Tomato Leaf Disease Classification

1. Problem Statement and Application

Tomatoes are one of the most commonly harvested crops, and they are consumed by people all over the world. However, leaf diseases are a serious threat to both the quality and quantity of tomato yields which directly reflects in the economic loss according to statistics [4]. Leaf disease identification is a resource-consuming process when done manually, and it also requires the help of an expert to classify the leaf diseases. Early and accurate diagnosis of these diseases is critical for maximizing yields.

Our proposed methodology uses Convolutional Neural Networks (CNNs) to classify tomato leaf diseases, with specific architectures such as ResNet18, MobileNetV2, and VGG16. For the best performance of these models, we will be fine-tuning the hyperparameters. In our project, we utilize pre-trained models to classify tomato leaf diseases, leveraging the learned features from a previous dataset, thus implementing transfer learning. We hope to ensure the accuracy and reliability of these models by training them on large datasets of tomato leaf disease images, and testing them with unseen images of leaf diseases to measure the accuracy. Potential challenges include disease similarities, which demand quality images with appropriate dimensions for precise classification. Images with excessive or insufficient lighting can make it hard for the model to identify the leaf diseases.

The primary goal of the project is to investigate the impact of dataset sizes, optimize hyperparameters, and evaluate the effectiveness of transfer learning, contributing valuable insights to enhance the model's performance and applicability. Our proposed model promises quick and accurate classification of tomato leaf diseases, eliminating the need for specialized agricultural expertise.

2. Image Dataset Selection

Dataset	Images	Dimensions	Classes
Dataset [1]	2k	227 x 227	3
Dataset [2]	14.6k	256 x 256	6
Dataset [3]	18.1k	256 x 256	10

After carefully reviewing numerous datasets on platforms such as Kaggle and other reputable websites, we chose the three datasets listed above to be used for our project. Each dataset was chosen based on its unique characteristics and relevance to our project objectives. The first dataset contains resized images of Taiwan tomato leaves for consistency and ease of analysis. The second dataset, on the other hand, contains a wide range of images of tomato leaves collected in both laboratory and natural field conditions, increasing its variety. The third dataset is the largest of the three, containing a diverse set of crop images from which we extracted specific tomato leaf disease categories.

3. Possible Methodology

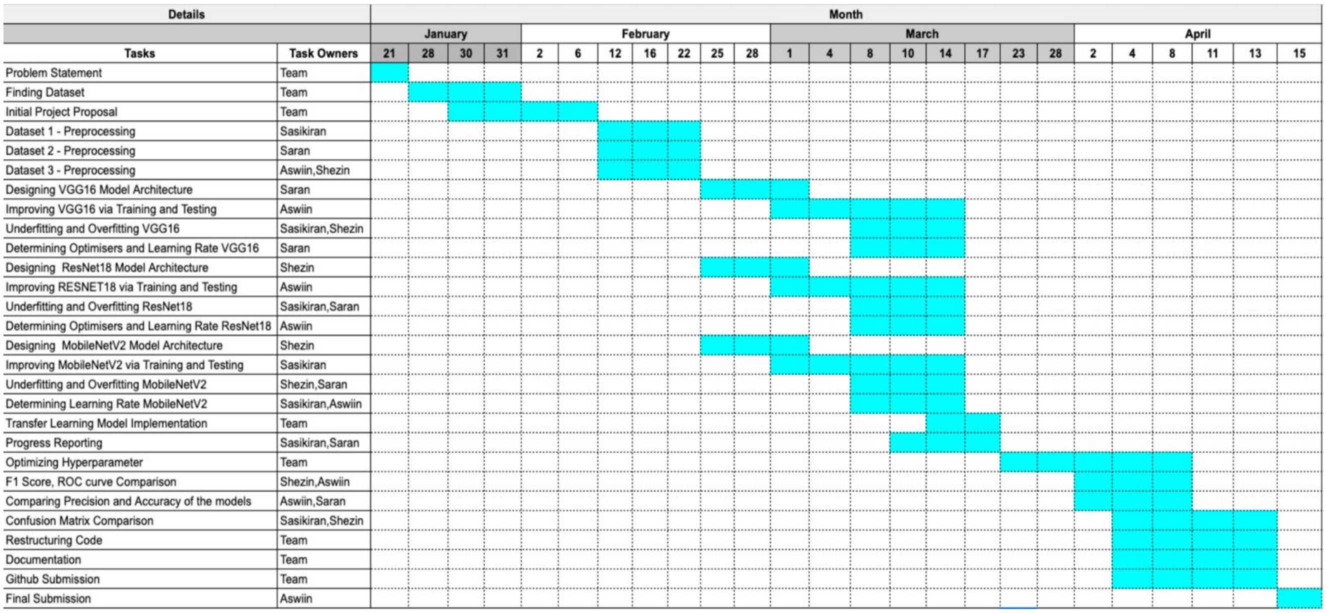
In the pre-processing stage, we will apply various image processing techniques such as resizing, normalization, enhancing color information in images by manipulating the colors, and using data augmentation techniques like random rotations, flips, and shifts which can improve the diversity of the training dataset crop. These preprocessing steps enhance model performance by extracting relevant features.

To address the given problem, we are using three different architectures using which 11 models are built. The selected architecture that may be appropriate for the given problem is: VGG16, This architecture with 16 layers is a classic one that is well suited for image classification problems and helps in reducing the spatial dimension [5]. ResNet18 is a relatively newer architecture that performs well on image classification tasks due to its unique feature 'Residual Learning', which addresses the vanishing gradient problem using the shortcut connections [7]. MobileNetV2 is a lighter architecture with 53 layers that comes pre-trained using the ImageNet dataset. MobileNetV2 uses Depth-wise Separable Convolutions which use Inverted residuals to preserve the information and It can give a good accuracy with the low parameters and mathematical operation that can help using deep learning in mobile devices [6]. Additionally, we'll select two best-performing combinations of architecture and dataset and apply transfer learning to them to build two new models.

To improve performance during the training process, we will use Adaptive Moment Estimation (Adam) optimizer and fine-tune the learning rate for optimal performance of the models. In our project, we will use various evaluation metrics such as accuracy score, precision, F1 score, ROC curve, and confusion matrix to compare and analyze the results of the 11 models. We will be using t-SNE to visualize the performance of the models.

The expected outcome is the development of optimized models using CNN architectures, specifically VGG16, MobileNetV2, and ResNet18, which could potentially help plant pathologists and agricultural researchers in classifying tomato leaf diseases in their research.

4. Gantt Chart



The projected timeline for our project is represented by a GANTT chart, with the expected milestones listed below.

Milestone 1: During this initial phase, the team will discuss and explore the given problem statement. The team is in charge of identifying the best fit dataset and image classification model for the project. This phase also includes discussing the project's scope and objective, as well as identifying datasets with similar classes that will be processed in subsequent phases.

Milestone 2: During this phase, the team will focus on dataset preprocessing. The data is cleaned and pre-processed using various techniques such as image scaling, resizing, color space enhancement, normalization, and data augmentation. This phase enhances the model's performance by extracting relevant features from the dataset.

Milestone 3: During the model training phase, the team will use the three selected pretrained model architectures and the preprocessed dataset to create a working model that must be trained and tested before the project can be implemented properly.

Milestone 4: During this phase, the team will fine-tune the pretrained model to change the behavior of the existing model in order to adapt to the dataset and perform a particular task. This phase includes determining a good learning rate and optimizers to ensure the model's best performance.

Milestone 5: In the evaluation phase, the team will compare all of the models' confusion matrices, F1 scores, and ROC curves to determine which model performs the best. It also compares each model's performance on the same dataset and identifies areas for improvement.

Milestone 6: In this phase, we would select two best performing models among the nine trained models and train two additional models using the Transfer Learning technique to improve the performance.

References

[1] Tomato leaf disease dataset 1. https://www.kaggle.com/datasets/joseenriquelopez/tomato-leaf-diseases. 1

[2] Tomato leaf disease dataset 2. https://www.kaggle.com/datasets/cookiefinder/tomato-disease-multiple-sources. 1

[3] Tomato leaf disease dataset 3. https://www.kaggle.com/datasets/abdallahalidev/plantvillage-dataset. 1

[4] H. D. Gadade and D. K. Kirange. Tomato leaf disease diagnosis and severity measurement. *2020 Fourth World Conference on Smart Trends in Systems, Security and Sustainability (WorldS4)*, 2020. 1

[5] M. Gehlot and M. L. Saini. Analysis of different cnn architectures for tomato leaf disease classification. *2020 5th IEEE International Conference on Recent Advances and Innovations in Engineering (ICRAIE)*, 2020. 1

[6] M. H. Anuz R. Moyazzoma, M. A. A. Hossain and A. Sattar. Transfer learning approach for plant leaf disease detection using cnn with pre-trained feature extraction method mobilnetv2. *2021 2nd International Conference on Robotics, Electrical and Signal Processing Techniques (ICREST)*, 2021. 1

[7] N. Sharma R. Singh and R. Gupta. Classification and detection of corn leaf disease using resnet 18 transfer learning model. *2023 8th International Conference on Communication and Electronics Systems (ICCES)*, 2023. 1