AUTOMATED ASSESSMENT FOR EARLY AND LATE BLIGHT LEAF DISEASES USING EXTENDED SEGMENTATION AND OPTIMIZED FEATURES

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DEDICATION

Specially dedicated to my Mom and Dad,

Whom without I could not have gained my achievements,

and find myself in the position that I am today.

I really love both of you.

Alhamdulillah.

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ABSTRACT

Early and late blight diseases lead to substantial damage to vegetable crop productions and economic losses. As a modern solution, machine learning-based plant disease assessment aims to assess the disease incidence and severity through the disease region of interest (ROI) and its extracted features. In the case of existing conventional classifier methods, extracting the features involves generalized ROI segmentation that loosely follows the disease inference. As a result, accuracy is reduced, and the fuzzy boundary region that carries potential properties for improving feature characterization capability is truncated from the ROI. Besides, most of the existing practices extract only the global features, This leads to redundant and extensive feature vector, which causes increased complexity and underperformance. Furthermore, individual lesion severity is not considered in the assessment. This thesis addresses the issue of the ROI segmentation by using color thresholding based on ratios of leaf green color intensity to incorporate the fuzzy boundary region, denoted as extended ROI (EROI). Secondly, the issue of the feature extraction is addressed by the proposed localized feature extraction method to reduce complexity and improve disease classification performance. Based on the color and texture morphological properties of the individual lesions within the EROI, color coherence vector and local binary patterns features are extracted. As a result, a pathologically optimized feature vector is obtained, which is used to build a support vector machine classifier to classify between the disease types of early blight, late blight, and healthy leaves. lastly, a 2-tier assessment is proposed. The disease type classification is given as the first tier, while the leaf lesion area ratios of the individual lesions are given as severity quantification for the second tier. Overall, the proposed EROI segmentation method reduced under-segmentation by up to 80%. The proposed optimized feature reduced the execution run-time by up to 50% and achieved an average classification performance of up to 99%. Finally, the quantified severity is in close agreement with the ground truth by achieving an average accuracy of 93%.

ABSTRAK

Penyakit hawar awal dan hawar akhir menyumbang kepada kerosakan besar hasil tanaman sayur-sayuran dan impak kerugian ekonomi. Sebagai penyelesaian moden, penilaian penyakit tumbuhan berasaskan pembelajaran mesin bertujuan untuk menilai insidens dan keparahan penyakit melalui kawasan penyakit (ROI) dan ciri-ciri yang diekstrak daripadanya. Daripada pengelas konvensional sedia ada, pengekstrakan ciri melibatkan segmentasi ROI umum adalah berdasarkan inferens penyakit secara kasar. Akibatnya, ketepatan menurun dan kawasan sempadan kabur yang berpotensi untuk meningkatkan kemampuan pencirian terpangkas daripada ROI. Selain itu, kebanyakan amalan sedia ada hanya mengekstrak ciri global. Ini membawa kepada vektor ciri yang bertindih dan ekstensif, menyebabkan pertambahan kompleksiti dan prestasi rendah. Tambahan pula, keparahan belur individu tidak dipertimbangkan dalam penilaian. Tesis ini menangani masalah segmentasi ROI tersebut dengan menggunakan pengambangan warna berdasarkan nisbah intensiti warna hijau daun untuk mengambilkira kawasan sempadan kabur. Keduanya, isu pengekstrakan ciri ditangani dengan mencadangkan kaedah pengekstrakan ciri secara lokal bagi mengurangkan kompleksiti proses dan meningkatkan prestasi klasifikasi penyakit. Berdasarkan sifat morfologi warna dan tekstur kawasan belur individu dalam EROI, ciri vektor koheren warna dan corak binari tempatan diekstrak. Hasilnya, vektor ciri yang dioptimumkan secara patologi diperoleh, seterusnya digunakan untuk membina pengelas mesin vektor sokongan bagi mengelas antara jenis penyakit hawar awal, hawar akhir dan daun sihat. Yang terakhir, 2 peringkat penilaian dicadangkan. Klasifikasi jenis penyakit dilaksanakan pada peringkat pertama, sementara nisbah kawasan belur daun pada belur individu dilaksanakan sebagai pengkuantitian keparahan untuk peringkat kedua. Secara keseluruhannya, kaedah segmentasi EROI yang dicadangkan telah mengurangkan segmentasi rendah sehingga 80%. Ciri lokal yang dicadangkan telah mengurangkan masa jalan pengekstrakan sehingga 50% dan mencapai prestasi klasifikasi purata sehingga 99%. Akhirnya, tahap keparahan yang diukur adalah hampir dengan kebenaran asas dengan mencapai ketepatan purata 93%.

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LIST OF ABBREVIATIONS

ACC	-	Accuracy
ANN	-	Artificial Neural Network
ANFIS	-	Advanced Neuro-Fuzzy Inference
APS	-	American Phytopathological Society
C-C	-	Connected Components
CC	-	Conventional Classifier
CCD	-	Charge-Coupled Device
CCV	-	Color Coherence Vector
CIE	-	International Commission on Illumination
CNN	-	Convolutional Neural Network
CR	-	Coherence Region
DL	-	Deep Learning
DNN		Deep Neural Network
EB	-	Early Blight
EROI	-	Extended Region of Interest
FN	-	False Negative
FP	-	False Positive
FT	-	Fine Tuning
FV	-	Feature Vector
GA	-	Genetic Algorithm
GLCM	-	Gray-Level Co-occurrence Matrix
GOA	-	Grasshopper Optimization Algorithm
GPU	-	Graphical Processing Unit
HIS	-	Hue Saturation Intensity
HL	-	Healthy
HSV	-	Hue Saturation Value
INIBAP	-	International Network for the Improvement of Banana and Plantain
IRRI	-	International Rice Research Institute
K-NN	-	K-nearest neighbour

Lab	-	Lightness Green-Red & Blue-Yellow
LB	-	Late Blight
LBP	-	Linear Binary Patterns
LDA	-	Linear Discriminant Analysis
LLR	-	Leaf Lesion Ratio
MD	-	Mahalanobis Distance
MDC	-	Minimal Distance Criterion
ML	-	Machine Learning
MLP	-	Multi-layer Perception
NB	-	Naïve Bayes
NN	-	Neural Network
NPE	-	Nearest Percentage
PSO	-	Particle Swarm Optimization
RBF	-	Radial Basis Function
RGB	-	Red Green & Blue
SAD	-	Standard Area Diagram
sgd	-	Stochastic Gradient Descent
SVM	-	Support Vector Machine
TN	-	True Negative
TP	-	True Positive
TL	-	Transfer Learning
DLC	-	Deep Learning Classifier
PSO	-	Particle Swarm Optimization
PV	-	Plant Village
ReLU	-	Rectifying Linear Unit
RNN	-	Recurrent Neural Networks
RST	-	Rough Set Theory
ROI	-	Region of Interest
SIFT	-	Scale-Invariant Feature Transform
UTM	-	Universiti Teknologi Malaysia
WLA	-	Whole Leaf Area

LIST OF SYMBOLS

m	-	Segmentation Mask
ξ	-	Xi
π	-	Pi
α	-	Alpha
β	-	Beta
γ	-	Gamma
I	-	Image
r	-	Ratio Percentage
R	-	Region
t	-	Threshold
$\mathbb{R}$	-	Real Number
p	-	Pixel

CHAPTER 1

INTRODUCTION

1.1 Introductory Background

There is over 37% of the world's total land surface that is being cultivated for crop production [1], and one of the most significant scientific researches in precision agriculture is plant disease assessment [2-5]. According to the Food and Agriculture Organization data, the human population is said to reach over 10 billion by 2050, with over 60% living in Africa and Asia [6]. Food production must effectively double from current levels each year to sustain the food demand [7]. This can be realizable either by the amount of cultivation of land or by enhancing throughput through the adoption of precision farming [8]. It is a key component that assesses variabilities in plants for better crop productivity through agricultural technologies [2, 3]. These variabilities are the negative impact of growth and production due to climate conditions (abiotic stress) and living variables (biotic stress). Over the past century, precision farming has gone through an agricultural revolution with rapid advancements in crop breeding and new methods of genetic modification for sustainability [9]. In effect, and as determined by the balance of this revolution, global food security has now become among the foremost international issue in recent years due to crop losses [10, 11]. For centuries, losses due to biotic stress such as insects, viruses, and fungi have been increasingly persistent issues, where 70% to 80% of these losses are attributed to pathogens [11, 12]. Some diseases caused by these pathogens, such as the early and late blight, are challenging to control and can lead to famine once they reach a certain level of severity [11, 13]. Rapid climate change and varying weather conditions contribute significantly to the spawn, mutation, and spread of various plant diseases. Notably, viral plant diseases are a great menace affecting both home gardeners and large productions [10, 11, 14].

As a crucial part of precision farming, the assessment of plant diseases, referred to as *modern phytopathometry*, primarily deals with the assessment of the diseases in plants by using different methods of symptom observation [11, 15, 16]. The symptom area on the plant unit, typically referred to as a region of interest (ROI), is the primary identifier of disease incidence. Thus, the observations involve the classification of the disease type and the measurement or quantification of its severity based on the ROI. The traditional methods of assessment involve using biochemical and molecular systems and innovative methods such as using biomarkers and remote sensing, which can have a direct or indirect way of symptom observation.

The traditional indirect methods include serology and molecular-based methods, often carried out in the laboratory, while the direct methods include biomarker and plant properties-based [9, 12, 17]. On the other hand, direct and indirect innovative methods identify the pathogens-related plant diseases through various parameters such as biomarkers and volatile organic compounds (*spores*) released by infected plant units [9, 17]. Other tools such as biosensors and optical cameras are used to encode the parameters into other forms of information data such as images, which can then be interpreted using standard and innovative systems of assessment. Some of the standard systems include the widely regarded pictorial or descriptive keys [9, 18]. Reasonably experienced individuals can interpret the encoded data into different findings ranging from disease incidence, type, severity, and the effect on crop growth. Over the last 80 years, different types of these standard area diagrams (SADs) are traditionally used for assessment and have now been combined with innovative image analysis algorithms to offer accurate disease assessments [12, 19]. These new innovative technologies offer flexible opportunities to assess plant diseases with a prompt response and greater objectivity in terms of precision, reliability, and accuracy.

The new innovative machine vision systems are non-destructive systems of plant disease assessment that efficiently assess plant diseases at advanced levels and with greater objectivity using pattern recognition [9, 20]. They have been increasingly used over the last 30 years [16, 21, 22]. Traditional direct assessment of diseases based on the ROI properties is mimicked by the machine learning (ML)-based methods. The disease classification is typically performed through the extraction of a feature vector and ML classifiers, and the determination of severity through ROI quantification [4, 9, 20]. The feature vector contains feature descriptors, which are typically extracted from the ROI and used to build the ML classifier for classification. These methods can provide information on disease assessment to help control the spread of plant diseases, with little or no human supervision. Visible-light images are among the main raw materials in using such assessment methods [3, 4]. These are images of diseased fields, plants, or leaves, sourced from either satellite imagery, sensors, or even cameras positioned in fields. Several research activities that have been conducted are towards the development of such technologies to create practical tools for a large-scale and even real-time disease assessment [4, 22-24]. Hence, the ML-based methods have now become the driving forces being used to close the gap that exists between traditional and innovative systems of plant disease assessment.

1.2 Research Background

The four dominant solanaceous plant species widely considered as vegetables, which include the tomato, potato, pepper, and eggplant, are rich sources of vitamins and minerals vital to human health [25, 26]. These plant species represent more than 60% of horticultural production in Europe alone and about 39% globally. They are also considered among the world's most important crops [26] but are also highly susceptible to diseases due to large productions and adaptability. Hence, lately, much attention is given to plant research within this domain. Therefore, advanced ML-based plant disease assessment methods have become imperative. However, not many of these methods for the early and late blight viral disease category exist.

According to the literature, there are two main approaches in implementing the ML-based methods, which are deep learning classifier (DLC) and conventional classifier (CC) [21, 22, 27]. The principle process in both approaches involves three stages, of which feature extraction is the most crucial that determines the performance of the entire method because it relates to how the disease patterns are identified, learned, or interpreted [20]. Correct identification of the ROI leads to a good feature vector and improved classification [4, 5]. Current studies in this context are focusing on solutions to improving performance via the feature extraction stage. These include enhancement of feature learning in the DLC methods and improving the accuracy of ROI segmentation and the quality of feature vectors in the CC methods. However, another difficult challenge to address is the significant degree of similarity that exists between some viral disease symptoms, such as that of early and late blight [28, 29]. In such cases, there is increased difficulty and subjectivity in the correct identification and segmentation of the ROI. Furthermore, most of the existing researches are focused mainly on the disease classification aspect of the plant disease assessment without consideration of severity quantification [17, 30]. Thus, there is still a gap between the traditional real-world methods of plant disease assessment and the existing ML-based methods.

1.3 Problem Statement

There is a lack of precision in the way the ROI is segmented, which is attributed to the issue of symptoms to healthy tissue transition boundaries [31, 32]. Viral diseases such as early and late blight have symptoms that are often similar and observe blur cross-over borders that slowly transition into the healthy tissue [28, 33]. These fading transitions are the fuzzy boundary regions separating the ROI and the healthy tissue. It is neither a healthy or disease tissue but characterized as a fuzzy greenish zone for which either classification (healthy or diseased) can be applied [32]. These regions significantly affect the boundary limit of segmentation as the darker symptoms are generally prioratized in existing segmentation methods. As a result, the fuzzy boundary region is often discarded by the genaralized ROI segmentation algorithms and affect the effectiveness of the ROI in producing quality feature vectors for disease classification. However, the research in this study hypothesized that the fuzzy boundary region carries some information that will improve the disease characterization capability of the extracted features. Hence, different levels of subjectivity and disparate accuracy still exist, mainly due to loosely characterized algorithm implementations on the true pathological inference used in traditional plant disease assessment methods [30, 31].

Even with good ROI segmentation, typical ML-based methods extract the disease patterns as global features from the ROI as a whole [4, 34, 35], often resulting in an extensive feature vector with 100s of descriptors, most of which are redundant and negatively affect disease classification performance. As a result of this, low accuracy still exists. In such cases, other existing works use complex optimization algorithms to optimize the feature vector, which then reduces the feature vector size and some improved performance. Even then, the optimization compounds on the method complexity often without significant performance improvement.

As practiced by Raters, severity quantification is typically based on the quantified progressive area of ROI lesion in comparison to the total area of the leaf [19]. Most of the existing ML-based methods are not in close agreement to this standard and have not given actual value for agreement comparison with the traditional methods [2, 17, 36, 37]. Hence, the synergy between ML-based methods and plant pathology for severity quantification is still lacking. Furthermore, regardless of its importance in post-processing [16], the severity quantification based on individual ROI lesion is not being prioritized. Therefore, using optimized features and localized ROI, this research aims to provide an automatic 2-tier plant disease assessment method for improved classification performance and individual lesion severity quantification.

1.4 Research Questions

1. Early & Late blight symptoms have significant degree of similarity between them and exhibit the fuzzy boundary region across the vegetable species. Consider the fuzzy bounbary region as part of the ROI, how can the extended ROI be segmented and localized?

2. The decision-making ability of experts is often not properly portrayed in characterizing the EB and LB diseases and providing accurate severity. By taking

advantage of the localized EROI, how can knowledge from expert pathologists' point of view be implemented for extracting optimized features to improve characterization while maintaining no more than 15 features with less complex algorithms?

3. Which ML classifier Model architecture determines the computational power, and training data are also extremely vital in the relevance of image processing-based plant disease detection algorithms. Using the acquired features and localized regions, which machine learning model can best be used to provide improved classification performance and individual lesion severity?

1.5 Objectives of Study

The hypothesis derived in this study is that the fuzzy boundary region carries important disease characterization information for feature optimization and improved classification performance. Hence, the research objectives are given as follows:

1. To develop ROI segmentation and lesion localization algorithms that incorporate the fuzzy boundary region based on the pathological inference of vegetable early and late blight disease symptoms for feature extraction optimization.

2. To improve performance and reduce complexity in the ML classification using a pathologically optimized feature vector based on localized feature extraction and the morphological properties of the ROI lesions.

3. To develop a 2-tier assessment method for disease classification with three severity levels (mild, moderate, severe) of the early and late blight diseases based on the leaf lesion ratio of the localized lesion regions.

1.6 Scope of Study

The scope of the study includes the following:

1. The study in this thesis uses visible light image data from the PlantVillage dataset [38], which comprises over 54,000 leaf images of several plant species. Only the 2,400 pre-processed images of potato and tomato healthy and diseased (early blight and late blight) leaves are considered. The illumination is uniformly fixed in all images.

2. K-nearest neighbor (K-NN), Naïve Bayes, and Support Vector Machine (SVM) ML classifiers are used as the CCs for implementation. AlexNet, ResNet-50, and NasnetLarge are used as the DLCs for benchmarking.

3. The disease severity is given in three levels of mild, moderate and severe based on leaf lesion ratios of the localized lesion regions. All implementations of the proposed algorithms in this study are applied using the MATLAB software.

1.7 Research contributions

The contributions of this study are stated as follows:

1. Development of an algorithm for ROI segmentation and individual lesion localization with the incorporation of the fuzzy boundary region based on the pathological inference of vegetable early and late blight plant diseases.

2. The conceptualization and implementation of a localized feature extraction method with respect to individual lesion region morphological properties for minimization of the feature vector length and improved ML-based disease classification performance.

3. The acquirement of disease severity based on quantified proportions of individual leaf lesion ratio (LLR) for 2-tier assessment.

1.8 Thesis Outline

This thesis has been organized into five chapters. The content of each chapter is organized as follows:

Chapter 1: General introduction to precision farming and the effects of plant diseases, as well as the methods of plant disease assessment, are given in this chapter. The research background, problem statements, objectives, scope, and research contributions with respect to the undertaken research are also presented.

Chapter 2: The literature review on the pathological background of early and late blight diseases, their characteristics relative to the vegetable plants is presented along with the traditional methods of the disease assessment. Techniques and methods carried out by previous researchers are also discussed in this chapter, which includes progresses achieved and existing problems.

Chapter 3: This chapter details the proposed ROI segmentation and localization, localized feature extraction, and severity quantification methods. Following the established analogies in Chapter 2, the different techniques, algorithms and methods used in development of the study methodology are presented.

Chapter 4: The detailed implementation results, the analysis, and discussions of the proposed 2-tier ML-based plant disease assessment method are presented in this chapter. Benchmarking and performance comparison with other methods and existing works are also given in this chapter.

Chapter 5: This chapter concludes the thesis along with suggestions for future work based on the derived analogies and obtained results.

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LIST OF PUBLICATIONS

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