Plant Disease Detection and Classification using Deep Learning

1. Problem Statement & Application

Agriculture is a major sector that impacts society and the environment while defining the economy of a nation [7], this necessitates precise plant disease identification for timely intervention. Traditional methods require a manual inspection and expertise, which is exhaustive [8] [9]. Deep Learning resolves this problem by learning diverse disease symptoms, imperceptible to the human eye in early stages [7]. However, challenges such as image variations due to lighting, growth stages, and environmental factors pose obstacles. Striking a balance between model size and performance is also critical during solution development.

While our primary focus is on building a robust and versatile plant disease detection system, we will also broaden our attention to conduct a thorough study of various architectures and attributes, such as dataset size, hyperparameters, etc. This approach aims to enhance our understanding of their impact on the model's performance and generalization capabilities. Our overarching goal is to develop a system that can demonstrate practical applicability, ensuring its effectiveness across a wide range of plant species and diseases.

2. Datasets

To solve the problem at hand, we have selected the *Cassava Dataset*, *Crop Pest and Disease Dataset*, and *PlantVillage Dataset*. The Cassava Dataset contains leaf images of the cassava plant crowd sourced from farmers and analysed by experts at the National Crops Resources Research Institute (NaCRRI) and AI lab in Makarere University, Kampala [1]. The Crop pests/diseases dataset contains leaf images sourced from farms in Ghana with multiple classes of different diseases [2]. The PlantVillage dataset contains healthy and unhealthy leaf images divided into various classes across multiple species and diseases [3]. For our study, we will allocate 80% to training, 10% to validation, and 10% to testing across the datasets.

	Cassava	**Crop Pest**	**PlantVillage**
Images	5,656	24,881	50,091
Shape	Var.	Var.	Var.
Format	JPG	JPG	JPG
Classes	5	22	37
Trimmed Datasets			
Images	5,656	16,754	35,320
Classes	5	15	30

Table 1. Agricultural Datasets Summary

3. Methodology

Our solution pipeline begins with data preprocessing as the datasets exhibit varying geometric and photometric properties. The data will pass through the augmentation pipeline composed of various geometric transforms, including resizing, flipping, rotation, etc., as well as photometric transforms such as segmentation, brightness correction, contrast adjustment, etc., as discussed in [4] [5] [6]. This approach aims to enhance the diversity and richness of the training data. The final step in the augmentation pipeline involves converting the images to tensors, followed by normalization. This ensures that the data fed into each architecture is consistent and facilitates effective training.

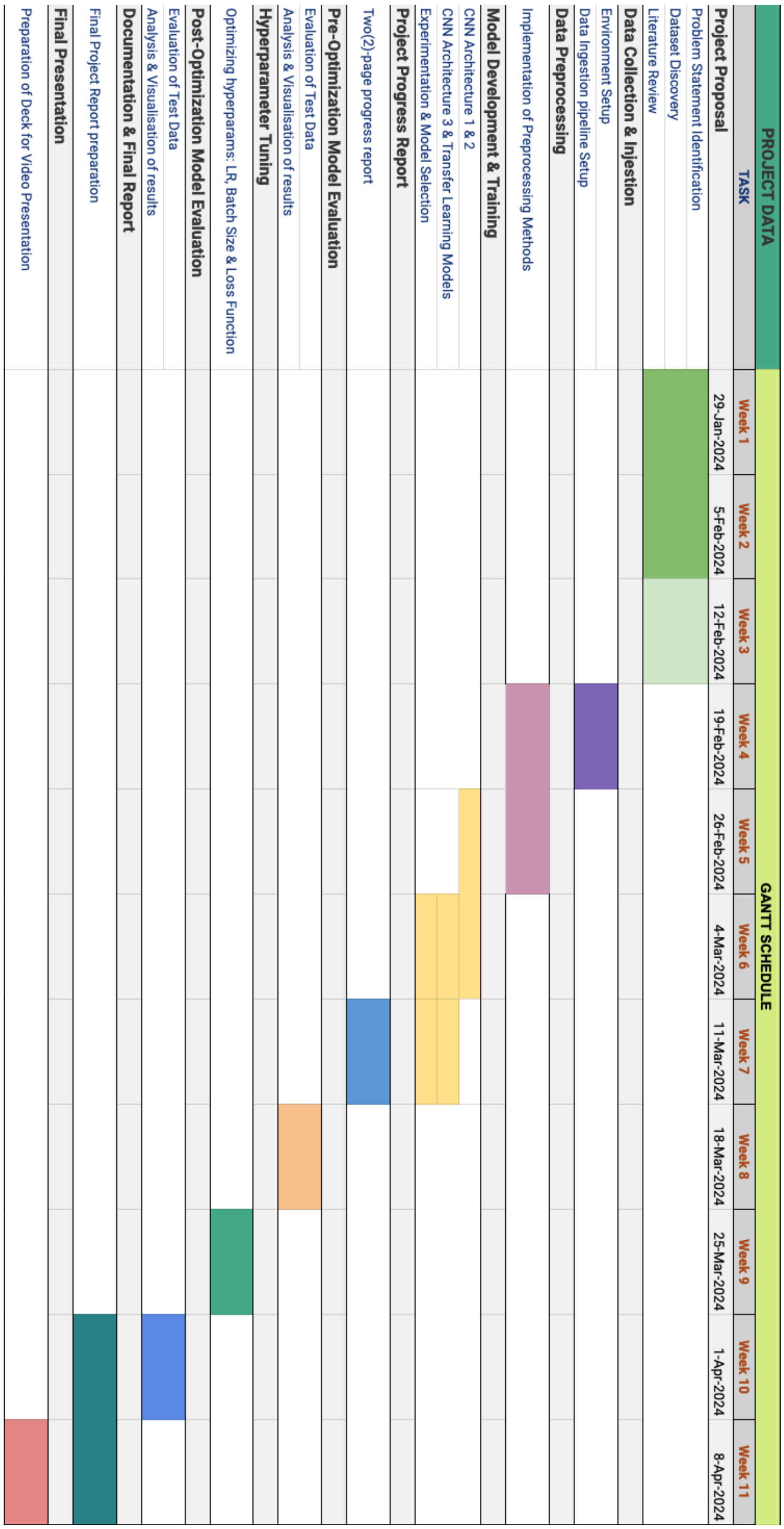
To strike a balance between model size and performance, our study focuses on training from scratch and comparing three architectures (available on PyTorch): Quantized GoogleNet, EfficientNet, and MobileNetV2 [10,11,16–18]. GoogleNet is known for its inception modules and its ability to achieve improved computational efficiency through the use of lower-precision numbers for calculations [16]; EfficientNet is designed for balancing accuracy and efficiency across various resource constraints through scaling network size (width and depth) smartly [17]. MobileNet is an architecture optimized for edge devices that reduces computation while maintaining performance by leveraging depthwise separable convolutions [18].

In our study, we will also analyze the performance of GoogleNet [16] and MobileNetV2 [18] when fine-tuned on the datasets through a transfer learning approach, thereby comparing their performance when trained from scratch. Additionally, to achieve better results, we plan to optimize the learning rate and batch size hyperparameters for the model that performs best before optimization, to gain deeper insights of their impact on the model's performance.

The performance of these models will be evaluated on Accuracy, Precision, Recall, F1 Score and ROC Curve. The overall correctness of the model can be observed based on the Accuracy score [14]. Considering the consequences of both false positives and negatives, we aim to develop a model that delivers a balanced performance and prioritizes high precision ensuring that when the model predicts a disease, it is highly likely to be true. Additionally, we will also use t-SNE to visualize how instances are distributed relative to each other and positioned in the feature space by capturing the overall structure of the data.

Our solution will empower agricultural scientists to develop effective treatment strategies by identifying patterns and gaining insights into the factors influencing disease outbreaks. Furthermore, additional research and development could significantly expand its scope to detect a wider variety of plant diseases.

4. Project Timeline



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