SALIENT MAP IMAGE FOR PLANT DISEASE USING DEEP LEARNING

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DEDICATION

This report is dedicated to my parent, who taught me always do one’s best and never to give up. It is also dedicated to my siblings, who made me stronger and better by providing the moral support to me throughout the entire period of the project.

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ABSTRACT

Plant diseases are a critical factor that impacts the yield and quality of crops and economics in the agricultural sector. This can shown in the incident of a fungal wheat disease in North Texas caused $250 million loss of revenue of the affected country in the year of 2001. Hence, there is essential in protecting the crops from diseases to ensure production quality and quantity. Early detection of the plant diseases is necessary, and it can help to prevent the spreading of the diseases by choosing an appropriate treatment for the plants. However, the process is often trailed by the lack of necessary infrastructure that offers simplicity in performing accurate classifications. Thus, rapid and accurate detection of plant disease through machine learning is essential to minimizing or averting this hardship. On top of that, the existing work does not segment the progression area of the disease on the leaf. In which, this area giving a lot of information on the disease. Especially to the pattern of disease symptoms that are very similar such as in the case of vegetable early and late blight is currently not given much consideration in the machine learning process. Hence, the objective of this project is to construct a salient map image that tracks the disease progression right from inception to manifestation following the pathological disease anatomy. Semantic segmentation with Convolutional Neural Network (CNN) is used to construct the salient map image, through transfer learning with SegNet. In this project, 460 images of early blight and late blight diseases plants from PlantVillage dataset is used for the training and testing processes of the CNN. Next, the training parameters are fine-tuned in order to optimize the deep learning model accuracy. At the end of the project, the deep learning model will be able to segment the leaf image into several regions with the overall accuracy of 89.567% and overall IOU of 52.5448%. Also, although the transfer learning on FCN with same data-set and training parameters has slightly better performance with overall accuracy of 89.91% and IOU of 53.92%, its main drawbacks of long model training duration and consumption of huge memory size has made SegNet more preferable in this project. With the gradient map image generated, the pattern of each disease manifestation along the leaf surface can be tracked and quantified for better understanding and characterization based on their anatomy.

ABSTRAK

Penyakit tumbuhan adalah faktor kritikal yang memberi kesan kepada hasil dan kualiti tanaman dan ekonomi dalam sektor pertanian. Ini dapat ditunjukkan dalam kejadian penyakit gandum di North Texas menybabkan $250 juta kerugian hasil pada tahun 2001. Pengesanan awal penyakit tumbuhan adalah penting untuk melindungi tanaman daripada penyakit untuk menjamin kualiti dan kuantiti pengeluaran. Namun begitu, proses ini amatlah rumit disebabkan kekurangan infrastruktur yang canggih untuk melakukan klasifikasi yang tepat. Oleh itu, pengesanan penyakit yang cepat dan tepat melalui pembelajaran mesin adalah penting untuk meminimumkan masalah ini. Tambahan pula, kerja yang sedia ada tidak mengenalpasti bahagian kawasan perkembangan penyakit pada daun di mana kawasan ini memberi banyak informasi dan maklumat penyakit. Bukan itu sahaja, corak gejala penyakit yang hampir serupa terutamanya dalam penyakit "early blight" dan "late blight" tidak diberikan pertimbangan lebih dalam proses pembelajaran mesin yang sedia ada. Oleh itu, matlamat projek ini adalah untuk membina imej peta ayata untuk menjejaki perkembangan penyakit dari awal hingga manifestasi berdasarkan anatomi penyakit patologi. Segmen Semantik dengan Rangkaian Neural Konvensional (CNN) digunakan untuk membina imej peta kecerunan, melalui pembelajaran pemindahan dengan SegNet. Dalam projek ini, 460 imej penyakit "early blight" dan "late blight" yang diperoleh daripada dataset PlantVillage digunakan untuk proses latihan dan ujian CNN. Seterusnya, parameter latihan dipertingkatkan untuk mengoptimumkan ketepatan model pembelajaran. Pada akhir projek ini, model pembelajaran mendalam dapat mengklasifikasikan imej daun ke beberapa kawasan mengikut formula kecerunandengan dengan keseluruhan ketepatan sebanyak 89.567% dan keseluruhan IOU sebanyak 52.5448%. Bukan itu sahaja, walaupun pembelajaran pemindahan pada FCN dengan menggunakan data dan parameter latihan yang sama mempunyai prestasi yang lebih baik dan ketepatan keseluruhan sebanyak 89.91% serta IOU sebanyak 53.92% berbanding dengan keputusan SegNet, tempoh latihan model yang lama dan keperluan saiz memori yang besar telah menjadi faktor kelemahannya. SegNet telah menjadi pilihan utama dalam projek ini. Dengan peta kecerunan ini, corak setiap manifestasi penyakit di permukaan daun dijejaki untuk pemahaman yang lebih baik berdasarkan anatomi mereka.

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LIST OF ABBREVIATIONS

US	-	United States
CNN	-	Convolutional Neural Network
DL	-	Deep Learning
MLP	-	Multilayer Perceptron
ReLU	-	Rectified Linear Unit
L	-	Lightness
RGB	-	Red,Green,Blue
HSI	-	Hue,Saturation,Intensity
UCS	-	Uniform Chromaticity Scale
LDA	-	Linear Discriminant Analysis
SVM	-	Support Vector Machine
IOU	-	Intersection Over Union
TP	-	True Positive
TN	-	True Negative
FP	-	False Positive
FN	-	False Negative

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CHAPTER 1

INTRODUCTION

1.1 Problem Background

Over the years, the agriculture sector has been rapidly grown, and it has become the primary source of food supply for the population. Moreover, it plays an important role in promoting economic development in many countries, such as China, India, and the United States (US) [9] [10]. For instance, the economic contribution of the agriculture sector in US is more than $300 billion every year [10]. According to the report from David and Marcel, the production of food needs to be increased by around 70% in 2050 in order to support the predicted population size of over 9 billion people [11]. However, there are numerous diseases that impact the plant's quality and yield [12]. On top of that, the yield of the crops is averagely decreased by 40% and as worst as 100% of yield losses due to the infectious diseases.

Also, there was a case of fungal wheat disease in North Texas in 2001, which caused about $250 million loss of revenue from the four affected countries [13]. Besides, the yield of crops is affected by the plant diseases, causing insufficient food, which will lead to famine and death in the worst cases. This is shown in the case where lots of potato plants were destroyed in Ireland during 1845 - 1850 due to late blight disease that attacked potato plants. As a result, famine cost about one million peoples' lives, and millions of other peoples were forced to emigrate to USA, Canada, and other countries [14]. Hence, it is important to protect the crops from diseases to ensure production quality and quantity. Early detection of the plant diseases is necessary, and it can help to prevent the spreading of the plant diseases by choosing an appropriate treatment for the plants at the early stage.

1.2 Problem Statement

An effective way to protect the plant in order to ensure the quality and quantity of crops production is to detect the plant diseases in the early stage. This is because a proper treatment can be applied to the infected plants at the correct time to refrain the disease from spreading and cause a greater loss [15]. Generally, the detection of plant diseases is based on visual examination methodologies in which pathologists will classify the leaf into several segments, and the illness of the leaf is identified according to the criteria on each of the segments. This process requires human expertise and labour-intensive to continually monitor the leaf of the plants which is very time-consuming and challenging for a human being [16] [17]. Hence, a system or machine that is able to identify the plant diseases automatically is crucial in order to prevent the disease from spreading to other parts of the plants [18].

In the research of plant analysis, the area and colour of the leaf are the main parameters that reflect the healthfulness and physiological processes of the plants [19] [20] [21]. The progression area on the leaf provides a lot of useful information about the physiological processes and diseases information of the plant. In the existing work, most of the automatic disease identification approaches do not segment the progression area on the leaf but instead uses the whole image to extract features and identify the diseases. This results in low accuracy for diseases with almost similar symptoms, such as in the case of early and late blight.

1.3 Objective

The goal of this project is to construct a gradient map image that tracks the plant disease by using deep learning technique. The gradient map image is a way to segment the leaf image into meaningful regions. The reliance on handcrafted topographies can be removed by applying the deep learning approach. Figure 1.1 shows the sample of gradient map image that shows the disease progression area in light green color region.

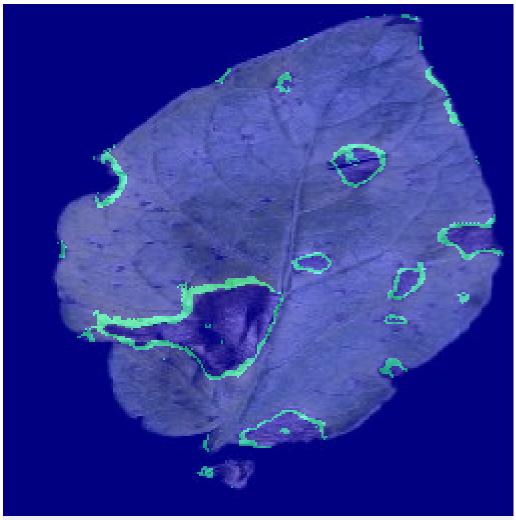

Figure 1.1: Example of gradient map image that shows the disease progression area.

1.4 Scope of Work

This project is concentrated on the segmentation of leaf images into two regions on leaf images. The name of region is labelled as "foreground" for the progression area or salient area and "background" for the non-progression area respectively. The plant leaf images used in this project is obtained from a well known public database– PlantVillage as PlantVillage has released over fifty thousand proficiently curated images on diseases and healthy leaves of different crop plants through online platform. Throughout this project, total number of 460 segmented potato and tomato plant leaf images from PlantVillage with early and late blight diseases are used for transfer learning with SegNet.

1.5 Thesis Outline

This project report is divided into five chapters, which are: 1.) introduction, 2.) literature review, 3.) research methodology, 4.) results and discussion, and 5.) conclusion respectively.

In Chapter 1, an introduction of this project is discussed, followed by the problem background, problem statement, objective, and scope of this project. The early part of this chapter is discussed about the motivation of this project and followed by the challenges or problems that are existed in the current plant disease identification approaches. Next, the objective and the scope of this project are discussed in detail.

In Chapter 2, the background of research materials that are related to this project is studied thoroughly. A background of deep learning (DL) and convolutional neural network (CNN) are discussed in the early part of chapter 2. Related works that were done by other researches are presented in chapter 2 as well.

Chapter 3 covers the details of the methodology of the project development. This chapter describes the flow, algorithm, and tools that are used in this project.

In Chapter 4, detail discussions and analysis of the results obtained from this work are presented. The results obtained from this work are illustrated in table and graph forms for analysis and discussion purposes.

In Chapter 5, the summary of this project is reviewed. Besides, the further development of this work is discussed in this chapter as well.

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