# PLANT DISEASE SEVERITY CLASSIFICATION USING DEEP LEARNING

LEE SAN KONG

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Faculty of Engineering
Universiti Teknologi Malaysia

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## DEDICATION

This thesis is dedicated to my father, who taught me that the best kind of knowledge to have is that which is learned for its own sake. It is also dedicated to my mother, who taught me that even the largest task could be accomplished if it is done one step at a time.

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# ABSTRACT

Over the years, there are improvements in food accessibility and production. However, food security is a major concern in which various factors, such as plant diseases, threaten it. Plant diseases cause significant damage to the crops and substantially reduce food production. In the past, early detection of plant diseases is done by experts equipped with academic knowledge background and practical experience on plant symptoms. This process is complicated and time-consuming when it comes to the classification task of plant disease with a limited resource of knowledge and plant experts. Also, the current image analysis has a limitation of localizing and classifying diseases with almost the same and similar symptoms, such as early blight and late blight. This will impact the best treatment time for the plant before the disease spreading out. Hence, the objective of this work is to develop a high accuracy deep learning model that can classify early blight and late blight disease into low, mild, and severe levels based on transfer learning with ResNet. The process involves in this project is collecting leaf images of the diseased and healthy plant from the Plant Village dataset and classifying them into low, mild, and severe folders. With the dataset ready, the deep learning model is trained based on the transfer learning with ResNet. The model's parameters and training settings will be varied and optimized to enhance the accuracy of the model. Performance comparison will be made before and after the optimization. Based on the results, the best accuracy that has been archived by plant disease severity level classification system is 80.01%. Also, the recall rate achived by the system for low, mild and severe are 89.55%, 100%, and 76.32% respectively. This project will ease the process of classifying the severity level of the plant disease, which reduces the damage on the crops due to the early detection of the diseases.

# ABSTRAK

Setelah sekian tahun, terdapat peningkatan dalam pemprosesan dan pengeluaran makanan. Namun begitu, keselamatan adalah suatu kebimbangan di mana pelbagai faktor seperti penyakit tumbuhan menjadi ancamannya. Penyakit tumbuhan telah merosakkan tumbuhan dan secara langsungnya mengurangkan pengeluaran makanan. Terdahulu, proses pengesanan penyakit tumbuhan adalah dilakukan oleh pakar yang mempunyai latar belakang pengetahuan akademik dan pengalaman praktikal terhadap gejala tumbuhan. Proses ini amat rumit dan akan mengambil masa yang panjang terutamanya dengan kekurangan sumber pengetahuan dan bilangan pakar tumbuhan. Selain itu, analisa imej semasa amat terhad untuk proses penentuan kawasan dan mengklasifikasikan penyakit yang mempunyai simptom yang hampir sama dan serupa seperti "early blight" dan "late blight". Ini akan memberi impak yang besar kepada tumbuhan jika rawatan segera tidak diberikan sebelum penyakit tersebar ke bahagian tumbuhan yang lain. Oleh itu, objektif projek ini adalah untuk menghasilkan satu model pembelajaran mendalam berkejituan tinggi yang boleh mengklasifikasikan penyakit "early blight" dan "late blight" kepada tahap penyakit rendah, sederhana, dan teruk berpandukan konsep pemnidahan pembelajaran dengan model ResNet-50. Proses yang terlibat dalam projek ini adalah mengumpulkan imej daun tanaman berpenyakit dan sihat daripada set data "Plant Village" dan mengklasifikasikannya ke tahap penyakit rendah, sederhana dan teruk. Dengan set data tersebut, sebuah model pembelajaran mendalam akan dilatih berdasarkan pemindahan pembelajaran daripada ResNet-50. Parameter model dan tetapan proses latihan akan diubah-ubah dan dioptimumkan untuk meningkatkan kejituan model. Perbandingan prestasi akan dibuat sebelum dan selepas pengoptimuman. Berdasarkan keputusan, kejituan terbaik yang dicapai oleh sistem klasifikasi tahap keterukan penyakit tumbuhan ini adalah sebanyak 80.01%. Bukan itu sahaja, kadar penarikan semula yang dicapai oleh sistem tersebut untuk tahap penyakit rendah, sederhana, dan teruk adalah sebanyak 89.55%, 100%, and 76.32%. Projek ini akan memudahkan proses mengklasifikasikan tahap keterukan penyakit tumbuhan yang dapat mengurangkan kerosakan pada tanaman akibat pengesanan awal penyakit.

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| | | |
|---|---|---|
| DL | - | Deep Learning |
| CNN | - | Convolutional Neural Network |
| SL | - | Supervised Learning |
| DNN | - | Deep Neural Network |
| RNN | - | REcurrent Neural Network |
| MLP | - | Multilayer perceptron |
| RELU | - | Rectified Linear Units |
| ILSVRC | - | ImageNet Large Scale Visual Recognition Challenge |
| SVM | - | Support Vector Machine |
| HSV | - | Hue Saturation Value |
| ROI | - | Region of Interest |
| SIFT | - | Scale Invariant Feature Transform |
| LRN | - | Local Response Normalization |
| TP | - | True Positive |
| TN | - | True Negative |
| FP | - | False Positive |
| FN | - | False Negative |
| GUI | - | Graphic User Interface |
| GUIDE | - | Graphic User Interface Development Environment |

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# CHAPTER 1

# INTRODUCTION

## 1.1 Background of the Problem

Over the years, the advancement in technologies improves food accessibility and also food production in order to meet the food demand of more than 7 billion people[6]. However, food security remains a significant concern in which the plant diseases are among the threat. This is because plant diseases can cause considerable damages to the crops, resulting in decreasing food production[7]. On top of that, plant disease affects not only at the global scale, but also to the small-holder farmers in which their livelihoods depend heavily on the healthy crops. Studies shown that more than 80 percent of the agricultural production in the developing world actually comes from smallholder farmers, and it is reported that more than half of the yield loss is primarily due to pests and diseases. Early blight and late blight are common plant diseases that attack tomato and potato plants[8]. These two diseases attack the plants by slowly affecting the leaves, stems and finally the fruits. The attacked plants are not able to produce good yield. Therefore, it is crucial to protect the plants from diseases such as early and late blight to ensure the quality and quantity of the crops. Identifying the disease correctly when it first appears is an important step in efficient disease management.

## 1.2 Statement of the Problem

In the past, early plant disease detection is done by experts with strong academic knowledge and experience of disease symptoms. Moreover, continually monitoring the plants is needed to avoid spreading the disease to other plants[9]. The detection and monitoring process is complicated and time-consuming due to the limited amount of plant experts, and the justification would likely be error-prone and ineffective. Thus, it is crucial to make the process of plant disease detection and classification automated.

There are intensive studies on the plant disease detection and classification using image processing and machine learning. In the studies, the researchers successfully built the plant disease classifier using the images taken from the crops. However, the existing classifiers are built based on the hand-crafted features where the relevant information is extracted from the images. This information will be used to detect and classify the plant diseases. The drawback of these hand-crafted features is these disease classifiers are actually suffered from the lack of automation due to the heavy dependency on the hand-crafted feature[9]. The images used to train the classifiers come from manual labelling by the botanists. Factors such as high cost and time consuming for labelling has forced the researchers to train and test the classifiers with limited and small labelled datasets. This will lead to overfitting for the trained classifiers, resulting in inaccuracy of the plant disease detection. In the last decade, Deep Learning (DL) started to be used by the researchers to train the models, and they are applied in the plant disease detection area. As a result, the deep learning model shows competitive results if compared to the traditional hand-featured classifiers in terms of accuracy and training efforts. However, the existing deep learning model is immature, and it requires improvement in some practical cases. It is ineffective and found hard to localize multiple regions with the same or almost similar features of the plant disease. For instance, early blight and late blight disease are hard to be detected and differentiated as both symptoms are very similar and looked alike.

## 1.3 Objectives

The objective of this project is to develop a high accuracy deep learning model that can classify early blight and late blight plant disease into three severity levels based on transfer learning with ResNet. By using the proposed deep learning approach, the dependency on the hand-crafted features can be eliminated at the same time it is able to localize and classify the early blight and late blight images having multiple regions with the same or similar features.

## 1.4 Scope of Work

The scope of this project is to focus on the classification of the images of early blight and late blight plant disease into three different stages, which are low, mild and severe. Matlab is used as the training tool to develop deep learning model using transfer learning on ResNet. Fine tuning will be carried out during the model training from time to time by varying the training parameters in order to increase the model classification accuracy.

## 1.5 Thesis Outline

This project report is separated into five chapters. Chapter 1 is the project background, objectives, and followed by the scope of the study. Chapter 2 covers the literature review conducted for this project. The general background of deep learning and related prior works were thoroughly discussed. Also, the architecture of ResNet and transfer learning were presented. Chapter 3 is the research methodology of this project. In this chapter, the project flow of this project is proposed. The tools used and the proposed algorithm are presented. Chapter 4 presents the results obtained from the proposed system. Details analysis and interpretation on the results obtained as well as comparison with previous related works are presented. Lastly, the recommendation and suggestions for future works are discussed.

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