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Quantification and Localisation of Individual Leaf Disease Lesion for Grading Severity of Late Blight

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Abstract. Detecting incidence and grading the severity of plant diseases caused by pathogens is among the essential activities in precision agriculture. This research proposes novel noetic integration between pathology and advanced yet straightforward image processing technique for grading the severity of vegetable late blight. Until recently, most of the presented image processing techniques had been, and some still are, grading severity based on the visual understanding of disease symptom as a single lesion colony. One of the most significant advantages of the proposed method is quantifying and localising disease symptom colonies into symptomatic and necrotic in accordance with pathological disease analogy for actual severity grading. In the 1st phase of the study, individual symptomatic (RS), necrotic (RN), and blurred (RB, in-between healthy and symptomatic) regions were identified and segmented. The isolated diseased lesions are then quantified and localised for correlation with a standard area diagram which gives the accurate grading of disease severity. Results obtained indicated great potential for accurate grading by which pathological knowledge and advance computer network operate in proper synergy. It is also envisaged that this research method would provide meaningful insight into the critical current and future role pathological integration in machine learning for food security.

1. Introduction

The detection and grading of plant disease is a crucial part of precision agriculture that essentially deals with the observation of the earliest stages of diseases in plants [1, 2]. Through this process, the outcome can be used for disease diagnosis, control, and damage assessment [3]. Furthermore, the information can also help in the application of disease-specific remedy or chemical applications such as pesticide and fungicide for improved productivity and avert losses that can range into billions [2, 4-7]. From literature, disease grading is referred to as phytometry the measurement and quantification of plant disease [8, 9]. In other words, disease assessment is the process while phytometry is the theory and practice. In pathology, the traditional also a most popular method of grading is based on visual estimations, consisting of “evaluations that raters give based on their observation of plant symptoms” [9]. However, the process is marred with subjectivity [8-10]. Another popular method is by using ratio scales and standard area diagrams (SADs) [11], both of which find frequent use in processes of disease assessment. Through the integration of pathological knowledge, the great potential for the success of digital technology-driven machine learning techniques will motivate easier and faster development and control in herbicide applications and even in crop loss assessment [2, 12, 13].



There have been several works of literature in the application of digital technology using images in agriculture and other plant sciences, and sadly there is a lack of necessary consideration to synergise the integration for disease severity measurements [14-16]. Earlier Pioneers demonstrated the capacity of image analysis to measure disease severity such as that of Lindow and Webb (1983) and Lindow (1983)[14, 17]. The authors attempted to utilise the factors that influence disease assessment which is the number of lesions, actual area (of disease), and sometimes leaf size even though the lesion number and leaf size are thought to have less influence [15]. Nilsson (1980, 1995) also described using LTA (Leitz texture analysis system) to measure disease severity by calculating the area of fungal infection on leaves and lesion sizes distribution [18, 19] while Blanchete used image analyser system and demonstrated its technological approach to measure the severity of wood decay [20]. Bronson and Klittch (1984) reported Photoscan 83[21], Blasque and Edwards (1985) used digitised light absorption and image analysis to measure and compare potato late blight severity with arbitrary visual rating scale[4]. Subsequent future studies also demonstrated modern image analysis in comparison to traditional visual ratings in various disease assessments. Medina *et al.* quantified multiple symptoms by estimating the area covered by chlorosis using FPGA sensor [22]. Xu *et al.* presented a morphological process to quantify the area ratio of disease spots in wheat leaves [23]. Mondal *et al.* used a ratio scale of symptom area to healthy tissue in estimating the severity of yellow mosaic virus [24]. Borges *et al.* also utilised the ratio scale in correlation with rater assessment to estimate bacterial spot severity in potato [25]. Diseased tissue is divided into chlorosis and necrosis counted as the number of disease patterns [14, 15]. Severity and grading measurements should be reliably in agreement with actual severity based on the actual symptoms (Necrosis and chlorosis) caused by pathogens [13, 14, 26-28].

Despite the amount of literature and successes severity measures through image analysis were found in most cases, not in close agreement to actual values [2, 9, 10, 28]. The vast majority of presented studies within the content of plant disease detection and severity measurement have not given actual value for agreement comparison. Severity measurement should not always be quantitative but qualitative especially for aggregated disease patterns. Generally, detection is much simpler to assess than severity[12]; however, severity is considered more in a practical sense and useful measurement for many diseases [9]. Thus, the importance of ensuring the best method to estimate severity, identify and engage its magnitude of the error and reduce that error cannot be overemphasized. It is in this regard that this paper presents a proposed pathologically inspired method based on image analysis to grade the severity of late blight of vegetables based on actual individual diseased pattern symptomatic and necrotic. This research serves as a novel pilot study aimed at producing a complete machine learning system for plant disease detection and grading. Thus, the results are presented to demonstrate the efficacy of the methodology in an ongoing project[29].

1.1. The vegetable late blight

Late blight, caused by the pathogen *Phytophthora infestans*, is the sole cause of the Irish potato famine responsible for the death and immigration of over 2 million people back in the 19th century [7, 30, 31]. Until this day, late blight remains one of the apparent threats to potato and tomato production worldwide trickling expenses for the control to the tune of billions every year. An entire farm field can be destroyed by the end of a fortnight (two weeks) after being exposed to the disease [30]. The vegetable plants suffered from other diseases in the past, but none had ever been as destructive as the late blight disease [15, 30]. With the same symptoms across the vegetable species, initial infection on the leaf surface starts with small dark symptomatic lesions often on leaf tips, after which it manifests to dark Brown or black water-soaked necrotic lesions occasionally with a pale yellowish-green symptomatic border that fades into the healthy tissue. Within another day or two from initial infection depending on moderate temperature and moisture, the lesion tissue spreads, and more symptomatic and necrotic lesions manifest, eventually killing the leaf [7, 31]. Therefore, the symptomatic and

necrotic lesions have separate characteristics and may have different areas across the leaf surface that when combined, give the actual severity.

1.2. Grading vegetable late blight

Grading the severity of late blight with the highest degree of quality in terms of accuracy and precision should be done through accurate, precise and reliable disease estimate tools such as the standard area diagram (SAD)[32]. SADs are an illustration of plant parts within different range of severity values used as ground truth to compare samples when estimating the severity and to evaluate control measures, typically reducing the time taken to assess severity visually as well as standardize results among experiments [33, 34]. Thus, typical symptoms must first be identified. However, despite its broad applicability by plant pathologist, so far the use of SADs with the concept of lesion type (symptomatic and necrotic) for automatic grading of severity are not given considerable attention within the computer vision and machine learning domain. The nature of both the disease symptoms and complexity comprising of symptomatic and necrotic lesions which are both captured in the SAD are often not taken into consideration when grading[13]. The disease symptoms are instead treated as a single diseased lesion as reported in recent works [34-36]. By localizing and quantizing the disease symptoms individually, this research pilot towards using SADs in such a way that both symptomatic and necrotic lesions would be captured during the grading of plant disease severity.

2. Materials and methods

2.1 Image dataset

A comprehensive public dataset was composed by Mohanty *et al.* (2016) which is a collection of images of diseased and healthy plant leaves spread across 38 assigned labels each with disease pair (diseased and healthy) [37]. Potato images from the dataset showing late blight diseases with varying degree of severity were used for the research. The images were of the same scale size of 256×256 pixels used for the model optimisation and predictions of both the machine learning algorithms. Furthermore, all the experiments were performed on the version of the potato dataset where all the leaves were segmented from the background to allow for a proper basis for comparative analysis with SAD. Figure 1 shows sample images of each disease level.



Figure 1: Potato leaf image samples from the segmented version of the Plant Village data set showing: initial (left), moderate (center), and late (right) stages of disease.

2.2. Disease lesion segmentation

There are several disease lesion segmentation methods in the literature. One of the first attempts to use digital imagery in plant pathology was by Lindow and Webb (1983), in which the absorption of red light and monochromatic images were used to detect, and segment leaf lesions caused by four different diseases [17]. Since then, several other methods have essential with varying degrees of success [3, 38, 39]. However, until recently, none perform lesion segmentation based on the pathological analogy of disease[40]. A novel pathological analogy-based segmentation concept to automatically segment disease lesion with a focus on the blight disease analogy had being established from the 1st phase [29]. The healthy green tissue is removed using generated binary masks based on the computed ratio of green colour to red and blue, leaving only the diseased lesion referred to as extended region of interest (EROI)[29].

2.3. Lesion quantification and localisation

Individual lesions are localised based on the pathological analogy of the blight disease and quantified based on leaf surface area each lesion occupies. Thus, lesion isolation also referred to as lesion quantisation, will not only lead to accurately measuring disease severity but could aid in predicting the stage of disease development as well. Pathologists are known to use the ratio of healthy leaf tissue area to symptomatic/ necrotic (leaf lesion area, LLA) in determining the susceptibility of plant against a particular pathogen attack [8, 9, 14]. Hence, given the leaf surface area in pixels as $I(x, y)$, total number of diseased pixels will be:

$$I_D(x, y) = I(x, y) - I_{EROI}(x, y) \quad (1)$$

where $I_{EROI}(x, y)$ is segmented diseased lesion (symptomatic, necrotic and blurred). For every segmented lesion colony, the area was measured as the total number of pixels it contains such that:

$$I_{EROI}(x, y) = R_S(x, y) + R_N(x, y) + R_B(x, y) \quad (2)$$

where R_S, R_N , and R_B denote symptomatic, necrotic and blurred quantised region areas. Figure 2 shows the quantified region areas.



Figure 2: Quantified and localised disease lesion colonies. The leaf simple is that of a potato infected with late blight

Each localised lesion area position is then marked and superimposed on the original image for correlation with a digital SAD.

3. Main results

The disease symptoms boundary were manually adjusted by an expert pathologist using a cropping software, and using the lesion boundaries and unit areas as the ground truth the following were computed: the percentage of missed disease lesion pixels in each category (false negatives, FN and false positives, FP), and the rate (in %) of missed blurred pixels (SB). The first two statistics represent the error in measurement, while the third statistic demonstrates the general behaviour of the algorithms in dealing with the blurred regions. The distribution of error N_e for each of the localised areas that indicates the magnitude of error expected in each case was calculated as N_d/N_T , where N_d is the number of pixels misclassified, and N_T is the total number of pixels in the leaf. The recall, also known as true positive rate, was computed as $TP/(TP + FN)$ where TP and FN are true-positive and false-negative rates. These also reflect the performance of the proposed algorithm in accurately classifying lesion pixels.

Table 1 presents the segmentation performance of the proposed algorithm following the three disease lesion regions. The proposed algorithm was consistently accurate when compared to the ground truth: not only were the error rates lower in all disease categories, but the proposed algorithm was consistently robust quantifying and localising disease lesion from the lesion colonies.

Table 1. Summary of segmentation performance (in % of cases in each class) of the proposed algorithm. fp , fn , represent missed disease lesion pixels, sb represent missed blurred pixels, ne distribution of error and tp true positive rate.

Result Summary	Proposed Algorithm				
	FP	FN	SB	N_e	TP
Lesion Region					
Symptomatic	1.33	4.4	15.2	2.8	94.6
Necrotic	0.35	1.8	03.6	0.6	97.8

The results (Table I) show FP of the proposed method is lower (0.35% to 1.33%) in all lesion categories. The proposed algorithm is more robust in characterising symptomatic and necrotic regions from the blurred, as indicated by FN (0.8% to 4.4%). Though the ratio of the blurred region in relation to disease lesion size is small ranging from 5% to 22%, its significance cannot be underrated considering its potential to provide vital information about the disease progression. The true-positive rate indicated the performance of the algorithm in accurately localising the disease lesion pixels into symptomatic and necrotic regions. Having an average accuracy of 96.2% the success of the proposed algorithm is partly featured to the EROI segmentation [29] as it accurately captures the border region between blurred and healthy tissue. However, the primary source of error was the most frequent causes of FPs and FNs due to the nature of late blight of not always having pronounced diseased border [31]. The blurred region, particularly for late blight disease, often have several pixels that should have been included in either the healthy tissue or symptomatic region in the ground truth. This explains the slightly high proportion of pixels (15.2%) identified by the algorithm as symptomatic.

4. Conclusion

The main contribution of this paper is on integrating the pathological concept of identifying and grading visual symptoms in automatically quantifying and localising late blight disease lesion types. The proposed algorithm is simple to implement and based on advanced image processing algorithms. This substantiates the efficacy of the proposed algorithm in localising the three lesion colonies for grading severity in accordance with the disease's analogy as a pioneer of an intelligent blend of human expert system concept with the computer vision techniques.

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