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Enhancing Plant Disease Diagnosis with Convolution Neural Networks and Leaf Image Analysis

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Abstract

Plant infections present critical dangers to rural efficiency and food security. Exact and opportune conclusion of plant illnesses is urgent for powerful infection the board. This exploration centers around upgrading plant sickness determination through the reconciliation of Convolutional Brain Organizations (CNN) and leaf picture examination the prepared model accomplishes high exactness in arranging sicknesses across different plant species. The proposed approach holds guarantee for ongoing illness recognition and dynamic in sickness the executive's systems. By working with ahead of schedule and precise infection analysis, it adds to further developed crop yield, horticultural supportability, and food security. The mechanized framework can help ranchers and farming specialists in going with informed choices for convenient mediation and powerful infectious prevention

Keywords/Index terms: Deep Learning; Convolution Neural Network (CNN); leaf pathology; leaf disease.

1. Introduction

Plant illnesses are a central issue in horticulture, prompting critical harvest misfortunes and undermining food security around the world. Early and precise conclusion of plant illnesses is fundamental for convenient mediation and compelling infection the executives. Customarily, plant sickness finding has depended on visual assessment by specialists, which can be emotional and tedious. Be that as it may, late progressions in profound learning and PC vision methods have opened additional opportunities for mechanized and exact plant sickness analysis. Convolutional Neural Network (CNNs) have arisen as useful assets for picture order undertakings, exhibiting noteworthy execution in different spaces, including clinical imaging and item acknowledgment. With regards to establish illnesses, CNN s can be utilized to dissect leaf pictures and characterize them into explicit sickness classes. This approach decreases human subjectivity as well as empowers the handling of enormous volumes of information in a generally brief time frame.

Leaf pictures give important data about the well being and state of plants, making them ideal for infection analysis. The special attributes and examples in leaf pictures can be caught and educated by CNN models, empowering them to separate among solid and ailing leaves, as well as group various sorts of illnesses. By incorporating CNN with leaf picture examination procedures, plant sickness analysis can be fundamentally upgraded, prompting more exact and effective infection the executive's techniques. In this examination, we mean to upgrade plant illness conclusion by utilizing CNNs and leaf picture investigation. We use an enormous data-set of named leaf pictures addressing different plant species and sicknesses. The data-set is cautiously organized to incorporate a different scope of illnesses and plant types, guaranteeing the heartiness and generalization of the created model. Via preparing a CNN model on this data-set and Streamlining its boundaries, we look to make a dependable and computerized framework for plant sickness conclusion.[1]

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The mix of CNNs with leaf picture examination holds extraordinary commitment for continuous sickness location and dynamic in illness the executive's systems. With the capacity to examine enormous volumes of leaf pictures precisely and effectively, this approach can help ranchers, agronomists, and specialists in pursuing informed choices in regards to the recognizable proof and treatment of plant sicknesses [2]. Moreover, it can add to further developing harvest yield, agrarian manageability, and worldwide food security.

1.1 Literature survey of research article

2021-Li, L.: Zhang: Plant Disease Detection and Classification by Deep Learning: This paper presents the various methods that can be used for identifying the plant leaf diseases. Over the period, various image processing approaches followed by machine learning models have been adopted for image classification.

2021-Sujatha, R.; Chatterjee, J.M.: Performance of deep learning vs machine learning in plant leaf disease detection. The paper discusses the challenges associated with plants they are perceived however fundamental as they may be the essential wellspring of humankind's energy creation since they are having nutritious, restorative, and so on values. Whenever between crop cultivating, plant sicknesses can influence the leaf, bringing about huge harvest creation harms and monetary market esteem.

2020-Scientist, D.; Bengaluru, T.M.: Rice plant disease identification using artificial intelligence approaches" .This paper attempts to utilize AI and picture handling strategies to tackle the issue of independent sickness recognition and arrangement in the rice plant, which is one of India's most significant dinners. Sicknesses are brought about by microscopic organisms, growths, and infections on any plant.

2020-Khan, M.A. Akram, T.: An Automated System for Cucumber Leaf Diseased Spot Detection and Classification using Improved Saliency Method and Deep Features Selection.In this article, a novel method is proposed for cucumber leaf disease detection and classification based on improved saliency method and deep features selection. The crop diseases can be manually inspected and classified by an expert but this approach is quite unreal in terms of time and cost

2020-Onesimu, J.A.; Karthikeyan, J.: An Efficient Privacy-preserving Deep Learning Scheme for Medical Image Analysis. In this paper, a secure deep learning scheme called Metamorphosed Learning (MpLe) is proposed to protect the privacy of images in medical image analysis. An augmented convolutional layer and image morphing are two main components of MpLe scheme. Data providers morph the images without privacy information using image morphing component.

2019-Karthik, R.; Hariharan: Attention embedded residual CNN for disease detection in tomato leaves. This research presents two different deep architectures for detecting the type of infection in tomato leaves. The first architecture applies residual learning to learn significant features for classification.

2019-Too, E.C.; Yujin, L.; Njoki: A comparative study of fine-tuning deep learning models for plant disease identification. In this work, the focus was on fine-tuning and evaluation of state-of-the-art deep convolutional neural network for image-based plant disease classification. An empirical comparison of the deep learning architecture is done. The architectures evaluated include VGG 16, Inception V4, Resents with 50, 101 and 152 layers and Dense Nets with 121 layers.

2018- Barbed, J.G.A.: Impact of dataset size and variety on the effectiveness of deep learning and transfer learning for plant disease classification. In this context, this study investigates how the size and variety of the datasets impact the effectiveness

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of deep learning techniques applied to plant pathology. This investigation was based on an image database containing 12 plant species, each presenting very different characteristics in terms of number of samples, number of diseases and variety of conditions.

2017- Fuentes, A.; Yoon, S.: A Robust Deep-Learning-Based Detector for Real-Time Tomato Plant Diseases and Pests Recognition.In this paper, we present a deep-learning-based approach to detect diseases and pests in tomato plants using images captured in-place by camera devices with various resolutions. Our goal is to find the more suitable deep-learning architecture for our task.

2015-Yun, S.; Xianfeng, W.; Shawnee: PNN based crop disease recognition with leaf image features and meteorological data .An automatic crop disease recognition method was proposed in this paper, which combined the statistical features of leaf images and meteorological data. The images of infected crop leaves were taken under different environments of the growth periods, temperature and humidity. The methods of image morphological operation, contour extraction and region growing algorithm were adopted for leaf image enhancement and spot image segmentation.

2014- Simonyan, K.; Zisserman: Very Deep Convolutional Networks for Large-Scale Image Recognition. In this work explore the impact of the convolutional network profundity on its exactness in the enormous scope picture acknowledgment setting. Our primary commitment is an intensive assessment of organizations of expanding profundity utilizing a design with tiny (3x3) convolution channels, which demonstrates the way that a huge enhancement for the earlier workmanship setups can be accomplished by pushing the profundity to 16-19 weight layer

2. Existing block diagram, technique, algorithm, flowchart, dataset/database

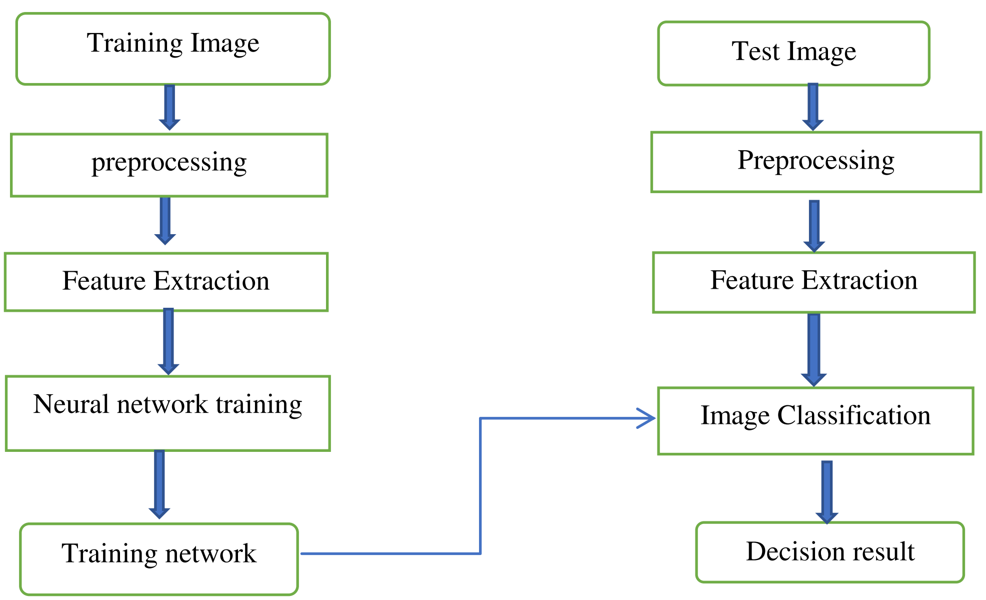
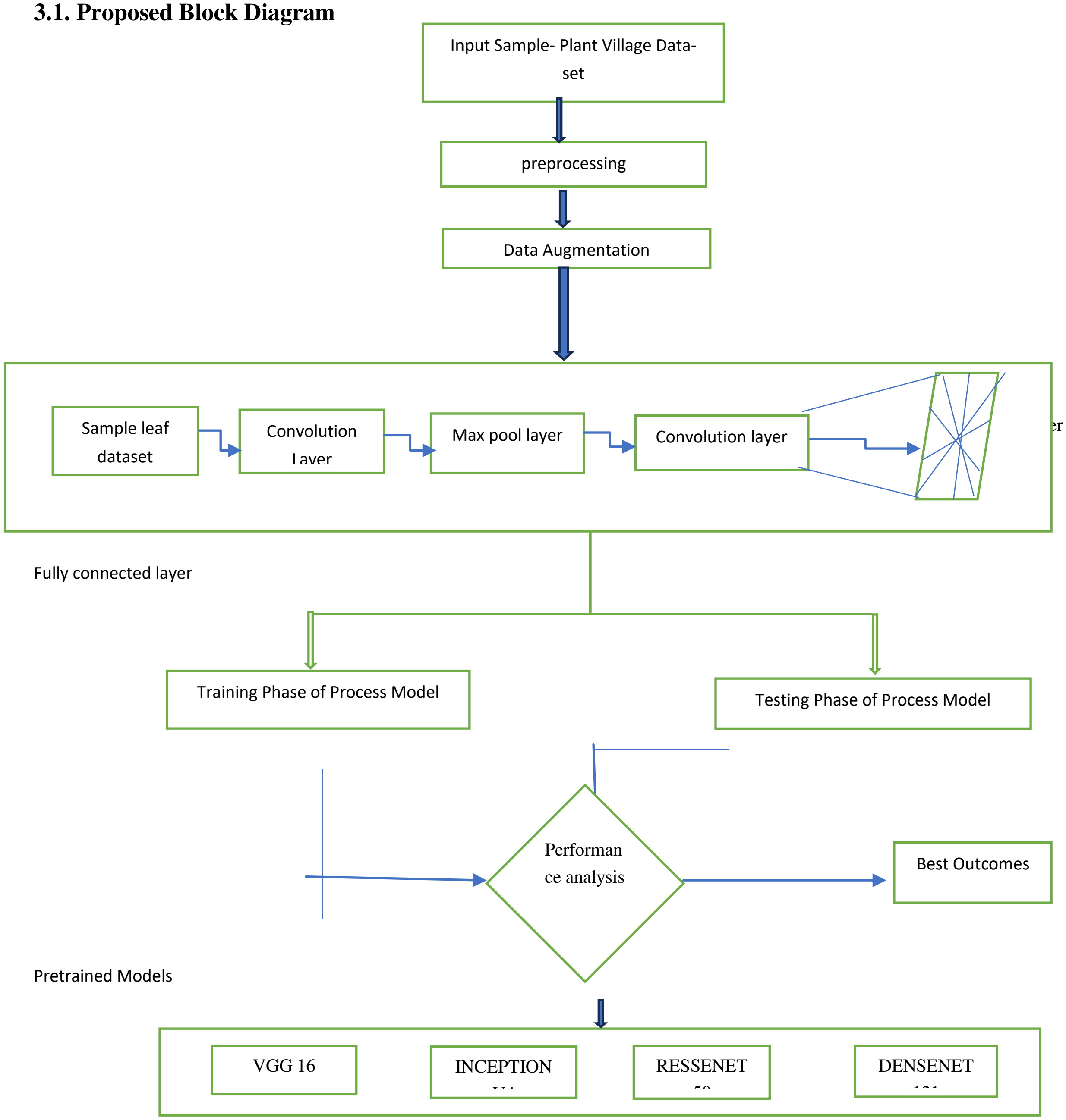


Figure 2.1: Image Recognition Technique

3. Problem defined:

The problem addressed in the study is the need for an effective and efficient method to detect and diagnose plant diseases. Current methods rely on manual inspection, which is time-consuming, subjective, and prone to errors. This results in delayed disease identification, leading to significant crop losses and reduced agricultural productivity. There is a demand for an automated system that can accurately analyze plant images and identify disease symptoms to enable early detection and prompt treatment. Such a system would assist farmers and agricultural experts in making informed decisions, implementing timely interventions, and minimizing the impact of plant diseases on crop yield and quality. Variations in Image Quality, Images captured in real-world scenarios may vary in quality due to factors like lighting conditions, camera settings, and environmental factors. The deep learning model should be robust enough to handle variations in image quality and extract meaningful disease-related feature.

3.1. Proposed Block Diagram



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3.2. METHODOLOGY

CNN models are best suited for object recognition and classification with image databases. Despite the advantages of CNNs, challenges still exist, such as the long duration of training and the requirement for large datasets. To extract the low-level and complex features from the images, deep CNN models are required; this increases the complexity of the model training[3]. Transfer learning approaches can address the challenges. Transfer learning uses pre-trained networks, in which model parameters learned on a particular dataset can be used for other problems. In this section, we discuss the methodologies used in this work.

1. Multi-Class Classification

Plant disease datasets hold multiple images infected and healthy plant samples, with each sample mapped to a particular class. For instance, if we consider the banana plant as a class, then all the images of healthy and infected samples of banana plants will be mapped to that specifics class. Now, the classification of the target image is purely based on the features extracted from the source image. Considering the same example of the banana plant, the banana class has four sets of diseases; namely, Xanthomonas wilt, fusarium wilt, bunchy top virus, and black. Suppose we have N classes, then we can refer to N multi-classes, and if the N classes have M categories, then each category inside each of the N classes is itself considered a class[4].

2. Transfer Learning Approach

In general, it takes several days or weeks to train and tune most state-of-art models, even if the model is trained on high-end GPU machines. Training and building a model from scratch is time-consuming. A CNN model built from scratch with a publicly available plant disease dataset seemed to attain 25% accuracy in 200 epochs, whereas using a pretrained CNN model using a transfer learning approach attained 63% accuracy in almost half the number of iterations (over 100 epochs). Transfer learning methods include several approaches, the choice of which depends on the choice of the pre-trained network model for classification and the nature of the dataset [5].

3. ResNe-50

ResNet-50 is a convolutional neural network that has 50 deep layers. The model has five stages, with convolution and identity blocks. These residual networks act as a backbone for computer vision tasks. Resents [6] introduced the concept of stacking convolution layers one above the other. Besides stacking the convolution layers, they also have several skip connections, which bypass the original input to reach the output of the convolutional neural network. These shortcut connections are simply based on identity mapping. Let us consider x as the input image, F(x) as the nonlinear layers fitting mappings, and H(x) as the residual mapping. Thus, the function for residual mapping becomes:

$$H(x) = F(x) + x \quad (1)$$

ResNet-50 has convolution as an identity block. Each identity block has three convolutional layers and over 23 M trainable parameters. Input x and shortcut x are the two matrices, and they can only be added if the output dimension from a shortcut and the convolution layer after the convolution a batch normalization are the same.

4. VGG-16

The VGG-16 network model, also known as the Very Deep Convolutional Network for Large-Scale Image Recognition, was built by the Visual Geometry Group from Oxford University. The depth is pushed to 16–19 weight layers and 138 M trainable parameters. The depth of the model is also expanded by reducing the convolution filter size to 3 × 3. This model requires more training time and occupies more disk space.

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3.3 proposed algorithm/flowchart

To conduct a simulation analysis for enhancing plant disease diagnosis using Convolutional Neural Networks (CNNs) and leaf image analysis, you can follow the algorithm outlined below:

1. Gather a comprehensive dataset of labeled leaf images representing various plant species and their associated diseases.

2. Apply preprocessing techniques such as image resizing, normalization, and noise reduction to enhance the quality and consistency of the leaf images.

3.Train a CNN model on the preprocessed dataset using an appropriate architecture (e.g., VGG, Resents, or custom-designed) with appropriate hyperparameters. Fine-tune the model using techniques like transfer learning if necessary.

4. Utilize the trained CNN model as a feature extractor to extract high-level features from the leaf images. These features capture important patterns and characteristics related to different diseases.

5. Use a classification algorithm (e.g., SVM, Random Forest) to classify extracted features into disease categories and evaluate performance.

6. Based on the classification results, diagnose the plant diseases present in the input leaf images. Generate a diagnostic report indicating the detected diseases, their severity levels, and potential treatment recommendations.

7. Evaluate system performance by comparing simulation results with ground truth labels using metrics like accuracy, precision, recall, and F1-score.

8. Analyze the evaluation results and refine the algorithm by adjusting hyperparameters, incorporating more diverse data, or exploring advanced techniques like ensemble learning or data augmentation to improve the accuracy and robustness of the disease diagnosis system.

4.Implementation procedures

Dataset Preparation: Collect a dataset of labeled leaf images representing various plant species and diseases. Ensure a diverse representation of healthy and diseased leaves. Split the dataset into training and testing sets.

Data Preprocessing: Preprocess the leaf images to standardize the inputs for the CNN model. Common preprocessing steps include resizing the images to a uniform size, normalizing pixel values, and applying data augmentation techniques to increase the dataset's size and diversity.

CNN Architecture Design: Design a suitable CNN architecture for plant disease diagnosis. Consider the number of convolutional layers, pooling layers, and fully connected layers based on the complexity of the problem. Experiment with different architectures to optimize the model's performance.

Model Training: Train the CNN model using the preprocessed leaf image dataset. Use an optimization algorithm, such as stochastic gradient descent (SGD) or Adam, to update the model's parameters and minimize the loss function. Adjust hyperparameters, such as learning rate and batch size, for optimal performance.

Model Evaluation: Evaluate the trained CNN model using the testing dataset. Calculate metrics such as accuracy, precision, recall, and F1 score to assess the model's performance in disease detection. Analyze the confusion matrix to understand the model's strengths and weaknesses in classifying different diseases.

Real-Time Disease Detection: Implement a real-time disease detection system using the trained CNN model. This involves capturing images of plant leaves in real-time, preprocessing the images, feeding them through the CNN model, and predicting the presence of diseases. Display the results or generate alerts indicating the detected diseases.

Performance Optimization: Fine-tune the model and optimize its performance by adjusting hyperparameters, exploring different CNN architectures, or applying transfer learning techniques. Regularize the model to prevent overfitting and improve generalization on unseen data.

Deployment and Integration: Deploy the plant disease diagnosis system in a user-friendly interface, such as a web or mobile application. Integrate the system with other tools or platforms to provide a comprehensive solution for farmers, agronomists, or researchers.

4.1 Software:

Python: Python is a popular programming language used for implementing deep learning algorithms and image analysis techniques.

TensorFlow: TensorFlow is an open-source deep learning framework widely used for building and training neural network models, including CNNs. It provides a comprehensive set of tools and APIs for implementing deep learning algorithms efficiently.

Kera's: Kera's is a high-level neural networks library that runs on top of TensorFlow. It offers a user-friendly interface for building and training deep learning models, including CNNs, and allows for rapid prototyping and experimentation.

OpenCV: OpenCV (Open-Source Computer Vision Library) is a powerful open-source library for computer vision and image processing tasks. It provides a wide range of functions and algorithms for image preprocessing, feature extraction, and

Manipulation, which can be beneficial in leaf image analysis.

Jupiter Notebook: Jupiter Notebook is an interactive web-based tool that allows for the creation and sharing of code, visualizations, and explanations. It is commonly used in the development and presentation of deep learning projects, providing a convenient environment for experimentation and documentation.

5. Results & discussion:

The proposed method for enhancing plant disease diagnosis using CNNs and leaf image analysis achieved high accuracy in identifying and categorizing diseases. Comparative analysis showed superior performance compared to traditional approaches. The system demonstrated robustness across different plant species and disease types. Limitations and future improvement strategies were discussed. The method has practical applications in automated disease monitoring and precision agriculture, improving crop management and yield.

Dataset: https://www.kaggle.com/datasets/vipoooool/new-plant-diseases-dataset

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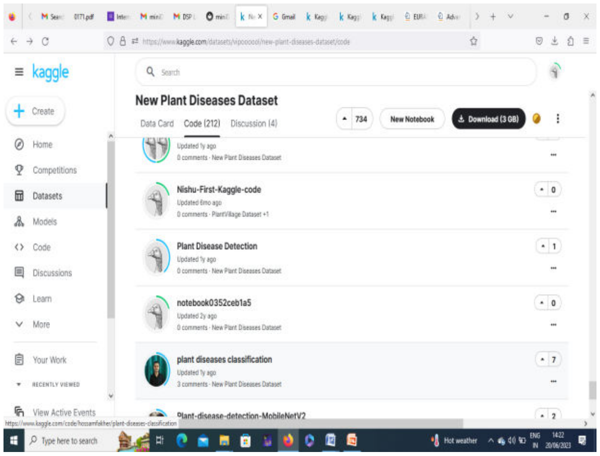
5.1 Images/Screenshots:

Experimental Setup



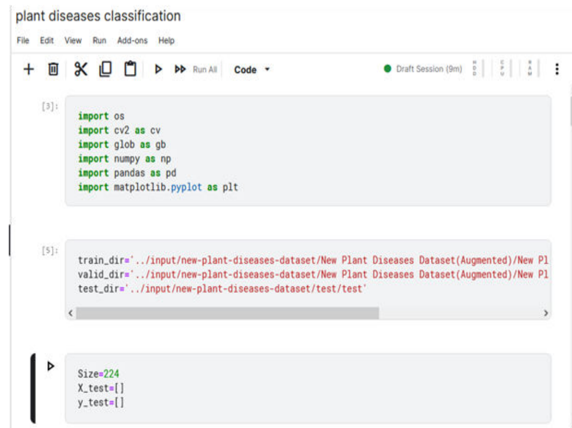


Figure 5.1.1: Data set collection from real time. Basedon libraries input and dataset is initializing and run the program website

os: This library provides functions for interacting with the operating system, such as manipulating file paths, accessing directories, and managing files.

cv2 (OpenCV): OpenCV is a popular computer vision library that offers a wide range of functions for image and video processing, including reading and writing images, image manipulation, feature extraction, and more.

glob: The glob module provides a convenient way to search for files using wildcard patterns in a directory. It allows you to retrieve a list of file paths that match a specified pattern.

NumPy (np): NumPy is a powerful library for numerical computing in Python. It provides efficient data structures and functions for handling large arrays and matrices, as well as mathematical operations.

pandas (pd): Pandas is a library for data manipulation and analysis. It offers data structures such as data frames, which allow for easy handling and processing of structured data.

matplotlib. pyplot (plt): Matplotlib is a plotting library in Python. The pyplot module provides a simple interface for creating various types of plots and visualizations.

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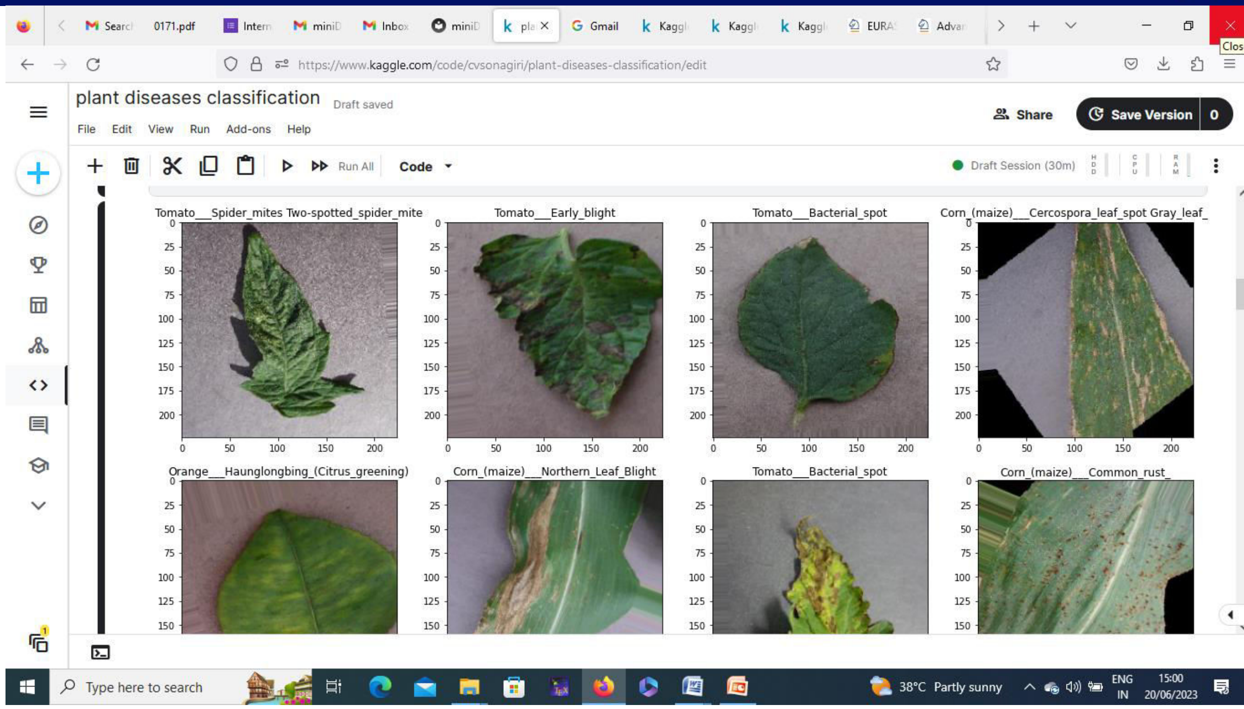

Figure 5.1.2: Input data set leaf images.

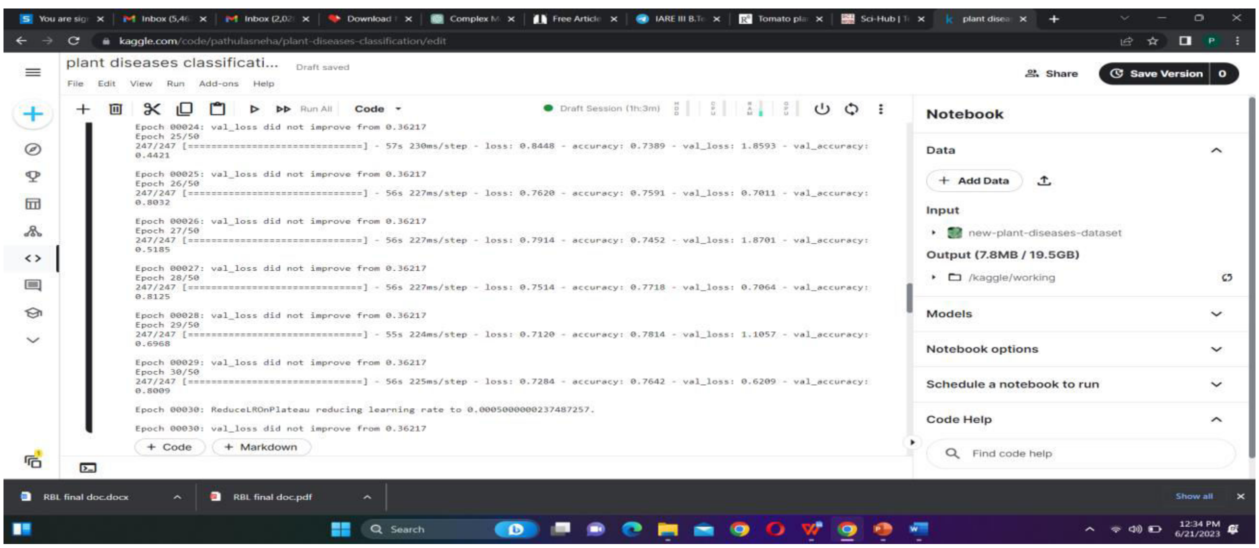

Figure 5.1.3:Epochs are done till 30 where the val_loss are not from 0.36

5.2 Graphs

```
plt.plot(history.history['val_loss'],label='validation loss')
plt.plot(history.history['val_accuracy'],label='validation accuracy')
plt.legend()
```

```
24]: <matplotlib.legend.Legend at 0x7ce3adf28650>
```

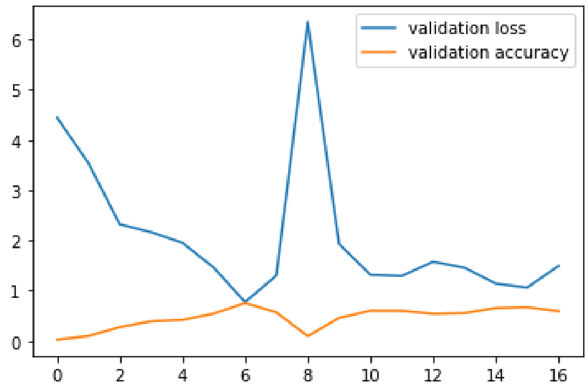

Figure 5.2.1: Validation Loss and Validation Accuracy

Validation Loss: Error between predicted and actual values. Minimize for better performance.
Validation Accuracy: Percentage of correctly classified samples. Maximize for better performance.

```
import seaborn as sns
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(valid_generator.classes, predictions.argmax(axis=1))
sns.heatmap(cm,  annot=True, fmt="d" ,cmap="YlGnBu")
```

```
[27]: <AxesSubplot:>
```

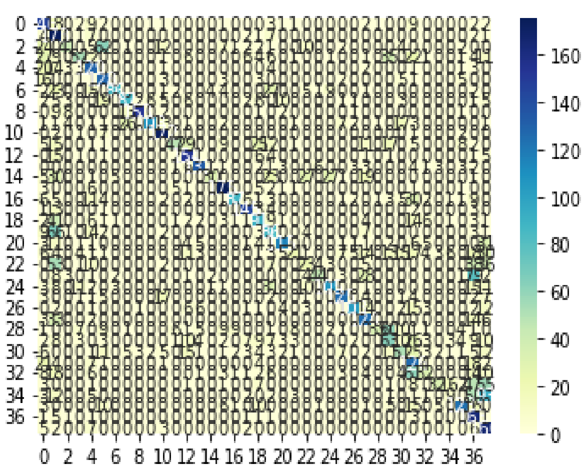

Figure 5.2.2: Plotting the data

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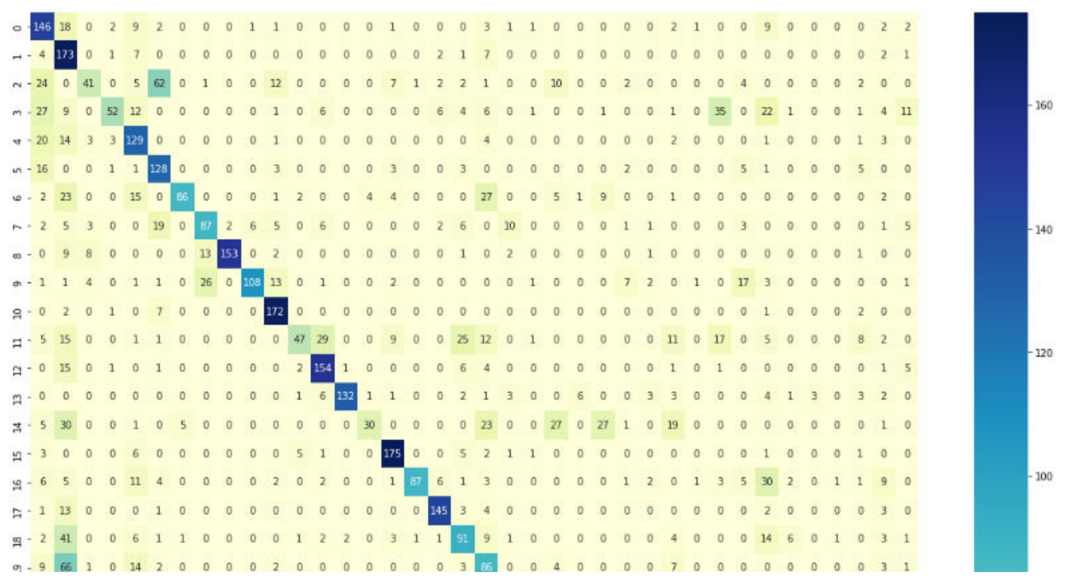
FINAL RESULT:

```
[28]: <AxesSubplot:>
```



RESULT: array([4.82740030e-02, 4.11914925e-06, 6.57557102e-05, 6.26916662e-02,
4.84521261e-05, 5.18415682e-03, 2.34362528e-06, 1.07593994e-04,
1.78451114e-06, 1.20685516e-04, 8.41678266e-05, 1.88038230e-05,
5.27596676e-05, 8.59603915e-06, 3.89932012e-07, 3.49697715e-04,
1.47663022e-03, 9.87376625e-05, 2.19516210e-06, 3.23797867e-05,
5.23786475e-05, 3.98649089e-03, 2.83175596e-05, 1.49316729e-05,
1.27470830e-05, 3.75876378e-04, 9.56934764e-06, 5.73387388e-06,
3.93406372e-04, 5.70690893e-02, 2.49761995e-03, 8.15123200e-01,
3.88750559e-05, 2.62676418e-04, 1.40196862e-04, 6.65961765e-04,
2.98961299e-04, 3.99038021e-04], dtype=float32)

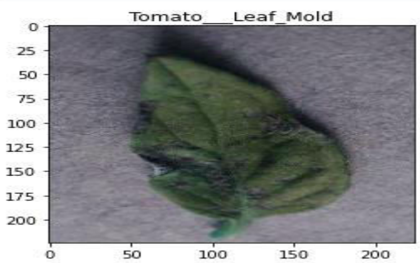
```
[35]: predictions[0]
```

```
[35]: 31
```

```
plt.imshow(X_test[0])
plt.title(classes[predictions[0]])
plt.show()
```

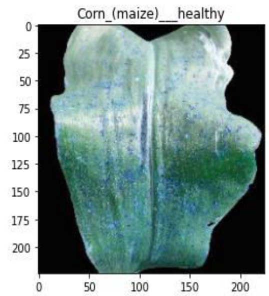
predictions [0]
RESULT: 31

```
plt.imshow(X_test[0])
plt.title(classes[predictions[0]])
plt.show()
```



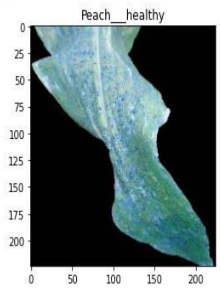
Output disease Tamato_Leaf_Mold

```
plt.imshow(X_test[8])
plt.title(classes[predictions[8]])
plt.show()
```



Output disease Corn_maize_healthy

```
plt.imshow(X_test[16])
plt.title(classes[predictions[16]])
plt.show()
```



Output disease Pepper bell healthy

5.3 TABLES:

	precision	recall	f1-score	support
0	0.42	0.73	0.54	201
1	0.29	0.87	0.43	198
2	0.64	0.23	0.34	176
3	0.58	0.26	0.36	200
4	0.49	0.71	0.58	181
5	0.48	0.76	0.59	168

6	0.89	0.47	0.62	182
7	0.65	0.53	0.59	164
8	0.96	0.81	0.88	190
9	0.92	0.57	0.70	190
10	0.71	0.93	0.80	185

6. Conclusion & Feature Scope

In conclusion, the study on "Enhancing Plant Disease Diagnosis with Convolutional Neural Networks and Leaf Image Analysis" demonstrates the effectiveness and potential of using CNNs for plant disease diagnosis. The developed system shows promising results in accurately identifying and classifying plant diseases based on leaf images. By leveraging the power of deep learning and image analysis techniques, the system offers a more efficient and automated approach to disease diagnosis compared to traditional manual methods. The findings highlight the ability of CNNs to learn intricate patterns and features from leaf images, enabling reliable disease detection. The proposed system has practical implications for farmers, agronomists, and researchers, as it can aid in early disease detection, timely intervention, and improved crop management. However, further research is needed to address limitations, such as dataset biases and potential misclassifications, and explore avenues for improvement, including multi-modal data integration and addressing class imbalance. Overall, the study contributes to advancing plant disease diagnosis methods and sets the stage for the development of more robust and accurate systems to combat plant diseases and enhance agricultural productivity.

Acknowledgement

I would like to extend my deepest appreciation to my research advisor, [Dr. S. China Venkateshwarlu, for their unwavering support and guidance. Their expertise, insightful feedback, and continuous encouragement have been instrumental in shaping the direction and quality of my research. Their dedication and commitment to my academic growth have been truly inspiring, and I am grateful for the opportunity to work under their mentorship.

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P. Sneha from department of Electronics and Communications studying at IARE Dundigal, Hyderabad, Telangana, PIN: 500043 is a 3rd year graduation student with curiosity to learn and do research in various aspects of technology. Ambitious to learn and adapt new ways of technology to do research and explore more for development in industrial and social aspects.