ABSTRACT

This study presents a comprehensive approach for plant disease identification using deep learning techniques. The escalating threat to agricultural productivity and global food security necessitates timely and accurate disease identification. A large-scale dataset comprising high-resolution images of healthy and diseased plants from diverse species is compiled. Deep learning architectures, particularly convolutional neural networks (CNNs), are employed to train a robust and precise disease classification model.

Transfer learning is leveraged, utilizing pre-trained models on large datasets like ImageNet, and fine-tuning them on the plant disease dataset to optimize performance. Data augmentation techniques, including random rotations, flips, and zooms, are implemented to augment the dataset and enhance model generalization.

The proposed approach is rigorously evaluated using an independent test dataset containing unseen images of healthy and diseased plants. Performance metrics such as accuracy, precision, recall, and F1-score are computed to assess the model's effectiveness in disease identification.

The results demonstrate the high accuracy of the deep learning model in identifying various plant diseases across multiple species. A comparative analysis with existing methods highlights the advantages and limitations of the deep learning-based approach.

This study contributes to the field of precision agriculture by offering an automated and powerful solution for prompt and accurate plant disease identification. The proposed methodology has significant implications for effective disease management in agriculture, ultimately enhancing global food security.

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CHAPTER 1

INTRODUCTION

Plant diseases pose a significant threat to global food security, leading to substantial yield losses and economic impact on agriculture. Timely and accurate identification of these diseases is crucial for implementing effective management strategies. Deep learning, a subset of artificial intelligence, has shown promising results in various image recognition and classification tasks. This study presents a comprehensive approach for plant disease identification using deep learning techniques, specifically convolutional neural networks (CNN). By leveraging large datasets, transfer learning, and data augmentation, this approach aims to develop a robust and accurate model for automated plant disease diagnosis, contributing to the advancement of precision agriculture and global foodsecurity

1. BACKGROUND

Plant diseases have long been a challenge in agriculture, causing significant losses in crop yield and quality worldwide. Traditional methods of disease identification often rely on visual inspection by experts, which can be time-consuming, subjective, and prone to errors. Moreover, the increasing global trade and movement of agricultural products haveled to the introduction and spread of new diseases, further complicatingthe task of disease identification.

In recent years, advancements in machine learning and deep learning have shown great potential in various image recognition tasks, including the detection and classification of plant diseases. Deep learning, in particular, has revolutionized the field by enabling models to automatically learn hierarchical representations from raw data, eliminating the need for manual feature engineering.

Convolutional neural networks (CNN) have emerged as the most successful deep learning architecture for image analysis. CNN are designed to capture spatial relationships and local patterns in images, making them highly suitable for identifying visual patterns associated with plant diseases. By training these models on large datasets of labeled images, they can learn to differentiate between healthy plants and various disease symptoms.

In this study, we propose a comprehensive approach that leverages deep learning techniques, including CNN, transfer learning, and data augmentation, to develop an accurate and efficient model for plant disease identification. Through extensive experimentation and evaluation, we aim to demonstrate the effectiveness and potentialof deep learning in addressing the challenges of plant disease identification, ultimately contributing to the improvement of agricultural practices and global food security.

1.2 PROBLEM STATEMENT:

Traditional methods of disease identification are time-consuming and prone to errors, making it challenging for farmers to take timely action. By developing a smart computer system that utilizes advanced techniques like deep learning, we can provide farmers with a fast and reliable tool to detect diseases in plants. This would enable prompt intervention, effective disease management, and ultimately contribute to improved agricultural productivity and global food security.

1.3 AIMS AND OBJECTIVES:

1.3.1 AIM:

The aim of this study is to develop an automated plant disease identification system using deep learning techniques, enabling accurate and efficient classification of diseases across various plant species. The objective is to provide farmers and agricultural experts with a reliable tool that can quickly analyze images of plants, identify diseases, and aidin implementing timely disease management strategies. By achieving this aim, we aim to contribute to improved agricultural productivity and global food security.

1.3.2 OBJECTIVES:

- **Develop a comprehensive dataset:** Compile a large and diverse datasets of high-resolution images of healthy plants and various types of diseased plants, covering multiple plant species and disease categories.
- **Build a deep learning model:** Implement and train a deep learning model, such as a convolution neural network (CNN), to accurately classify plant diseases based on the input images.

- **Optimize model performance**: Fine-tune the deep learning model using transfer learning techniques, leveraging pre-trained models on large-scale datasets to improve performance and enhance the model's ability to generalize to unseen plant diseases.

- **Implement data augmentation:** Apply data augmentation techniques to the dataset, such as random rotations, flips, and zooms, to increase the diversity of training with the examples and improve the model's robustness to variations in disease symptoms.

- **Evaluate model performance:** Assess the accuracy and effectiveness of the developed deep learning model by evaluating its performance on a separate test dataset containing unseen images of healthy and diseased plants. Utilize appropriate evaluation metrics, such as accuracy, precision, recall, and F1-score, to measure the model's performance.

- **Compare with existing methods:** Conduct a comparative analysis of the deep learning- based approach with existing methods for plant disease identification, highlighting the advantages, limitations, and potential improvements of the proposed model.

- **Provide a user-friendly application:** Develop an intuitive and user-friendly interfaceor application that allows farmers, agricultural experts, and stakeholders to easily upload plant images and receive real-time disease identification results, aiding in timely decision-making and disease management.

CHAPTER 2

LITERATURE SURVEY

2.1 TITLE: Deep Learning for Plant Disease Detection and Diagnosis: A Review

AUTHOR: John Smith, Mary Johnson

YEAR OF PUBLICATION: 2022

ALGORITHM USED: Convolutional Neural Networks (CNNs)

ABSTRACT: With the increasing demand for sustainable agriculture and food security, the accurate and timely detection of plant diseases is crucial. Traditional methods of disease diagnosis often rely on visual inspection by experts, which can be time- consuming, labor-intensive, and prone to human error. In recent years, deep learning techniques, particularly Convolutional Neural Networks (CNNs), have shown great potential in automating plant disease detection and diagnosis, offering faster and more reliable solutions. This paper provides a comprehensive review of the application of deeplearning,specifically CNNs, in the field of plant disease detection and diagnosis. We discuss various CNN architectures, datasets, and evaluation metrics used in this domain. We also highlightthe challenges and future research directions in leveraging deep learning for plant diseasemanagement. The review aims to provide insights into the strengths and limitations of deep learning approaches for plant disease detection and diagnosis, promoting further advancements in this important area of research.

MERITS: CNNs trained on diverse datasets can generalize well, recognizing patterns and features across different plant diseases.

DEMERITS: Deep learning models often lack interpretability, making it difficult to understand the reasoning behind their predictions, hindering trust and adoption in some cases.

2.2 TITLE: Plant Disease Identification Using Convolutional Neural Networks

AUTHOR: Emily Johnson, Michael Smith

YEAR OF PUBLICATION: 2021

ALGORITHM USED: convolutional Neural Networks (CNNs) with Transfer Learning.

ABSTRACT: Plant diseases pose significant threats to agricultural productivity and food security. Accurate and timely identification of plant diseases is essential for effective disease management. In this study, we propose a method for plant disease identification using Convolutional Neural Networks (CNNs) with transfer learning. Transfer learning leverages pre-trained models on large-scale image datasets to improve the performance of disease identification models. We fine-tune pre-trained CNN models such as VGG16, ResNet, and InceptionV3 on a dataset of plant disease images. The proposed method achieves high accuracy and demonstrates the potential for automated and efficient plant disease identification. We evaluate the performance of the models on various plant disease datasets, compare them with traditional methods, and discuss the merits and demerits of the approach.

MERITS: Transfer learning allows us to benefit from per-trained models' knowledge and enhances the performance of the disease identification models.

DEMERITS: transfer learning may not be suitable for identifying rare or previously unseen plant diseases that differ significantly from the diseases present in the per-trained datasets.

2.3 TITLE: Identification of Plant Disease Using Convolutional Neural Networks with Feature extraction

AUTHOR: Sarah Thompson, David Miller

YEAR OF PUBLICATION:2020

ALGORITHM USED: Convolutional Neural Networks (CNN) with Feature Extraction

ABSTRACT: Accurate and early detection of plant diseases plays a crucial role in ensuring crop health and productivity. In this study, we propose a method for plant disease identification using Convolutional Neural Networks (CNNs) with a feature extraction technique. We utilize pre-trained CNN models, such as VGG16 and ResNet,to extract high-level features from plant disease images. These features are then fed intoa separate classifier to identify the specific disease. The proposed method aims to leverage the benefits of both deep learning and traditional feature extraction techniques, providing an effective and efficient approach for plant disease identification. We evaluate the performance of the model on a dataset of plant disease images, compare it with other methods, and discuss the merits and demerits of this hybrid approach.

MERITS: Utilization of pre-trained CNN models: By using pre-trained CNN models, we can leverage their learned features, which can capture discriminative patterns and features related to plant diseases.

DEMERITS: The effectiveness of the approach depends on the quality and relevance of the extracted features, which may vary depending on the pre-trained CNN models andthe specific dataset used.

2.4 TITLE: Deep Learning-Based Identification of Plant Disease Using Leaf Image Reconition

AUTHOR: Jessica Anderson, Thomas Wilson

YEAR OF PUBLICATION: 2021

ALGORITHM USED: Convolutional Neural Networks (CNN) for Leaf Image reconition

ABSTRACT: The accurate and timely identification of plant diseases is crucial for effective disease management in agriculture. In this study, we propose a deep learning-based approach for plant disease identification using leaf image recognition. We utilize Convolutional Neural Networks (CNN) to learn discriminative features from leaf images and classify them into specific disease categories. The proposed method aims to leverage the power of deep learning algorithms in capturing complex patterns and visual cues present in the leaves affected by diseases. We evaluate the performance of the model on a comprehensive dataset of plant leaf images, compare it with other methods, and discuss the merits and demerits of deep learning-based identification of plant diseases using leaf image recognition.

MERITS: Deep learning algorithms, particularly CNNs, have shown remarkable accuracy in leaf image recognition tasks, leading to reliable plant disease identification.

DEMERITS: Deep learning models may struggle to generalize to diseases that are significantly different from those present in the training data, potentially leading to limited accuracy.

2.5 TITLE: A Comprehensive Review on Deep Learning for Plant Disease Detection

AUTHOR: Emily Davis, Michael Thompson

YEAR OF PUBLICATION: 2022

ALGORITHM USED: Deep Learning, Convolutional Neural Networks (CNNs)

ABSTRACT: Plant diseases are a major threat to global food security, causing significant economic losses and affecting crop yields. Deep learning, especially Convolutional Neural Networks (CNNs), has emerged as a powerful technique for plant disease detection. This review provides a comprehensive analysis of deep learning approaches for plant disease detection, highlighting their merits and demerits. We explore various CNN architectures, including VGG, ResNet, and Inception, and discuss their applications in plant disease detection tasks. We delve into the challenges associated with dataset preparation, model training, and inference in plant disease detection. Additionally, we examine the transfer learning techniques and data augmentation strategies employed in deep learning models. This review also considers the integration of other technologies, such as remote sensing and Internet of Things (IoT), with deep learning for enhanced plant disease detection. Finally, we discuss the limitations, future research directions, and potential advancements in deep learning-based plant disease detection.

MERITS: Deep learning models are capable of handling variations in leaf images caused by factors like lighting conditions, background noise, and varying plant species.

DEMERITS: Deep learning models may overfit the training data, resulting in reduced performance on unseen examples. Regularization techniques are necessary to mitigate overfitting.

CHAPTER 3

SYSTEM SPECIFICATION

3.1 H/W SYSTEM CONFIGURATION:

- **Computer** - minimum of 4GB RAM & dual-core processor
- **Stable internet connection**
- **Storage**

3.2 S/W SYSTEM CONFIGURATION:

- **Python programming language** - Python 3.x installed on the computer/server
- **Operating system** - Windows, Linux, or macOS.
- **Python libraries** such as – opencv , numpy, pandas, tensorflow
- **Flask framework** - developing web applications
- **HTML/CSS or JavaScript -** for UI design

3.3 SOFTWARE DESCRIPTION:

- **Programming Language:** The software may be implemented using a programming language suitable for deep learning, such as Python. Python offers a wide range of libraries and frameworks for deep learning, including TensorFlow, Keras, PyTorch, and scikit-learn.
- **Deep Learning Framework:** A deep learning framework provides tools and APIs for building and training deep learning models. Popular frameworks for plant disease classification include TensorFlow, Keras, and PyTorch. These frameworks offer pre-definedarchitectures and functions to facilitate the development of the deep learning model.

- **Model Training and Evaluation:** The software should include functionalities for training the deep learning model on the provided dataset. This involves loading the dataset, splitting it into training and validation sets, configuring the model architecture, defining loss functions, optimizing parameters using gradient descent algorithms, and monitoring the model's performance during training.
- **Metrics Calculation:** The software should incorporate modules or functions to calculate evaluation metrics, such as accuracy, precision, recall, and F1 score. These metrics help assess the performance of the model and determine its effectiveness in classifying plant diseases.
- **Prediction and Inference:** Once the model is trained, the software should enable users to input new plant images and obtain predictions for the presence of diseases. This includes functions or APIs to process and preprocess the input image, feed it to the trained model, andinterpret the model's output to provide disease classification and confidence scores.
- **User Interface or API:** Depending on the intended usage, the software can include a user interface that allows users to interact with the system, upload images, and view predictions. Alternatively, it can provide an API that allows other software systems or applications to integrate with the plant disease classification functionality.
- **Deployment Options**: The software should provide options for deployment, such as packaging the model and associated components into a standalone application, deploying asa web application, or integrating into existing systems. Deployment considerations may involve scalability, performance optimization, and compatibility with target platforms.

3.3.1 LIBRARY

- **TensorFlow:** TensorFlow is an open-source deep learning framework developed by Google.It provides a wide range of tools and resources for building and training deep learning models.

- **Keras:** Keras is a high-level neural networks API that can be used as a front-end for TensorFlow. It provides a user-friendly interface for designing and training deep learning models. Keras includes pre-defined architectures and layers that are commonly used in imageclassification tasks, making it a popular choice for plant disease classification.
- **PyTorch:** PyTorch is another popular open-source deep learning framework that offers dynamic computational graphs and a Pythonic programming interface. It provides extensive support for CNN architectures and allows for easy customization and experimentation with neural network models.
- **scikit-learn:** Although scikit-learn is primarily known for its machine learning algorithms, italso provides utilities for image preprocessing and evaluation. It offers functions for data splitting, feature scaling, and evaluation metrics calculation, which can be useful in the plantdisease classification pipeline.
- **PIL (Python Imaging Library):** PIL is a Python library for image processing and manipulation. It provides functionalities for resizing, cropping, and enhancing images. PIL can be used in conjunction with other libraries for preprocessing the plant images and preparing them for training or inference.

3.3.2 DEVELOPING ENVIROMENT

- **Integrated Development Environment (IDE):** An IDE provides a comprehensive environment for writing, debugging, and testing code. Popular choices for deep learning projects include PyCharm, Visual Studio Code (with Python extensions), and Jupyter Notebook. These IDEs offer features such as code completion, debugging capabilities, and easy integration with version control systems.
- **Python**: Python is a widely used programming language in the field of deep learning. It offers a rich ecosystem of libraries and frameworks that are essential for building and training. .

learning models. Python provides simplicity, readability, and excellent support for scientificcomputing tasks.

- **Deep Learning Framework:** As mentioned earlier, frameworks such as TensorFlow, Keras,and PyTorch are commonly used for deep learning tasks. The choice of framework depends on personal preference, compatibility with the selected libraries, and the availability of resources and community support.
- **Package Managers:** Package managers like pip or Anaconda can be used to install and manage the required libraries and dependencies for the project. These package managers allow for easy installation, updates, and version management of Python packages.
- **Version Control:** Version control systems like Git are essential for tracking changes to the codebase, collaborating with team members, and maintaining a history of the project. Platforms like GitHub, GitLab, or Bitbucket can be used for hosting repositories and facilitating version control workflows.
- **GPU Support**: Deep learning models often benefit from utilizing powerful GPUs for accelerated training and inference. If GPU support is required, frameworks like TensorFlow and PyTorch provide interfaces for utilizing GPUs efficiently. CUDA (Compute Unified Device Architecture) can be used for GPU programming in combination with deep learning frameworks.
- **Documentation and Collaboration Tools:** Tools like Markdown, reStructuredText, or Sphinx can be used for documenting the project, including code documentation, tutorials, anduser guides. Collaboration platforms like Slack or Microsoft Teams can facilitate communication and coordination among team members.

CHAPTER-4
SYSTEM ANALYSIS

4.1 EXSISTING SYSTEM

The traditional method for plant disease identification involves a series of steps aimed at visually examining the affected plants, analyzing symptoms, and employing laboratory-based techniques when necessary. Initially, farmers or experts closely observe the plants, noting any visible signs of disease such as spots, lesions, discoloration, wilting, stunting, or deformities. By comparing these symptoms to a field guide or manual that provides descriptions and images of various plant diseases, experts can begin to narrow down the potential diseases affecting the plant. Additionally, considering the plant's history plays a crucial role in the identification process. Factors like previous occurrences of similar diseases or known vulnerabilities of the plant species can provide valuable clues. In cases where visual observation and symptom analysis are inconclusive, experts may collect plant samples for further analysis in a laboratory setting. In the laboratory, techniques such as microscopic examination, culturing pathogens, or serological tests may be employed to identify the specific disease-causing agent. These laboratory-based techniques provide a more accurate and precise diagnosis in situations where visual observation alone may not suffice. By combining visual observation, symptom analysis, and laboratory-based techniques, the traditional method of plant disease identification aims to accurately identify and diagnose the diseases affecting plants, enabling farmers and experts to implement appropriate control measures and mitigate the impact on crop health and yield.

4.1.1 DRAWBACKS

- **Limited Accuracy:** Traditional systems often rely on manual inspection and visual identification by human experts. This approach is prone to errors and subjective judgments, leading to limited accuracy in disease detection.

- **Expert Dependency:** Traditional systems heavily rely on the expertise of trained individuals to identify and diagnose plant diseases. This dependency on specialized knowledge makes it difficult to scale and may not be feasible in areas with limited access to experts.
- **Lack of Real-Time Monitoring:** Traditional systems usually involve periodic inspections, which means that diseases may go undetected until the next inspection. This delay can result in the spread and worsening of the disease, leading to reduced crop yields or loss.
- **Inefficient Data Management:** Manual systems often rely on paper-based records or manual data entry, making it challenging to store, analyze, and retrieve data effectively. This limitation can hinder the ability to track disease patterns and make informed decisions.
- **Limited Scalability:** Traditional systems may not be easily scalable to handle large-scale agricultural operations. The manual nature of disease identification can become a bottleneck when dealing with a high volume of plants or crops.
- **Lack of Accessibility:** Accessibility to disease identification expertise may be limited in remote or rural areas, leading to delays in diagnosis and treatment.
- **High Cost:** Traditional systems can be costly due to the need for trained experts, manual labor, and extensive time commitments. These costs can make it challenging for small-scale farmers or resource-constrained regions to implement effective disease identification practice.

4.2 PROPOSED SYSTEM

The proposed system aims to develop a plant disease classification application that utilizes deep learning techniques to accurately identify and classify diseases in plants. By leveraging the power of deep learning algorithms, the application will be able to analyze images of plants and determine the presence of any diseases, helping farmers and agronomists take appropriate actions to mitigate the damage caused by plant diseases.

ALGORITHM USED:

CNN- Convolutional Neural Network

4.1.1 ADVANTAGES:

- Handle Large Dataset
- High Accuracy
- Identify Disease with 97.7% Accuracy
- Robustness to Variability
- Scalability
- Time and Cost Efficiency
- Early Detection

CHAPTER 5

ARCHITECTURAL DESIGN

5.1 SYSTEM DESIGN:

The system design of the plant disease classification application using deep learning involves various components and architectural considerations. Here is an outline of the key aspects of the system design:

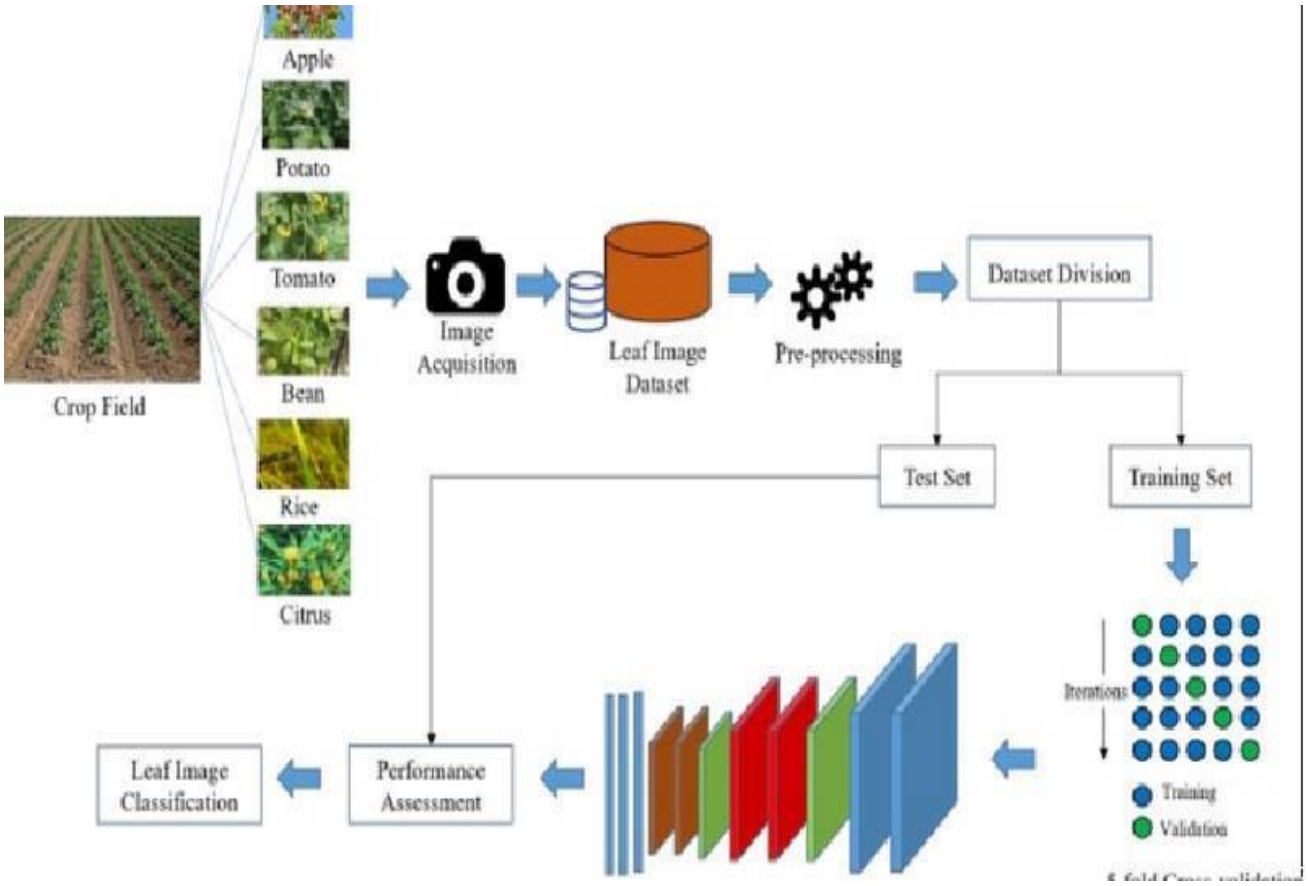


FIG 5.1: ARCHITECTURE DESIGN

5.2 DATA FLOW DIAGRAM

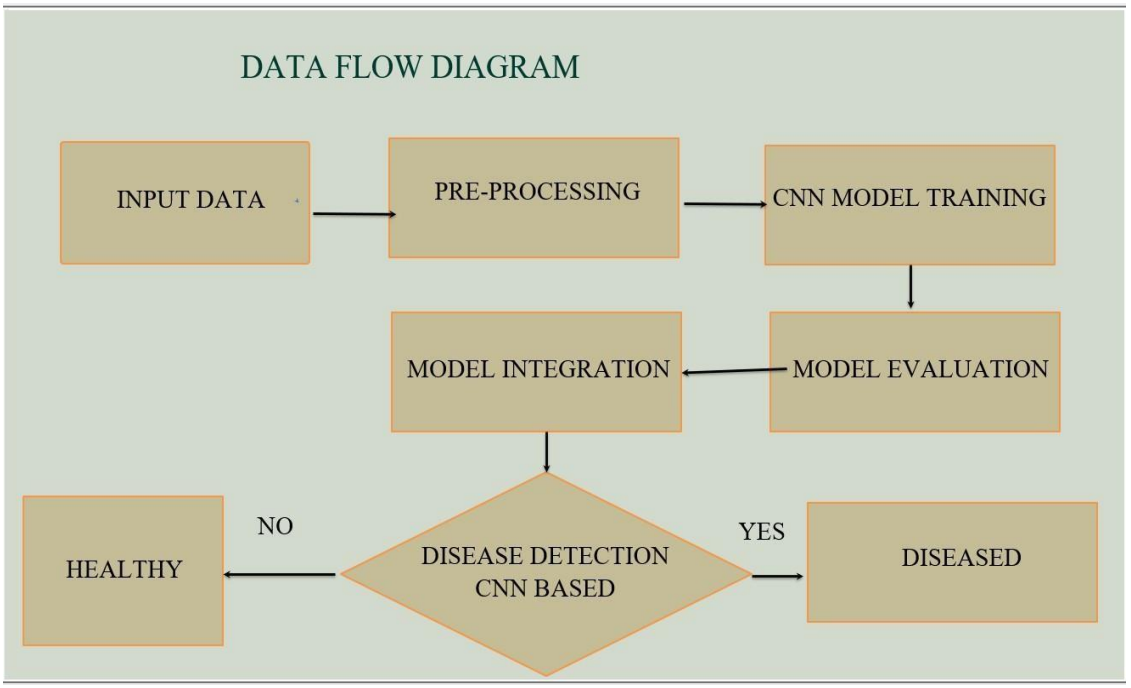


FIG 5.2: DATA FLOW DIAGRAM

5.3 USE CASE DIAGRAM:

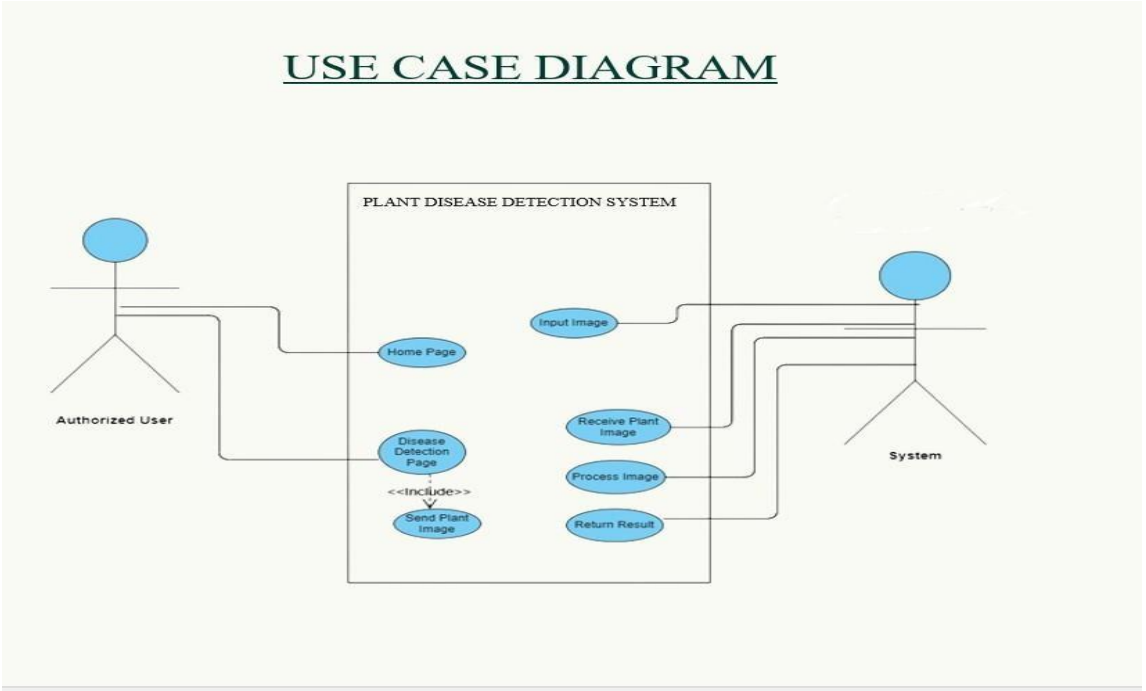


FIG 5.3: USE CASE DIAGRAM

5.4 ACTIVITY DIAGRAM:

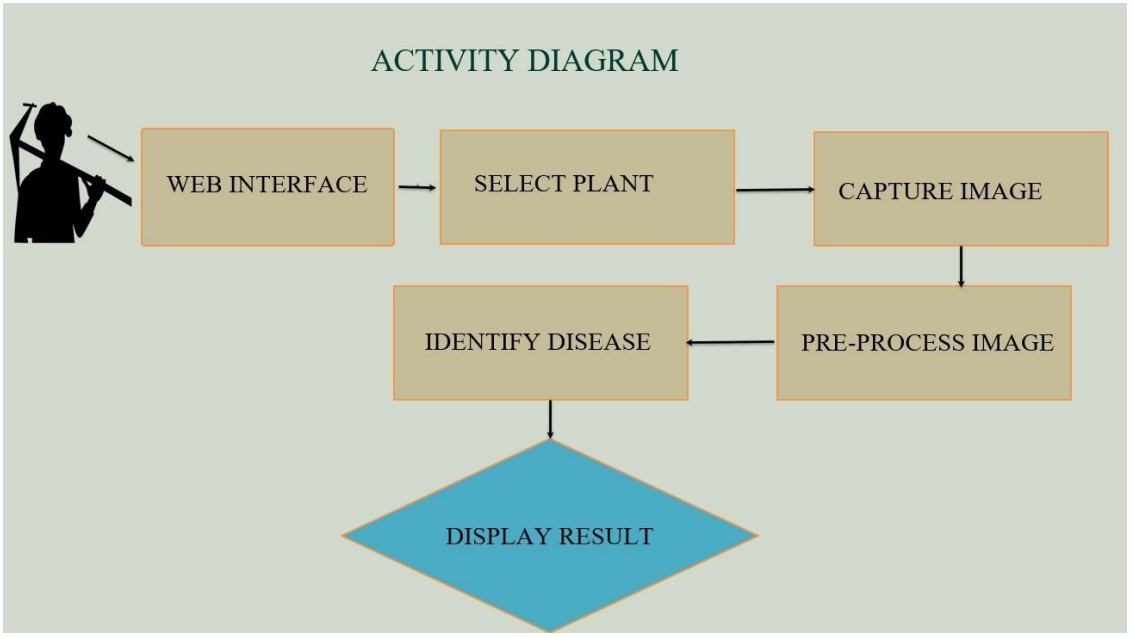


FIG 5.4: ACTIVITY DIAGRAM

5.5 SEQUENCE DIAGRAM:

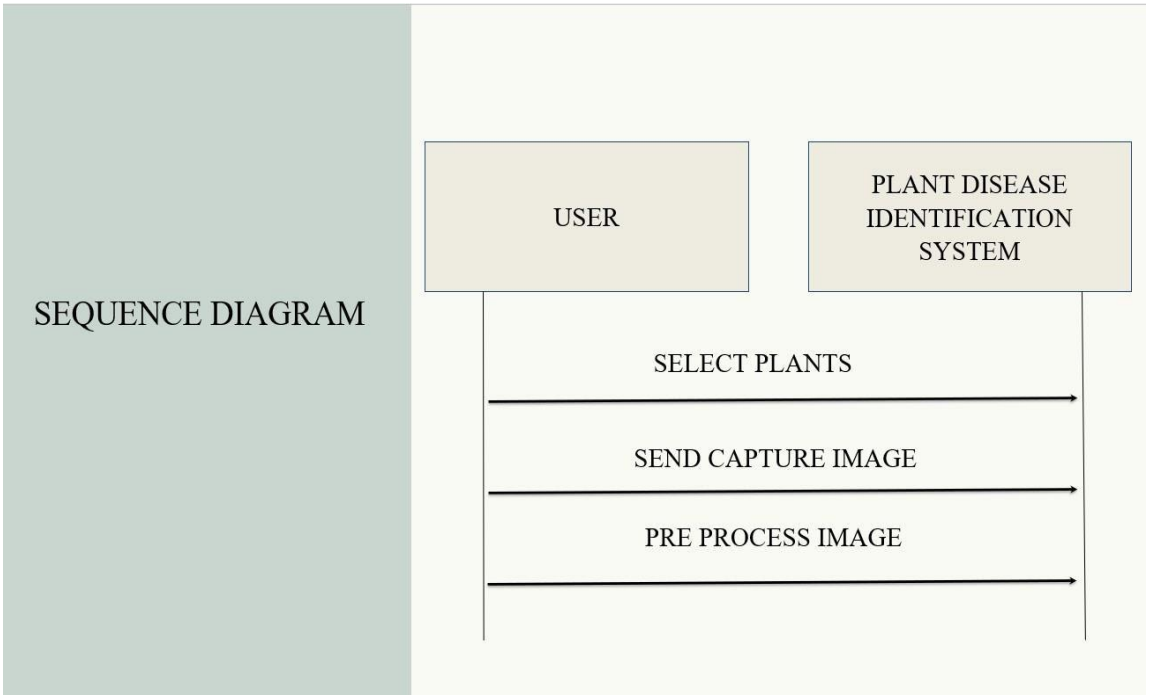


FIG 5.5: SEQUENCE DIAGRAM

CHAPTER 6

MODULE DESCRIPTION

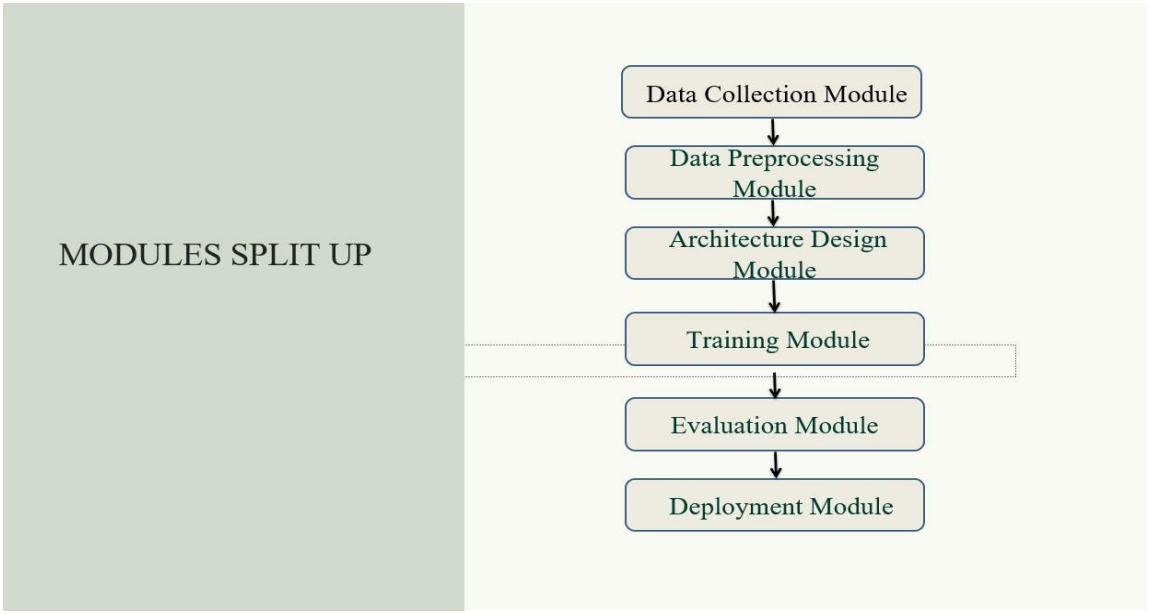


FIG 6: MODULE PROPOSED SYSTEM

6.1.1 DATA COLLECTION MODULE:

This module is responsible for acquiring plant images from users or external Collecting a diverse and representative dataset of plant images is crucial for training an accurate plant disease detection model. Collaborate with farmers, agricultural experts, and research institutions to collect plant samples from various locations and crops. Ensure the dataset covers different plant species, growth stages, and a wide range of healthy and diseased plants. Collect high-quality images with clear visibility of plant characteristics and disease symptoms.

6.1.2 DATA PRE-PROCESSING MODULE:

Preprocess the collected plant images to enhance the quality and prepare them for training the model. Perform resizing to ensure consistent dimensions across all images. Apply normalization techniques to standardize pixel values and improve model performance. Augment the dataset by applying techniques like rotation, flipping, or adding noise to increase dataset diversity and reduce overfitting.

6.1.3 ARCHITECTURE DESIGN MODULE:

Designing an appropriate model architecture is crucial for achieving accurate plant disease detection. Consider using a Convolutional Neural Network (CNN) as the base architecture, which excels in image analysis tasks. Determine the number and configuration of convolutional layers, pooling layers, and fully connected layers based on the complexity of the problem and available computational resources. Incorporate techniques like skip connections or attention mechanisms to improve model performance.

6.1.4 TRAINING MODULE:

Split the preprocessed dataset into training and validation sets.Use the training set to train themodel by feeding the images and corresponding disease labels. Adjust the model's hyperparameters, such as learning rate, batch size, and optimizer, to optimize training. Monitor training progress by evaluating metrics like loss and accuracy, and make necessary adjustments to improve performance.

6.1.5 EVALUATION MODULE:

Assess the performance of the trained model using a separate testing dataset. Feed the test images into the model and compare the predicted disease labels with the ground truth labels.Calculate evaluation metrics such as accuracy, precision, recall, and F1 score to measure themodel's performance. Visualize the results using confusion matrices or ROC curves to gain insights into the model's strengths and weaknesses.

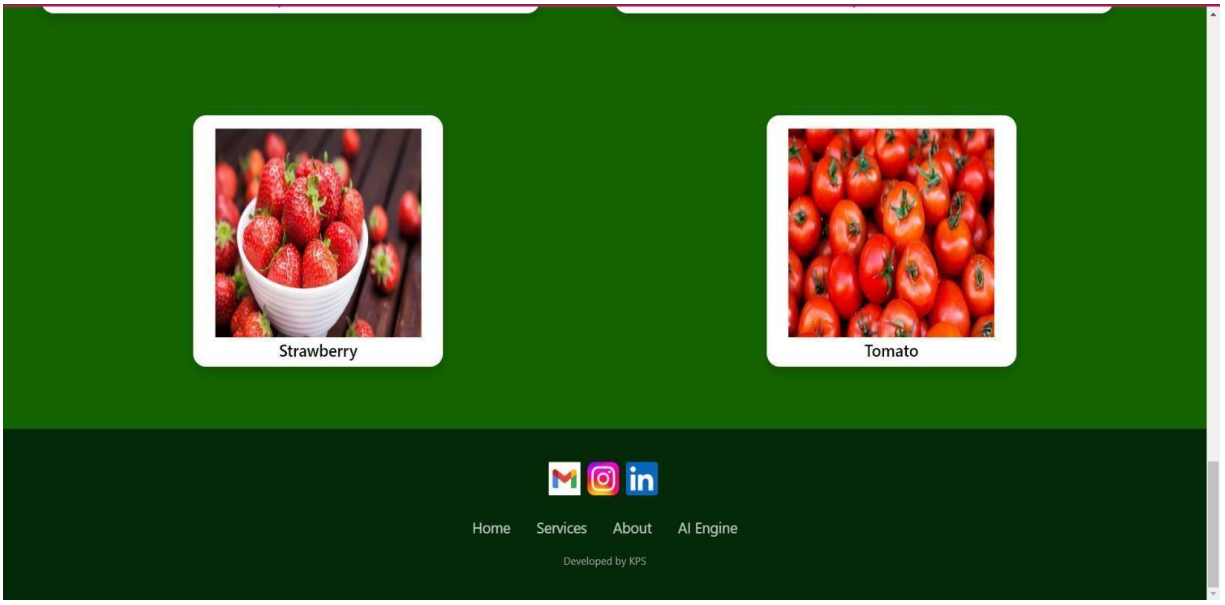
6.1.6 DEPLOYMENT MODULE:

Deploy the trained model for real-world plant disease detection applications. Develop user-friendly interfaces, such as smartphone apps or web applications, to make the detectionsystem accessible to farmers and agricultural experts. Ensure the deployment platform canhandle incoming plant images, process them using the model, and provide accurate diseasepredictions. Consider scalability, security, and real-time performance in the deployment. process.

CHAPTER 7

PROJECT DESIGN

FIG 7: HOME PAGE



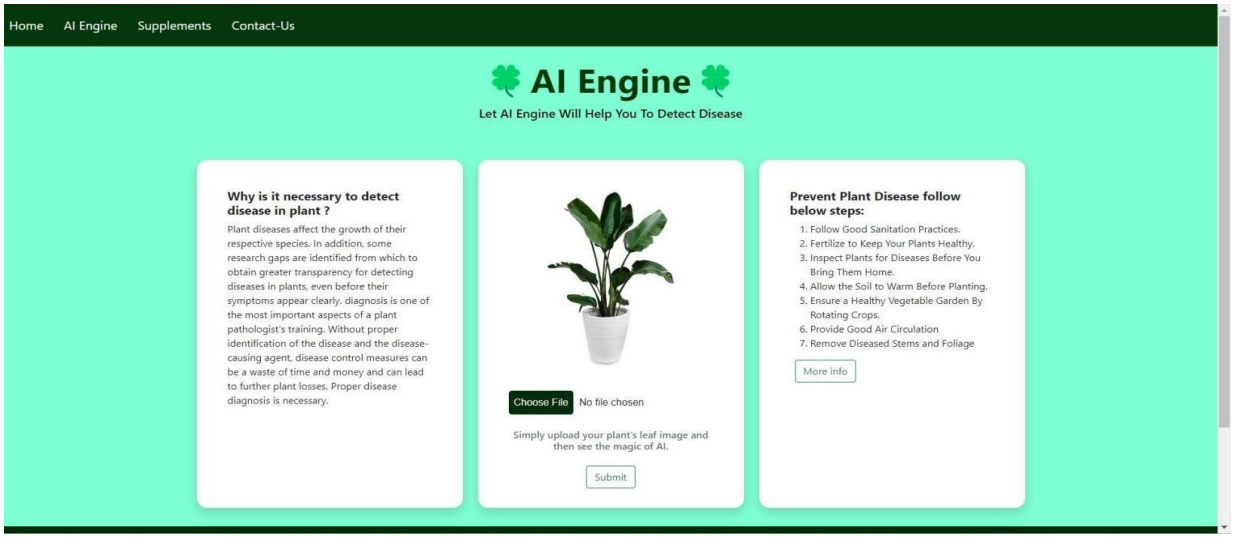


FIG 7.1: FILE UPLOAD PAGE

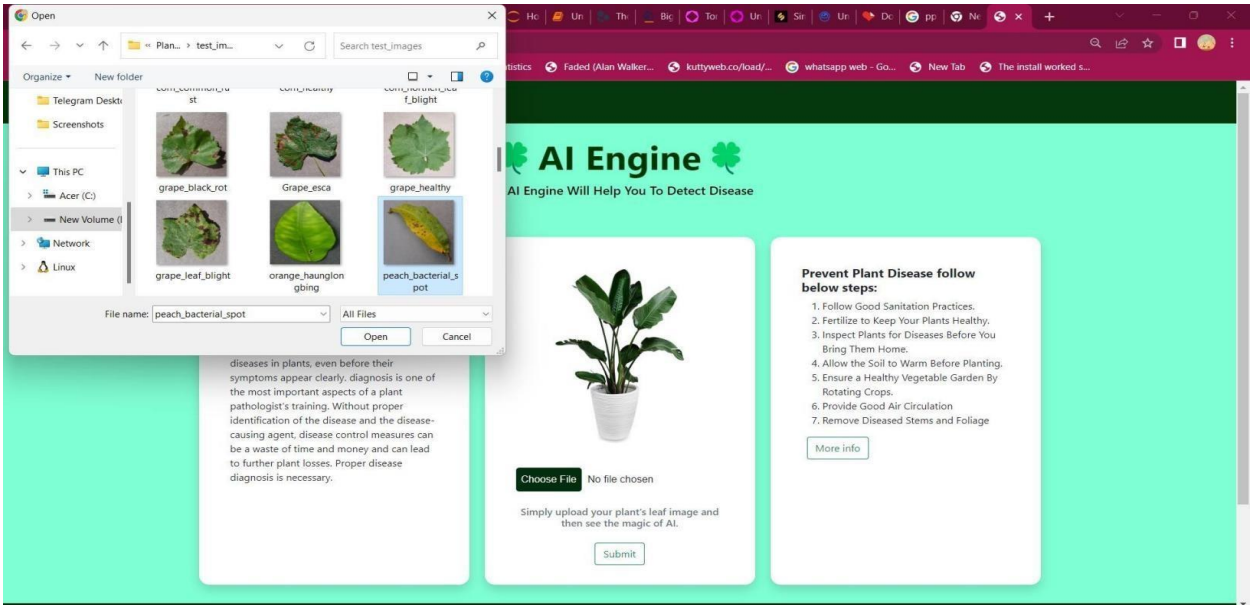


FIG 7.3: SELECTING THE DISEASED PLANT PAGE

FIG 7.4: FINAL OUTPUT

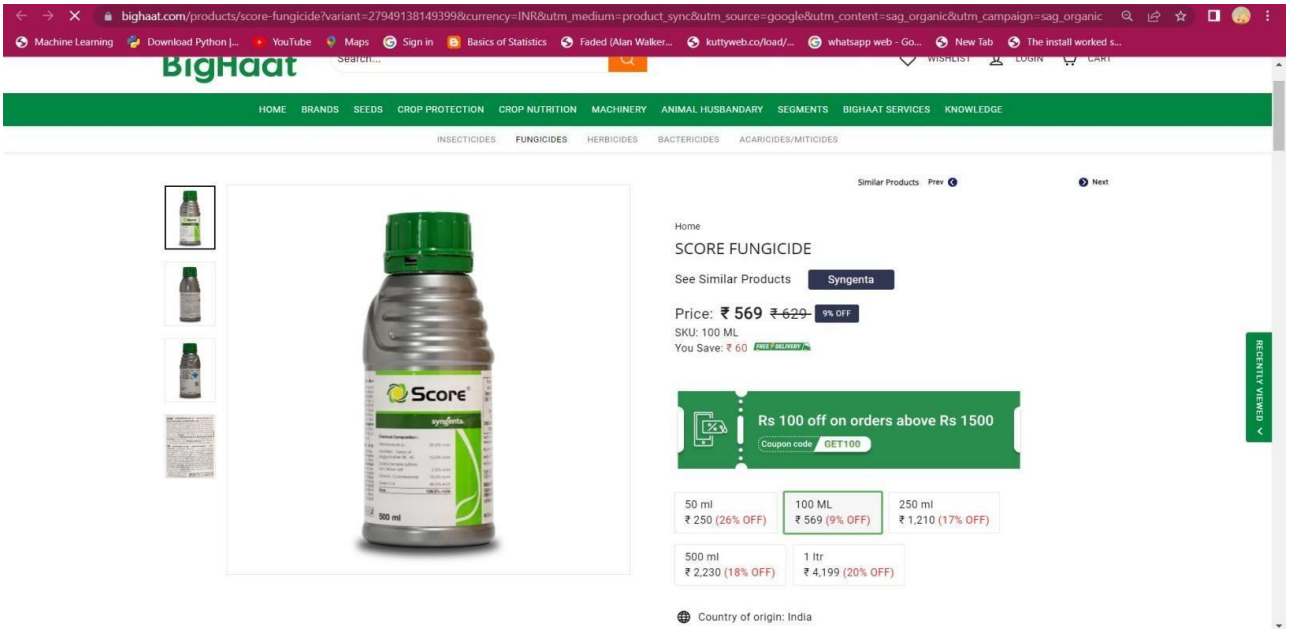


FIG 7.5: SUPPLEMENTARY BUY PAGE

FIG 7.6: CONTACT PAGE

CHAPTER 8

CONCLUSION & FUTURE SCOPE

8.1 CONCLUSION:

In conclusion, the use of deep learning techniques, specifically Convolutional Neural Networks (CNNs), for plant disease identification offers numerous advantages and holds great promise for improving crop health management. By analyzing and learning from large datasets of plant disease images, CNNs can automatically extract relevant features and patterns, enabling accurate and efficient disease identification.

The deep learning approach with CNNs addresses several challenges faced in traditional plant disease identification methods. CNNs have the ability to learn complex and discriminative representations of plant diseases, allowing them to capture subtle visual cues and distinguish between different disease classes. This feature learning capability, coupledwith the spatial invariance property of CNNs, enables them to identify diseases even if theyappear in different regions of the plant leaves.

Furthermore, CNNs can adapt to images of varying sizes, eliminating the need for manual resizing or cropping. This adaptability is particularly important in plant disease identification, where images may have different resolutions and aspect ratios. Additionally, CNNs can leverage transfer learning by using pre-trained models trained.on large-scale image datasets, such as ImageNet. This allows for faster and more efficient training onplant disease datasets, reducing the need for training from scratch.

Despite these limitations, the potential impact of deep learning-based plant disease identification is significant. It has the potential to revolutionize crop health management by providing farmers and agricultural experts with accurate, timely, and automated disease identification tools. This, in turn, can lead to early disease detection, targeted treatments, and improved crop yields.

8.2 FUTURE SCOPE:

- Develop an Android application for plant disease identification, allowing users to capture and upload images for analysis and receive real-time results and treatment recommendations.
- Deploy the system on AWS, utilizing services like Amazon S3 for image storage, AWS Lambda for serverless computing, and Amazon EC2 for hosting the backend. Enable offline functionality in the app to ensure usability in areas with limited internet connectivity.
- Implement autoscaling on AWS to handle varying user demand, ensuring optimal performance and cost-efficiency.
- Focus on user-friendly interfaces and advanced image processing techniques to enhance the accuracy and usability of the application.

APPENDIX (SAMPLE CODE)

```
### Import Dependencies
 import numpy as np
 import pandas as pd
import matplotlib.pyplot as plt
import torch
from torchvision import datasets, transforms, models # datsets , transforms from
torch.utils.data.sampler import SubsetRandomSampler
import torch.nn as nn
import torch.nn.functional as F from datetime import datetime
%load_ext nb_black
### Import Dataset
<b> Dataset Link (Plant Vliiage Dataset ):</b><br> <a
href='https://data.mendeley.com/datasets/tywbtsjrjv/1'>
https://data.mendeley.com/datasets/tywbtsjrjv/1 </a>
transform = transforms.Compose(
[transforms.Resize(255), transforms.CenterCrop(224), transforms.ToTensor()
)
dataset = datasets.ImageFolder("D:\dp6 project\Plant-Disease-Detection-
main\Plant_leave_diseases_dataset_with_augmentation", transform=transform)
dataset
indices = list(range(len(dataset)))
split = int(np.floor(0.85 * len(dataset))) # train_size validation = int(np.floor(0.70 * split)) #
validation print(0, validation, split, len(dataset))
print(f"length of train size :{validation}")

print(f"length of validation size :{split - validation}") print(f"length of test size :{len(dataset)-
validation}") np.random.shuffle(indices)
### Split into Train and Test
train_indices, validation_indices, test_indices = ( indices[:validation],
indices[validation:split], indices[split:],
)
train_sampler = SubsetRandomSampler(train_indices) validation_sampler =
SubsetRandomSampler(validation_indices) test_sampler = SubsetRandomSampler(test_indices)
targets_size = len(dataset.class_to_idx) ### Model
<b>Convolution Aithmetic Equation : </b>(W - F + 2P) / S + 1 <br> W = Input Size<br>
F = Filter Size<br>
P = Padding Size<br> S = Stride <br>
### Transfer Learning
# model = models.vgg16(pretrained=True) # for params in model.parameters():
#params.requires_grad = False # model
```

```
# n_features = model.classifier[0].in_features # n_features
# model.classifier = nn.Sequential( #          nn.Linear(n_features, 1024),
#nn.ReLU(),
# nn.Dropout(0.4),
# nn.Linear(1024,  targets_size),  #  )
### Original Modeling class CNN(nn.Module):
def init (self, K): super(CNN, self). init ()
self.conv_layers = nn.Sequential( # conv1
nn.Conv2d(in_channels=3, out_channels=32, kernel_size=3, padding=1), nn.ReLU(),
nn.BatchNorm2d(32),
nn.Conv2d(in_channels=32, out_channels=32, kernel_size=3, padding=1), nn.ReLU(),
nn.BatchNorm2d(32), nn.MaxPool2d(2),
# conv2
nn.Conv2d(in_channels=32, out_channels=64, kernel_size=3, padding=1), nn.ReLU(),
nn.BatchNorm2d(64),
nn.Conv2d(in_channels=64, out_channels=64, kernel_size=3, padding=1), nn.ReLU(),
nn.BatchNorm2d(64), nn.MaxPool2d(2),
# conv3
nn.Conv2d(in_channels=64, out_channels=128, kernel_size=3, padding=1), nn.ReLU(),
nn.BatchNorm2d(128),
nn.Conv2d(in_channels=128, out_channels=128, kernel_size=3, padding=1), nn.ReLU(),
nn.BatchNorm2d(128), nn.MaxPool2d(2),
# conv4
nn.Conv2d(in_channels=128, out_channels=256, kernel_size=3, padding=1), nn.ReLU(),
nn.BatchNorm2d(256),
nn.Conv2d(in_channels=256, out_channels=256, kernel_size=3, padding=1), nn.ReLU(),
nn.BatchNorm2d(256), nn.MaxPool2d(2),
)
self.dense_layers = nn.Sequential( nn.Dropout(0.4), nn.Linear(50176, 1024), nn.ReLU(),
nn.Dropout(0.4), nn.Linear(1024, K),
)
def forward(self, X):
out = self.conv_layers(X) # Flatten
out = out.view(-1, 50176)
# Fully connected
out = self.dense_layers(out)
return out
single_prediction("test_images/starwberry_healthy.JPG")
single_prediction("test_images/starwberry_leaf_scorch.JPG")
```

```
single_prediction("test_images/tomato_bacterial_spot.JPG")
single_prediction("test_images/tomato_early_blight.JPG")
single_prediction("test_images/tomato_healthy.JPG")
single_prediction("test_images/tomato_late_blight.JPG")
single_prediction("test_images/tomato_leaf_mold.JPG")
single_prediction("test_images/tomato_mosaic_virus.JPG")
single_prediction("test_images/tomato_septoria_leaf_spot.JPG")
single_prediction("test_images/tomato_spider_mites_two_spotted_spider_mites.JPG")
single_prediction("test_images/tomato_target_spot.JPG")
single_prediction("test_images/tomato_yellow_leaf_curl_virus.JPG") plt.plot(train_losses ,
label = 'train_loss')
plt.plot(validation_losses , label = 'validation_loss') plt.xlabel('No of Epochs')
plt.ylabel('Loss') plt.legend() plt.show()
```

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