**B.Tech. BCSE497J - Project-I**

**Plant Disease Classification using AI**

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# Abstract

This research presents an advanced approach to automated plant disease classification using a two-stage transfer learning technique based on the ResNet-50 architecture. The primary objective is to develop a highly accurate and scalable solution for identifying plant diseases from image inputs, addressing critical challenges in precision agriculture.

Our novel methodology employs a two-stage transfer learning process:

1. In the first stage, we pre-train a ResNet-50 model (Model A) on an extensive 25 GB dataset of diverse leaf images, enabling the network to learn robust, generalizable features across a wide range of plant species and conditions.
2. The second stage involves fine-tuning Model A on the Plant Village dataset, a curated collection of plant disease images, to specialize the model for specific disease recognition tasks.

The dataset undergoes comprehensive preprocessing, including advanced data augmentation techniques, intelligent shuffling, efficient caching, and optimized batching. Our pipeline leverages TensorFlow's *tf.data* API to enhance data handling, significantly improving training efficiency and model scalability.

Experimental results demonstrate the effectiveness of our approach, with the model achieving an impressive classification accuracy exceeding 96% on the Plant Village dataset. This marks a substantial improvement over previous benchmarks and single-stage transfer learning methods.

Key contributions of this work include:

1. Development of a two-stage transfer learning methodology that effectively leverages large-scale, diverse leaf data to improve disease classification accuracy.
2. Demonstration of superior model generalization across various plant species and disease types.
3. Implementation of an efficient data pipeline capable of handling extensive datasets, enhancing training speed and scalability.
4. Achieving state-of-the-art accuracy (>96%) in plant disease classification, setting a new benchmark for automated agricultural diagnostics.

This research significantly advances the field of precision agriculture by providing a highly accurate, efficient, and scalable tool for early plant disease detection. The proposed model has the potential to revolutionize crop health management, enabling timely interventions and substantially improving agricultural productivity and sustainability.

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# 1. Literature Survey

* Our base paper for this project is <https://ieeexplore.ieee.org/document/9726036>. Using our aim is to improve the results of the findings using 2 stage transfer learning as proposed below.
* We used [ResNet50](https://arxiv.org/abs/1512.03385) model as this model shows promising results when trained on big dataset and has great potential for transfer learning. ResNet models outperforms [VGG models](https://arxiv.org/abs/1512.03385) on imagenet dataset.
* [ResNet Strikes back](https://arxiv.org/pdf/2110.00476) paper shows how improved training and finetuning still keeps this model relevant and has great potential even to this date.

Plant disease detection and classification using deep learning techniques have become crucial in modern agriculture, offering the potential to significantly improve crop management and yield. This study aims to build upon and improve the results of Gosai et al. (2022), who proposed a comprehensive approach to plant disease detection using machine learning algorithms.

Base Study: Plant Disease Detection Using Machine Learning

Gosai et al. (2022) presented a thorough review and implementation of machine learning techniques for plant disease detection. Their study compared various classification algorithms, including Support Vector Machines (SVM), Artificial Neural Networks (ANN), K-Nearest Neighbors (KNN), and Convolutional Neural Networks (CNN). Key aspects of their work included:

1. A systematic approach to plant disease detection, including image acquisition, preprocessing, segmentation, feature extraction, and classification.
2. Comparison of traditional machine learning algorithms with deep learning approaches.
3. Implementation of data augmentation techniques to enhance model performance.
4. Achieving an accuracy of 70.14% using a Random Forest classifier on a dataset of papaya leaf images.

While their study provided a solid foundation, there is significant room for improvement in accuracy and generalization across different plant species and diseases.

***Proposed Improvement: Two-Stage Transfer Learning with ResNet50***

To enhance the results of Gosai et al., we propose utilizing a two-stage transfer learning approach based on the ResNet50 architecture. This choice is motivated by several factors:

1. ResNet50's Strong Performance: He et al. (2016) introduced the ResNet architecture, which has become a cornerstone in deep learning for image classification tasks. ResNet models have consistently outperformed other architectures, including VGG, on large-scale datasets like ImageNet.
2. Transfer Learning Efficacy: Zhang et al. (2023), although focused on steel surface defects, demonstrated the effectiveness of transfer learning using ResNet50, achieving 99.4% accuracy. Their success in a different domain suggests the potential for similar improvements in plant disease detection.
3. Recent Advancements in ResNet Training: Wightman et al. (2021), in their "ResNet Strikes Back" paper, showed that with improved training procedures and fine-tuning techniques, ResNet models remain highly competitive and relevant. They achieved state-of-the-art performance on ImageNet classification, demonstrating the untapped potential of ResNet architectures.

# 2. Gap Identification

### Current State of Research

The [base paper](https://ieeexplore.ieee.org/document/9726036) utilizes a deep learning approach, specifically ResNet18, to classify plant diseases. It applies a single-stage transfer learning method on a dataset of 54,306 images, achieving an impressive accuracy of 96%. This model effectively detects and classifies diseases from images of plant leaves, contributing significantly to precision agriculture by automating the disease detection process.

### Limitations and Gaps

Despite the success of the base paper, several key limitations exist:

* **Dataset Size and Specificity**: The dataset used in the base paper, while comprehensive, covers a generalized set of plant leaves and diseases. There is room for improvement by focusing on a more specialized dataset that better captures the nuances of specific plant diseases.
* **Single-Stage Transfer Learning**: The base paper relies on a single-stage transfer learning process, which may limit the model's capacity to leverage broader knowledge for enhanced fine-tuning on a smaller, more specific dataset.
* **Accuracy Limitation**: While 96% accuracy is commendable, there is a gap in further refining the model to push beyond this accuracy threshold, particularly by integrating a more nuanced, multi-stage learning process.

Given the importance of early and accurate plant disease detection in agriculture, enhancing model performance is crucial for practical implementation. The gap lies in the potential to improve accuracy beyond 96%, especially with better feature extraction from more specific datasets and optimized learning strategies. Addressing these gaps could lead to a more robust and generalizable model that performs better across various plant species and disease types.

We propose using a **2-stage transfer learning approach** to build on the work done in the base paper. Our approach first trains the ResNet50 model on a larger, general dataset of plant leaves, capturing broad feature representations. Then, we fine-tune this pre-trained model on the more specific Plant Village dataset, which focuses on distinct plant diseases. This method is expected to further refine the model's ability to generalize and improve classification accuracy, surpassing the 96% achieved in the base paper.

By addressing these identified gaps, our project aims to push the boundaries of plant disease classification accuracy and provide a more effective tool for precision agriculture.

# 3. Objectives

The primary goal of this research is to develop an advanced, highly accurate system for plant disease detection and classification using deep learning techniques. We aim to significantly improve the accuracy and generalization capabilities of plant disease recognition.

Our main objective is to implement a two-stage transfer learning approach using the ResNet50 architecture. This involves first pre-training a ResNet50 model on a large, diverse dataset of plant images, followed by fine-tuning the pre-trained model on specific plant disease datasets. Through this approach, we aim to achieve an accuracy of at least 96% in plant disease classification.

We will compare the performance of this two-stage transfer learning approach with traditional single-stage transfer learning and training from scratch. This comparison will help us understand the benefits of our proposed method in the context of plant disease detection.

To further enhance our model's performance, we will evaluate the effectiveness of recent advancements in ResNet training procedures. This includes exploring advanced data augmentation techniques, optimization strategies, and regularization methods. We will also implement and assess the impact of binary cross-entropy loss function on model performance.

An important aspect of our research will be to assess the model's ability to generalize across a wide range of plant species and diseases, evaluating its potential for real-world applications in precision agriculture. We will also analyze the computational efficiency and resource requirements of the proposed model, considering its potential for deployment in various agricultural settings.

To demonstrate the practical applicability of our research, we will develop a deployable web application prototype for real-time plant disease detection. This will involve implementing a backend API using FastAPI to serve the trained model and creating a user-friendly frontend interface using Streamlit for image upload and result display.

Through these objectives, we aim to contribute to the field of plant pathology and precision agriculture by developing a more accurate, robust, and interpretable solution for automated plant disease detection. Our goal is to advance the state-of-the-art in this field, providing a valuable tool for farmers, researchers, and agricultural professionals to improve crop management and yield.

# 4. Project plan

Project Plan for Plant Disease Classification

1. Data Acquisition and Preprocessing
   * Obtain 25 GB dataset of diverse leaf images
   * Acquire Plant Village dataset for disease-specific images
   * Implement data preprocessing pipeline:
     + Advanced augmentation techniques
     + Intelligent shuffling
     + Efficient caching
     + Optimized batching
   * Utilize TensorFlow's tf.data API for efficient data handling
2. First Stage: Pre-training ResNet-50
   * Implement ResNet-50 architecture
   * Set up training pipeline for the 25 GB dataset
   * Train Model A to learn generalizable features
   * Optimize for GPU/TPU usage
   * Aim to achieve 95% accuracy on the 25 GB dataset
3. Second Stage: Fine-tuning on Plant Village Dataset
   * Prepare Plant Village dataset for fine-tuning
   * Implement fine-tuning pipeline
   * Fine-tune Model A on Plant Village dataset
   * Optimize model for specialized disease recognition
4. Model Evaluation and Optimization
   * Develop evaluation metrics and procedures
   * Assess model performance on test datasets
   * Implement cross-validation for robust performance estimation
   * Optimize model based on evaluation results
5. Backend Development (FastAPI)
   * Set up FastAPI framework
   * Implement API endpoints for image upload and disease classification
   * Integrate trained model into the backend
   * Implement error handling and input validation
   * Optimize backend for performance and scalability
6. Frontend Development (Streamlit)
   * Design user interface for image upload and result display
   * Implement Streamlit application
   * Create intuitive user flow for disease classification
   * Integrate with backend API
   * Implement responsive design for various devices
7. Integration and Testing
   * Integrate backend and frontend components
   * Conduct thorough system testing
   * Perform user acceptance testing
   * Debug and resolve any integration issues
8. Deployment and Documentation
   * Set up deployment environment (cloud or on-premises)
   * Deploy the integrated application
   * Create user documentation and guides Analyze final model performance across various metrics
   * Compare results with baseline and state-of-the-art methods
   * Prepare final report and presentation
   * Document lessons learned and areas for future improvement
   * Prepare technical documentation for future maintenance

This project plan outlines the key steps from model development to deployment, ensuring a comprehensive approach to creating an automated plant disease classification system with a user-friendly web interface.

# 5. Requirement Analysis

## Functional Requirements

* System must require at least 32gb of RAM for pre-processing image data without overflowing RAM
* At least 16gb of V-RAM is recommended and for GPU Training Nvidia P100 or higher is preferred as ResNet50 occupies 12gb while training using AdamW optimizer
* For very fast training, Kaggle TPU 3.8 is recommended as the training code for model A is GPU/TPU agnostic
* 95% accuracy is attained in bigger dataset
* Backend should accept image and convert it into tensor for model to give output

## Libraries and Tools

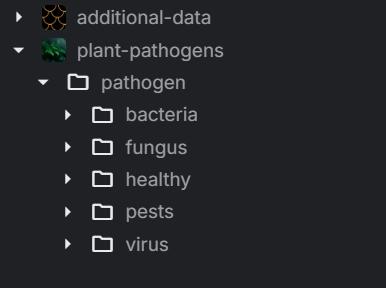
1. **Deep Learning Libraries**
   1. Tensorflow
   2. Keras
   3. Tensorflow data api
2. **Environment**
   1. Python 3
   2. Tensorflow support
   3. Pip
3. **Web Libraries**
   1. FastAPI (Backend)
   2. Streamlit (Frontend)
4. **Kaggle GPU and TPU facility**

# 5. Design and Implementation

### Overview of implementation so far

So far, we have successfully trained model A using TPU in Kaggle.

Model A is first model of two-stage transfer learning approach, Model A is trained on plant-pathogens dataset from Kaggle. Plant pathogen dataset is combination of various dataset. This dataset is huge and extensive. It will help our model to generalize well in tasks related to leaves.

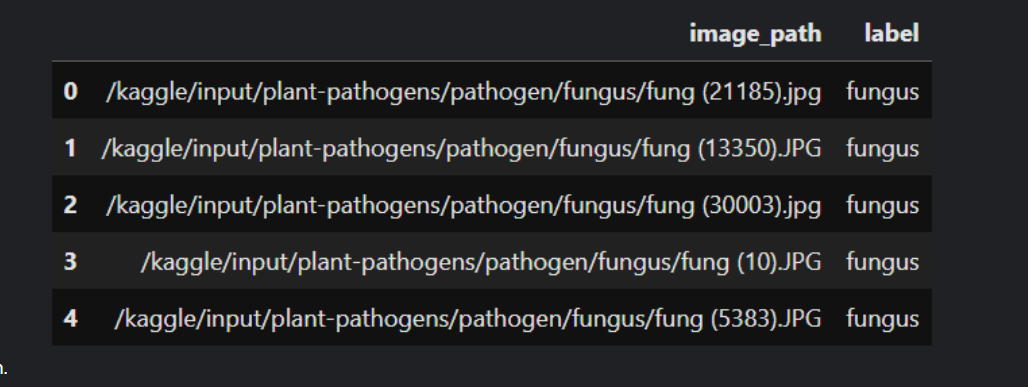


Model A is resnet50 model (with imagenet weights) which is finetuned model on plants-pathogen(25gb) dataset. We finetuned this model by training the whole model the dataset using Adam-W optimizer and utilizing weight – decay of Adam W to combat overfitting and we have successfully achieved 95% of accuracy in this dataset.

### A. Creating and Preparing Dataset

We must first create panda data frame containing path of image and use directory of image as label to

* perform basic EDA
* to perform necessary preprocessing
* to generate data pipeline (In later stages)



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After some basic preprocessing we have also implemented data pipeline using TensorFlow’s data api

Here to transform whole dataset, we first should apply transformation any random few images to get hang of what our code is doing and how it is affecting our image individually. Using this information, we can decide the input size of layer and and tune our deep learning model and re pre-processess our dataset on bigger resolution if needed.

##### A. Grayscale to RGB conversion

Firstly the image which are grayscale is converted into rgb using tf.image.grayscale\_to\_rgb function The code checks if the input image is grayscale (i.e., has only one channel). If it is, the code converts the image to RGB by repeating the channel three times. This is necessary because many machine learning models expect input images to have three channels (red, green, and blue).

##### B. Check image properties

The check\_image\_properties function is defined to check the properties of an input image. The function prints the data type of the image, the minimum and maximum values of the image, and whether the image is 8-bit and whether its values are in the 0-255 range.

##### C. Resize and Standardize image function

The resize\_and\_pad\_image function is defined to resize an input image to a target size of 124x124 pixels using bilinear interpolation. tf.image.resize\_with\_pad() code is used along with tf.image.ResizeMethod.BILINEAR interpolation.

The function also applies standardization to the image by subtracting the mean and dividing by the standard deviation of each pixel. The function returns both the resized and standardized images.

##### D. Lastly we normalize the image by dividing it by 255.0 (or maximum value of pixel)

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### B. Model Configuration and Training

In our final model, the input shape is (256,256,3)

GPU as well as TPU batch size is 128

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#### Model Architecture

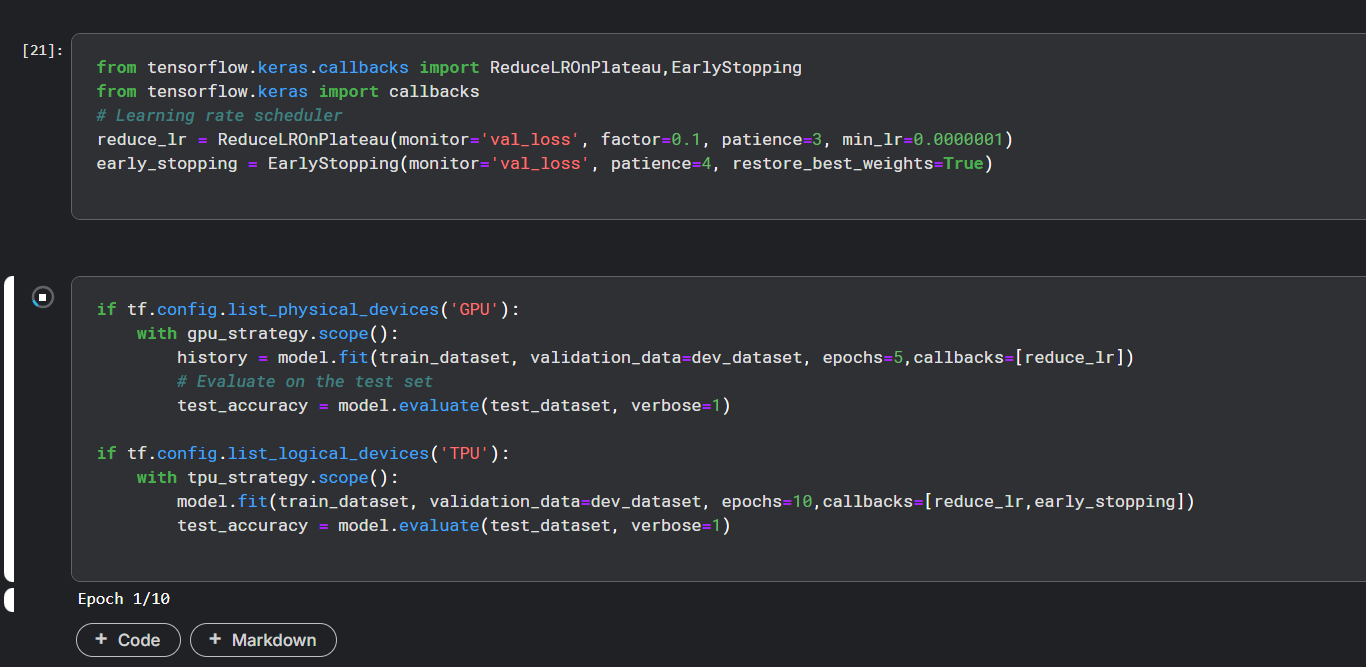
A diagram of a model architecture

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**A diagram of a slip connection

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#### Training and Validation



First epoch will take around 40 minutes then after every epoch will take around 3 minutes on TPU.

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Exporting Trained Model