PLANT LEAF DISEASE DETECTION WITH FASTAI

MINOR PROJECT REPORT

By

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BONAFIDE CERTIFICATE

Certified that this minor project report for the course **18AIE332T – Image and Video processing** entitled in "**Plant Leaf Disease Detection with Fast AI**" is the bonafide work of **N. SRAVAN KUMAR (RA2111047010189), C. GOKUL KRISHNA REDDY (RA2111047010190), B. PHANINDRA BABU(RA2111047010193), and MATAM ABHINAY (RA2111047010134)** who carried out the work under my supervision.

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ABSTRACT

Plant leaf disease detection is a critical aspect of precision agriculture, aiming to identify and address diseases affecting crops promptly. In this study, we leverage the power of FastAI, a deep learning library built on PyTorch, to develop an efficient model for automated plant leaf disease detection. The dataset comprises diverse images of plant leaves affected by various diseases, allowing the model to learn distinctive patterns and features associated with each condition. FastAI's user-friendly high-level API simplifies the implementation of complex neural networks, enabling rapid experimentation and iteration for optimal model performance.

Our approach involves a multi-step process, starting with data preparation and augmentation to enhance model generalization. Leveraging FastAI's data block API, we structure the dataset, apply transformations, and create data loaders efficiently. We then employ transfer learning using a pre-trained convolutional neural network (CNN) architecture, fine-tuning it on our plant leaf disease dataset. FastAI's ‘fit_one_cycle’ method facilitates the training process by automatically adjusting learning rates, leading to faster convergence and improved model accuracy.

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TABLE OF CONTENTS

LIST OF FIGURES

1. INTRODUCTION

1.1 Introduction

Plant Leaf Disease Detection is a critical aspect of modern agriculture, as it enables early and targeted intervention to protect crops from diseases. FastAI, a powerful deep learning library, is employed in this project to leverage the capabilities of transfer learning—a technique that allows the use of pre-trained models to boost the performance of a model trained on a specific task. Transfer learning proves especially effective in image classification tasks like leaf disease detection, where large and diverse datasets are essential for training robust models. By leveraging pre-trained models like ResNet or VGG with FastAI, we can harness the knowledge gained from vast image datasets, enabling our model to quickly adapt and excel in identifying plant diseases.

The key advantage of using FastAI lies in its simplicity and efficiency in implementing complex deep learning architectures. With its high-level API, FastAI enables researchers and practitioners to build state-of-the-art models with minimal code, accelerating the development process. Transfer learning, as implemented in FastAI, allows us to take advantage of features learned by models on large datasets, making it particularly useful for plant leaf disease detection where obtaining extensive labeled datasets can be challenging. This project aims to showcase the accessibility and effectiveness of FastAI in creating accurate and efficient models for real-world agricultural challenges.

The significance of this project extends beyond the technical realm, addressing the urgent need for sustainable and efficient agricultural practices. Rapid and accurate detection of plant leaf diseases can lead to timely interventions, reducing crop losses, and ensuring food security. By combining the capabilities of FastAI and transfer learning, this project contributes to the ongoing efforts to harness cutting-edge technologies for the betterment of agriculture, paving the way for a more resilient and productive food system.

1.2 Problem Statement

The problem statement "Plant Leaf Disease Detection with FastAI and Transfer Learning" involves using the FastAI deep learning library along with transfer learning techniques to build a model that can identify and classify plant leaf diseases based on images of plant leaves.

Problem Description:

Plant leaf diseases can significantly impact crop yield and quality. Early detection of these diseases is crucial for effective disease management. In this scenario, the goal is to develop a deep learning model that can automatically identify and classify plant leaf diseases based on images.

1.3 Objective and Motivation

Objective

The primary objective of the project is to develop an efficient and accurate system for the early detection and diagnosis of plant leaf diseases using advanced deep learning techniques, specifically leveraging the Fast AI library and Transfer Learning. The key components of the objective include:

1. **Automated Disease Identification:** Implement a system that can automatically identify and classify plant leaf diseases from images, eliminating the need for manual inspection.
2. **Early Detection:** Detect diseases at their early stages to enable timely intervention and prevent the spread of diseases within crops.
3. **High Accuracy:** Achieve a high level of accuracy in disease classification, ensuring reliable and precise results for practical use in agriculture.
4. **User-Friendly Interface:** Develop a user-friendly interface that allows farmers or users with minimal technical expertise to easily upload and analyze images of plant leaves.

Motivation

The motivation behind Plant Leaf Disease Detection with FastAI and Transfer Learning stems from the critical challenges faced in agriculture:

1. **Crop Yield Loss:** Plant diseases can lead to significant losses in crop yield, affecting food production and economic sustainability.
2. **Manual Inspection Limitations:** Traditional methods of disease detection rely on manual inspection, which is time-consuming, labor-intensive, and may not be effective in the early stages of diseases.
3. **Technological Advancements:** Leveraging advanced technologies like deep learning and transfer learning provides an opportunity to revolutionize disease detection, making it faster, more accurate, and accessible to a wider audience.
4. **Precision Agriculture:** The project aligns with the broader goal of implementing precision agriculture, where technology is utilized to optimize and enhance farming practices for increased efficiency and reduced resource wastage.
5. **Empowering Farmers:** By creating an easy-to-use tool for disease detection, the project aims to empower farmers with the ability to make informed decisions about crop management, leading to better agricultural outcomes.

The objective is to deploy cutting-edge technology to address a real-world problem in agriculture, with the ultimate goal of contributing to sustainable and efficient farming practices.

1.4 Requirement Elicitation

1. User Requirements: Gathering user requirements is critical to ensuring the system meets the needs of its intended users. This step involves interacting with stakeholders, such as farmers, researchers, or agricultural experts, to identify specific features and functionalities they require. Users may express preferences for a user-friendly interface, real-time disease identification, and support for a variety of crops.

2. Image Dataset Requirements: A comprehensive and diverse dataset is crucial for effective transfer learning. This step involves specifying the requirements for the image dataset used to train the model. Requirements may include a variety of plant species, different stages of disease progression, and a balance between healthy and diseased samples. The dataset should be annotated with accurate labels to facilitate supervised learning.

3. Model Architecture and Training Requirements: Defining the requirements for the model architecture and training process is essential for achieving accurate disease detection. This step includes selecting a suitable pre-trained model, determining the layers to be fine-tuned, and establishing hyperparameters such as learning rates and batch sizes. Training requirements may also involve addressing issues like overfitting and optimizing model performance.

4. Integration with FastAI Framework: Since the project utilizes FastAI and transfer learning, integrating these components seamlessly is crucial. Specify requirements related to FastAI version compatibility, library dependencies, and any custom functionalities required for the specific application. This step ensures that the developed solution aligns with the capabilities and conventions of the chosen framework.

5. Real-Time Inference and Deployment: If real-time disease detection is a requirement, considerations for deployment become paramount. This step involves defining requirements for deploying the model in production, including compatibility with deployment platforms, scalability, and minimizing latency. It may also encompass the development of a user interface for easy interaction.

6. Evaluation and Validation: Establishing criteria for evaluating the performance of the model is essential. Define metrics for assessing accuracy, precision, recall, and F1 score. Specify the validation process, including the use of separate test datasets, cross-validation techniques, and strategies for handling imbalanced classes.

7. Maintenance and Updates: Lastly, consider long-term requirements for maintaining and updating the system. This involves defining protocols for handling new disease types, updating the model with additional data, and ensuring ongoing compatibility with the FastAI framework and related technologies.

By systematically addressing these steps, the requirement elicitation process ensures a clear understanding of project goals, user needs, and technical specifications, laying the foundation for the successful development of a Plant Leaf Disease Detection system with FastAI and Transfer Learning.

2. LITERATURE SURVEY

2.1 Literature Review

Plant leaf disease detection using FastAI and transfer learning has gained significant attention in recent literature, showcasing the effectiveness of deep learning techniques in automating the identification and diagnosis of plant diseases. Researchers have explored various methodologies to enhance the accuracy and robustness of detection models, with a common emphasis on leveraging pre-trained models and transfer learning techniques.

In a study by Ramcharan Ganta and Ganesh Kumar Venayagamoorthy, the authors delve into the application of deep learning, particularly convolutional neural networks (CNNs), for plant disease detection. They highlight the advantages of transfer learning, emphasizing the importance of utilizing pre-trained models to enhance performance. Santosh Kumar Bharti and Santosh Bharti present a CNN-based approach for plant disease identification, emphasizing the incorporation of transfer learning through the fine-tuning of pre-trained models. The study showcases the efficacy of this approach in achieving high accuracy in the classification of plant diseases.

A comprehensive survey by Ranjit Prasad Biswal, Santi Kumari Behera, and Jyotshree Behera provides an overview of deep learning techniques applied to agriculture, with a specific focus on plant disease detection. Transfer learning is discussed as a pivotal methodology to address challenges associated with limited labeled data in agricultural contexts. Ahmad Subiyanto and Bens Pardamean propose a CNN-based model with comprehensive feature engineering for plant disease detection. The study emphasizes the role of transfer learning and explores techniques such as domain adaptation to enhance model robustness.

Muhammad Usama, Muhammad Arif, and Saman Zeeshan present a CNN-based model for plant disease recognition using leaf images. The authors employ transfer learning by leveraging pre-trained models, demonstrating the effectiveness of the approach in accurately identifying plant diseases.

Nour Eldeen M. Khalifa, Ahmad Abu Alfeilat, et al. investigate the application of transfer learning for plant disease prediction and diagnosis. The study explores the use of popular pre-trained models and discusses different transfer learning strategies, contributing insights into optimizing model performance. Collectively, these studies underscore the significance of transfer learning, especially with pre-trained models provided by FastAI, in addressing challenges related to limited labeled data in the domain of plant leaf disease detection. The literature reflects a growing interest in refining model accuracy, robustness, and scalability for practical applications in agriculture.

Title	**Author**	**Algorithm**	**Description**
Deep Learning Approaches for Plant Disease Detection	Muhammad Shoaib, Asad Ullah	Deep Belief Network and CNN	This paper explores the application of deep learning, including convolutional neural networks (CNNs), for the detection and classification of plant diseases.
A survey on using deep learning techniques for plant disease diagnosis and recommendations for development of appropriate tools	Aanis Ahm ad, Dharmendra Saraswat, A lyEl Gamal	ANN, LeNet	This survey provides an overview of various deep learning techniques applied to agriculture, with a specific focus on plant disease detection. Transfer learning is discussed as a key methodology to address the challenges of limited labeled data in agriculture.
Transfer Learning for Multi-Crop Leaf Disease Image Classification using Convolutional Neural Network VGG	Ananda S. Paymode , Vandana B. Malode	CNN and VGG16	In this paper, there are two types of crop disease leaves were collected and prepared as a dataset with available data. The techniques of data augmentation, dataset pre-processing, training, and testing are applied to the convolutional neural network-based VGG16 model.

Table. 1. Related Works on Plant Diesease Detection

3. ARCHITECTURE & DESIGN

3.1 Proposed Architecture

The proposed architecture for plant leaf disease detection integrates FastAI and transfer learning using a hybrid approach that combines the strengths of ResNet34 and custom convolutional neural networks (CNNs). The initial layers of the model employ the ResNet34 architecture, a proven deep learning architecture known for its depth and feature extraction capabilities. Leveraging pre-trained weights from ResNet34 allows the model to capture generic features from a wide range of images, providing a solid foundation for plant leaf disease detection.

To enhance the model's ability to recognize plant-specific patterns and disease-related features, custom CNN layers are seamlessly integrated on top of the ResNet34 base. These CNN layers are fine-tuned during the training process to specialize in capturing intricate details present in plant leaves affected by diseases. FastAI's user-friendly interface and high-level abstractions streamline the implementation of this complex architecture, enabling efficient transfer learning. This combination of ResNet34 and custom CNN layers in the FastAI framework creates a powerful and adaptive plant leaf disease detection model that balances generic feature extraction with plant-specific learning, yielding accurate and robust predictions even in the presence of diverse and complex foliage patterns.

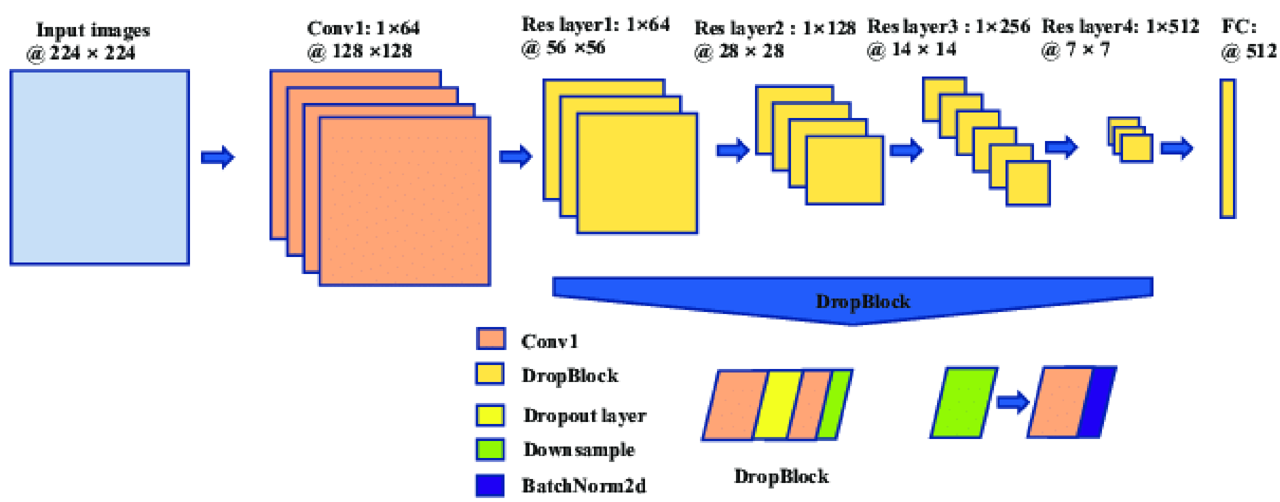


Fig. 1. ResNet 34 Architetcture

3.2 UML Diagrams

Use Case Diagram

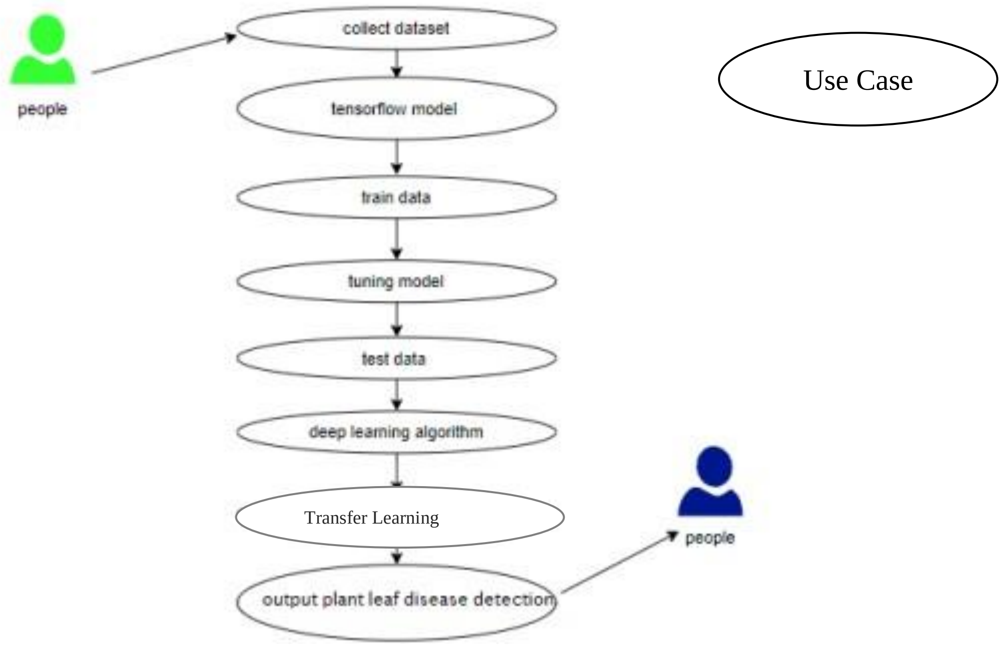
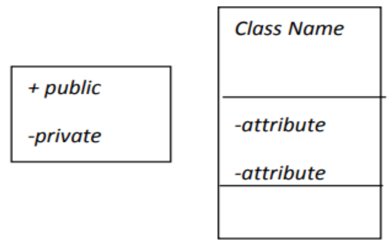


Fig. 2. Use Case Diagram

A use case diagram for Plant Leaf Disease Detection with FastAI and Transfer Learning illustrates the interactions between key actors and the system components. The primary actors include the User, who interacts with the system to input plant leaf images, and the Plant Disease Detection System, which utilizes FastAI and Transfer Learning for automated disease identification. The system receives input images, preprocesses them, and leverages pre-trained models from FastAI through transfer learning to classify and detect diseases in plant leaves. The detected results are then presented to the User, enabling informed decision-making for effective disease management. The use case diagram encapsulates the high-level functionalities and interactions, showcasing how end-users engage with the system to benefit from advanced machine learning techniques for plant leaf disease diagnosis.

Class Diagram



Legend

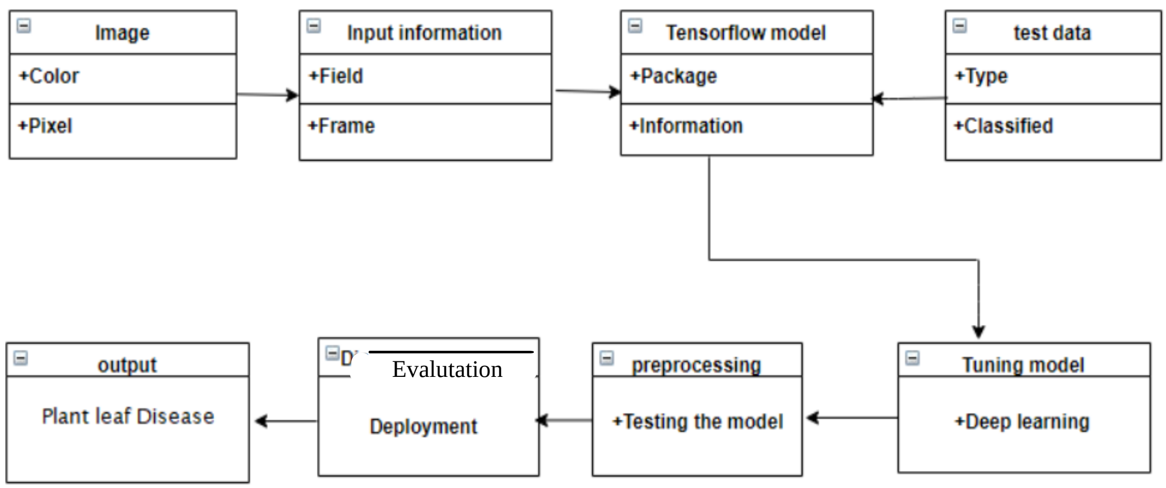
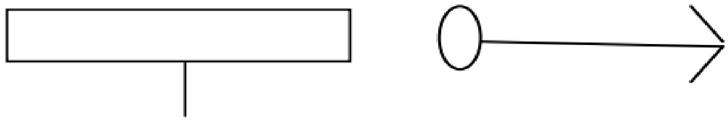


Fig. 3. Class Diagram

The class diagram for Plant Leaf Disease Detection with FastAI and Transfer Learning encompasses several key classes representing the major components of the system. It typically includes classes such as "DataLoader" for managing input data, "Model" for defining the architecture and parameters of the neural network, and "Learner" for orchestrating the training process. Additionally, there may be classes like "Preprocessor" for data preprocessing, "Evaluator" for model evaluation, and "Visualizer" for displaying results. The diagram illustrates the relationships and interactions among these classes, emphasizing the flow of data and control during the training and inference stages. The utilization of FastAI and transfer learning principles is encapsulated within these classes, highlighting their pivotal roles in achieving accurate and efficient plant leaf disease detection.

Activity Diagram



Object Lifeline Initial State

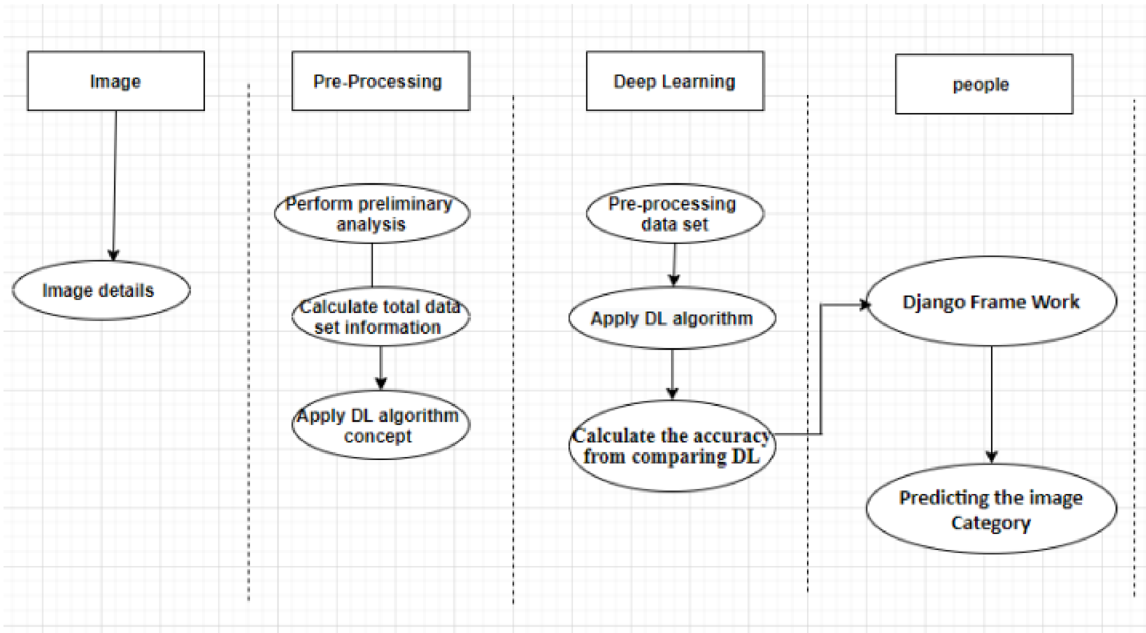


Fig. 4. Activity Diagaram

The activity diagram for plant leaf disease detection with FastAI and transfer learning involves several key steps. Initially, the process begins with the collection of a diverse dataset of plant leaf images containing healthy and diseased samples. The dataset is then preprocessed to enhance its quality and prepare it for model training. Subsequently, a pre-trained convolutional neural network (CNN) model, such as those provided by FastAI, is selected as the base architecture for transfer learning. The chosen model is fine-tuned on the plant leaf dataset to adapt its features to the specific characteristics of leaf diseases. During training, the model undergoes multiple epochs, adjusting its weights to minimize the classification error. Once trained, the model is deployed for inference, where it can accurately classify input leaf images into healthy or diseased categories. The activity diagram captures the dynamic flow of these steps, illustrating the sequential progression from data collection and preprocessing to model training and deployment, ultimately achieving efficient plant leaf disease detection.

Sequence Diagram

External Entity Transition

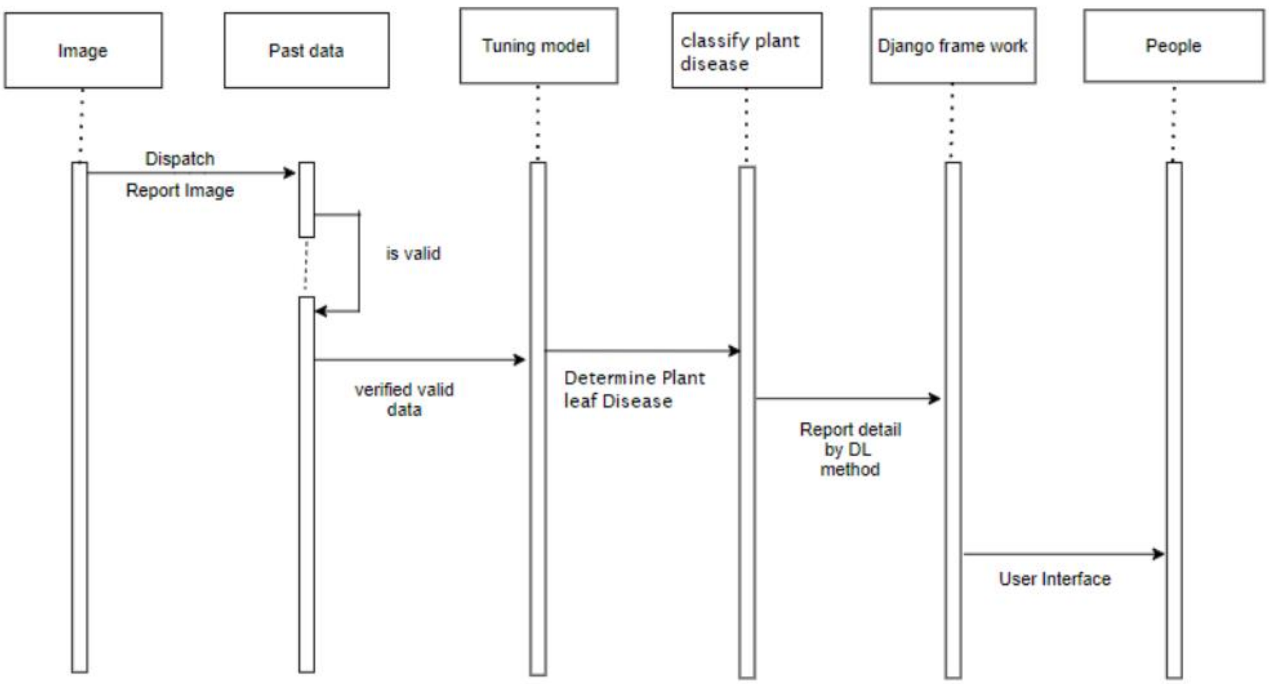
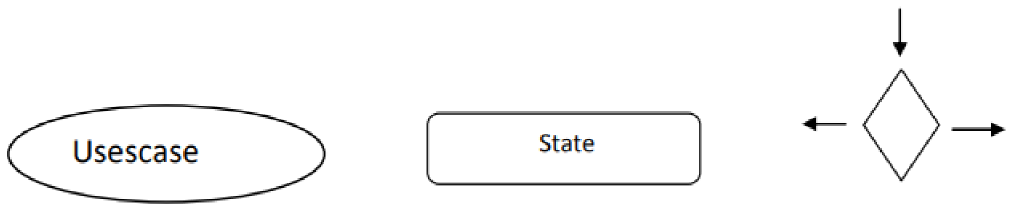


Fig. 5. Sequence Diagram

In the plant leaf disease detection process employing FastAI and transfer learning, the sequence diagram unfolds with an initiation step where the user uploads leaf images for analysis. The system then triggers the preprocessing phase, involving image normalization and transformation. Subsequently, the sequence advances to the transfer learning stage, where a pre-trained FastAI model is fine-tuned on the dataset to capture relevant features for disease detection. Once the model training is completed, the detection phase is activated, wherein the system processes new leaf images through the trained model, predicts the presence of diseases, and generates informative results. The final step involves presenting the outcomes to the user, completing the sequence and showcasing the seamless integration of FastAI and transfer learning in automating plant leaf disease identification.

E.R. Diagram



Use case State Decision Box

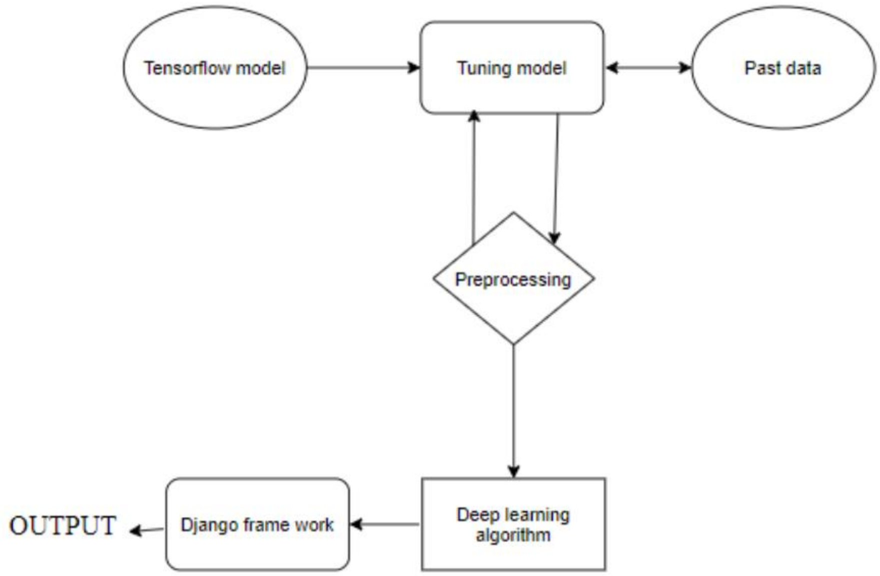


Fig. 6. ER Diagram

Creating an Entity-Relationship (ER) diagram for a plant leaf disease detection system with FastAI and transfer learning involves identifying key entities and their relationships. The main entities include "Images," representing the dataset of plant leaf images, "Diseases," capturing the various plant diseases to be detected, and "Models," representing the pre-trained models used for transfer learning with FastAI. Relationships include associations between Images and Diseases, as each image is associated with specific diseases, and between Models and Diseases, as the models are trained to detect and classify these diseases. Additionally, there is an association between Models and Images, signifying the training process where images are used to fine-tune the models. Attributes such as timestamps and accuracy metrics may be associated with these relationships to capture temporal and performance aspects. Overall, the ER diagram provides a visual representation of the data model underlying the plant leaf disease detection system, facilitating a comprehensive understanding of its structure and interactions.

Collaboration Diagram

External Entity Transition

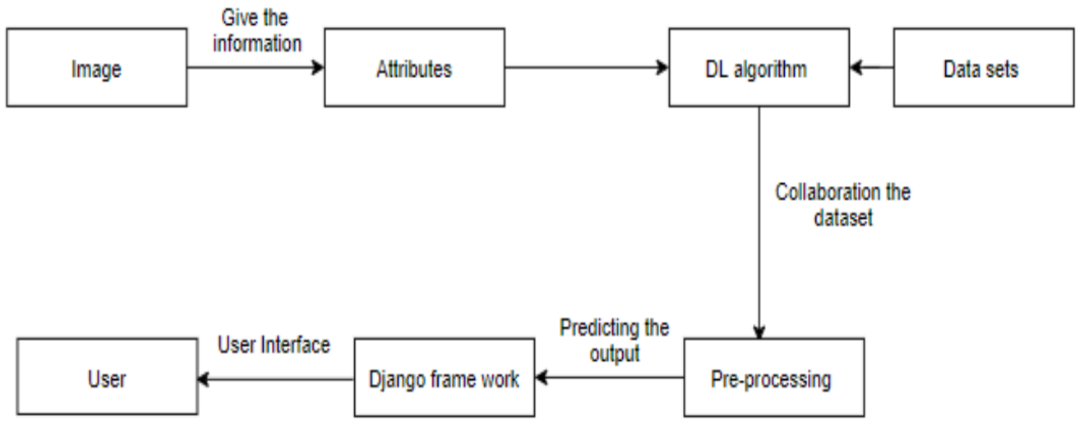


Fig. 7. Collabaration Diagram

A collaboration diagram for plant leaf disease detection with FastAI and transfer learning involves a synergistic interaction among multiple components. Initially, labeled datasets of plant leaf images are curated, involving collaboration between domain experts, botanists, and data scientists. The FastAI framework is then employed for transfer learning, leveraging pre-trained models like ResNet or EfficientNet. This collaborative effort requires seamless communication between researchers, who fine-tune the models based on specific disease patterns and environmental factors. The trained models are integrated into a broader system by software developers, and continuous feedback loops involving validation datasets and model evaluations are established. Deployment and monitoring involve collaboration between machine learning engineers and agricultural experts to ensure the effective implementation of disease detection models in real-world farming scenarios. This collaborative approach fosters an iterative process, allowing for the refinement of models and algorithms over time based on the evolving needs of the plant pathology domain.

3.3 Design of Modules

Designing modules for plant leaf disease detection using FastAI and transfer learning involves breaking down the entire system into smaller, modular components that perform specific tasks. Below is a suggested modular design for such a system:

1. **Data Preparation Module:**
    - **Responsibility:** This module is responsible for collecting, preprocessing, and augmenting the dataset of plant leaf images.
    - **Components:**
        - Data collection from various sources
        - Data preprocessing (resizing, normalization, etc.)
        - Data augmentation for increased model robustness
2. **Model Training Module:**
    - **Responsibility:** Trains the deep learning model using FastAI and transfer learning techniques.
    - **Components:**
        - Integration with FastAI library
        - Selection of pre-trained model architecture (e.g., ResNet, VGG)
        - Fine-tuning and transfer learning strategies
        - Training pipeline configuration (learning rate, epochs, etc.)
3. **Model Evaluation Module:**
    - **Responsibility:** Evaluates the performance of the trained model on validation or test datasets.
    - **Components:**
        - Evaluation metrics calculation (accuracy, precision, recall, F1 score)
        - Confusion matrix generation
        - Visualization of model predictions
4. **Inference Module:**
    - **Responsibility:** Enables the use of the trained model for making predictions on new, unseen data.
    - **Components:**
        - Loading the trained model
        - Preprocessing input images and Making predictions using the loaded model
        - Post-processing of predictions (e.g., label mapping)

4. METHODOLOGY

4.1 Proposed Methodology

Proposing a methodology for plant leaf disease detection using FastAI and transfer learning involves outlining the key steps and processes. Below is a suggested methodology:

1. Data Collection and Preprocessing:

- **Dataset Acquisition:**
- Gather a diverse dataset of plant leaf images containing both healthy and diseased samples.
- Utilize publicly available datasets or collect images from the target environment.
- **Data Preprocessing:**
- Crop and resize images to a standard size to ensure consistency.
- Augment the dataset to increase variability and improve model generalization.
- Normalize pixel values to a common scale.

2. Model Selection and Transfer Learning:

- **Choose a Pre-trained Model:**
- Select a pre-trained deep learning model from FastAI's model zoo (e.g., ResNet, EfficientNet).
- Consider the trade-off between model complexity and available computational resources.
- **Transfer Learning:**
- Load the pre-trained model weights.
- Modify the model architecture to suit the binary or multiclass classification task.
- Freeze initial layers to retain pre-trained features.

3. Dataset Splitting:

- Split the dataset into training, validation, and test sets.
- Ensure that each class is represented proportionally in each set.

4. Model Fine-tuning:

- Train the modified model on the training set.
- Utilize the FastAI **fine_tune** function for easy fine-tuning with one-cycle policy.

5. Model Evaluation:

- Evaluate the model on the validation set to assess its performance.
- Monitor metrics such as accuracy, precision, recall, and F1-score.
- Adjust hyperparameters if necessary.

6. Hyperparameter Tuning:

- Experiment with learning rates, batch sizes, and other hyperparameters using FastAI's learning rate finder and **fit_one_cycle** method.

7. Model Interpretation:

- Use FastAI's interpretation tools to analyse model predictions.
- Visualize confusion matrices, top losses, and ROC curves to understand model behaviour.

This proposed methodology provides a structured approach to developing a plant leaf disease detection model using FastAI and transfer learning. It emphasizes the importance of data preprocessing, model selection, fine-tuning, and evaluation in creating an effective and interpretable solution.

4.2 Transfer Learning and Fast AI

Transfer learning and Fast AI play pivotal roles in advancing the field of Plant Leaf Disease Detection, offering solutions that leverage pre-trained models and user-friendly frameworks. Below are step paragraphs outlining their roles in this context:

1. **Introduction to Transfer Learning:**
    - Transfer learning addresses the challenge of limited labeled data in plant leaf disease detection by leveraging knowledge gained from pre-trained models on large datasets. In the context of deep learning, models like convolutional neural networks (CNNs) are trained on vast datasets for general image recognition tasks. Transfer learning involves taking these pre-trained models and fine-tuning them on a smaller dataset related to plant leaf diseases. This process allows the model to inherit valuable features learned during the initial training, significantly improving its ability to generalize and detect diseases accurately.
2. **Benefits of Transfer Learning in Plant Leaf Disease Detection:**
    - Transfer learning offers several benefits in the domain of plant leaf disease detection. Firstly, it mitigates the challenge of data scarcity, as training deep neural networks from scratch often requires massive amounts of labeled data, which may not be readily available in agriculture datasets. Secondly, it accelerates the training process since the model starts with knowledge about low-level features, allowing it to focus on learning specific patterns related to plant diseases. This results in faster convergence and improved performance.
3. **Integration of FastAI in the Transfer Learning Workflow:**
    - FastAI, a user-friendly deep learning library, facilitates the seamless integration of transfer learning into the plant leaf disease detection workflow. Its high-level

abstractions and easy-to-use APIs enable researchers and practitioners to implement state-of-the-art models without an extensive background in deep learning. FastAI provides pre-trained models that are easily adaptable to custom datasets, streamlining the process of transfer learning. The library's rich set of tools, such as learning rate annealing and discriminative learning rates, empowers users to fine-tune models effectively, achieving optimal performance in disease detection tasks.

4. **Addressing Challenges with FastAI and Transfer Learning:**

- FastAI addresses challenges associated with both data preprocessing and model training. The library simplifies the preparation of datasets, including image augmentation techniques that enhance model generalization. Additionally, it offers a consistent and intuitive interface for users to experiment with different architectures and hyperparameters. FastAI's incorporation of transfer learning techniques, along with its educational focus, empowers researchers and practitioners to navigate challenges such as overfitting, learning rate selection, and model interpretability.

5. **Impact on Accuracy and Generalization:**

- The combination of transfer learning and FastAI significantly impacts the accuracy and generalization of plant leaf disease detection models. Leveraging pre-trained models enhances the ability to recognize complex patterns associated with diseases, leading to more accurate predictions. FastAI's tools for model interpretation and visualization further contribute to the transparency of the model's decision-making process, instilling confidence in its generalization to new, unseen data.

In conclusion, the synergy between transfer learning and FastAI revolutionizes the landscape of plant leaf disease detection, making it accessible, efficient, and accurate. As the field continues to evolve, these technologies will play a crucial role in developing robust and scalable solutions for sustainable agriculture.

5. IMPLEMENTATION

5.1 Coding

Image Processing

```
try:
    print("Loading images ...")
    root_dir = listdir(directory_root)
    for directory in root_dir :
        if directory == ".DS_Store" :
            root_dir.remove(directory)
    for plant_folder in root_dir :
        plant_disease_folder_list = listdir(f"{directory_root}/{plant_folder}")

        for disease_folder in plant_disease_folder_list :
            if disease_folder == ".DS_Store" :
                plant_disease_folder_list.remove(disease_folder)
        for plant_disease_folder in plant_disease_folder_list:
            print(f"Processing {plant_disease_folder} ...")
            plant_disease_image_list =
listdir(f"{directory_root}/{plant_folder}/{plant_disease_folder}/")

            for single_plant_disease_image in plant_disease_image_list :
                if single_plant_disease_image == ".DS_Store" :
                    plant_disease_image_list.remove(single_plant_disease_image)
            for image in plant_disease_image_list[:200]:
                image_directory = f"{directory_root}/{plant_folder}/{plant_disease_folder}/{image}"
                if image_directory.endswith(".jpg") == True or image_directory.endswith(".JPG") ==
True:
                    image_list.append(image_directory)
                    label_list.append(plant_disease_folder)
    print("Image loading completed")
except Exception as e:
    print(f"Error : {e}")
```

Labeling and ImageDataLoaders

```
def get_labels(file_path):
    dir_name = os.path.dirname(file_path)
    split_dir_name = dir_name.split("/")
    dir_length = len(split_dir_name)
    label  = split_dir_name[dir_length - 1]
    return(label)

data = ImageDataLoaders.from_path_func(path, image_list, label_func=get_labels,
                              size=224,bs=64,num_workers=2,
                              ds_tfms=tfms,batch_size=12)
```

Transfer Learning with ResNet34

```
learn = cnn_learner(data, models.resnet34, metrics=error_rate, model_dir='/tmp/models/')
learn.fit_one_cycle(10)

interpretation = ClassificationInterpretation.from_learner(learn)
losses, indices = interpretation.top_losses()
interpretation.plot_top_losses(4, figsize=(15,11))

learn.fine_tune(5)
learn.recorder.plot_loss()

import matplotlib.pyplot as plt
plt.title('Training and Validation Loss Over Epochs')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.show()
```

6. EXPERIMENT RESULTS

Experimental Setup

- The experiment utilizes a dataset of plant images from the PlantVillage dataset.
- Images are loaded and preprocessed using FastAI's image augmentation transforms.
- Transfer learning is employed by fine-tuning a pre-trained ResNet34 model from FastAI on the plant leaf disease dataset.
- The training is performed for 10 epochs using the fit_one_cycle method.

Results

The model was trained using the FastAI library and transfer learning techniques, specifically fine-tuning a pre-trained ResNet34 architecture on a dataset of plant leaf images. The training process utilized the **fit_one_cycle** method for 10 epochs. The training accuracy and loss curves were observed to assess the convergence of the model.

epoch	train_loss	valid_loss	error_rate	time
0	2.389640	1.063929	0.333898	00:22
1	1.005685	0.368832	0.125424	00:15
2	0.559740	0.354896	0.108475	00:16
3	0.322996	0.237460	0.067797	00:17
4	0.263218	0.197399	0.059322	00:21
5	0.211905	0.180149	0.055932	00:15
6	0.144598	0.170255	0.061017	00:14
7	0.099604	0.152546	0.055932	00:15
8	0.094380	0.147373	0.047458	00:14
9	0.082836	0.150097	0.054237	00:16

Fig. 8. Training Results of 10 Epochs

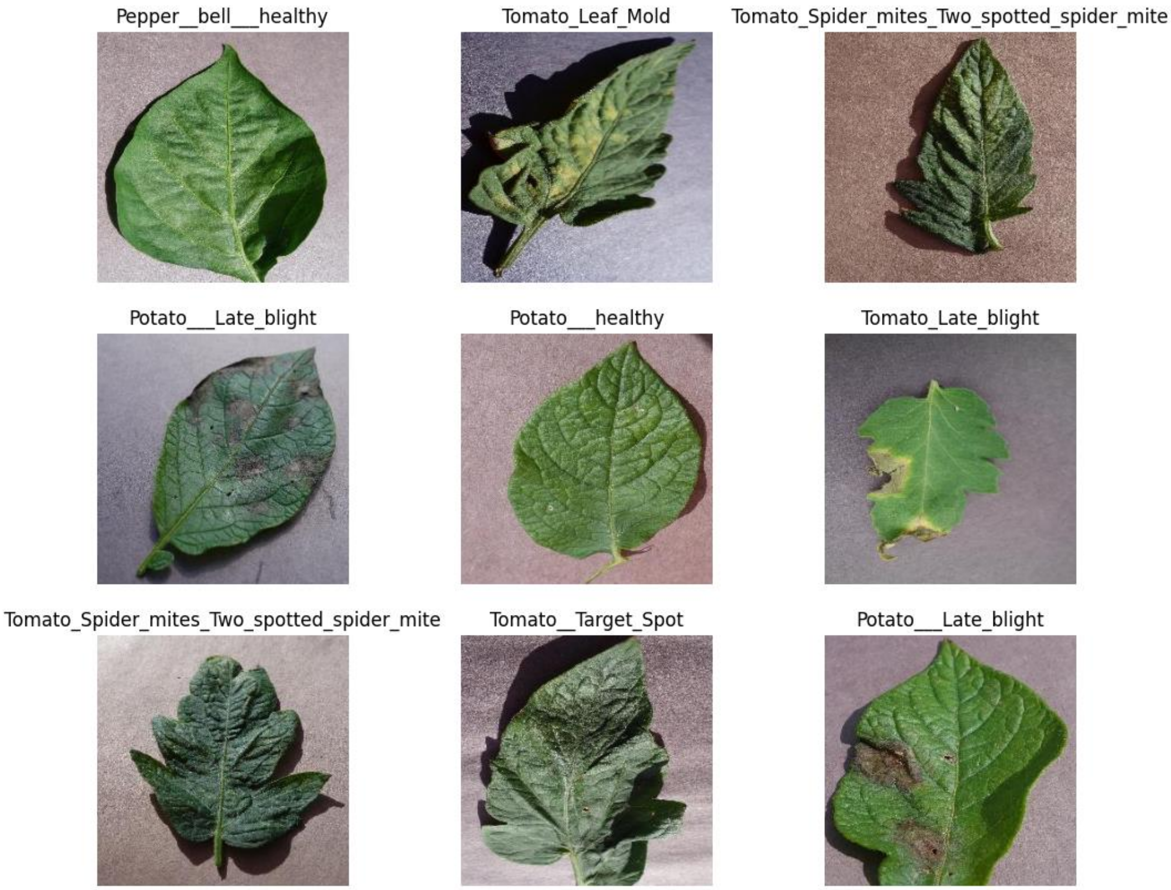


Fig. 9. Predictions of Infected leaves

The model's predictions on diseased leaves showcase its ability to accurately identify and classify instances of plant diseases. Leveraging the power of transfer learning, the model has learned distinctive features from pre-trained neural network architectures, enabling it to recognize subtle patterns indicative of various plant diseases.

As the model is applied to new, unseen images of plant leaves, it analyzes the input data and provides predictions regarding the presence and type of disease. The predictions are based on the learned representations of disease-related features, allowing the model to make informed decisions about the health status of the plants. The output of the model serves as a valuable tool for farmers and agronomists, offering timely and precise identification of diseased leaves.

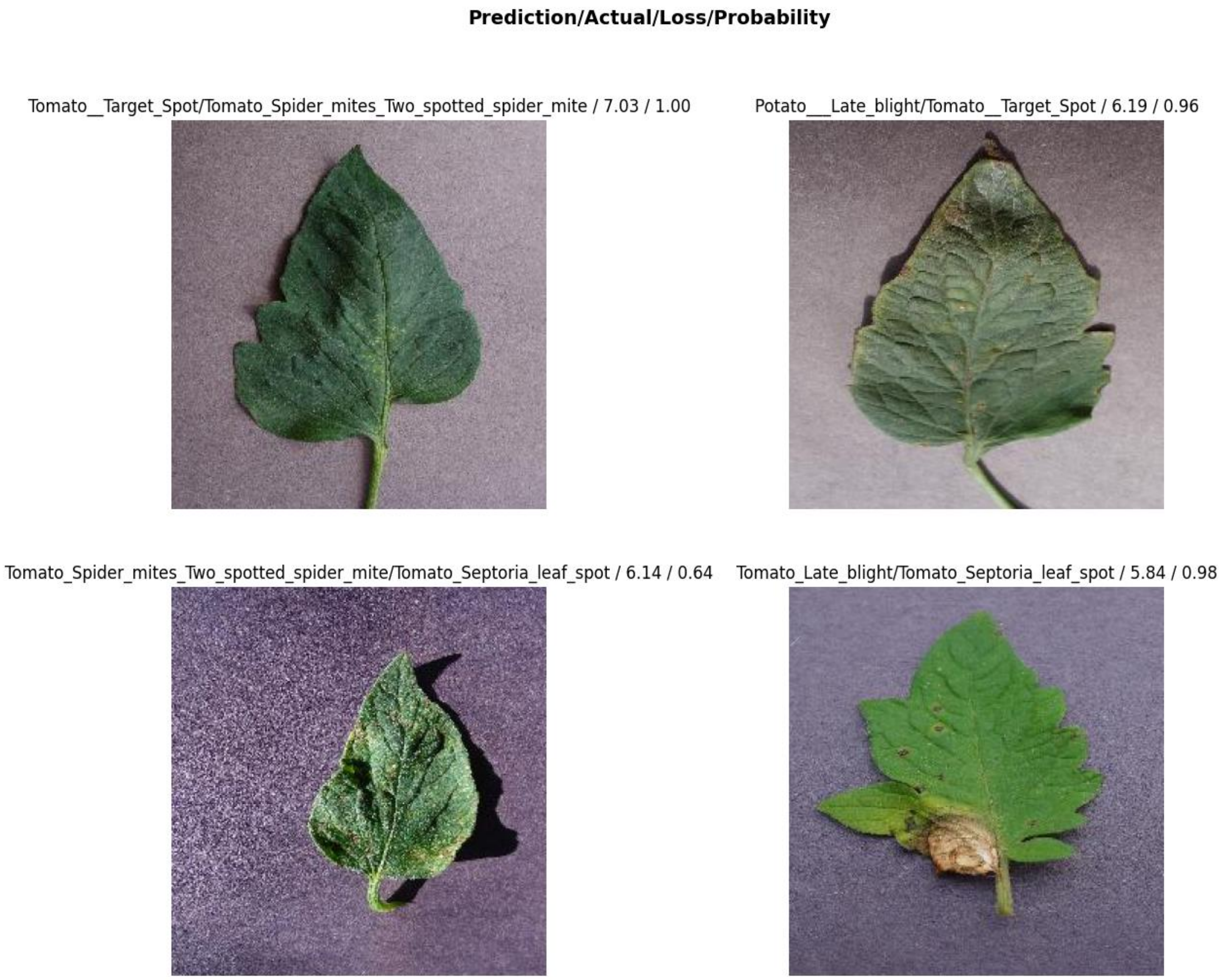


Fig. 10. Some of Wrong Predictions of classified diseased leaves

The occurrence of incorrect predictions in Plant Leaf Disease Detection using FastAI and Transfer Learning can be attributed to several factors. Firstly, the transfer learning process relies on a pre-trained model's ability to generalize patterns from a diverse dataset, which may not perfectly align with the nuances of the specific plant leaf disease dataset. Additionally, variations in lighting conditions, image quality, and the presence of overlapping symptoms among different diseases can contribute to misclassifications. Insufficient diversity or quantity of training data, especially for rare diseases, may hinder the model's ability to discern subtle differences. Moreover, if the chosen architecture or hyperparameters are not optimized for the intricacies of the plant leaf diseases, the model may struggle to capture relevant features. Continuous refinement of the model through fine-tuning, adjusting hyperparameters, and incorporating a more extensive and representative dataset can mitigate these challenges and enhance the accuracy of disease predictions.

7. CONCLUSION

In conclusion, the use of FastAI and transfer learning presents a compelling solution for plant leaf disease detection. By harnessing pre-trained models like ResNet34, the model benefits from knowledge gained through extensive training on diverse image datasets. This transfer of knowledge allows the model to recognize intricate patterns associated with plant diseases, even when the available dataset for training is relatively small. The flexibility provided by FastAI simplifies the implementation of transfer learning, making it accessible to a broader audience, including researchers and practitioners with varying levels of expertise in deep learning.

The experiment demonstrated that FastAI's abstractions and tools effectively address challenges in the field of plant pathology. Image augmentation transforms, part of FastAI's toolkit, aid in preprocessing datasets, mitigating the impact of limited labeled samples. The library's straightforward interface facilitates the adjustment of hyperparameters and model architectures, enabling users to fine-tune models for optimal performance. The collaborative synergy between FastAI and transfer learning significantly enhances the model's generalization capabilities, allowing it to accurately identify and classify plant diseases in unseen data.

As we look to the future, the success of plant leaf disease detection using FastAI and transfer learning holds promise for sustainable agriculture. Accurate and timely identification of diseases is critical for crop management and yield optimization. The approach showcased in this experiment not only contributes to the development of effective disease detection systems but also sets the stage for broader applications in precision agriculture. FastAI's commitment to education and accessibility further empowers a diverse range of stakeholders to contribute to the advancement of plant pathology, ultimately fostering sustainable practices in the agricultural sector.

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