PLANT LESION BOUNDARY DELINEATION USING LIGHTWEIGHT DEEP LEARNING WITH TWEAKING MECHANISM

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DEDICATION

This project report is dedicated to my family, who have supported me unconditionally throughout the process. They have taught me the value of hard work and unceasingly encourage me to strive towards excellence.

This is also for my siblings who have motivated me mentally and cognitively to be prepared for the erratic challenges.

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ABSTRACT

Ever since the dawn of agriculture, the devastating consequences of plant disease inevitably impacted the crop cultivation quantitatively and qualitatively. One of the plant disease incidents happened in 2007 in Georgia which lead to a $539.74 million loss in the total revenue. Intuitively, it is essential to tackle the disease outbreaks as early as possible to diagnose the underlying cause. The detection and classification of diseases carried out by the plant pathologists are subjected to cognitive error. To alleviate direct human intervention, machine learning is undoubtedly the key to avert this downfall. Over the years, numerous neural networks have been proposed to improve the existing state-of-art. Nevertheless, minimal works have been done on segmenting the region of the disease from the leaf. On the other hand, one of the inherent issues in machine learning is "What is the optimal configuration for the network to gain the highest performance?". Many researchers are probing, but no single solution can cater to all the models built for different purposes. The concept of fine-tuning is a critical step which generally left out of discussion due to divergence in solution. Hence, the first objective is to build a semantic segmentation network that create a salient map image tracking the boundary of the disease. The second objective is to regularize and optimize the built network to identify the optimal configuration. SegNet's fully convolutional architecture with transfer learning is chosen as the semantic segmentation network. A total of 1000 early and late blights of potato and tomato samples from PlantVillage are fed to the model. To capture the best network, optimizers such as SGD, RMSProp and Adam are benchmarked with regularization techniques such as adaptive learning rate, dropout layer and weight & bias rates re-initialization. Afterwards, hyperparameters such as mini-batch, initial learning rate, momentum, gradient, L2 regularization, number of samples and number of epochs are tuned progressively. Throughout the tweaking process, the global accuracy and mean IoU have increased from 86.96% and 50.72% to 93.86% and 60.24% respectively. In addition, the comparison between SegNet and FCN has proven that the former architecture is lightweight and powerful in delineating the boundary of plant lesion. With the delineated lesion's boundary, the manifestation along the leaf surface can be traced and appraised for pathological anatomy.

ABSTRAK

Sejak zaman pertanian awal, akibat buruk daripada penyakit tanaman telah mempengaruhi penanaman tanaman secara kuantitatif dan kualitatif. Salah satu insiden penyakit tanaman berlaku pada tahun 2007 di Georgia yang mengakibatkan kerugian keseluruhan $539.74 juta. Secara intuitif, mencegah wabak secepat mungkin adalah penting untuk mendiagnosis masalahnya. Pengesanan dan klasifikasi penyakit yang dilakukan oleh ahli patologi tumbuhan dipengaruhi oleh kesalahan kognitif. Untuk mengurangkan kesilapan manusia, pembelajaran mesin merupakan kunci mengelakkan kelemahan ini. Selama bertahun, banyak rangkaian neural telah dicadangkan untuk memperbaiki kaedah sedia ada. Walaubagaimanapun, hanya sedikit kerja yang telah dilakukan untuk mengsegmentasikan kawasan penyakit dari daun. Selain itu, salah satu masalah yang wujud dalam pembelajaran mesin adalah "Apakah konfigurasi optimum untuk sesuatu rangkaian memperoleh prestasi tertinggi?". Banyak penyelidikan telah dijalankan tetapi tiada satu penyelesaikan boleh memenuhi setiap model yang dibina untuk tujuan berbeza. Konsep talaan-halus adalah langkah kritikal yang biasanya diabaikan kerana perbezaan dalam penyelesaian. Oleh itu, objektif pertama adalah untuk membina rangkaian segmentasi semantik untuk membina imej peta kecerunan. Objektif kedua adalah "regularize" dan "optimize" rangkaian untuk mendapatkan konfigurasi yang optimum. Rangkaian Neural Konvolusi (CNN) dengan kaedah pembelajaran di SegNet telah dibina dengan 1000 imej penyakit "early blight" dan "late blight" kentang dan tomato daripada set data PlantVillage. Untuk memdapatkan rangkaian yang terbaik, optimizers seperti SGD, RMSProp dan Adam telah dilaksanakan teknik "regularization" seperti "adaptive learning rate", "dropout layer" dan "weight & bias rates re-initialization". Selepas itu, hiperparameters seperti "mini-batch", "initial learning rate", "momentum", "gradient", "L2 regularization", "number of samples" dan "number of epochs" telah disuaikan. Pada akhir talaan-halus, ketepatan dan mean IoU meningkat daripada 86.96% dan 50.72% kepada 93.86% dan 60.24%. Selain itu, perbandingan antara SegNet dan FCN menunjukkan bahawa SegNet yang lebih ringan dan berkuasa dalam sempadan segmentasi. Dengan peta kecerunan, corak setiap manifestasi penyakit di permukaan daun dijejaki untuk pemahanan yang lebih baik berdasarkan anatomi pathologi.

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LIST OF ABBREVIATIONS

CNN	-	Convolutional Neural Network
RGB	-	Red Green Blue
HSV	-	Hue Saturation Value
MLP	-	Multilayer Perceptron
ReLU	-	Rectified Linear Unit
MNIST	-	Modified National Institute of Standards and Technology Database
DNN	-	Deep Neural Network
VGG	-	Visual Geometry Group
FCN	-	Fully Convolutional Network
BPNN	-	Back-propagation Neural Network
AET	-	Adjustable Exponential Transform
GLCM	-	Gray Level Co-occurrence Matrix
CCD	-	Charged-coupled Device
HSI	-	Hue Saturation Intensity
RIA	-	Ratio of Infected Area
RCA	-	Rust Color Index
LBPH	-	Local Binary Pattern Hue
GWT	-	Gabor Wavelet Transform
SVM	-	Support Vector Machine
DIGITS	-	Deep Learning GPU Training System
DCNN	-	Deep Convolutional Neural Network
PSO	-	Particle Swarm Optimization
GBDT	-	Gradient Boosting Decision Tree
CIFAR	-	Canadian Institute for Advanced Research
SGD	-	Stochastic Gradient Descent
RMSProp	-	Root Mean Square Propagation
Adam	-	Adaptive Moment Estimation
GPU/CPU	-	Graphics/Central Processing Unit
API	-	Application Programming Interface

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CHAPTER 1

INTRODUCTION

1.1 Problem Background

For decades, the agricultural sector plays a critical role in the national economy in developed countries, the US and China. In the US, it is estimated to produce around $330 billion per year, accounting both agricultural and livestock [1]. For developing countries such as Nigerian, a comparative analysis was conducted to realize that the contribution of agriculture outweighed both petroleum and manufacturing sectors [2, 3]. A study in the US [4] claimed that there is a need to raise food production by almost 70% by 2050 to cater for 9 billion population. Nevertheless, [5] demonstrated that the food supply decreases on an average of 40% annually despite the enforced protection against infectious diseases. In a small farm, the farmer can easily yield 80% to 100% loss due to pests and diseases. In 2007, a statistic report in Georgia [6] showed that the plant disease has contributed to $539.74 million losses which were 11.03% of the total revenue.

Phytophthora infestans is a microorganism that brings early and late blights to the essential horticulture commodities such as potato and tomato. One of the infamous late blight disease of potato incident occurred in 1845-1849 [7], the main crop potatoes were destroyed due to the outbreak of plant disease in Ireland. The resulted from Great Famine leads to a million of deceases and another million of emigrations. Phytophthora infestans rapidly became pandemic and remains as one of the most intractable plant diseases today. In consequence, it is crucial to prevent history from repeating itself. To enable the early treatment of early and late blights, early detection of such diseases is important so that the root of causes can be removed before wide-spreading.

1.2 Problem Statement

The obsolete technique practiced for early detection was through naked eye observation. [8] criticized this manual method to identify leaf spot diseases is highly stochastic, time-consuming and insensible in a large farm. A paper summarized the traditional techniques in capturing the plant disease up to 2015 [9]: Direct detection method utilizes the serological to analyze the pathogens; Indirect detection method identifies the external parameters of infected plants; Portable sensors to detect the analytes electrically or chemically. The work in [10] outlined the advantage of deep learning against the traditional technique such as the image-based samples, low-cost real-time application and surrounding-adaptive. As the classification networks have hit the bottleneck due to the inability to identify the location, size, shape and color of the disease region, segmentation of disease symptom from leaf becomes one of the key focus. A few studies [11, 12] in plant science claimed that the leaf area and color are the potential parameters to reflect the plant health and physiological process. Rather than the whole region of disease, the boundary of the disease does impart essential information for the pathologist to study. [13] facilitated the segmentation process by converting RGB into HSV, this effectively eliminates the issue of different illuminations.

The existing segmentation networks are computational exhaustive due to the massive memory consumption during the up-sampling stage in the decoder. The consequence is a redundant network training phase and subpar adaptivity in a portable device. In this work, the input image will be segmented into disease boundary and non-disease boundary through the lightweight deep learning to provide more constructive information and ease the diseases' classification process. Moreover, an exhausting endeavour exists in deep learning is to find the optimum configuration for a network designed for a specific purpose. [14, 15] claimed that the efficiency could be further improved by fine-tuning CNN for plant identification. Therefore, regularization and optimization techniques (tweaking mechanism) will be applied to the designed deep neural network to identify the best configuration to achieve the highest accuracy with a limited number of samples.

1.3 Research Objectives

The objectives of this project are:

- To build a lightweight semantic segmentation network using deep learning architecture to detect early and late blights on potato and tomato.
- To output a salient map image which outlined the size and shape of the disease boundary.
- To study the effect of network's accuracy using regularization and optimization techniques.

1.4 Scopes of the Study

The scopes of this project are:

- To segment the leaf image into 2 classes: 'foreground' and 'background' to extract the salient area.
- To prepare the dataset for segmentation using the leaf image from PlantVillage online database.
- To design the network using SegNet architecture through transfer learning using MATLAB R2019a.
- To implement the training model using a personal laptop with Intel Core I7 8th Gen and a NVIDIA GeFORCE GTX 1060.

1.5 Outline of Project Report

This project report is broken down into 5 chapters: Introduction; Literature Review; Research Methodology; Results and Discussion; Conclusion and Recommendations.

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