNs) and their variations as Recurrent Neural Networks (RNNs) to uncover underlying patterns.

Data Pre-processing: - Pre-processing pipelines are defined using TensorFlow's Sequential API for resizing, rescaling, and data augmentation (random flip and rotation).
Maps the preparation procedures to the training data.

Building the Model: - Creates a CNN (Convolutional Neural Network) model with Keras' Sequential API. The model is made up of many convolutional layers (Conv2D), max-pooling layers (MaxPooling2D), a flattened layer, and dense layers.

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The convolutional layers use ReLU activation, whereas the output layer uses SoftMax activation. Compiles the model using the Adam optimizer, sparse categorical cross-entropy loss, and accuracy as a metric.

1 CONVOLUTION OPERATION
This formula represents the convolution operation where f is the input image matrix, g is the filter matrix (kernel), and t represents the position in the output feature map.

$$(f * g)(t) = \int_{-\infty}^{\infty} f(\tau) g(t-\tau)\, d\tau$$

2. RECTIFIED LINEAR UNIT (RELU)ACTIVATION FUNCTION:
The ReLU activation function introduces non-linearity by outputting the input value if it's positive otherwise it will be zero.

$$f(x) = f(x) = \begin{cases} x, & if x > 0 \\ 0, & if x \leq 0 \end{cases}$$

3. SIGMOID ACTIVATION FUNCTION:
The sigmoid activation function squashes real – valued inputs between 0 and 1, commonly used for binary classification tasks.

$$f(x) = \frac{1}{1+e^{-x}}$$

4. TANH (HYPERBOLIC TANGENT) ACTIVATION FUNCTION:
The Tanh activation Function squashes input between -1and 1,it is the hidden layer of neural networks.

$$\boldsymbol{f(x) = \frac{e^{x} - e^{-x}}{e^{x} - e^{-x}}}$$

5. K-MEANS CLUSTERING:-
Using unsupervised neural algorithms, such as K-means clustering based on cluster selection, image segmentation can be accomplished. Based on the computed centroid values, the data are divided into multiple categories. This algorithm's goals are to increase efficiency and decrease the squared distance sum between the coordinate points. Improve it.

$$J = \sum_{i=1}^{m} \sum_{k=1}^{k} w_{ik} \|x^1 - \mu_k\|^2$$

6. PERCEPTRON WITHOUT ACTIVATION FUNCTION:-
In our project, we focus on the function of mathematical functions in the CNN model and the optimizations that result from applying these functions to classification tasks.

Perceptron with a single layer can be utilized for dataset binary categorization, as shown in Figure 5.

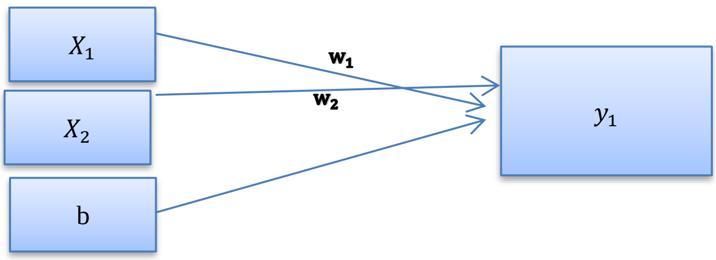

Figure 5

7. CROSS-ENTROPY LOSS FUNCTION: -
The formula calculates the cross-entropy loss between predicted probabilities p_1 and actual labes y_1

$$Cross - Entropy\ Loss = -\sum_{i=1}^{N} y_{1 \mathrm{LOG}\,(p_1)}$$

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Application Development: -

Our application offers a simple user interface designed for farmers and plant enthusiasts, making it easy for them to understand and use. If they notice any unusual changes in their crops or plants, like discolouration or spots on the leaves, they can simply upload a picture of the affected area. Our AI model then analyses the image to determine the cause of the issue, whether it's a disease or another problem, and provides detailed guidance on how to address it.

Using React for the front end and JavaScript for functionality, our app ensures a smooth and intuitive user experience. It's convenient and accessible, allowing users to get help for their plants with just a few clicks or taps.

Additionally, our app goes beyond basic diagnosis. It includes advanced features like a chatbot with AI capabilities, which guides users through the steps of treating the infection. Whether it's suggesting specific treatments or providing personalized advice, our app offers comprehensive support to help users restore their plants to health , as shown in Figure 6.

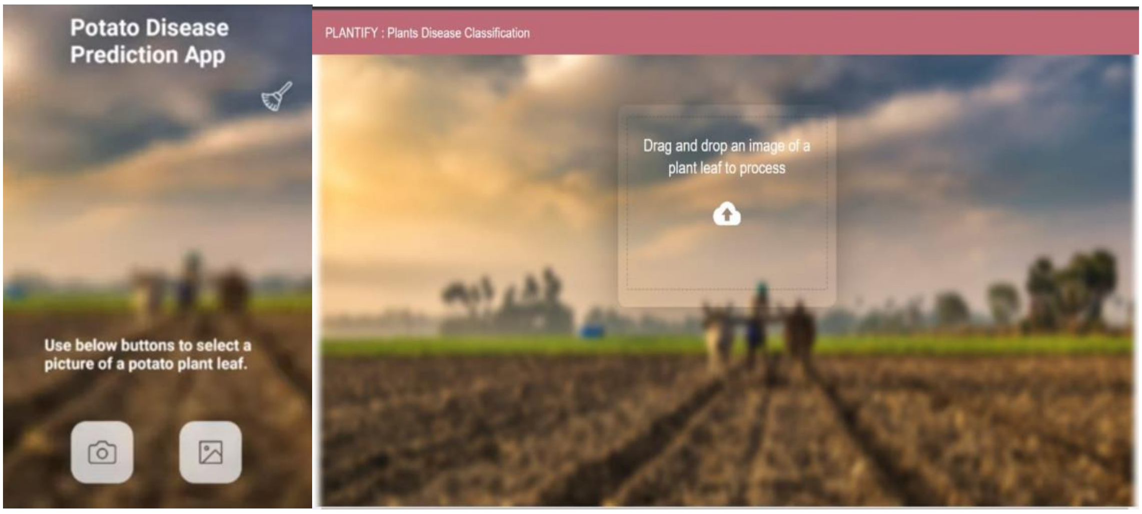

Figure 6: WEB INTERFACE

Result and analysis: -
This system identifies diseases in leaves in their early stages.
the leaf image, which is processed in both Anaconda navigator and ARM processor used for illness classification with CNN. The processed image is clustered using the clustering algorithm in MATLAB to identify the damaged area.

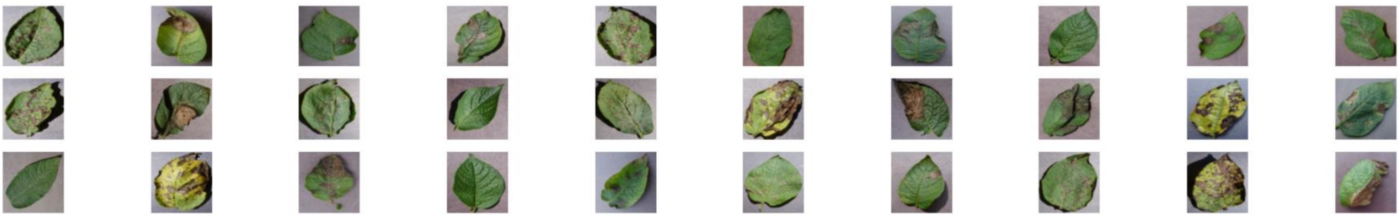

Figure 7

Figure 7 Shows the trained dataset used for the CNN model. It consists of 30 leaf image infected with disease. Similarly separated dataset of 30 images.

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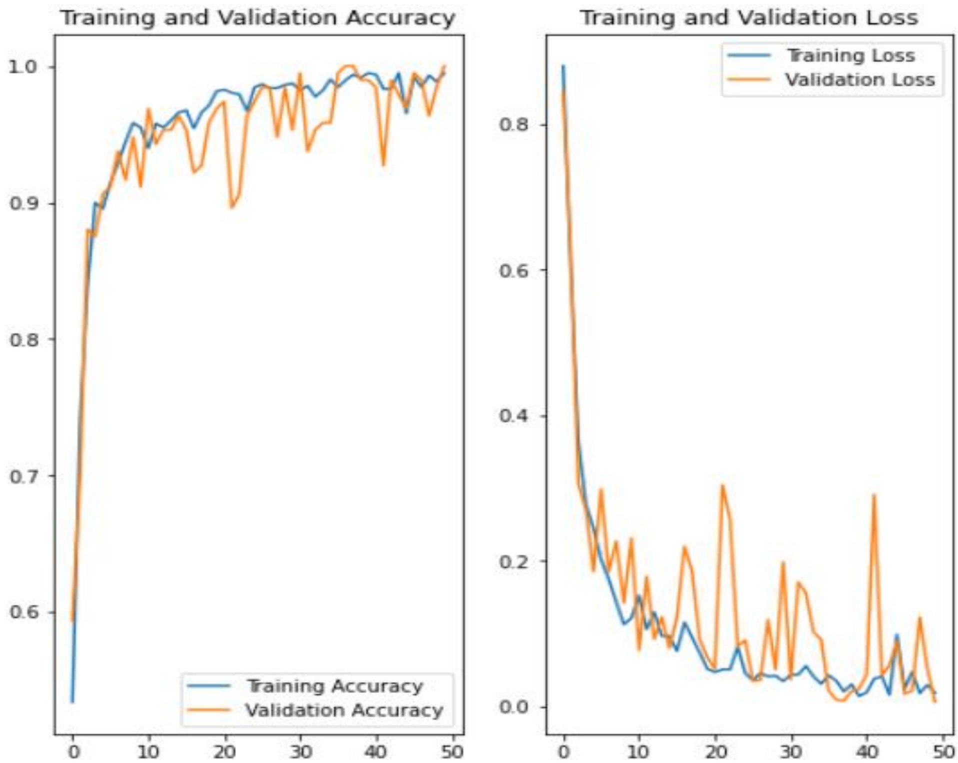

Figure 8:Training and Accuracy Graph

The Figure 8 shows the accuracy and loss of potato-disease prediction. More iterations lead to higher prediction accuracy. The model may be evaluated for Blight Blight, Healthy Leaf, and Late Blight, with accuracy and loss plots obtained.

IV. CONCLUSION

This research highlights the advancements made in utilizing machine learning, particularly deep learning, to address crop diseases in Indian agriculture. By employing Convolutional Neural Networks (CNNs), Artificial Neural Networks (ANNs), and Recurrent Neural Networks (RNNs), the study demonstrates the effectiveness of these algorithms in automating plant disease detection.

The developed hybrid model represents a significant improvement in disease detection systems, offering enhanced accuracy and efficiency in analyzing large datasets. By integrating deep learning techniques, the system not only improves disease prediction but also optimizes resource allocation, such as fertilizer application, based on precise localization of affected areas.

Moreover, the research underscores the importance of software environments like Anaconda Navigator in facilitating development processes. The utilization of TensorFlow's Sequential API streamlines data preprocessing and model architecture, making the process more accessible and efficient. By elucidating various components of the system, including data preprocessing and model architecture, this study aims to deepen understanding of plant disease detection methodologies and inspire further innovation in this field. Overall, this research represents a significant step towards achieving early and precise detection of plant diseases, crucial for ensuring food security and promoting sustainable agricultural practices in India.

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