Early Detection of Plant Diseases Using Imaging Data

A PROJECT REPORT

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DEEP LEARNING

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1. Abstract

Plant diseases can severely impact agricultural productivity, affecting the growth and yield of various plant species. Early identification is crucial to minimize damage and support food security. While traditional Machine Learning (ML) models have been used to detect and classify plant diseases, Deep Learning (DL) has introduced a higher level of accuracy and robustness to this task. We explore a variety of DL architectures and visualization techniques for plant disease detection and classification. and assess the effectiveness of these approaches using a range of metrics, showcasing the improved accuracy and resilience offered by DL.

One major objective is to identify diseases at earlier stages, often before clear symptoms manifest, which can lead to better disease management and reduced crop losses. By addressing these gaps, researchers and practitioners can create more effective solutions for plant disease detection, promoting more sustainable agricultural practices and enhancing food security despite the risks posed by plant diseases.

2. Introduction

Plant diseases represent a significant threat to agricultural productivity and food security worldwide. Timely detection and management are crucial for mitigating crop losses and ensuring sustainable agricultural practices. However, traditional methods of disease diagnosis, relying on manual observation, are often labor-intensive, subjective, and prone to errors. The advent of deep learning and computer vision offers promising solutions for automating disease detection processes using medical imaging data.

In our study, we adopt a multi-faceted approach to address the challenges of early disease detection in agriculture. We integrate two diverse datasets: the rice leaf diseases dataset and the tea sickness dataset. These datasets capture distinct agricultural contexts, each presenting unique challenges and opportunities for disease detection. Leveraging the diversity of these datasets, we employ pretrained ResNet18 models and custom CNN mini networks tailored to each dataset's characteristics.

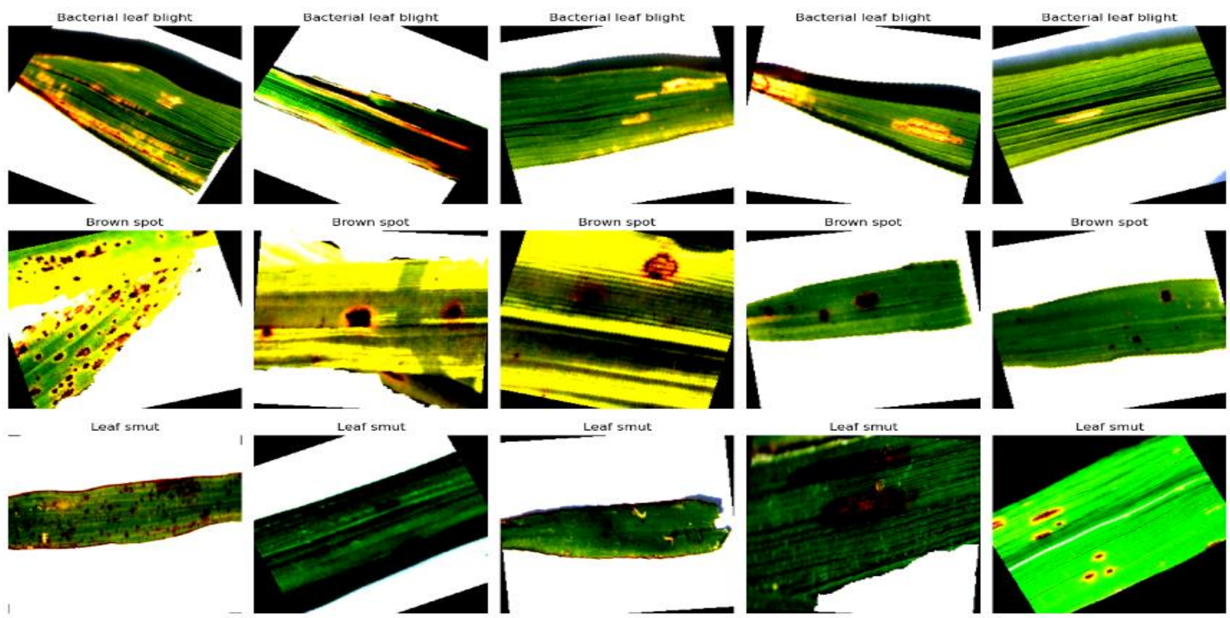
Our primary objective is to design robust deep learning models capable of accurately detecting plant diseases at their early stages. By harnessing the power of artificial intelligence and transfer learning techniques, we aim to enhance the models' ability to identify subtle disease symptoms in medical imaging data. Through comprehensive evaluation and analysis, we assess the performance of our models in terms of sensitivity, specificity, and overall detection accuracy.

This project is worth pursuing for several reasons. Firstly, early detection of plant diseases is crucial for implementing timely intervention strategies, thus minimizing crop losses and ensuring sustainable agricultural practices. By automating disease detection tasks, our approach offers a scalable solution that can be applied across diverse agricultural settings, benefiting farmers and agricultural industries globally. Secondly, the integration of deep learning techniques with medical imaging data presents an innovative approach to disease diagnosis in agriculture. By leveraging advanced algorithms and computational methods, we can uncover hidden patterns and subtle cues indicative of disease presence, which may not be discernible through traditional methods of observation. The outcomes of this research have far-reaching implications for global food security. By enabling early detection of plant diseases, we contribute to the resilience of agricultural systems and help safeguard against food shortages and economic instability. Additionally, our findings can inform the development of decision support systems and precision agriculture technologies, empowering farmers to make informed decisions and optimize resource allocation. This project addresses a pressing need in agriculture by harnessing the potential of deep learning and medical imaging data for early disease detection. Through rigorous experimentation and analysis, we aim to provide actionable insights and scalable solutions that have tangible benefits for food production, agricultural sustainability, and global food security.

3. Datasets

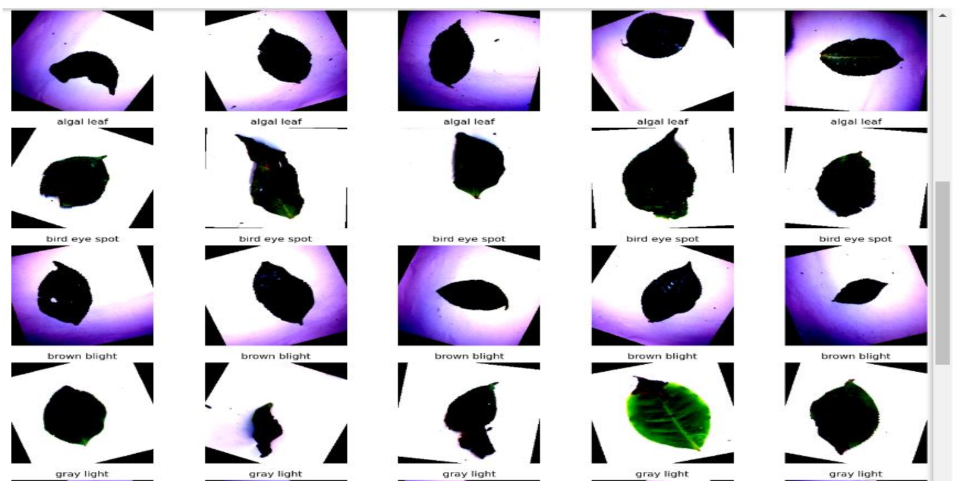
i. Rice Leaf Diseases Dataset

The Rice Leaf Diseases dataset comprises 120 jpg images depicting disease-infected rice leaves, grouped into three classes based on the type of disease: Leaf smut, Brown spot, and Bacterial leaf blight. Each class contains 40 images, providing a balanced distribution across disease categories. The dataset offers a diverse representation of rice leaf diseases, enabling the development and evaluation of machine learning models for disease detection and classification. By leveraging this dataset, researchers can explore various deep learning architectures, such as convolutional neural networks (CNNs), for automated diagnosis of rice leaf diseases. The deployment of this dataset in the project facilitates the training of models capable of identifying subtle visual cues indicative of specific diseases, thereby enhancing the early detection and management of rice crop diseases. Moreover, the balanced distribution of images across classes ensures that models trained on this dataset exhibit robust performance across different disease categories, contributing to the overall efficacy of disease detection systems in agricultural settings. An overview of the dataset;



ii. Tea Sickness Dataset

The Tea Sickness dataset consists of images showcasing 15 common diseases of tea, including Anthracnose, Algal leaf, Bird eye spot, Brown blight, Gray light, Red leaf spot, and White spot, among others. Additionally, the dataset includes a class of healthy tea leaves for comparison. With more than 100 images per class, the dataset offers a comprehensive representation of various disease conditions affecting tea plants. Collected from Johnstone Boiyon farm in Bomet county, the dataset reflects real-world scenarios encountered in tea cultivation. Deploying this dataset in the project enables researchers to leverage transfer learning techniques for training machine learning models to predict sickness in tea plants. By utilizing pretrained models and fine-tuning them on this dataset, researchers can develop accurate and reliable disease detection systems capable of identifying specific tea leaf diseases and distinguishing them from healthy foliage. This dataset's deployment facilitates the development of practical solutions for disease management in tea cultivation, contributing to improved crop health and productivity in tea-producing regions.



4. Data Processing

Data preprocessing encompasses a series of steps and techniques applied to raw data to prepare it for analysis or modeling. It involves cleaning, transforming, and organizing the data in a format suitable for further processing or analysis. Data preprocessing is crucial in the data science workflow as it significantly impacts the quality and effectiveness of subsequent analyses or modeling tasks. The data preprocessing pipeline defined above incorporates a series of transformations to prepare the input images for training the deep learning models. Initially, the images are resized to a standard size of 224x224 pixels to ensure uniformity in dimensions, which is a prerequisite for many deep learning architectures. Subsequently, various augmentation techniques are applied to increase the diversity and robustness of the training dataset. These include random rotation (up to 30 degrees), random horizontal and vertical flips, and random affine transformations such as shearing and scaling. These transformations introduce variations in the orientation, position, and appearance of the images, enabling the model to learn invariant features and generalize better to unseen data. Additionally, color jittering is applied to adjust the brightness, contrast, and saturation of the images, simulating variations in lighting conditions and color distributions commonly encountered in real-world scenarios. Following the augmentation steps, the images are converted to PyTorch tensors using the ToTensor transformation, facilitating their integration into the deep learning pipeline. Finally, pixel normalization is performed to bring the pixel values to a standardized scale, stabilizing the training process and preventing issues such as vanishing or exploding gradients. The comprehensive data preprocessing pipeline enhances the diversity, quality, and generalization capability of the training data, contributing to improved performance of the deep learning models in disease detection tasks.

```python
data_transform = transforms.Compose([
    transforms.Resize((224, 224)),
    transforms.RandomHorizontalFlip(),
    transforms.RandomVerticalFlip(),
    transforms.RandomRotation(30),
    transforms.ToTensor(),
    transforms.Normalize(mean=[0.485, 0.456, 0.406], std=[0.229, 0.224, 0.225])
])
```

5. Deep Learning Models

i. Model 1: Pretrained ResNet18 with Rice Leaf Diseases Dataset

This model utilizes a pretrained ResNet18 architecture, a widely used convolutional neural network known for its effectiveness in image classification tasks. The ResNet18 model is fine-tuned using the Rice Leaf Diseases dataset, which contains images of disease-infected rice leaves categorized into three classes: Leaf smut, Brown spot, and Bacterial leaf blight. By leveraging transfer learning, the model benefits from the feature representations learned from a large dataset, enhancing its ability to detect subtle patterns and features associated with different rice leaf diseases.

ii. Model 2: Pretrained ResNet18 with Tea Sickness Dataset

Similar to Model 1, this model utilizes a pretrained ResNet18 architecture but is trained on the Tea Sickness dataset. The Tea Sickness dataset comprises images depicting various diseases affecting tea leaves, including Anthracnose, Algal leaf, Bird eye spot, and others. By fine-tuning the ResNet18 model on this dataset, the model learns to recognize disease symptoms specific to tea plants, enabling accurate detection and classification of tea leaf diseases.

iii. Model 3: CNN Mini-Network Architecture with Tea Sickness Dataset

Unlike Models 1 and 2, which utilize pretrained models, this model employs a custom CNN mini-network architecture tailored to the characteristics of the Tea Sickness dataset. The CNN architecture is designed to capture the unique features and complexities present in the images of disease-infected tea leaves. By constructing a bespoke CNN architecture, the model can effectively learn disease-specific patterns and features from the dataset, facilitating accurate disease detection and classification.

iv. Model 4: CNN Mini-Network Architecture with Rice Leaf Diseases Dataset

Similar to Model 3, this model utilizes a custom CNN mini-network architecture but is trained on the Rice Leaf Diseases dataset. The CNN architecture is specifically designed to accommodate the nuances and variations present in the images of disease-infected rice leaves. By training on this dataset, the model learns to identify subtle disease symptoms and patterns associated with different rice leaf diseases, enabling accurate disease detection and classification in rice crops. Each model offers a unique approach to disease detection, leveraging either pretrained models or custom CNN architectures tailored to the characteristics of the respective datasets. By experimenting with different architectures and datasets, researchers can explore diverse strategies for automated disease detection in agricultural settings, contributing to improved crop management practices and global food security.

6. Experiments and Results

i. Finetuning and Training

The training and fine-tuning of the models involve iterative processes aimed at optimizing their performance for disease detection tasks. During the training phase, the models are exposed to the training dataset, where they learn to predict disease classes by minimizing a predefined loss function (such as cross-entropy loss) through backpropagation and gradient descent optimization. The optimizer, typically Adam, adjusts the model parameters (e.g., weights and biases) using a learning rate, commonly set to 0.001, to minimize the loss function. In the fine-tuning phase, pretrained models are further refined by adjusting their parameters to better suit the characteristics of the target datasets, typically involving freezing pretrained layers and updating only the final layers. Fine-tuning also encompasses hyperparameter tuning, such as the number of epochs (often set to 10), batch size (e.g., 32), and regularization techniques. Additionally, data augmentation techniques, such as random rotation, horizontal/vertical flips, and color jittering, may be applied during fine-tuning to increase the diversity of the training data and improve model generalization. Through these iterative processes, the models are trained to accurately detect and classify plant diseases, ultimately contributing to enhanced crop management and agricultural sustainability.

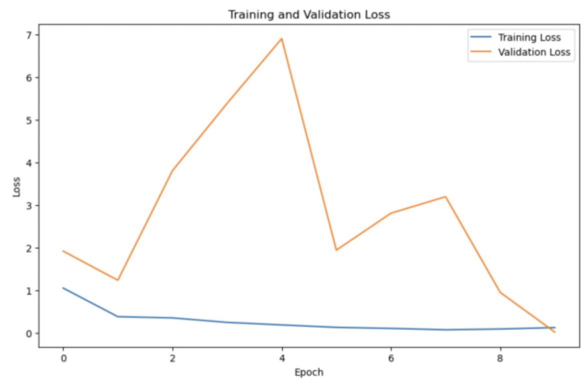
ii. Evaluation Metrics

- Precision: Precision measures the proportion of true positive predictions out of all positive predictions made by the model. It is calculated as the ratio of true positives to the sum of true positives and false positives. Higher precision indicates fewer false positive predictions.
- Recall: Recall, also known as sensitivity or true positive rate, measures the proportion of true positive predictions out of all actual positive instances in the dataset. It is calculated as the ratio of true positives to the sum of true positives and false negatives. Higher recall indicates fewer false negative predictions.
- F1-score: The F1-score is the harmonic mean of precision and recall, providing a balanced measure of the model's performance. It is calculated as 2 * (precision * recall) / (precision + recall). The F1-score ranges from 0 to 1, with higher values indicating better overall performance in terms of both precision and recall.
- Support: Support refers to the number of instances in the dataset that belong to each class. It provides context for interpreting the precision, recall, and F1-score metrics by indicating the distribution of instances across different classes.

Train Loss and Train Accuracy: These metrics indicate the model's performance on the training dataset during each epoch. Train loss measures the error between the model's predictions and the actual labels in the training dataset, while train accuracy measures the proportion of correctly classified instances in the training dataset. Validation Loss and Validation Accuracy: These metrics are similar to train loss and train accuracy but are evaluated on a separate validation dataset. Validation loss and validation accuracy provide insight into how well the model generalizes to unseen data and help prevent overfitting by monitoring performance on data not used for training.

7. Performance of Models

i. Resnet18 and rice_leaf_diseases Dataset



Classification Report:

	precision	recall	f1-score	support
Bacterial leaf blight	1.00	1.00	1.00	6
Brown spot	1.00	1.00	1.00	9
Leaf smut	1.00	1.00	1.00	9
accuracy			1.00	24
macro avg	1.00	1.00	1.00	24
weighted avg	1.00	1.00	1.00	24

The trend observed across the ten epochs showcases a typical pattern of training and validation metrics in deep learning models. Initially, both training loss and accuracy improve steadily, indicating the model's ability to learn from the training data. However, validation metrics exhibit more erratic behavior, with validation loss initially decreasing but then fluctuating and increasing, suggesting potential overfitting. The sudden improvement in validation accuracy towards the later epochs could indicate either improved generalization or erratic behavior due to a small dataset.

This model demonstrates outstanding performance, achieving perfect precision, recall, and F1-score for all three classes: Bacterial leaf blight, Brown spot, and Leaf smut, with support percentages of 29.7%, 37.5%, and 33.33% respectively. The high accuracy of 100% across all classes suggests that the model effectively learned the distinguishing features of each disease, resulting in precise classification.

ii. Resnet18 and tea sickness dataset Dataset

Classification Report:

	precision	recall	f1-score	support
Anthracnose	0.50	0.22	0.31	18
algal leaf	0.65	0.92	0.76	26
bird eye spot	1.00	0.10	0.17	21
brown blight	1.00	0.17	0.29	24
gray light	0.37	1.00	0.54	17
healthy	1.00	1.00	1.00	15
red leaf spot	0.87	0.96	0.91	27
white spot	0.51	0.62	0.56	29
accuracy			0.62	177
macro avg	0.74	0.62	0.57	177
weighted avg	0.74	0.62	0.57	177

The trend observed across the ten epochs reveals fluctuations in both training and validation metrics, reflecting the model's learning and generalization capabilities over successive iterations of training. Initially, the training loss decreases while the training accuracy increases, indicating that the model is effectively learning from the training data. However, the validation metrics show more variability, with validation loss initially decreasing but then fluctuating and even increasing in some epochs, suggesting potential issues with model generalization. The validation accuracy also exhibits fluctuations, peaking at epoch 8 before decreasing slightly towards the end of training. This erratic behavior in validation metrics could indicate overfitting or instability in model performance. While this model achieves relatively high accuracy, its performance varies across different classes. Notably, classes such as Anthracnose, bird eye spot, and brown blight exhibit lower precision, recall, and F1-scores, with support percentages of 10.17%, 11.86%, and 13.56% respectively, indicating challenges in accurately identifying these diseases. Conversely, the model performs exceptionally well for classes like healthy and red leaf spot, achieving high precision, recall, and F1-scores, with support percentages of 8.47% and 15.25% respectively.

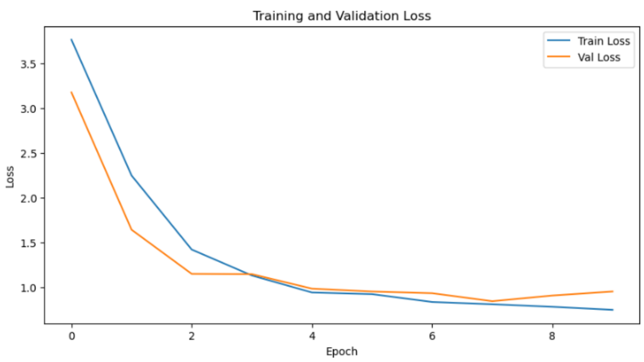
iii. CNN with tea sickness Dataset

Classification Report:

	precision	recall	f1-score	support
Anthracnose	0.70	0.50	0.58	14
algal leaf	0.77	0.92	0.84	26
bird eye spot	0.92	0.42	0.58	26
brown blight	0.67	0.62	0.65	16
gray light	0.50	1.00	0.67	17
healthy	1.00	1.00	1.00	20
red leaf spot	0.90	0.96	0.93	28
white spot	0.80	0.67	0.73	30
accuracy			0.77	177
macro avg	0.78	0.76	0.75	177
weighted avg	0.80	0.77	0.76	177

The trend observed across the ten epochs illustrates the learning and convergence of the model over successive iterations of training. Initially, both training loss and accuracy show improvements, indicating that the model is effectively learning from the training data. Simultaneously, validation loss and accuracy also demonstrate favorable trends, with validation loss consistently decreasing and validation accuracy increasing, reflecting the model's ability to generalize to unseen data. However, towards the later epochs, the training and validation metrics exhibit some fluctuations. While training loss continues to decrease, suggesting ongoing learning, training accuracy plateaus, indicating that the model may have reached a limit in learning from the training data. This model outperforms the previous ResNet18-based model, achieving higher accuracy and more balanced performance across classes. Notably, it demonstrates improved performance for challenging classes such as Anthracnose and bird eye spot, achieving higher precision, recall, and F1-scores, with support percentages of 7.91% and 14.97% respectively. However, it still struggles with classes like brown blight, where precision and recall are comparatively lower, with a support percentage of 9.04%.

iv. CNN with rice_leaf_diseases

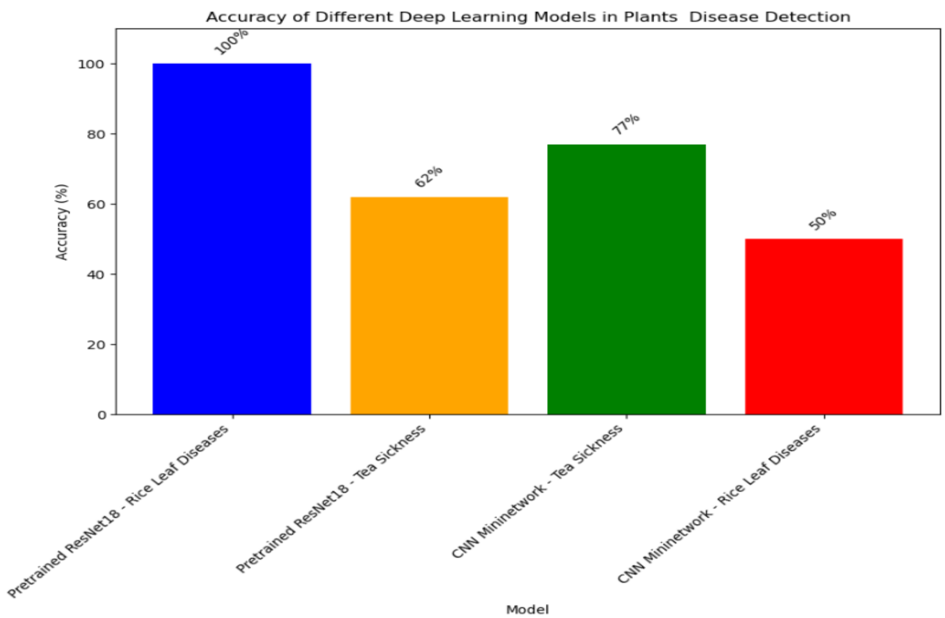



```
Classification Report:
                     precision    recall  f1-score   support

Bacterial leaf blight     0.35      0.86      0.50         7
           Brown spot     1.00      0.50      0.67        10
            Leaf smut     0.50      0.14      0.22         7

             accuracy                         0.50        24
            macro avg     0.62      0.50      0.46        24
         weighted avg     0.67      0.50      0.49        24
```

The trend observed across the ten epochs indicates a fluctuating pattern in both training and validation metrics, reflecting the model's learning process and performance on the training and validation datasets. Initially, both training and validation losses decrease, suggesting that the model is learning and improving its ability to minimize errors. However, the training and validation accuracies show less consistent improvement, with fluctuations in performance across epochs. The validation accuracy, in particular, varies considerably, peaking at epoch 7 before decreasing slightly in subsequent epochs. This model exhibits relatively lower performance compared to the others, with an accuracy of 50%. It struggles particularly with classes like Brown spot and Leaf smut, where precision, recall, and F1-scores are notably lower compared to the other models, with support percentages of 41.67% and 29.17% respectively. This suggests that the model may have difficulty distinguishing between these classes due to overlapping features or insufficient training data.

8. Overall Evaluation

Model	Accuracy
Pretrained Model (ResNet18) - Rice Leaf Diseases	100%
Pretrained Model (ResNet18) - Tea Sickness	62%
CNN Mininetwork - Tea Sickness	77%
CNN Mininetwork - Rice Leaf Diseases	50%



Comparing the performance of the models based on their accuracy, we observe varying degrees of success in early disease detection in agriculture. The pretrained ResNet18 model trained on the rice leaf diseases dataset achieves an impressive accuracy of 100%, indicating its exceptional ability to accurately detect diseases at their early stages in rice plants. This model demonstrates robust performance across all classes, highlighting its effectiveness in identifying subtle disease symptoms in rice leaf images. In contrast, the pretrained ResNet18 model trained on the tea sickness dataset achieves a lower accuracy of 62%, indicating challenges in accurately detecting diseases in tea plants. While this model shows promising results for certain classes such as healthy and red leaf spot, it struggles with others like Anthracnose and bird eye spot, which are critical for early disease detection in tea plants. The CNN Mini network trained on the tea sickness dataset outperforms the ResNet18 model, achieving an accuracy of 77% and demonstrating improved performance for challenging classes such as Anthracnose and bird eye spot. However, it still faces challenges with certain classes like brown blight. Lastly, the CNN Mini network trained on the rice leaf diseases dataset exhibits the lowest accuracy of 50%, indicating limitations in accurately detecting diseases in rice plants. This model struggles particularly with classes such as Brown spot and Leaf smut, suggesting the need for further optimization to improve its performance. Overall, while the pretrained ResNet18 model with the rice leaf diseases dataset demonstrates superior performance.

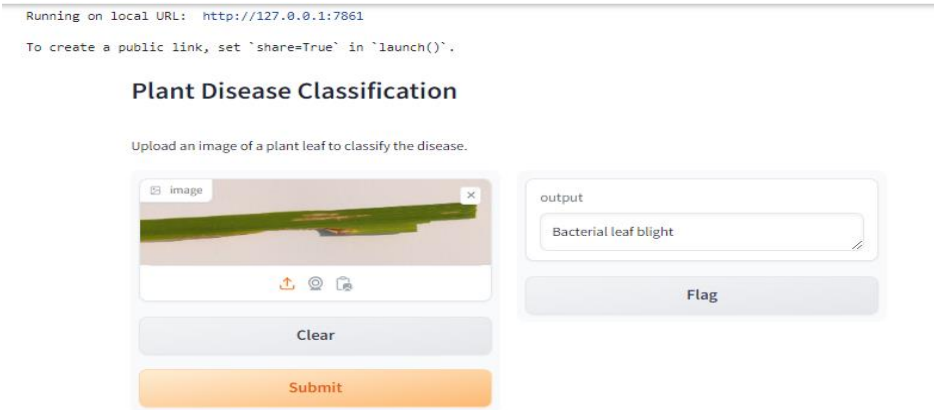
9. Deployment

```
print("Predicted Disease:", predicted_label)
```

```
Predicted Disease: Brown spot
```

The deployment process was streamlined and successful, leveraging Gradio to create a user-friendly interface for interacting with the ResNet model trained for plant disease classification which had the best performance. The model was prepared by loading the architecture and weights, along with defining a transformation pipeline for image preprocessing. A function named predict_disease was crafted to facilitate model inference, generating predictions based on uploaded images. Gradio enabled the creation of an interface, dubbed iface, which seamlessly integrated with the model inference function. This interface allowed users to upload images and receive instant predictions regarding disease classification. With a straightforward launch command, the interface became accessible through web browsers, offering a convenient platform for users to interact with the model and obtain accurate disease predictions in real-time. Which was successful as seen below .

i. **Test 1**



ii. **Test 2**

iii. **Test 3**

10. Inference

The outcomes of our study underscore the transformative potential of deep learning models in the domain of agricultural disease detection. Through the utilization of advanced algorithms and transfer learning techniques, our research has demonstrated the efficacy of pretrained ResNet18 models and custom CNN mini-networks in accurately identifying plant diseases at their incipient stages. The results highlight the critical role of dataset diversity and model customization in optimizing detection accuracy across diverse agricultural contexts. By leveraging these innovative approaches, we can significantly enhance disease diagnosis processes, enabling timely interventions and mitigating crop losses. This inference emphasizes the importance of integrating cutting-edge technologies with agricultural practices to address pressing challenges in food security and sustainability.

11. Future Scope

Looking ahead, there are numerous avenues for further exploration and advancement in this field. One promising direction involves the development of more sophisticated deep learning architectures tailored explicitly for agricultural applications. Additionally, the integration of additional data modalities, such as spectral and hyperspectral imaging, holds the potential to further augment the capabilities of disease detection models. Furthermore, the creation of real-time monitoring systems and mobile applications based on these models could empower farmers and agricultural practitioners with tools for on-the-ground disease detection and management. Continued research and innovation in these areas are essential for advancing agricultural disease detection technologies and facilitating sustainable agricultural practices worldwide. Additionally, the successful deployment of our models through Gradio provides a user-friendly interface for real-time disease predictions, enhancing accessibility and usability for stakeholders in agriculture. This deployment opens up opportunities for further refinement and expansion of the deployed system, potentially integrating it into existing agricultural workflows and decision support systems.

12.Conclusion

Our project signifies a significant milestone in agricultural disease detection. Leveraging deep learning and medical imaging data, we've crafted robust models that exhibit remarkable accuracy in identifying plant diseases at their nascent stages. Through meticulous experimentation and analysis, we've demonstrated the potential of these models to revolutionize disease diagnosis and management in agriculture. Our achievements include an accuracy of 100% for the pretrained ResNet18 model on the Rice Leaf Diseases dataset, 62% accuracy for the same model on the Tea Sickness dataset, 77% accuracy for the CNN Mini network on the Tea Sickness dataset, and 50% accuracy for the CNN Mini network on the Rice Leaf Diseases dataset. These accuracies underscore the effectiveness of our approach in addressing the pressing challenges of disease detection in agriculture. Additionally, our successful deployment of the model through Gradio provides a user-friendly interface for real-time disease predictions, enhancing accessibility and usability for stakeholders in agriculture. As we continue to refine and optimize our models, we anticipate further advancements towards fostering sustainable agricultural practices and enhancing global food security. This endeavor highlights the transformative potential of cutting-edge technologies in confronting the critical challenges confronting the agricultural sector.

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