Project Overview and Plan(PoP)

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April 2023

1 Introduction

According to the Food and Agriculture Organisation(abbreviated as FAO hereafter) in their 'International Year of Plant Health 2020' estimated that around 20%-40% of global crop production could be lost due to plant and pest disease annually[1]. With the growing population worldwide, it is essential that all food crop production losses are kept to a minimum in order to reduce the chance of people suffering from famine. In addition, a scientific overview overseen by the FAO has concluded that climate change is also a main factor in altering or increasing the risk of plant and pest disease. According to an article from Harvard Business Review, the rising global population and income contributes to the rising food demands. With this in mind, global food production must be secure in order to meet the demand otherwise it will lead to famine and malnutrition around the world.

Therefore, the objective of this project is to address this problem by creating a lightweight Convolution Neural Network(CNN) which can identify plant disease by analysing images of affected leaves and deploying the model to a mobile device in later stages. This project will use data from "Mendeley Data" which includes 39 different classes of plant leaves and background images. In this project, only one class of plant leaf will be considered unless there is extra time available. At the end of this project, we hope to create a mobile application that has a neural network embedded into it. Hopefully, this application could contribute to society by helping farmers recognise plant disease early so that they can take action to reduce potential losses.

2 Background

There have been multiple studies and research on this subject area over the past decades and we will be going over a few of them in this section. In this field of study, the machine learning approaches to identify plant diseases can be mainly separated into three categories namely Image-based, traditional machine learning based and deep learning based.

2.1 Image Processing

There are limited works on plant disease detection that rely solely on image processing techniques. In 2019, Sharath and Akhilesh et al. developed an Image based system for detecting pomegranate plant disease[2]. In their paper, they were able to develop a system to detect pomegranate plant disease and based on the affected percentage the system will then provide suitable measures to either prevent or solution for the disease. The system can be decomposed into several components: image acquisition, preprocessing and segmentation, feature extraction and finally edge detection and disease classification. Image acquisition will simply be captured through a camera in RGB form. During preprocessing and segmentation, noise removal and colour transformation are performed during this stage. Then the authors perform Grab cut segmentation to separate foreground and background and refine the foreground repeatedly until it precisely matches the desired object. In the stage of disease classification, the authors suggest using edge detection as the classification method for identifying bacterial blight disease in pomegranates. This method of detection is specifically useful for pomegranates because the pomegranate fruits that are affected by the disease will have big cuts in them and edge detection is incredibly useful in finding the edges. The edge detection algorithm used in the system is Canny edge detection since it is extremely accurate in detecting the edges and noise in the image does not produce false edges. During the classification stage, the amount of edges in pixels is calculated and then based on a threshold the system will produce an output whether the fruit is affected or not.

2.2 Traditional Machine Learning

Suhaili Beeran Kutty et al. in 2013 used an artificial neural network to classify watermelon leaf diseases.[3] The classification is based on the extracted colour feature from the RGB model where the RGB colour pixels are obtained from the identified region of interest which is the infected area of the leaves. The proposed method uses packages from MATLAB and it achieved an accuracy of 75.9%.

In 2020, Chaudhari and Patil proposed to detect banana leaves using K-means clustering and feature extraction techniques[4]. In their experiment, they developed a system that uses image processing techniques and machine learning techniques to classify diseases. The authors used a K-means clustering algorithm to perform image segmentation followed by extracting the colour and texture features of the region of interest. Finally, they trained the model using Support Vector Machine(SVM). The proposed work achieved an average of 85% accuracy in classifying 4 kinds of banana plant diseases.

Shima Ramesh et al. discuss the use of machine learning to detect crop diseases and proposed the use of the Random Forest technique to identify healthy and unhealthy leaves[5]. In the proposed methodology, the authors extract features from the preprocessed images using the Histogram of an Oriented Gradient(HOG). In addition, they made use of three feature descriptors: Hu Moments, Haralick texture and Colour Histogram for feature extraction where each descriptor provides different functionalities. Hu Moments is used to identify the shape of the leaves; Haralick texture is used to differentiate the texture of healthy and unhealthy leaves; Colour Histogram is used to represent the distribution of the colours in the images. Finally, Random forest is used for classification and the authors managed to achieve an accuracy of 70%.

In 2012, Faisal Ahmed et al. conducted a study focusing on the application of SVM to classify crops and weeds in digital images[6]. In their experiments, a range of fourteen features is used to characterise crops and weeds in digital images to find the optimal features combination that yields the highest accuracy. The results of the study demonstrate that SVM is an effective algorithm for classifying as there is no misclassification of weeds as crops and vice-versa. The features used include but are not limited to colour features, size-independent shape features, and moment-invariant features. The automated machine vision system proposed in this study could potentially be a cost-effective alternative to mitigate the excessive use of herbicides.

2.3 Deep Learning Based

In 2022, Nirmal M.D et al. published a research paper "Deep Learning-based Disease Detection using Pomegranate Leaf Image"[7]. In their research paper, the authors proposed a deep convolution neural network(CNN) to locate and identify the disease. After the standard preprocessing procedures of the raw images, they are used in training the models which the authors integrated Long-Short Term Memory(LSTM) with CNN. In their findings, the combination of CNN and LSTM outperform the models that only utilised CNN, they were able to achieve an accuracy of 90.546% in identifying healthy and unhealthy leaves and an accuracy of 97.246% in the classification of Pomegranate leaves diseases.

In 2018, Prajwala Tm et al. proposed a CNN-based approach to detecting Tomato Leaf disease[8], the authors conduct their experiments in various circumstances and conditions such as varying the image sizes, different colour spaces and different types of tomato leaf diseases. They managed to achieve an average accuracy of 94%-95% with their proposed method which proves that the model is robust and can handle variations effectively which is quite impressive. The architecture of the CNN model used for the classification of tomato leaf diseases is a variation of the LeNet model where the authors added an additional block of convolutional, activation and pooling layers.

Hassan et al. presented an innovative approach in 2021 to identify plant-leaf diseases using CNN and transfer-learning[9]. The authors discussed the limitation of standard CNN models where most of them require a large number of parameters and computation costs, and they proposed to use depth separable convolution as an alternative which reduce computation cost while maintaining accuracy. According to Howard et al., a depth-separable convolution is a type of convolutional operation that decomposes ordinal convolution into two operations: depthwise and pointwise convolution[10]. Howard described that the depthwise convolution applies a single filter to each input channel and pointwise convolution then applies a 1×1 convolution to combine the outputs from the depthwise operation the objective of doing this is to drastically reduces the computational cost and model size. Going back to disease identification, Hassan et al. use different CNN architectures such as InceptionV3, InceptionResNetV2, MobileNetV2, and EfficientNEtB0 in their work.

With all these different architectures, they were able to achieve incredible results where the disease classification accuracy rates of 98.82%, 99.11%, 97.02% and 99.56% respectively. These results are magnificent as they are way above the accuracy that we have seen in previous works.

3 Research Methodology

The proposed research methodology for the project will be discussed in this section. It should be noted that at the moment, the project is still in the planning phase therefore the research methodology proposed in this section is subject to change during the implementation phases.

3.1 Image acquisition

The images that will be used in the training and testing phases are acquired from a publically available dataset from Mendeley data[11]. In this dataset, 39 different classes of plant leaf and background images are available. The authors of this dataset used six different augmentation techniques to increase the dataset size, the techniques include image flipping, Gamma correction, noise injection, PCA colour augmentation, rotation and scaling. In this project, the initial aim and objective are to focus on classifying healthy apple plant leaves and diseases. In the dataset, apple plant diseases include Apple Scab, Cedar Apple Rot and Black Rot. If time allows at the later stages of the project, then I will try to introduce new plant diseases to the CNN model.

3.2 CNN architecture

After going through the related works in the previous sections, I will be adopting MobileNet-V2 and Inception-V3 architectures. Even though the previous work suggests that InceptionResNetV2 and EfficientNEtB0 have the best performance, the number of parameters in these two architectures is much higher which leads to a larger model size. Since the aim of this project is to create a lightweight CNN model, these two architectures are the most suitable for the purpose. Then I will be accessing the performance of the models and then selecting the best performance architecture for the final CNN model.

3.2.1 MobileNet-V2 and Inception-V3

In the study done by Hassan et al., they also incorporate the MobileNet-V2 and Inception-V3. While the two CNN architectures are both popular, they differ in terms of their approach to convolutions, model size and the balance between efficiency and accuracy. The main difference in MobileNet is that it focused on the use of depth-wise separable convolution that I mentioned in the previous section. In contrast, Inception-V3 employs more traditional convolutions that use Inception modules which are composed of multiple parallel convolutional branches[12]. I should highlight here that the primary goal of this section is not to compare the two architectures but to explore which will be more suitable for the main purpose of the project rather than a comparative analysis.

3.3 Mobile application development

During stage 2 implementation of the mobile application, I would like to primarily focus on building the application for iOS devices. Since I have minimal mobile development experience, I expect to encounter multiple challenges during this phase. However, looking through the resources on the internet for deploying machine learning models to the mobile environment, I am confident that I can overcome the obstacles. On the other hand, deploying the model onto an Android device will be my backup strategy as the Android platform faces more variety of users and hence more resources available.

4 Ethics and Professional considerations

When it comes to ethics and professional considerations, the mobile application and the CNN model that will be developed in this project strictly follow the ACM code of ethics. Clear disclaimers and limitations will be provided in the final dissertation to ensure users understand the application's scope and limitations, thereby avoiding overreliance or unrealistic expectations of the technology and encouraging users to consult with professionals when necessary.

5 Risk Consideration

After evaluating each stage of the project and the final expected product, currently, I think that the project poses a minimal risk at any stage of the project. Since the data used is publically available online, the end product is a mobile application that does not require connecting to the internet. The only potential risk that could be considered is the risk of privacy of taking pictures of other people or reading users' photos on their devices. To mitigate this potential risk, the mobile application is designed and will be implemented so that the application can only read but not store any images, images that have been read by the application will not be transferred to other databases since it is not connected to the internet. All of the above will require users' consent in order to proceed.

6 Project Evaluation

To evaluate the project, there are two stages that can be potentially evaluated.

6.1 Evaluating CNN Model

To evaluate the CNN Model, I will be measuring the accuracy of the model in two aspects: classifying health or affected leaves, and classifying plant diseases. Based on the related works discussed in the previous section and considering the balance between model size and performance, the target accuracy for classifying healthy or affected leaves is to be $\geq 90\%$ and $\geq 80\%$ for classifying plant diseases. The confusion matrix and ROC curve will also be used in evaluating the performance of the CNN model.

6.2 Evaluating Mobile Application

Since the objective of the project is to produce a lightweight CNN mobile application, the main goal of the mobile application is to be lightweight. To measure and evaluate this objective, the size of the application should be kept minimal and the current goal is to have the size of the application be less than 100 MB. Since the average iOS machine learning application is around 100MB according to this guide[13].

In addition, the mobile application should be able to perform main functionalities including but not limited to Importing images by uploading or taking pictures and classifying plant diseases with reasonable smoothness.

7 Planning

A proposed timeline for the project is shown in Figure 1, where the timeline is separated into a number of weeks over a span of 22 weeks from mid-March to the end of August. During the first 3 weeks, I have been doing some background research on the effect of plant disease on food crop production. Also, gathering research papers that might be useful for this project. From week 3 to week 6, overlapping with writing this document and background research, I have been learning image processing and mobile development techniques through online videos. As of today shown in the dotted line is the end of week 8 which is when the "Project Overview and Planning" is submitted. After this milestone, the project is ready to move on to the next stage. In weeks 9 and 10, the majority of the background and literature review can be finished since the work in this document can be transferred over. In week 11, there will be an empty week as it is when exams take place, this week can also act as a buffer week for the previous work that is yet to be done.

When the exams are over, from week 12 to week 15, I will be implementing the CNN for this project. And over these 4 weeks, I will try to perfect the accuracy of the CNN and only move on to stage 2 if the accuracy is acceptable. During stage 2 implementation which will take place from week 15 to week 19, I will be developing a mobile application and then deploying the CNN model onto it. After both stages of implementation, then I will be able to finish the remaining parts of the 1st draft of the dissertation in week 19 to 20. In the final two weeks in August, I will be going over the entire dissertation to refine and polish it for the final submission.

A more detailed Gantt chart can be found in the link here [Notion: Gantt Chart]

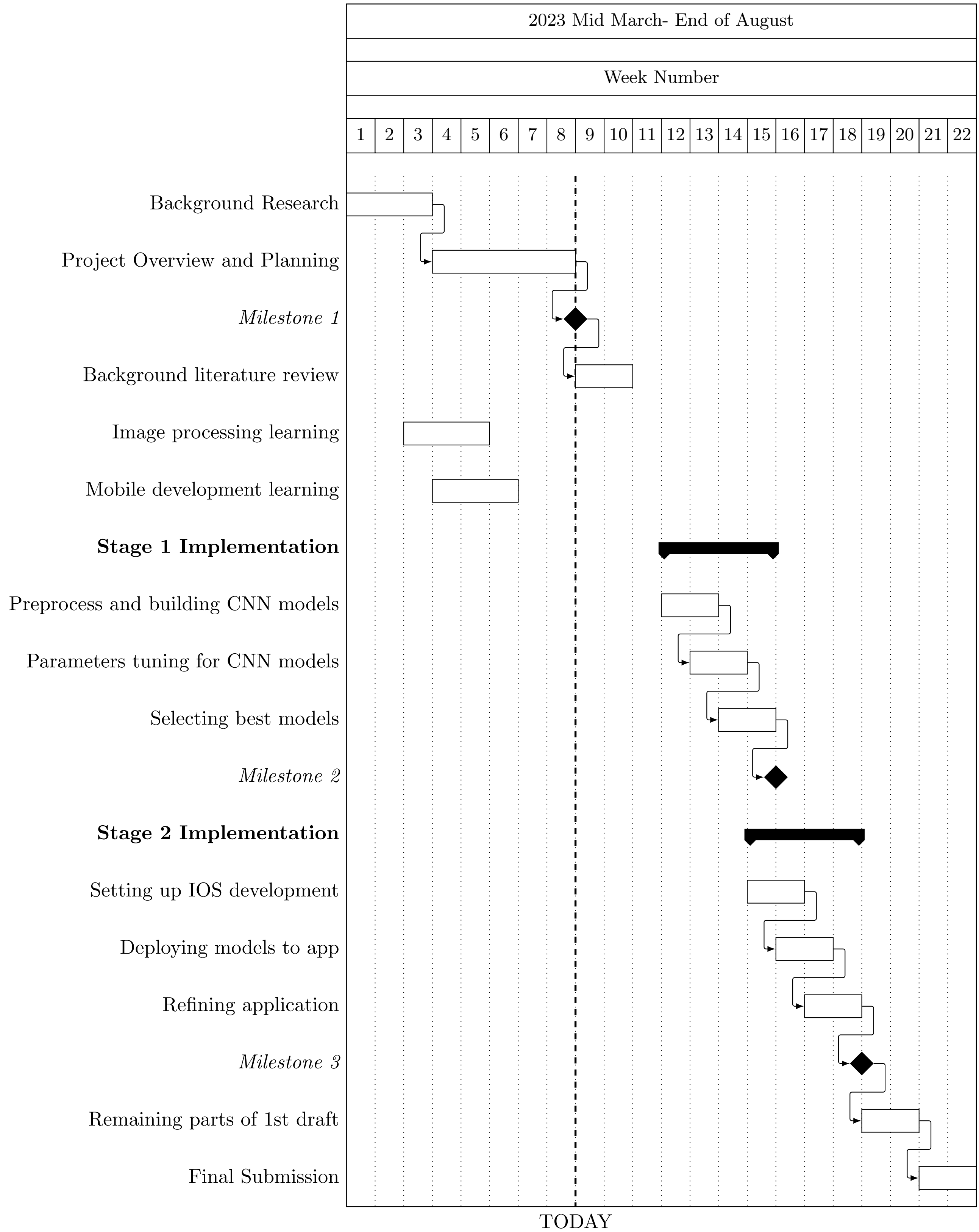

Figure 1: Gantt chart

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