DETERMINATION OF LEAF RUST (*Puccinia Allii Rudolphi*) **SEVERITY AND ITS MANAGEMENT ON GARLIC** (*Allium Sativum L.*) **USING IMAGE PROCESSING TECHNIQUES**

M.Sc. THESIS

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Determination of Leaf Rust (*Puccinia Allii Rudolphi*) **Severity and Its Management on Garlic** (*Allium Sativum L.*) **using Image Processing Techniques**

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POSTGRADUATE PROGRAMS DIRECTORATE

As Thesis advisors, we here by certify that we have read and evaluated this Thesis prepared under our guidance, by Yohanis Boki entitled: **"Determination of Leaf Rust** (*Puccinia Allii Rudolphi*) **Severity and Its Management on Garlic** (*Allium Sativum L.*) **using Image Processing Techniques".** We recommend that it be submitted as fulfilling the Thesis requirements.

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DEDICATION

This thesis manuscript is dedicated to my wife Chaltu Lamessa and my family members whose understanding and support have truly made this Thesis possible.

STATEMENT OF THE AUTHOR

By my signature below, I declare and affirm that this Thesis is my own work. I have followed all ethical and technical principles of scholarship in the preparation, data collection, data analysis and compilation of this Thesis. Any scholarly matter that is included in the Thesis has been given recognition through citation.

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BIOGRAPHICAL SKETCH OF THE AUTHOR

The author, Mr. Yohanis Boki, was born to his father Boki Adugna and his mother Yeshi Marsha at Yaya Gulale woreda, North Shoa Zone, Oromia Region, Ethiopia in 1994 G.C. He attended his junior school at Dire Dalati Primary School and his secondary and Preparatory education at Fital Preparatory School.

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ABBREVIATIONS AND ACRONYMS

AD	Area Disease
AT	Area Total
AUDPC	Area Under Disease progress curve
DAP	Diammonium Phosphate
DIP	Digital Image Processing
DLA	Disease Leaf Area
FAO	Food and Agriculture Organization
FAOSTAT	Food and Agriculture Organization/Statistics Database
JPEG	Joint Photographic Experts Groups
MatLab	Matrix Laboratory
NLA	Normal Leaf Area
PDA	Percent Leaf Area of Diseased
RGB	Red, Green and Blue
TLA	Total Leaf Area
USB	Universal Serial Bus
WA	Water Agar

TABLE OF CONTENTS

LIST OF TABLES

Table **Page**

LIST OF FIGURES

Figure **Page**

LIST OF TABLES IN APPENDIX

Table **page**

LIST OF FIGURES IN APPENDIX

Determination of Leaf Rust (*Puccinia Allii Rudolphi*) **Severity and Its Management on Garlic** (*Allium Sativum L.*) **using Image Processing Techniques**

ABSTRACT

Traditionally, fungicides are applied manually without objectively quantifying the severity of garlic rust disease. In this research, digital image processing techniques were employed to develop and test an algorithm that could measure the severity of leaf rust on garlic and manage the disease at various levels. Data on leaf rust were collected from seven groups of garlic plants, with samples taken from the top, middle, and lower leaves. Each group consisted of three pots, each containing two plants after thinning. The control group received no fungicide (Tilt or Propiconazole), while group 4 was treated with the recommended 60 mL of Tilt fungicide. Groups 1-3 received 10%, 5%, and 0% less than the recommended volume (6 mL, 3 mL, and 0 mL, respectively). Groups 5-7 received 5%, 10%, and 100% more than the recommended volume (3 mL, 6 mL, and 60 mL, respectively). The fungicide was sprayed on garlic leaves four times to observe the treatment progression and optimize the fungicide volume. A total of 504 garlic leaf images were captured across four rounds: before spraying fungicide, after the first spray, after the second spray, and after the third spray. The total leaf area and the diseased areas were extracted from these images. The relative error between experts' assessments and the imaging algorithm was found to be 4.2%. The algorithm developed for estimating disease severity using image processing technology demonstrated an accuracy of 95.80%. The results indicate the potential of this technology for measuring garlic rust severity and optimizing fungicide application.

Keywords: Disease Quantification, Fungicide Optimization, Garlic Leaf Rust, Image Processing Techniques, Plant Disease Management, Severity Estimation.

1. INTRODUCTION

1.1. Background of the Study

Garlic (*Allium sativum L.)* is the most important crop of the *Alliaceae* family and the second most used allium after onion (*Allium cepa* L.). It grows worldwide in all temperate, subtropical, and tropical mountain regions as an important aromatic and medicinal plant (Rabinowitch, 2002) and is commercially farmed (Metasebia and Shimelis, 1998). Garlic is now one of the twenty most important vegetables in the world, growing on one million hectares. About 10 million metric tons of garlic is produced worldwide each year, with the main producers being the United States, China, Egypt, South Korea, Russia, and India (FAO, 2017).

Garlic is produced in Ethiopia on 2,255,598 small-scale farmers' fields covering 19,412.49 hectares of land. From these hectares of land, 178,221.893 tons of garlic was produced in 2018, with a national average productivity of 9.181 tons per hectare. The production was carried out throughout the country under both irrigation and rain-fed conditions in different agro-climatic conditions (CSA, 2018). For instance, Ambo, Debrework, Adiet, Sinnana, and many other areas of the Ethiopian Highlands produced the most coverage of garlic production (Shege, 2015). The vegetable is produced mainly as a cash vegetable to earn foreign currency by exporting it to Europe, the Middle East, and the USA. It had also been under commercial production by the Horticultural Development Corporation at DebreZeit, Guder, and Tseday State Farms (Getachew and Asfaw, 2000). In this regard, Ethiopia is the second-largest producer of garlic next to Egypt in Africa, and it ranks 13th in the world, with an annual bulb production of 138,664 tons (FAOSTAT, 2016).

Garlic production is challenged by several similar other biotic and a biotic factor. Despite its multifaceted uses, garlic productivity is affected by many problems that cause low production and poor quality, largely attributable to the use of unimproved local seeds (Dessie and Mulat, 2019). The productivity of this crop across the globe or in Ethiopia is generally low due to numerous and prominent production problems, which encompass lack of proper planting material, inappropriate agronomic practices, absence of proper fungicide and disease management practices, marketing facilities, and abiotic and biotic factors. Yeshiwas *et al*. (2017) also indicated that lack of improved varieties and garlic rust are among the major factors responsible for low production and productivity of garlic in Ethiopia.

The production has been significantly reduced due to fungal diseases, of which garlic rust caused by *Puccinia allii Rudolphi* is the most damaging to the crop in all garlic-producing areas of Ethiopia (Worku and Mashila, 2012). The genus *Puccinia* is the first in the order Uredinales. *Puccinia allii* infects garlic at the bulb formation stage (Koike *et al*., 2001). The fungus does not affect the garlic bulb directly, but its damage on the leaves has the indirect effect of reducing the size and quality of the bulbs at harvest time (Tahir *et al*., 2006). As the study conducted by Worku, (2017), the disease is found in every area of Ethiopia where garlic is cultivated. Therefore, this study was carried out with the intention of determination on garlic rust severity levels using image processing techniques and applying fungicide to control the progression of the disease.

1.2. Statement of the Problem

Agriculture is the leading sector of the economy in the world and in Ethiopia; the land is cultivated by old production techniques, which lead to different structural problems (Mengistu, 2016). Therefore, suitable actions have to be taken manage diseases in agricultural products while reducing the use of chemicals to suppress them. Because it reduces confusion and assists experts in avoiding abuses during the diagnosis and control of plant image processing has become a key technique for the diagnosis of various features of plants in agricultural areas (Tiumay, 2020). Even if the percentage of agriculture is high in our country, we do not have enough food for the people. This is because different factors affect our agriculture. Many of these factors are plant-related, such as disease, temperature, the traditional plowing systems, and so on.

In particular, in our country, Ethiopia, farmers face different plant disease problems every year. The main way to detect plant diseases is with the naked eye, which involves huge manpower, is inaccurate, time-consuming, and not applicable for larger fields (Annabel, 2019) and cannot identify the severity of disease.

In this case, they don't have any information on what type of disease it is. In addition, different diseases have different behaviors. That means some diseases spread within a day while others spread over time. Therefore, if early detection and classification of disease are not applied and the disease spreads as soon as it catches a plant, it may spread to other plants within a short period of time and damage whole plants. So, differentiate clearly whether the plant is healthy or unhealthy, as well as which type of disease affects the plant. Also, understand that disease severity is crucial for determining the volume of fungicides applied to plants to kill fungus.

Most of the time, our farmers apply fungicides without determining the severity of the plants. These are the causes of fungicides overuse or inadequacy, both of which can have an impact on plants. Furthermore, if the type of disease and the severity of the disease are clearly identified, the correct fungicides that kill fungus and the optimum volume of fungicides can be applied. The main aim of this research work is to develop an automatic system for disease severity determination and management that may be achieved using the concepts of image processing and computer vision. Design a system that accepts garlic leaves from those affected by rust and then calculates disease severity properly and recommend the optimum chemicals to control the pathogens.

1.3. Objectives of the Study

1.3.1. General objective

The general objective of this study is to develop, test an appropriate routine algorithm that could measure the severity and managing rust on garlic at various severity levels using image processing techniques.

1.3.2. Specific objectives

- To segment the lesion leaf area of garlic affected by leaf rust using image processing;
- To quantify the lesion area and severity of garlic rust on leaves; and
- To determine the optimal fungicide Tilt250EC rates of application on the garlic leaf.

1.4. Scope of the Study

The purpose of this research was to explore the possibility of using image processing techniques to detect the symptoms of the garlic leaf rust and also determine the severity level of an affected garlic leaf specimen using image processing techniques. This research addresses the problem of determining the optimal fungicides level to be sprayed on garlic affected by leaf rust *(Puccinia allii).* The recommended volume of fungicides for a given level of severity was determined and evaluated. As a result, the work culminated in the growth of garlic in the controlled experimental glass house, followed by the determination of the level of severity and recommended volume of fungicides using existing imaging processing techniques.

1.5. Significance of the Study

Digital image processing has an expanding range of applications in our day-to-day lives. Many image processing and analysis techniques have been developed to aid in the interpretation of remote sensing images and to extract as much information as possible from the image. Such a technology is also employed to grade agricultural products. The application of image technology to the determination and management of garlic leaf rust severity, which is related to garlic bulb yield, will be critical in eliminating the subjectivity of the traditional method and human-induced errors.

2. LITERATURE REVIEW

2.1. Digital Image Processing

An image is defined as the 2-D representation of the scene. A digital image is regarded as the numeric representation of the 2D image in a sampled and quantized form. The basic picture element is called a pixel, and an M ×N image has M rows of pixels and N columns of pixels. It can also be thought of as a 2D grid or matrix whose elements are represented by f(x, y), where x and y are the coordinates of the grid or the indices of the matrix elements (Jebamalar and Asir, 2014). When x, y, and the amplitude values of f are all finite, discrete quantities, we call the image a digital image (Gonzalez, 2004). Each of these coordinate positions is referred to as a "pixel." A pixel is the smallest unit of an image, also known as a picture element. So digital images are composed of pixels; each pixel represents the grayscale image level and color image at a single point in the image.

Grayscale images are made of different shades. These different shades lie between 0 and 255, where 0 refers to black, 255 refers to white, and intermediate values refer to different shades of black and white. Gray-scale refers to the range of neutral tone values (shades) from black to white (Vikas *et al*., 2017).

Color images are made up of colored pixels. Color can capture a much broader range of values than grayscale. The spectrum band of colors produced when sunlight passes through a prism which includes billions of colors, of which the human eye can perceive seven to ten million includes a wide range of hues. The electronic capture and display of color is complicated; Red, Green, and Blue (RGB) are the most commonly adopted color system (Vikas *et al*., 2017).

2.2. Image Acquisition

Image acquisition is the first and most important step in image processing. The digital images will be acquired using a digital camera or mobile camera and used as input to the identification system.

2.3. Image Pre-Processing

Image pre-processing techniques are the preliminary steps for enhancing the quality of a raw image. In the image processing step, the image is enhanced in quality level to be prepared for the next process. These are RGB to gray-scale conversion, binarization, boundary enhancement, and a clear border (Wuo *et al*., 2007). A grayscale image is a data matrix whose values represent intensities within some range. Grayscale image pixel values range from 0 to 255. Converting RGB to Grayscale. The RGB image is a true color image, which is stored as an m-by-n-by-3 data array that defines red, green, and blue true color components for each individual pixel. The conversion process from RGB to grayscale is done using a Mat Lab function called rgb2gray (Jamil *et al*., 2012).

2.4. Median Filter

The median filter is a popular nonlinear filter in digital image processing. The median filter is a rank-order filter. Its noise-reducing effects depend on the size and shape of the filter. Median filtering is a technique for image enhancement in the spatial domain. This method is included in the category of non-linear filtering (Boateng *et al*., 2012).

2.5. Image Enhancement

It is the process of manipulating an image so that the result is more suitable than the original for specific applications. The enhancement improves the quality of the images so that the information contained in them can be extracted in a meaningful sense (Poonam *et al*., 2014).

2.6. Image Segmentation

Segmentation is the name given to the generic process by which an image is subdivided into its constituent regions or objects. The basic goal of segmentation, then, is to partition the image into mutually exclusive regions to which we can subsequently attach meaningful labels. The segmented objects are often termed the foreground, and the rest of the image is the background. Image segmentation divides an input image into a number of the same nature as the category to extract the region of interest (Yuheng and Hao, 2017).

2.6.1. Image thresholding

In this current study, different thresholding techniques, including Otsu's method, were segment total leaf and diseased leaf areas. Many image processing and computer vision applications usually require binary images (i.e., black and white) as an introductory step in do further processing. By choosing a particular intensity value as the threshold, images can be segmented by setting those pixels whose original intensity is above the threshold as white pixels and the other pixels as black pixels. Thresholding is the transformation of an input image $f(i,j)$ into an output (segmented) binary image $G(i,j)$, as follows:

$$G(i,j) = \begin{cases} 1, & \text{for } f(i,j) \geq T \\ 0, & \text{for } f(i,j) < T \end{cases} \tag{2.1}$$

Where, T is threshold, $G(i,j) = 1$ for image elements of objects $G(i,j) = 0$ for image elements of the background and the image original image. Thresholding is a vital part of image segmentation when one wishes to isolate objects from the background. It is also an important component of robot vision (Zhihua *et al*., 2013).

2.6.2. Edge-based segmentation

Edge detection methods transform original images into edge images, considering the changes in gray tones in the image. In image processing, especially in computer vision, edge detection treats the localization of important variations of a gray level image and the detection of the physical and geometrical properties of objects in the scene. Edge detection is the most familiar approach for detecting significant discontinuities in intensity values (Muthukrishnan and Radha, 2011).

2.6.3. Region-based segmentation

It is easy to construct regions from their borders, and it is easy to detect borders within existing regions. However, segmentation resulting from edge-based methods and region-growing methods is not usually exactly the same, and a combination of results may often be a good idea. Region-growing techniques are generally better in noisy images, where borders are extremely difficult to detect.

2.7. Morphological Features Extraction

An image feature is a distinguishing primitive characteristic or attribute of an image. Morphological features are the geometric properties of an image such as shape and size; for instance, area and perimeter are some of the most commonly measured characteristics of an image (Gonzalez *et al*., 2009).

Area (A): the number of pixels inside the region of the disease garlic leaf, including the boundary region. It is measured by counting the number of pixels.

$$A = \sum_i \sum_j O(i,j) \tag{2.2}$$

where A is area and $O(i,j)$ represents the object pixels in the image.

2.8. Related Works

A sustainable and integrated approach to managing leaf rust in garlic production areas is crucial. Common management tactics include the removal or incorporation of vegetable residues into the soil after harvest, with burning these residues being an effective method to minimize spore loads. Rotating garlic with non-Allium species and using irrigation practices such as drip irrigation, which reduces leaf wetness, are preferred over overhead irrigation for rust management (Worku and Azene, 2015). Additionally, fungicides are essential for protecting leaves from infection and managing the fungal pathogen Puccinia allii (Tony, 2012).

Adopting a variety of management practices widely used in garlic production areas is important. Detecting garlic rust early and applying fungicides when the disease is less severe is critical for effective management (Ahmed et al., 2017). In Ethiopia, the use of the Tilt 250EC fungicide for managing garlic rust has been extensively studied (Worku and Mashilla, 2012). Field experiments conducted by Hassen and Tefera (2018) examined the effects of different fungicide application rates of propiconazole (Tilt) at 0.25, 0.5, and 0.75 L/ha and various application frequencies (every 7, 14, 21, and 28 days, and no spray) on the spatial epidemics of garlic rust. The treatments were evaluated using percentage severity, disease progress rate, and area under the disease progress curve (AUDPC). The final disease severity levels were approximately 89.9% at Madda Walabu University Research Site and 87.2% at Sinana Agricultural Research Center.

3. MATERIALS AND METHODS

3.1. Description of the Study Area

The survey of garlic rust and field experiments were conducted at the “Raaree” Experimental Station of Haramaya University's Research Center, located in the East Hararghe Administrative Zone of Oromia Regional State, Ethiopia. The experimental site at Haramaya is situated at 9°0' N latitude and 42°03' E longitude, with an elevation of 2043 meters above sea level. The annual rainfall at this site is 800 mm, and the mean maximum and minimum temperatures are 24.18°C and 9.9°C, respectively (Paulos and Tadele, 2005).

3.2. Experimental Materials

To conduct the research, the necessary materials are: a personal computer (laptop), fungicide Tilt250EC, artificial fertilizers (DAP and urea), digital camera, compound microscope, Petri dishes with agar, rust-infected garlic leaves, garlic seeds, white paper sheets, ethyl alcohol or Clorox, USB (universal serial bus), and Matlab R2018a for developing computer routines and algorithms.

3.3. Treatments and Experimental Design

Field experiments are conducted in the glasshouse at the Rare Experimental Station of the Haramaya University main campus research center. The experiment is designed in such a way that the sample images could be collected before inculcation after 30 old garlic plants and after the inculcation of the pathogens and fungicides of different rates four of Tilt250EC spraying frequencies of intervals. To maintain the uniformity of extraneous factors, the garlic plants were grown in pots filled with soil of similar proportions and twenty-one equal sized pots were utilized to conduct the experiment. To estimate the progression of the disease, live leaf samples are taken every 8 days for the next three consecutive intervals after the first onset of symptoms of the disease severity level was seen. To get the desired results, serious attention was given for sampling techniques. The samples were collected as follows. Generally, twenty-one infected garlic plants were randomly taken from the pool of pots on which the plants were grown. While data collection, three diseased leaves one from the bottom, one from the middle and one from the top of each plant were taken randomly. Every 8-day interval, after observation of the symptoms, one hundred twenty-six diagnosed images of garlic leaves affected by rust leaf. This trend was continued for the following four consecutive days.

3.4. Experimental Procedures

The fungal pathogen was isolated from severely diseased garlic rust plant leaves collected from Haramaya University farmland. The presence of spores was confirmed under a compound microscope. Standard procedures were followed to extract the lesion regions, assess the disease area, and estimate the disease severity levels of garlic leaf rust.

The study comprised three main stages:

1. **Algorithm Development**: The first stage involved creating a computer routine algorithm for extracting morphological features from pathogen-affected garlic plant leaves.

2. **Disease Severity Measurement**: The second objective was to develop a method for automatically measuring disease severity and progression over one month from the initial onset. The garlic leaves under investigation were monitored to determine the severity of the disease based on the infected area. A computer routine algorithm was developed to automatically estimate the disease's progression and severity from the infected leaf images.

3. **Fungicide Optimization**: The final part of the research focused on estimating the optimal volume of fungicide needed to control the severity of garlic leaf rust.

A total of 504 garlic leaf rust samples were collected from the laboratory in four rounds, including samples from the top, middle, and lower parts of the garlic leaves.

3.4.1. Planting garlic seeds in pots

Seeds of garlic were sown in plastic trays containing soil with 1:2:3 proportions of sand, compost, and clay, respectively. The trays were kept in the Haramaya University Main Campus Research Center glasshouse.

Twenty-one pots of 20 cm diameter each were washed with water and detergent. Two to three garlic seeds per pot were planted 7 cm deep Three-grown garlic plants were thinned after two weeks to maintain one plant per pot. Di-ammonium phosphate (DAP) fertilizer was applied at rate of 1 kg during planting time. A 2 kg urea fertilizer was applied in two splits: half at planting and the rest at 15 days after emergence (Debela *et al*., 2017)

3.4.2. Preparation for inoculation

The pathogen is isolated from severely diseased garlic plant leaves. The diseased garlic leaves are collected from Haramaya University farm land, and the presence of spores was checked under a compound microscope. Standard procedure was followed to extract. 5 g powder of garlic leaf rust, 500 mL of distilled water, 1×10^6 Haemocytometer fungal spores.

3.4.3. Inoculation

Deliberate inoculation of the pathogen was performed on 30-day-old garlic plants. This process involved spraying a garlic rust spore suspension onto the garlic leaves and introducing the suspension into the plant whorls using an atomizer in the late evening. After inoculation, the seedlings were covered with plastic bags moistened with distilled water for 24 hours to increase the relative humidity, which is essential for infection (see Appendix C3). Additionally, the ground surfaces in the greenhouse were sprinkled with water to further raise the relative humidity and lower the temperature.

Figure 3.1. Garlic rust onto leaves before inoculation.

3.4.4. Fungicide spraying

The treatments were arranged in a factorial experiment combining different fungicide rates and four spray frequencies, using a row and column design with three replications. Including a control (unsprayed plot), the first fungicide application occurred 45 days after planting, with subsequent applications based on the assigned spray frequency every four days. Pots were spaced uniformly, 50 cm apart in rows and 60 cm in columns, following recommended cultural practices.

The experiment included seven groups, each with three pots, containing two to three plants per pot. Fungicide application began with the appearance of the first typical disease symptoms. Four different spray frequencies were applied at four-day intervals.

Groups were treated with varying fungicide volumes: Group 1 served as the control with no fungicide. Group 2 was sprayed with 10% less than the recommended volume (54 mL), Group 3 with 5% less (57 mL), and Group 4 with the recommended volume (60 mL). Conversely, Group 5 received 5% more (63 mL), Group 6 received 10% more (66 mL), and Group 7 received 100% more (120 mL).

The volume of fungicide needed to minimize disease was considered the optimum volume (see Appendix C4). Data collected determined the maximum volume of fungicide effective in controlling the disease.

3.5. Disease Severity Measurements

Disease severities were recorded on seven groups of plants at four-day intervals, starting 45 days after the appearance of disease symptoms. Five assessments were performed during the test period. Severity was rated by estimating the percentage of leaf area affected using a standard disease scale from 0 to 4, as suggested by Koike et al. (2001) and shown in Table 3.1. Each group was assessed using these criteria to determine the extent of rust lesions on the leaf surface.

Table 3.1. Scaling Labels for disease severity.

Scaling label	Severity level
0	0% (non-infected leaves)
1	1 – 25% (very low infected leaves)
2	26 – 50% (medium infected leaves)
3	51 – 75% (high infected leaves)
4	76 – 100% (very high infected leaves)

3.6. Determination of Optimum Fungicide Volume

To determine the optimum volume of fungicide, Tilt 250 EC was sprayed depending on the severity of the disease. Field experiments were conducted in the glasshouse at the Rare Experimental Station of the Haramaya University Main Campus Research Center. Tilt250EC at different rates and four different spraying frequencies was used. During fungicide application, plastic sheet was used to separate the plot being sprayed from the neighboring plots to prevent inter-plot interference due to spray drift.

3.7. Image Processing and Analysis

The image data were collected using a camera and loaded onto a computer for further analyses. The computer routine algorithm that can measure the severity level of garlic rust based on acquisition, image pre-processing, image enhancement, segmentation, and morphological feature extraction and estimate the severity level was developed using the Mat Lab R2018a platform. The software used the infected live and detached leaf area images under investigation to extract essential features and estimated the severity level (see Figure 3.2).

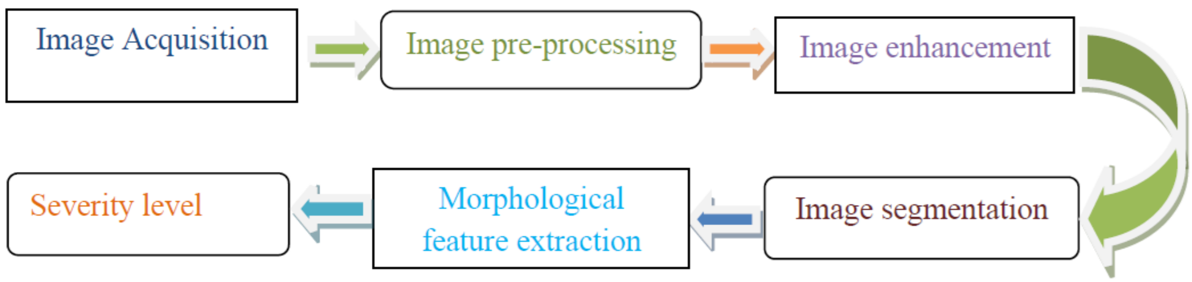


Figure 3.2. Proposed Architecture.

3.7.1. Image acquisition

The sample of 504 garlic leaf images were captured using digital camera with 20 Mega pixel resolution using white background (paper) and stored in the Joint Photographic Expert Group (JPEG) format. Light sources were placed at 45 degrees on the leaf so as to avoid reflection and ensure even illuminations over the field of view, thus there could be better sight and intensity.

3.7.2. Image pre-processes

Following the acquisition of the images pre-processing was used to remove the noise, poor resolutions of images, unwanted background of the image, conversion of RGB images into intensity images for morphological features extraction, resizing to a standard resolution to reduce the storage capacity and the computational burden and enhancement of images by contrast adjustment technique. Image enhancement produces an output image that subjectively looks better than the original image by changing the pixel's intensity in the input image. It's the intensity difference among objects and background (Poonam *et al.*, 2014).

3.7.3. Image segmentation

Image segmentation is an important step to separate the different regions with special significance in the image; these regions do not intersect each other, and each region should meet consistency conditions in specific regions (Rafael *et al*., 2008). Image segmentation means partitioning of an image into various parts of the same features or having some similarity measure. The segmentation can be done using various methods like the Otsu' method (Mollazade *et al*., 2013; Yasikka and Santhi, 2015). In this study, two different segmentation techniques were implemented to obtain total leaf pixels and lesion area leaf pixels Otsu's method of thresholding segmentation. Using Otsu's thresholding method (Otsu, 1979) was used to segment the diseased and normal parts of the leaves. Thresholding is the transformation of an input image f to an output (segmented) binary image G as follows

$$G(i,j) = \begin{cases} 1, & \text{for } f(i,j) \geq T \\ 0, & \text{for } f(i,j) < T \end{cases} \quad (3.1)$$

Where T is the threshold value, for image elements of objects and $G(i,j) = 0$, for image elements of the background.

3.7.4. Disease region segmentation

The image is transformed from RGB color space, which is more suitable for the visual characteristics of human beings. Since the brightness component is independent of the color component and the human eye is more sensitive to hue than saturation, the color component can be useful to eliminate glare, shadow, and other light factors during color image segmentation. The similar gray value of the shallow color of the midrib and the leaf in the color component can decrease the interference of the midrib in the follow-up lesion image segmentation to a large extent. If the lesion characteristics are varied, the boundaries between the lesion and the healthy part are also varied, so there is a weak edge.

3.7.5. Morphological features extraction

Image feature extraction means transforming input image data into a set of representative features or characteristics, which can most meaningfully represent important information for analysis. Morphological feature is used to represent shape, size and boundary regions of objects of the image. Morphological features of an image include area. (Gonzalez *et al*., 2009). Among these features, area is the main morphological component considered in this work. The following morphological features were extracted from garlic leaf images:

Area (A): area of a test object was measured by counting the number of pixels inside the region covered having a value of one.

$$A = \sum_{i}\sum_{j} O(i,j)\,, \tag{3.2}$$

where A is area and $O(i,j)$ represents the object pixels in the image.

3.8. Measurement of Disease Severity

Leaf disease symptoms can be predictable using a tool that measures the prevalence, incidence and severity of disease (intensity is the sum of incidence and severity). Disease severity is expressed as a percentage of diseased leaf area to total leaf area of the sample (Hitimana and Gwun, 2014). Using the image processing technique, it can be expressed as equation (3.2). The result obtained from image processing technique was put in parallel with visual assessment result (expert scoring) for live leaves, which was done on the basis of the five scales (0-4) of Horsfall and Heuberger reported by (Sanjay and Shrinkant, 2011) with little modification. The scale was used to estimate percent leaf area of diseased (PLAD) visually. Each scale was assigned a specific PLAD range for each disease as indicated by lesion size, intensity and distribution on an individual leaf. Severity is the proportion or percentage of diseased tissue to that of the total leaf area assessed (James and Teng, 1979). The severity of disease was measured based on the total area and diseased area of a leaf. The total area of the leaf was calculated from the number of pixels in the image, while the diseased area of the leaf has been calculated based on the clusters formed from the color segmentation. A mathematical formula can be expressed as follows:

$$S(\%) = \frac{A_d}{A_t} \times 100\%, \quad (3.3)$$

where S is the disease severity, A_d is the affected plant leaf area, and A_t is the total leaf area.

3.9. Area Under Disease Progress Curve

The area under the disease progress curve (AUDPC) is a useful quantitative measure of disease intensity over time, allowing for comparisons across years, locations, or management tactics. It was calculated using disease severity data with the formula suggested by Campbell and Madden (1990):

$$\text{AUDPC} = \sum_{i=1}^{n-1} \frac{1}{2}(x_{i+1} + x_i)(t_{i+1} - t_i), \quad (3.4)$$

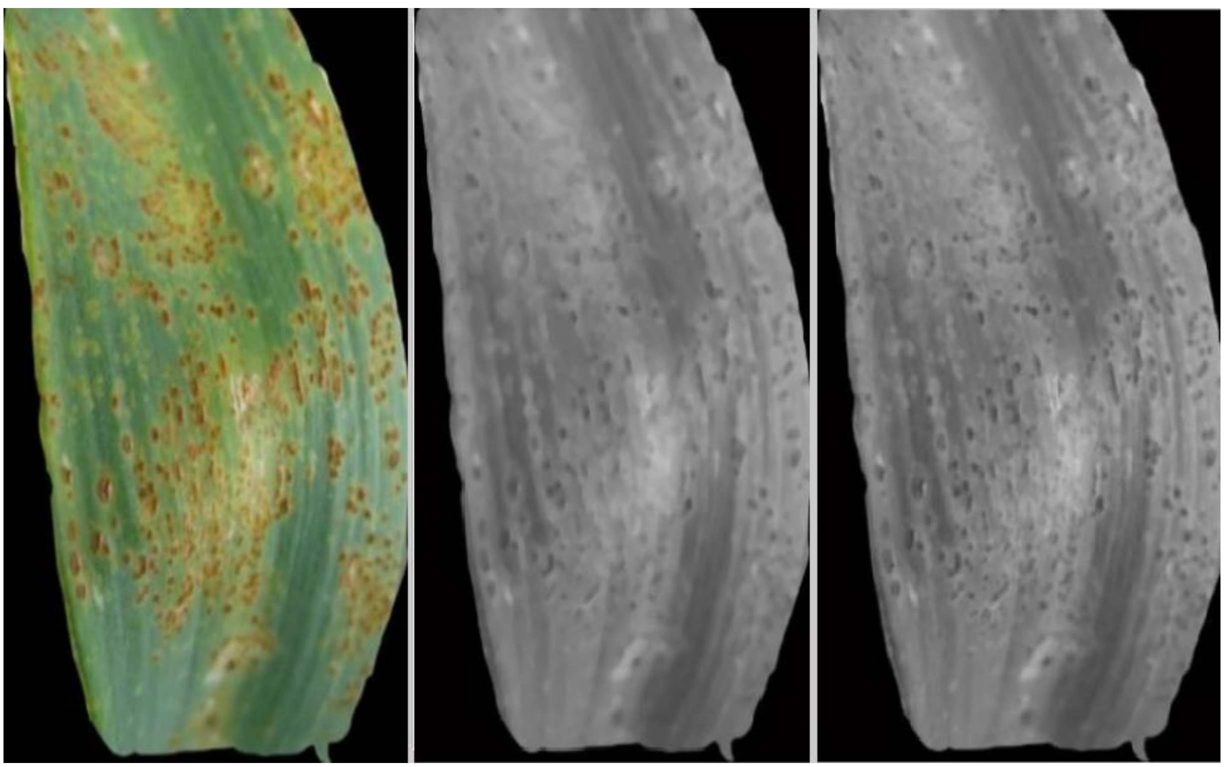
where AUDPC is the area under disease progress curve and indicates the disease over time and expressed as AUDPC-%days, x_i is the disease severity expressed as a proportion at the observation, and t_i is time (days) after planting at the observations and n is the total number of observations in days.

4. RESULTS AND DISCUSSION

This chapter explains about the extracted morphological features of the diseased garlic leaves, percentage of disease its severity using image processing techniques. All the techniques were employed using the MATLAB R2018a platform.

4.1. Image Pre-Processing Results

After acquiring sample images, pre-processing such as conversion of RGB images into intensity images, resizing to a fixed resolution (384×576) and median filtering to remove unwanted noise were carried out as shown in Figure 4.1.



a) b) (c)

Figure 4.1. (a) RGB image, (b) gray scale garlic rust image, and (c) filtered image.

4.2. Result of Image Segmentation Using Otsu Thresholding

The pre-processed garlic leaf image shown Figure 4.2 was segmented using Otsu's thresholding to segment the area of the diseased part of the garlic leaf. The result of segmented garlic leaf was then eroded to be show the diseased part is show in Figure 4.2 a-e.

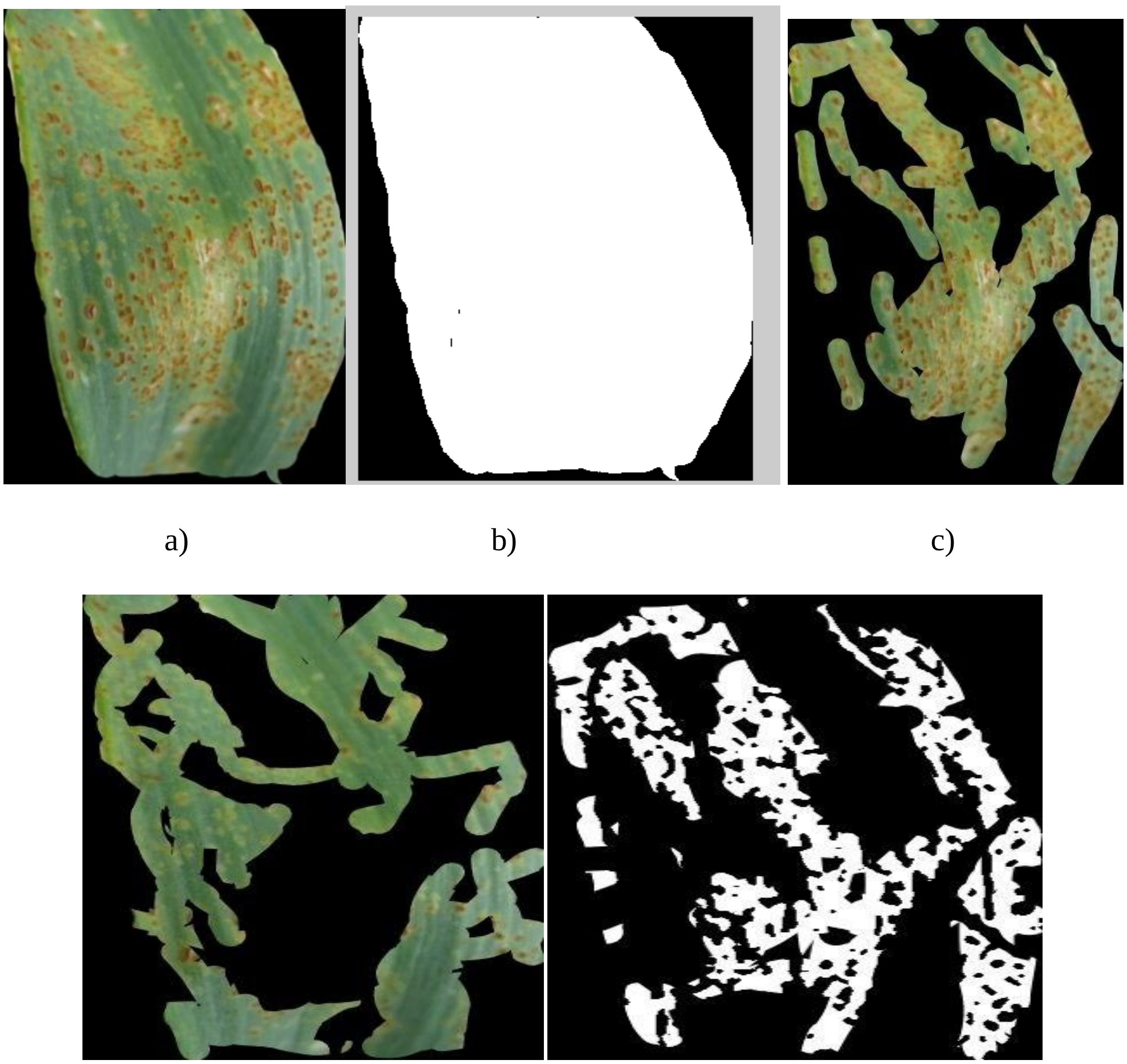


Figure 4.2. (a) RGB image, (b) Segmentation of the total leaf area extraction from the background, (c) diseased leaf area, (d) Normal part of the leaf area and (e) Segmented diseased leaf area.

4.3. Morphological Features Extraction

In this study, morphological feature area was extracted. Hence this feature was the main morphological components considered to estimate the severity of garlic rust images. The results of morphological features of the garlic leaf rust images are show in Table 4.1.

Table 4.1. Results of total leaf and normal area before spraying fungicide of the plant leaf.

Group	Pot Number	Garlic Leaf	TLA	NLA	DLA	Severity (%)	Severity per pot (%)	Severity per group (%)
1	1	UL	8953	7383	1570	18%	17.00%	15.69%
		ML	6206	5208	998	16%		
		LL	7396	6098	1298	18%		
	2	UL	4820	4207	613	13%	16.00%	
		ML	5458	4378	1080	20%		
		LL	9366	7865	1501	16%		
	3	UL	6201	4686	1515	24%	14.00%	
		ML	6716	6102	614	9%		
		LL	7261	6685	576	8%		
2	4	UL	5224	2507	2717	52%	24.00%	19.40%
		ML	6219	5474	745	12%		
		LL	7366	6763	603	8%		
	5	UL	4038	3327	711	18%	18.00%	
		ML	4904	4209	695	14%		
		LL	8234	6291	1943	24%		
	6	UL	8241	5996	2245	27%	16.00%	
		ML	8896	8528	368	4%		
		LL	9707	8218	1489	15%		
3	7	UL	8126	6979	1147	14%	19.80%	20.21%
		ML	9010	6788	2222	25%		
		LL	9606	7636	1970	21%		
	8	UL	8988	6751	2237	25%	21.00%	
		ML	8848	7502	1346	15%		
		LL	9816	7675	2141	22%		
	9	UL	8158	6488	1670	20%	20.00%	
		ML	10706	8500	2206	21%		
		LL	11110	8931	2179	20%		
4	10	UL	7118	5438	1680	24%	23.30%	22.19%

		ML	7844	6234	1610	21%		
		LL	9108	6769	2339	26%		
		UL	12221	9349	2872	24%		
	11	ML	12459	10200	2259	18%	21.00%	
		LL	12897	10075	2822	22%		
		UL	9238	7176	2062	22%		
	12	ML	10373	8085	2288	22%	22.00%	
		LL	10926	8518	2408	22%		
		UL	13796	10539	3257	24%		
	13	ML	14366	10434	3932	27%	25.40%	
		LL	14476	10830	3646	25%		
		UL	5954	4441	1513	25%		
5	14	ML	8422	6428	1994	24%	24.70%	23.69%
		LL	9043	6791	2252	25%		
		UL	10676	8588	2088	20%		
	15	ML	11100	8535	2565	23%	21.00%	
		LL	11421	9096	2325	20%		
		UL	8311	6507	1804	22%		
	16	ML	9221	7224	1997	22%	22.40%	
		LL	8929	6788	2141	24%		
		UL	6129	4719	1410	23%		
6	17	ML	7018	5520	1498	21%	22.30%	21.67%
		LL	8108	6285	1823	22%		
		UL	5154	4149	1005	19%		
	18	ML	6147	4844	1303	21%	20.30%	
		LL	7319	5843	1476	20%		
		UL	4344	3700	644	15%		
	19	ML	5982	4790	1192	20%	18.40%	
		LL	9890	7858	2032	21%		
7		UL	6725	5179	1546	23%		
	20	ML	7240	5555	1685	23%	22.10%	20.14%
		LL	9785	7828	1957	20%		
	21	UL	5748	4700	1048	18%		
		ML	5743	4467	1276	22%	20.00%	
		LL	6890	5565	1325	19%		

UL = upper leaf, ML = middle leaf, and LL = lower leaf of the garlic; G_i = group at which samples were taken, TLA = total leaf area, NLA = normal leaf area, DLA = disease leaf area.

4.4. Estimation of Disease Severity

Garlic leaf images were taken in four rounds. The first round is before spraying fungicide, the second was after spraying fungicide for first time, the third round is after spraying fungicides for second time and the fourth round was after spraying fungicides for third round time. In every round, 126 images were captured. The level of severity was estimated as ratio of area of diseased leaf region to total area of leaf and categorized using the severity criteria stipulated. Then after, the disease severity of every round was compared with each other to estimate the optimal volume of fungicide that should be sprayed.

4.5. Experimental Results Analysis

In total, 504 leaf images were used in due process and all the images were stored in JPEG (Joint Photographic Expert Group). First, from all images total area of leaves (normal leaf region and disease leaf region) were calculated. Then after area of diseased regions of the leaves were calculated for every image taken in all rounds. Finally, the ratio of area of disease region to total leaf area was taken to estimate the disease severity. The severity of garlic rust disease was calculated using the total leaf area and diseased area of the garlic leaf images.

$$S(\%) = \frac{A_d}{A_t} \times 100\% \quad = \frac{1570}{8953} \times 100\% \approx 18\%,$$

where S is the disease severity, A_d is the affected plant leaf area and A_t is the total leaf area.

The fungicide application followed a specific protocol where the volumes were adjusted progressively across different groups. Starting from Group 4 to Group 2, each subsequent group received 5% less fungicide volume than the previous group. For example, Group 3 received 5% less than Group 4, and Group 2 received 5% less than Group 3. Group 1 served as the control group without any fungicide spray. Similarly, this procedure was mirrored in Groups 5 to 7, where each group received increasing fungicide volumes relative to the recommended amount. This experimental setup aimed to evaluate the effect of varying fungicide concentrations on disease severity.

First round image data were collected before spraying fungicide, the second data were collected after first term fungicide sprayed on each group different volume of fungicides was sprayed except group one which is a control group (no fungicide is sprayed) and the disease severity value is shown here under Table 4.2. Finally, the optimum volume of fungicide was recognized from the data collected, the third data was collected after second term fungicide sprayed and the fourth data were collected after spraying the third-round fungicide.

Table 4.2. Average disease severity for round four vs the fungicide volumes.

Round		**G1**	**G2**	**G3**	**G4**	**G5**	**G6**	**G7**
I	Severity (%)	15.69	19.40	20.21	22.19	23.69	21.67	20.14
	Volume fungicide(mL)	0	0	0	0	0	0	0
II	Severity (%)	14.1	15.16	18.58	21.78	22.08	21.26	20.07
	Volume fungicide(mL)	0	54	57	60	63	66	120
III	Severity (%)	16.43	17.12	18.30	19.70	20.12	24.28	23.06
	Volume fungicide (mL)	0	54	57	60	63	66	120
IV	Severity (%)	15.69	16.81	19.82	21.02	22.08	21.67	20.59
	Volume fungicide (mL)	0	54	57	60	63	66	120
Average severity (%)		15.48	17.15	19.23	21.17	21.99	22.22	20.97

The data represents the results of a factorial experiment involving seven groups (G1 to G7) of plants over four rounds. The measurements recorded were the severity of disease (%) and the volume of fungicide applied (mL) for each group. In Round I, no fungicide was applied, and disease severity ranged from 15.69% in G1 to 23.69% in G5. From Round II onwards, fungicide was applied to groups G2 to G7, resulting in a noticeable reduction in disease severity for most groups. However, in subsequent rounds (III and IV), the severity fluctuated, with groups receiving higher fungicide volumes not consistently showing a decrease in severity.

The effectiveness of fungicide application showed an initial positive impact in Round II, with reduced severity compared to Round I. However, the inconsistency in subsequent rounds suggests potential issues such as fungicide resistance or other influencing factors. Groups G2, G3, and G4, which received moderate fungicide volumes, showed some reduction in severity, but this effect was not sustained. Conversely, groups G5, G6, and G7, which received higher fungicide volumes, did not consistently exhibit a proportional decrease in severity, indicating that simply increasing fungicide volume is not always effective.

According to Figure 4.3, it is revealed that G1, with no fungicide application, had the lowest average severity at 15.48%. Groups G2 to G4, with moderate fungicide application, showed moderate average severity, suggesting some effectiveness of the fungicide. Interestingly, G6 had the highest average severity at 22.22%, despite receiving high fungicide volumes. This highlights the complexity of disease management and suggests that other factors, such as environmental conditions, plant resistance, or pathogen adaptation, play significant roles. Future research should focus on optimizing fungicide application rates and integrating other management practices to achieve consistent disease control.

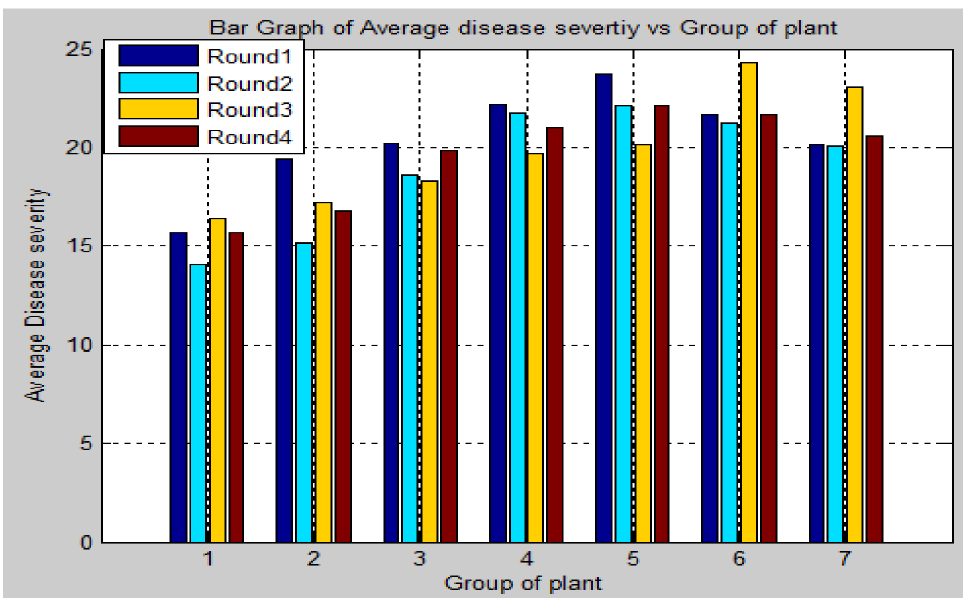


Figure 4.3. Bar Graph of Average disease severity vs Group of plant.

In all groups, disease severity decreased significantly from the first round to the second round. However, there was a slight increase in severity from the second round to the third round, followed by a slight decrease from the third round to the fourth round. The average disease severities over the rounds, measured in days, are illustrated in Figure 4.4, with the MatLab code algorithm provided in Appendix A6.

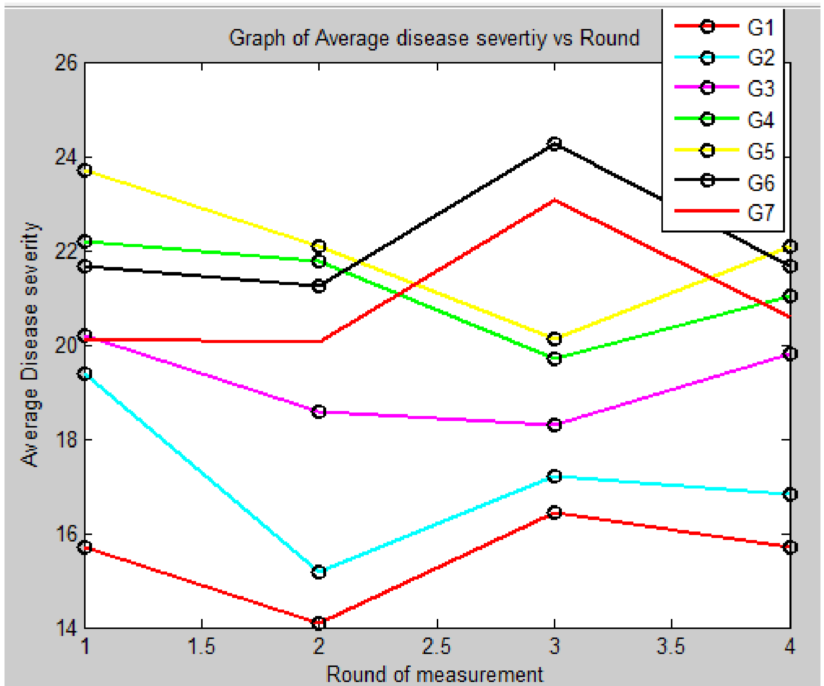


Figure 4.4. Average disease severities vs round of measurement (time).

Figure 4.5 illustrates the relationship between the volume of fungicide applied (in mL) and the average disease severity. The x-axis represents the volume of fungicide ranging from 0 to 140 mL, while the y-axis shows the average disease severity ranging from 15% to 23%. Initially, at 0 mL of fungicide, the severity is at the lower end of the scale. As the volume of fungicide increases, there is a sharp rise in disease severity up to a certain point. After this initial increase, the severity plateaus, indicating that further increases in fungicide volume do not significantly reduce disease severity. This graph suggests an optimal range for fungicide application, beyond which increased volumes do not provide additional benefits. Identifying this optimal fungicide volume is crucial for effective disease management to avoid unnecessary application. The plateau effect observed may be due to factors such as fungicide resistance or the natural progression of the disease. Further research and analysis are needed to draw more definitive conclusions.

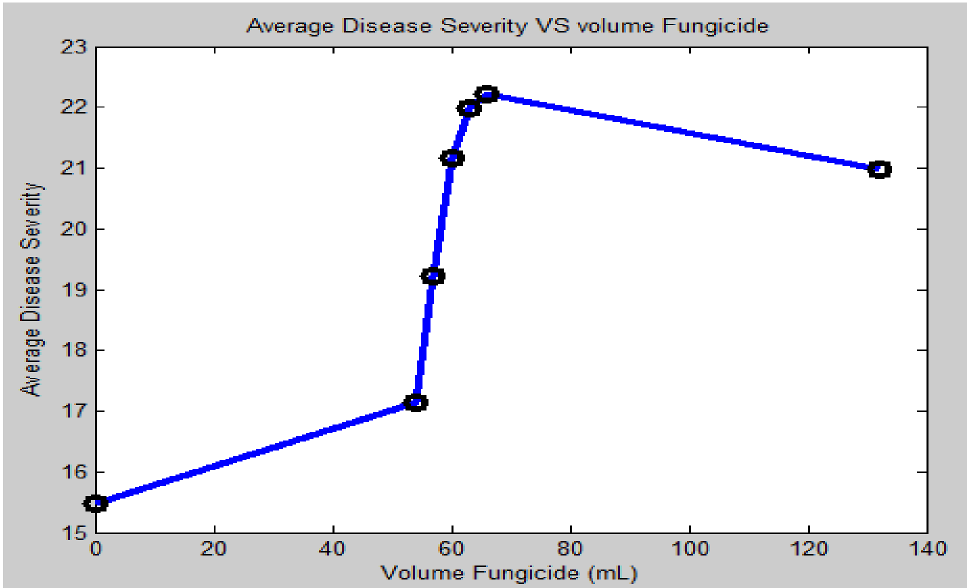


Figure 4.5. Average disease severity for round four vs the volume fungicide.

The volume needed to minimize the disease was considered as optimum volume of fungicide. As shown in Figure 4.5, the disease severity is very low on group 2, 3 and 7, which means that fungicide is effective in these groups 10%, 5% and 100% additional to the recommended 60 mL volume of fungicide.

4.6. Comparison for Estimation of Disease Severities

The average scores given by the experts for each group of the garlic leaf in the garlic rust images were compared with the corresponding scores obtained by the algorithm.

Table 4.3. Comparison of the scores of our algorithm with that of an expert.

Group	Algorithm score					Experts score	Percentage error (%)
	Round I	Round II	Round III	Round IV	Average		
1	15.69	14.1	16.43	15.69	15.48	15.60	0.77
2	19.40	15.16	17.21	16.81	17.15	16.00	7.19
3	20.21	18.58	18.3	19.82	19.23	17.65	8.95
4	22.19	21.78	19.7	21.02	21.17	20.80	1.78

5	23.69	22.08	20.12	22.08	21.99	22.00	0.05
6	21.67	21.26	24.28	21.67	22.22	21.00	5.81
7	20.14	20.07	23.06	20.59	20.97	20.00	4.85
			Average percentage error				4.20

Table 4.3 compares scores assigned by an algorithm (see Appendix A7) with those given by experts across four rounds for seven groups, including average scores and the percentage error for each group. The results show that the algorithm's scores are generally close to the experts' scores. Group 5 has the smallest percentage error at 0.05%, indicating a near-perfect match between the algorithm and experts' scores, while Group 3 shows the largest percentage error at 8.95%, indicating a more significant discrepancy. Overall, the average percentage error across all groups is 4.20%, which suggests that the algorithm's performance is relatively acceptable.

According Figure 4.6, these observations indicate that the algorithm generally aligns well with the experts' scoring, though some variability exists across different groups. The lower percentage errors indicate higher accuracy, with Group 5 being the most accurate. In contrast, Group 3's higher percentage error suggests areas for improvement. To enhance the algorithm's performance, further analysis could focus on understanding the underlying factors contributing to discrepancies in groups with higher errors. This approach would help refine the algorithm, making it more reliable and effective in matching expert evaluations.

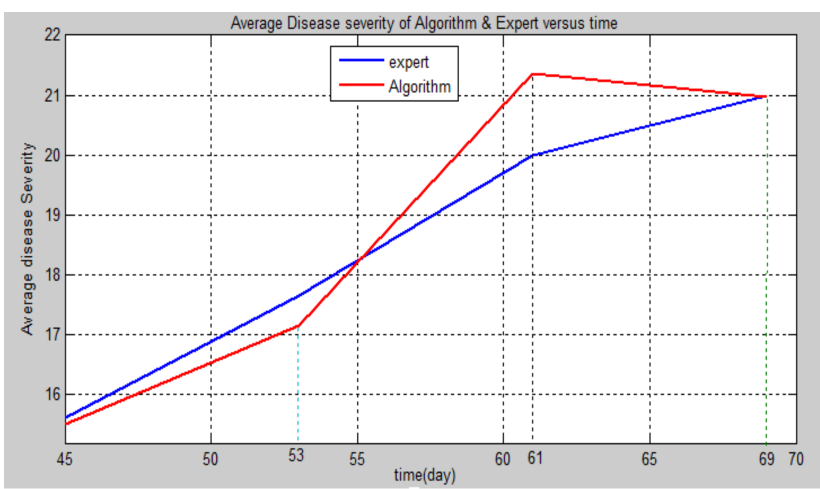


Figure 4.6. Average disease severity for algorithm and expert score vs time.

The comparison between the algorithm and expert scores is presented in Figure 4.7, based on the data in Table 4.2. The average disease severity of garlic leaves was calculated and compared with the experts' evaluations. The differences between the experts' assessments and the algorithm's results were minimal, and the average percentage differences between the two methods were not statistically significant.

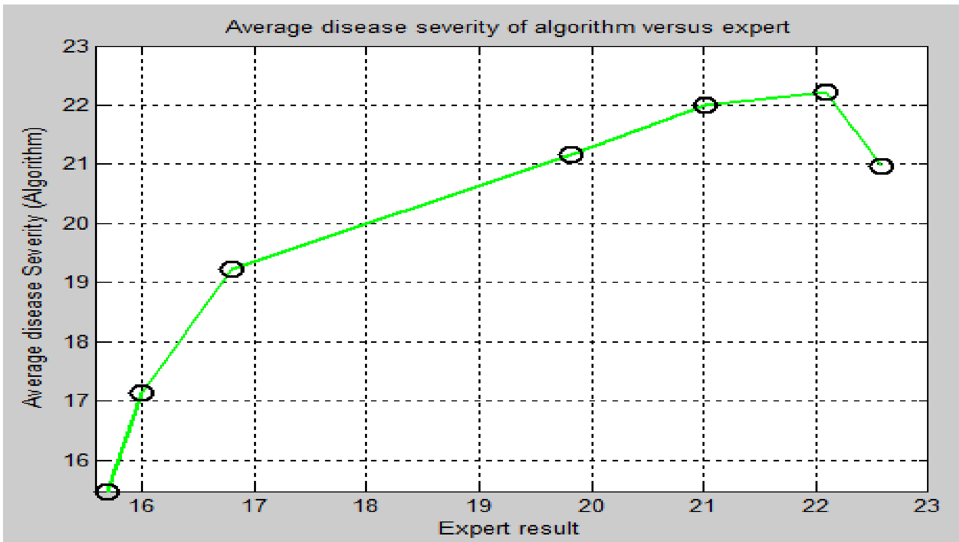


Figure 4.7. Average disease severity of algorithm versus expert score.

4.7. Calculating AUDPC and its interpretation

AUDPC is often helpful to plot the percentage of leaf area infected versus the evaluation date to get a better idea of how cultivars or varieties perform in terms of resistance to pathogens infestation in the experiment as shown in Figures 4.8 and 4.9.

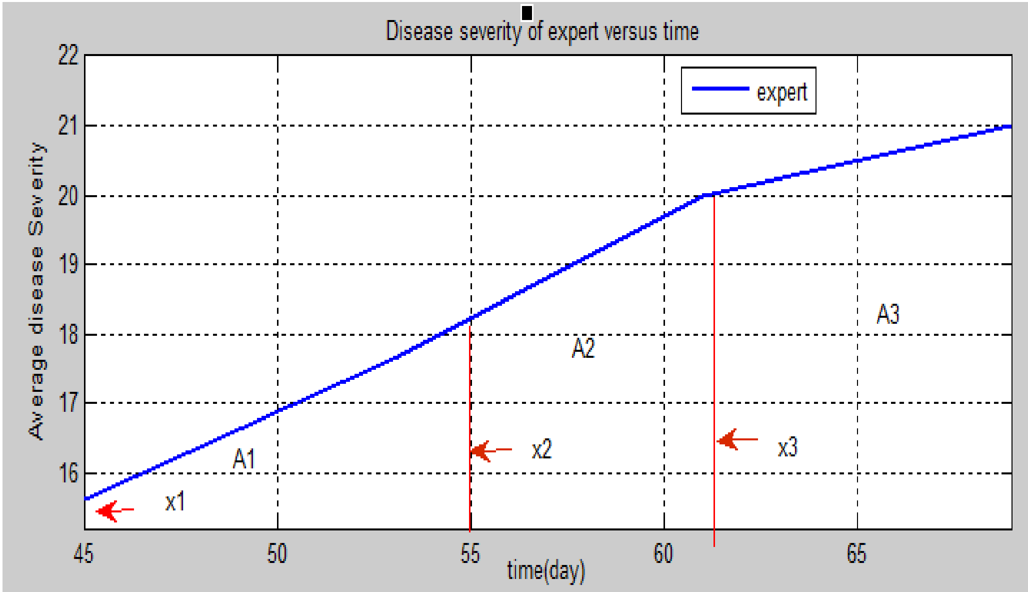


Figure 4.8. The disease severity-time curve of average value using expert data.

A_1 and A_2 are area from the imaging data by manual calculation and Matab's trapezoidal rule, respectively, Since the unit of s is percent (%) and that of t is day, the unit of A (A_1, A_2, A_3), i.e., area under severity-time (s-t) curve, is %-days. The result of manual calculation was obtained from Figure 4.8 using equation (4.1) as follows:

$$x_1 = 15.6\,, \qquad x_2 = 17.65, \qquad x_3 = 20, \qquad x_4 = 21,$$

where time is constant at interval $t = 8$ days.

Putting the above values into Eq. (3.4), the following results are obtained for each area of the trapezoidal region as shown in Figure 4.8

$$A_1 = \frac{1}{2}(x_1 + x_2)t_1$$
$$= \frac{1}{2}(15.6 + 17.65) \times (8) = 133\% - \text{days} \qquad (4.1)$$

Similar procedures were followed to calculate the values of A_2 and A_3 and the result were obtained as 150.6%-days and 164%-days, respectively. Then, the total area under the disease progress curve of the average value AUDPC was calculated as follows:

$$\text{AUDPC} = A_1 + A_2 + A_3 = 447.6\% - days$$

The calculation of AUDPC from disease s-t curve was performed based on the data set obtained from imaging techniques results. Matlab code of algorithm (Appendix A7 and A8) was the results were obtained by manual calculation (A_1) and the MatLab trapezoidal rules (A_2) and the MatLab algorithm developed to calculate the area under severity-time curve (AUDPC).

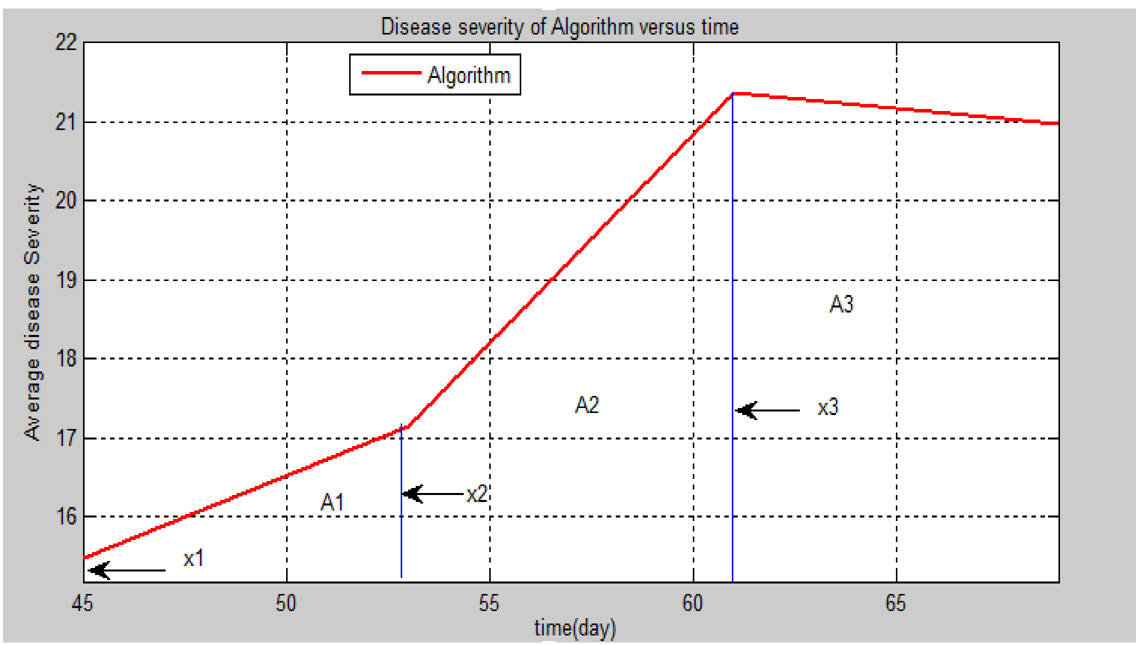


Figure 4.9. The disease severity-time curve of average value using algorithm data.

The result of manual calculation was obtained from Figure 4.9 using equation (4.1) as follows:

$$x_1 = 15.48, \quad x_2 = 17.15, \quad x_3 = 21.37, \quad x_4 = 20.97,$$

and

$$t_1 = 8 - 0 = t_2 = 16 - 8 = t_3 = 24 - 16 = t_4 = 32 - 24 = 8 \text{ days.}$$

Putting the above values into equation (4.1), the following results are obtained for each area of the trapezoidal region as shown in Figure 4.9

$$A_1 = \frac{1}{2}(15.48 + 17.15) \times (8) = 130.52\% - days$$

Similar procedures were followed to calculate the values of A_2 and A_3 and the result were obtained as 154.08%-days and 168.48%-days, respectively. Then, the total area under the disease progress curve of the average value AUDPC was calculated as follows:

$$\text{AUDPC} = A_1 + A_2 + A_3 = 453.08\% - \text{days}$$

The overall AUDPC result, as analyzed above from s-t curves of garlic leaves, discloses that the disease severity on each garlic leaf during the test period increased progressively; this assures that the disease severity increased accordingly.

Table 4.4. Result of AUDPC from garlic leaf (Algorithm and experts).

Group	Area from Algorithm A_i(% − day)	Area from Expert A_i(% − day)	Difference	Relative error (%)
1	130.52	133.00	0.018	1.80
2	154.08	150.60	0.023	2.31
3	168.48	164.00	0.027	2.73
4	172.64	171.20	0.008	0.84
5	176.84	172.00	0.028	2.81
6	172.76	164.00	0.053	5.34
7	170.24	162.00	0.050	5.08
Average Relative error				2.98

where A_i is the area from the imaging data by manual calculation and MatLab's trapezoidal rule, respectively, and is the area from the expert data. The relative percentage errors of the AUDPC for imaging techniques and experts score results were determined as:

$$E_r = \frac{|X_e - X_a|}{X_e} \tag{4.2}$$

So that

$$P_r = E_r \times 100\% \tag{4.3}$$

Where, X_e, X_a and P_r represent the expert score, algorithm score and percentage error, respectively for AUDPC.

The findings indicated that, despite the small differences between the experts' assessments and the imaging (algorithm) results, the average percentage difference between the two approaches was minimal. A slight discrepancy was observed in evaluating the AUDPC manually compared to using MATLAB, primarily due to the time required for manual analysis. The relative error in evaluating AUDPC from the s-t curve using the trapezoidal rule was 2.98%, which was not significant as determined by Eqs. (4.2) and (4.3). The image processing algorithm demonstrated an accuracy of 97.02%, aligning well with the results reported by Saranya et al. (2014), indicating that the algorithm's accuracy was satisfactory.

5. SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

5.1. Summary

The research focused on determining leaf rust (Puccinia allii Rudolphi) severity levels and managing it on garlic (Allium sativum L.) using image processing techniques. Garlic seeds were obtained from Haramaya University's "Raaree" Research Station, and the experiment was conducted in a glasshouse. Typically, the severity and management of garlic leaf rust are assessed visually by experts, which is time-consuming, costly for large farms, and subjective. In this study, severity levels were estimated by two experts involved in data collection. Traditional fungicide application was done manually without quantifying disease severity, leading to potential errors. Excessive fungicide use also contributes to environmental pollution, non-target organism toxicity, and increased production costs.

The experiment involved 21 pots of garlic plants selected from seven groups at Haramaya University's "Raaree" Research Station glasshouse. Each group had three pots, and two garlic leaves were randomly taken from each pot, resulting in 126 leaves for each of the four data collection rounds. A total of 504 images were captured. These images were pre-processed to reduce computational burden and enhance contrast between background and objects. Image segmentation algorithms, using Otsu’s thresholding techniques, converted gray-scale images into binary images. MATLAB 2018a algorithms were developed to determine the total and infected lesion areas of the leaf samples. Disease severity and AUDPC values were then assessed from these processed images.

5.2. Conclusions

This work presents a possibility to determine the severity and manage garlic leaf rust disease using digital image processing. MatLab2018a algorithms were developed to determine the total area and infected lesion area of the leaf samples. The average disease severity of garlic leaves was obtained and a comparison was made with the experts. The difference between the experts and imaging results is found to be very little and the average percent differences of the two approaches were not significantly different from each other. The relative error between experts' and imaging result relative error is only 4.20%. It was found that the accuracy of the algorithm developed for estimation of disease severity using image technology was 95.80%. Thus, the image technology can be used efficiently for the estimation of disease severity. Based on the finding of the study and discussion above, it is possible to conclude that using technological support, determination of disease severity on garlic leaf gives accurate result. This avoids subjectivity, and enables to determine the extent of disease severity to optimize the amount of fungicide to be sprayed. The relative error between experts' and imaging result relative error in evaluating AUDPC from severity-time (s-t) curve using trapezoidal rule (2.98%) and accuracy of the image processing algorithm developed was found to be 97.02%.

5.3. Recommendations

Based on the finding of this study, the following recommendations are forwarded.

1. This work considered only garlic leaf rust disease that is potentially harmful. As a result, future work should consider other garlic and other crop leaf diseases. Since this thesis focused only on garlic leaf disease, futures study needs to extend to cereal and vegetable diseases using image processing techniques.
2. By considering this study for determining and managing the disease severity levels of garlic and optimum volumes of fungicides, future study can be carried out to check its repeatability by taking more dataset using image processing techniques at different temperatures and different diseases.
3. The fungus does not affect the garlic bulb directly, but its damage on the leaves has the indirect effect of reducing the size and quality of the bulbs at harvest time. Future studies could also focus on garlic bulb product using image processing techniques.

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APPENDICES

APPENDIX A: MATLAB Functions and codes

Appendix A1: MATLAB Code for Image Enhancement and Segmentation

```
clc
close all
I=imread('garl.jpg');
%Ir=imrotate(I,-90);
%imshow(Ir)
I1=rgb2gray(I);
% imshow(I1)
CLAHE_Img = adapthisteq(I1,'clipLimit',0.01,'Distribution','uniform');%exponential, rayleigh, uniform
% imshow(CLAHE_Img)
% Filtering image using median filter
% figure,histeq(CLAHE_Img),title('plaq1 image enhanced')
medfilt_CLAHE_Img = medfilt2(CLAHE_Img ,[5 5]);
% figure,subplot(2,2,1),imshow(I,'InitialMagnification',[]),title('Original RGB Image');
imshow(medfilt_CLAHE_Img,'InitialMagnification',[]),title({'Plaq1 Image Filtered using Median '});
bw=im2bw(medfilt_CLAHE_Img);
imshow(bw),title('binaryimage');
```

Appendix A2: MATLAB Code for area extraction of normal leaf

```
% Area Extraction of normal leaf of garlics leaves
a = imread('g5p1M.JPG');%Read the RGB image
I=imresize(a,[ 384 576  ]);%re-sized image because %the image is too large to be displayed
cform=makecform('srgb2lab');
hold on
l=graythresh(A);
bw =~im2bw(A,l); % threshold
x=imfill(bw,'holes');
d = bwlabel(x, 8); % Label each blob so we can make measurements of it
se = regionprops(d, 'Centroid');
boundaries = bwboundaries(x);
numberOfBoundaries = size(boundaries);
hold on
for k = 2 : numberOfBoundaries
thisBoundary = boundaries{k};
plot(thisBoundary(:,2), thisBoundary(:,1), 'g', 'LineWidth', 2);
end
for k = 2:numel(se)
```

```
c = se(k).Centroid;
text(c(1), c(2), sprintf('%d', k), ...
'HorizontalAlignment', 'center', ...
'VerticalAlignment', 'middle');
end
hold off
 disp('garlic Leaf')
fprintf(1,'Sample \t Area \t Perimeter \n');
se = regionprops(d, 'all');
for k = 1 : numel(se)
TLArea = se(k).Area; % Calculate area of each object
TLPerimeter =se(k).Perimeter; % find perimeter of each object.
fprintf(1,'TL%d \t%8.1f \t%8.1f  \n' ,k,TLArea, TLPerimeter);
end
figure,subplot(2,2,1),imshow(I),title('Original image')
subplot(2,2,2),imshow(Lab),title('Objects in LAB space')
subplot(2,2,3),imshow(L),title('L component')
subplot(2,2,4),imshow(A),title('A component')
figure, imshow(x), title('The normal part of the leaf')
figure,imhist(x)
```

Appendix A3: MATLAB Code for area extraction of total leaf Garlic leaves

```
% Area Extraction of total leaves
I=imread('g5p1M.JPG'); %Read in image and display
R=imresize(I,[ 384 576]);
im=rgb2gray(R);%convert the rgb image to gray-level
X=imadjust(im);
bw =~im2bw(X,0.4); % threshold
bw = imfill(bw,'holes'); % fill holes
imshow(bw); %Display resulting binary image
title('Segmented Garlic Leaf')
y=imhist(im);
L = bwlabel(bw, 8); % Label each blob so we can make measurements of it
se = regionprops(L, 'Centroid');
hold on
boundaries = bwboundaries(bw);
numberOfBoundaries = size(boundaries);
for k = 2 : numberOfBoundaries
thisBoundary = boundaries{k};
plot(thisBoundary(:,2), thisBoundary(:,1), 'r', 'LineWidth', 2);
end
for k = 2:numel(se)
c = se(k).Centroid;
text(c(1), c(2), sprintf('%d', k), ...
'HorizontalAlignment', 'center', ...
```

```
'VerticalAlignment', 'middle');
end
hold off
disp('Garlic Leaf')
fprintf(1,'Sample \t Area \t Perimeter \n');
se = regionprops(L, 'all');
for k = 2 : numel(se)
TLArea = se(k).Area; % to find area of each objects.sqrt(4 * objArea / pi)
TLPerimeter =se(k).Perimeter; % to find perimeter of each objects.
fprintf(1,'TL%d \t%8.1f \t%8.1f  \n' ,k,TLArea, TLPerimeter);
end
figure,imhist(im)
```

Appendix A4: MATLAB Code for severity estimation

```
clear all
close all
clc
%Severity analysis of average garlic leaves
%Inputs:
t=[            ];
IA =[           ];% insert infected area of the leaf
TA =[             ];% insert total area of the leaf
S=((IA)./(TA))*100 % Evaluate the severity level
plot(t,S,'*'),title('Severity-Time graph of average garlic leaves'),...
   xlabel('Time(Day)'),
   ylabel('Severity (Percent)')
axis([         ])
```

Appendix A5: Matlab code used for drawing Bar Graph of Average disease severtiy vs Group of plant

```
% spraying pesticide
% average disease severity  group  in percent from round 1-4
y=[15.69,14.10,16.43,15.69
19.40,15.16, 17.12, 16.81
20.21, 18.58, 18.30, 19.82
22.19, 21.78, 19.70,21.02
23.69,22.08, 20.12, 22.08
21.67, 21.26, 24.28,21.67
20.14,20.07,23.06, 20.59];
bar(y)
legend('Round1','Round2','Round3','Round4')
grid on
title('Bar Graph of Average disease severtiy vs Group of plant')
ylabel('Average Disease severity')
```

```
xlabel('Group of plant')
```

Appendix A6: % MATLAB code used for drawing a graph of average severity versus time

```
G1=[15.69,14.1,16.43,19.82] ; %  average disease severity group one in percent from round 1-4
G2=[19.40,15.16,17.12,16.81] ; % average disease severity group two in percent from round 1-4
G3=[20.21,18.58,18.30,19.82] ; % average disease severity group three in percent from round 1-4
G4=[22.19,21.78,19.20,21.02] ; % average disease severity  group four in percent from round 1-4
G5=[23.69,22.08,20.12,22.08] ;% average disease severity group five in percent from round 1-4
G6=[21.67,21.26,24.28,21.67] ; %average disease severity group six in percent from round 1-4
G7=[20.14,20.07,23.06,20.59] ; %average disease severity group seven in percent from round 1-4
x=1:4; % plants in each group
plot(x,G1, '-ro','LineWidth', 2, 'MarkerEdgeColor', 'k', 'MarkerSize', 6)
hold on
plot (x,G2,'-co','LineWidth', 2, 'MarkerEdgeColor', 'k', 'MarkerSize', 6)
hold on
plot(x,G3, '-mo','LineWidth', 2, 'MarkerEdgeColor', 'k', 'MarkerSize', 6)
hold on
plot(x,G4, '-go','LineWidth', 2, 'MarkerEdgeColor', 'k', 'MarkerSize', 6)
hold on
plot(x,G5, '-yo','LineWidth', 2, 'MarkerEdgeColor', 'k', 'MarkerSize', 6)
hold on
plot(x,G6, '-ko','LineWidth', 2, 'MarkerEdgeColor', 'k', 'MarkerSize', 6)
 hold on
plot(x,G7, '-r','LineWidth', 2, 'MarkerEdgeColor', 'k', 'MarkerSize', 6)
 hold on
legend('G1', 'G2',  'G3', 'G4',  'G5', 'G6', 'G7');
title('Graph of Average disease severtiy vs time')
ylabel('Average Disease severity')
xlabel('Round of measurement')
```

Appendix A7: Matlab Code for Drawing graph Average disease severity for algorithm and%expert versus time

```
close all
fontsize=20;
x=[45 53 61  69];% time
y1=[15.6 16 17.65 20.8 22  21 20];% expert score
```

```
y2=[15.48 3 17.15 19.23 21.77,21.97, 22.22, 20.97];% Algorithm score
 figure,plot(x,y1,'-r',x,y2,'-o','LineWidth',2,...
    'MarkerEdgeColor','k',...
    'MarkerSize',10);
title('Average disease severity for algorithm and expert versus time ')
xlabel('time(day)'),ylabel('Average disease Severity')
legend('expert','Algorithm')
grid on
axis([41 90 15 30])
```

Appendix A8: Matlab Code for Average Disease severity of Algorithm & Expert versus time

```
%expert versus time
close all
fontsize=20;
x=[45 53 61 69];% time
y1=[15.6 17.65 20 21];% expert score
y2=[15.489 17.15 21.37 20.97];% Algorithm score
 figure,plot(x,y1,'-b','LineWidth',2,...
    'MarkerEdgeColor','k',...
    'MarkerSize',10);
title('Average Disease severity of Algorithm & Expert versus time ')
 xlabel('time(day)'),ylabel('Average disease Severity')
legend('expert','Algorithm')
legend('Algorithm')
grid on
axis([45  70  15.16  22])
```

Appendix A9: MATLAB code for AUDPC calculation

```
close all
clc
%AUDPC-time curve of detached leaves
%Analysis
%Inputs:
t = [45 53 61 69];% insert t-values
S =[15.6 17.65 20 21 ];%insert severity values
bar(t,S),title('AUDPC-Time graph'), xlabel('Time(Day)'),...
    ylabel('AUDPC(%-day)')
axis([        ])
```

Appendix A10: MATLAB code for Average Disease Severity vs Volume of fungicide

```
close all
fontsize=5;
x=[0 54 57 60 63 66 132 ];% volume fungicide
```

```
y=[15.48,17.15,19.23,21.17,21.99,22.22,20.97];% Average severity
figure,plot(x,y,'-ob','LineWidth',2,...
    'MarkerEdgeColor','k',...
    'MarkerSize',8);
title('Average Disease Severity vs Volume of fungicide)
xabel('Volume fungicide'),yabel('Average disease Severity')
%axis([0 130 10 42])
grid on
hold on
```

APPENDIX B: List of Tables

Table 1. Result of Disease Severity before spraying fungicide of the plant Leaf.

Group	No. of pots	Garlic Leaf	Total Leaf Area (TLA)	Norma Leaf Area (NLA)	Disease Leaf Area (DLA)	Severity (%)	Severity % Per pot	Severity % per group
1	1	UL	8953	7383	1570	18%	17%	15.69%
		ML	6206	5208	998	16%		
		LL	7396	6098	1298	18%		
	2	UL	4820	4207	613	13%	16%	
		ML	5458	4378	1080	20%		
		LL	9366	7865	1501	16%		
	3	UL	6201	4686	1515	24%	14%	
		ML	6716	6102	614	9%		
		LL	7261	6685	576	8%		
2	4	UL	5224	2507	2717	52%	24%	19.4%
		ML	6219	5474	745	12%		
		LL	7366	6763	603	8%		
	5	UL	4038	3327	711	18%	18%	
		ML	4904	4209	695	14%		
		LL	8234	6291	1943	24%		
	6	UL	8241	5996	2245	27%	16%	
		ML	8896	8528	368	4%		
		LL	9707	8218	1489	15%		
3	7	UL	8126	6979	1147	14%	19.8%	20.21%
		ML	9010	6788	2222	25%		
		LL	9606	7636	1970	21%		
	8	UL	8988	6751	2237	25%	21%	
		ML	8848	7502	1346	15%		
		LL	9816	7675	2141	22%		
	9	UL	8158	6488	1670	20%	20%	
		ML	10706	8500	2206	21%		
		LL	11110	8931	2179	20%		
4	10	UL	7118	5438	1680	24%	23.3%	22.19%
		ML	7844	6234	1610	21%		
		LL	9108	6769	2339	26%		

	11	UL	12221	9349	2872	24%	21%	
		ML	12459	10200	2259	18%		
		LL	12897	10075	2822	22%		
	12	UL	9238	7176	2062	22%	22%	
		ML	10373	8085	2288	22%		
		LL	10926	8518	2408	22%		
5	13	UL	13796	10539	3257	24%	25.4%	23.69%
		ML	14366	10434	3932	27%		
		LL	14476	10830	3646	25%		
	14	UL	5954	4441	1513	25%	24.7%	
		ML	8422	6428	1994	24%		
		LL	9043	6791	2252	25%		
	15	UL	10676	8588	2088	20%	21.0%	
		ML	11100	8535	2565	23%		
		LL	11421	9096	2325	20%		
6	16	UL	8311	6507	1804	22%	22.4%	21.67%
		ML	9221	7224	1997	22%		
		LL	8929	6788	2141	24%		
	17	UL	6129	4719	1410	23%	22.3%	
		ML	7018	5520	1498	21%		
		LL	8108	6285	1823	22%		
	18	UL	5154	4149	1005	19%	20.3%	
		ML	6147	4844	1303	21%		
		LL	7319	5843	1476	20%		
7	19	UL	4344	3700	644	15%	18.4%	20.14%
		ML	5982	4790	1192	20%		
		LL	9890	7858	2032	21%		
	20	UL	6725	5179	1546	23%	22.1%	
		ML	7240	5555	1685	23%		
		LL	9785	7828	1957	20%		
	21	UL	5748	4700	1048	18%	20%	
		ML	5743	4467	1276	22%		
		LL	6890	5565	1325	19%		

Table 2. Result of Disease Severity after spraying the first round fungicide of the plant Leaf

Group	Plant per Plan Pot leaf	Total Leaf Area (TLA)	Norma Leaf Area (NLA)	Diseas e Leaf Area (DLA)	Severit y%	Average Severity %per pot	Average Severity % per group

1	1	UL	5560	4784	776	14%	15.52%	14.17%
		ML	4730	3897	833	18%		
		LL	7920	6732	1188	15%		
	2	UL	5344	4777	567	11%	13.05%	
		ML	4982	4108	874	18%		
		LL	9890	8801	1089	11%		
	3	UL	7725	6636	1089	14%	13.93%	
		ML	6240	5426	814	13%		
		LL	7785	6645	1140	15%		
2	4	UL	5748	5180	568	10%	13.91%	15.16%
		ML	6743	5587	1156	17%		
		LL	7890	6729	1161	15%		
	5	UL	3562	2752	810	23%	20.54%	
		ML	5428	4502	926	17%		
		LL	6759	5284	1475	22%		
	6	UL	7765	6482	1283	17%	11.01%	
		ML	8420	7722	698	8%		
		LL	9230	8471	759	8%		
3	7	UL	8650	7754	896	10%	16.31%	18.58%
		ML	8534	7069	1465	17%		
		LL	10130	7963	2167	21%		
	8	UL	7512	6547	965	13%	18.27%	
		ML	9372	7709	1663	18%		
		LL	10340	7836	2504	24%		
	9	UL	7682	5942	1740	23%	21.17%	
		ML	11230	9152	2078	19%		
		LL	11634	9032	2602	22%		
4	10	UL	5642	4581	1061	19%	26.58%	21.78%
		ML	7368	5142	2226	30%		
		LL	7632	5287	2345	31%		
	11	UL	11745	9580	2165	18%	18.41%	
		ML	14983	12460	2523	17%		
		LL	12421	9943	2478	20%		
	12	UL	10762	8528	2234	21%	20.35%	
		ML	10897	8752	2145	20%		
		LL	11450	9090	2360	21%		
5	13	UL	13320	10444	2876	22%	19.16%	22.08%
		ML	14890	12258	2632	18%		
		LL	15000	12270	2730	18%		
	14	UL	5478	4143	1335	24%	25.48%	

		ML	8946	6573	2373	27%		
		LL	9567	7124	2443	26%		
	15	UL	11200	9136	2064	18%	21.61%	
		ML	11624	8987	2637	23%		
		LL	11945	9111	2834	24%		
6	16	UL	7835	5581	2254	29%	21.53%	21.26%
		ML	8745	7817	928	11%		
		LL	9453	7071	2382	25%		
	17	UL	4653	3275	1378	30%	22.84%	
		ML	6542	5178	1364	21%		
		LL	7632	6253	1379	18%		
	18	UL	4678	3298	1380	29%	19.40%	
		ML	5671	4846	825	15%		
		LL	7843	6734	1109	14%		
7	19	UL	3245	2170	1075	33%	23.64%	20.07%
		ML	3956	3060	896	23%		
		LL	4671	3963	708	15%		
	20	UL	4782	3551	1231	26%	16.11%	
		ML	7532	6646	886	12%		
		LL	6891	6145	746	11%		
	21	UL	4939	3883	1056	21%	20.46%	
		ML	5123	3836	1287	25%		
		LL	5342	4547	795	15%		

Table 3. Result of Disease Severity After spraying 2nd round fungicide of the plant Leaf.

Group	No. of pots	Plant Leaf	Total Leaf Area (TLA)	Norma Leaf Area (NLA)	Disease Leaf Area (DLA)	Severity%	Average severity %per pot	Average severity%per group
1	1	UL	12874	12874	2720	21.13%	17.07%	16.43%
		ML	36528	33808	7546	20.66%		
		LL	20295	12749	1915	9.44%		
	2	UL	8948	7033	1517	16.95%	15.81%	
		ML	23397	21880	3581	15.31%		
		LL	19068	15487	2895	15.18%		
	3	UL	11965	9070	3045	25.45%	16.41%	

		ML	26291	23246	2042	7.77%		
		LL	23664	21622	3791	16.02%		
2	4	UL	10842	7051	4180	38.55%	18.98%	17.12%
		ML	23087	18907	1058	4.58%		
		LL	22837	21779	3152	13.80%		
	5	UL	15945	12793	4872	30.56%	17.94%	
		ML	22643	17771	1302	5.75%		
		LL	29105	27803	5098	17.52%		
	6	UL	17520	12422	4457	25.44%	14.44%	
		ML	22768	18311	3431	15.07%		
		LL	24704	21273	694	2.81%		
3	7	UL	7521	6827	1425	18.95%	18.15%	18.30%
		ML	23969	22544	1564	6.53%		
		LL	13148	11584	3810	28.98%		
	8	UL	9287	5477	1542	16.60%	18.39%	
		ML	18642	17100	3080	16.52%		
		LL	31486	28406	6942	22.05%		
	9	UL	8311	1369	1662	20.00%	18.35%	
		ML	30388	28726	2916	9.60%		
		LL	21427	18511	5453	25.45%		
4	10	UL	17502	12049	5337	30.49%	16.25%	19.70%
		ML	22879	17542	1546	6.76%		
		LL	15871	14325	1824	11.49%		
	11	UL	8864	7040	2277	25.69%	16.60%	
		ML	24185	21908	2728	11.28%		
		LL	15870	13142	2037	12.84%		
	12	UL	10311	8274	2662	25.82%	26.24%	
		ML	11912	9250	3167	26.59%		
		LL	11929	8762	3140	26.32%		
5	13	UL	9129	5989	2301	25.21%	26.00%	20.12%
		ML	9914	7613	2814	28.38%		
		LL	11095	8281	2707	24.40%		
	14	UL	8057	5350	2070	25.69%	20.74%	
		ML	9342	7272	1482	15.86%		
		LL	9931	8449	2053	20.67%		
	15	UL	18925	16872	2215	11.70%	13.64%	
		ML	33221	31006	4072	12.26%		
		LL	18711	14639	3171	16.95%		
6	16	UL	7762	4591	1911	24.62%	13.36%	24.28%
		ML	20229	18318	1564	7.73%		
		LL	18116	16552	1402	7.74%		

	17	UL	5781	4379	1803	31.19%	26.94%	
		ML	6437	4634	1356	21.07%		
		LL	6893	5537	1970	28.58%		
	18	UL	7287	5317	2189	30.04%	32.53%	
		ML	7756	5567	2484	32.03%		
		LL	7931	5447	2818	35.53%		
7	19	UL	5123	2305	1845	36.01%	34.03%	23.06%
		ML	5431	3586	1875	34.52%		
		LL	6132	4257	1935	31.56%		
	20	UL	4912	2977	745	15.17%	16.43%	
		ML	5213	4468	740	14.20%		
		LL	5723	4983	1140	19.92%		
	21	UL	9834	8694	1363	13.86%	18.71%	
		ML	10120	8757	3053	30.17%		
		LL	11134	8081	1347	12.10%		

Table 4. Result of Disease Severity After spraying 3rd round fungicide of the plant Leaf.

Group	No. of pots	Plant Leaf	Total Leaf Area (TLA)	Norma Leaf Area (NLA)	Disease Leaf Area (DLA)	Severity%	Average severity per pot	Average severity per group
1	1	UL	5925	5079	846	14.28%	14.64%	15.69%
		ML	30221	27418	2803	9.28%		
		LL	15711	12509	3202	20.38%		
	2	UL	4762	3820	942	19.78%	14.85%	
		ML	17229	15734	1495	8.68%		
		LL	15116	12683	2433	16.10%		
	3	UL	9874	8123	1751	17.73%	17.56%	
		ML	33528	26651	6877	20.51%		
		LL	17295	14799	2496	14.43%		
2	4	UL	5948	5200	748	12.58%	17.07%	16.81%
		ML	20397	16485	3912	19.18%		
		LL	16068	12942	3126	19.45%		
	5	UL	8965	7189	1776	19.81%	14.69%	
		ML	23291	22008	1283	5.51%		
		LL	20664	16792	3872	18.74%		

	6	UL	7842	6231	1611	20.54%	18.67%	
		ML	20087	17098	2989	14.88%		
		LL	19837	15754	4083	20.58%		
3	7	UL	12945	9842	3103	23.97%	20.37%	19.82%
		ML	19643	17110	2533	12.90%		
		LL	26105	19776	6329	24.24%		
	8	UL	14520	11232	3288	22.64%	18.54%	
		ML	19768	16006	3762	19.03%		
		LL	21704	18679	3025	13.94%		
	9	UL	4521	3665	856	18.93%	20.56%	
		ML	20969	17874	3095	14.76%		
		LL	10148	7307	2841	28.00%		
4	10	UL	6287	4114	2173	34.56%	26.79%	21.02%
		ML	15642	12031	3611	23.09%		
		LL	28486	22013	6473	22.72%		
	11	UL	5311	4118	1193	22.46%	21.50%	
		ML	27388	22541	4847	17.70%		
		LL	18427	13943	4484	24.33%		
	12	UL	14502	11134	3368	23.22%	14.76%	
		ML	19879	18402	1477	7.43%		
		LL	12871	11116	1755	13.64%		
5	13	UL	5864	4556	1308	22.31%	16.98%	22.08%
		ML	21185	18526	2659	12.55%		
		LL	12870	10802	2068	16.07%		
	14	UL	7311	5118	2193	30.00%	26.32%	
		ML	8912	6714	2198	24.66%		
		LL	8929	6758	2171	24.31%		
	15	UL	6129	4797	1332	21.73%	22.94%	
		ML	6914	5569	1345	19.45%		
		LL	8095	5857	2238	27.65%		
6	16	UL	5057	4056	1001	19.79%	21.21%	21.67%
		ML	6342	4829	1513	23.86%		
		LL	6931	5547	1384	19.97%		
	17	UL	5781	3978	1803	31.19%	26.94%	
		ML	6437	5081	1356	21.07%		
		LL	6893	4923	1970	28.58%		
	18	UL	7287	6098	1189	16.32%	16.86%	
		ML	7756	6192	1564	20.17%		

		LL	7931	6813	1118	14.10%		
7	19	UL	5123	3778	1345	26.25%	21.45%	20.59%
		ML	5431	4456	975	17.95%		
		LL	6132	4897	1235	20.14%		
	20	UL	4912	4167	745	15.17%	20.26%	
		ML	5213	3873	1340	25.70%		
		LL	5723	4583	1140	19.92%		
	21	UL	9834	8471	1363	13.86%	20.06%	
		ML	10120	7567	2553	25.23%		
		LL	11134	8787	2347	21.08%		

APPENDIX C: List of Figures

Appendix C1: Planting Garlic Seeds

a) b) c)

(a) Measuring the weight of soil composition, (b) mixing soil and (c) mixing soil in to pot

a) b) c)

(a) Planting garlic researcher with expert, (b) field observation two week garlic plant after planted.(c) garlic plant after planted 25 days.

Appendix C2: Preparation of the Inoculation

a) b) c) d) e)

Inculcation preparation procedures (a) diseases garlic leaves, (b) measuring powder garlic leaf rust, (c) distilled of water, (d) mixture two dropped tween20 and (e) spores checked by compound microscope.

Appendix C3: Inoculation of Garlic Leaf.

a) b) c)

Deliberate Inoculation of garlic leaf: (a) Inserting spore suspension into the whorl of garlic leaf and (b) and (c) covering plants after inoculation.

Appendix C4: Spraying the Fungicides Tilt 250 EC

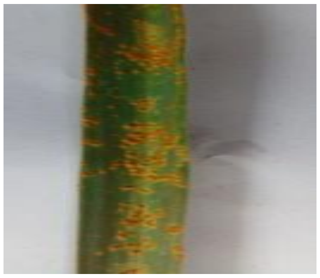
a) b)

Spraying the fungicides: (a) tilt 250EC and (b) spraying the fungicide 250EC

Appendix C5: Original Infected Garlic Rust Images Detached Leaf

a) b) c) d)

Appendix C6: Original Infected Garlic Rust Images Round One.



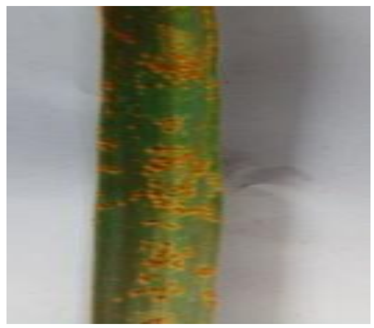
R1I1

R1I2

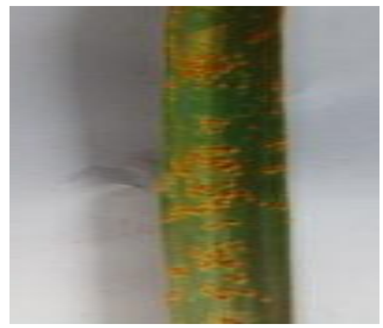
R1I3

R1I1

R1I5

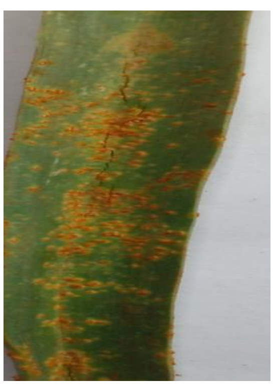


R1I6

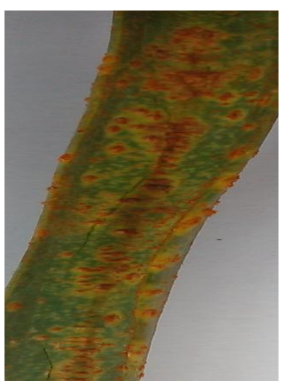


R1I7

AppendixC7: Original Infected Garlic Rust Images Round Two.



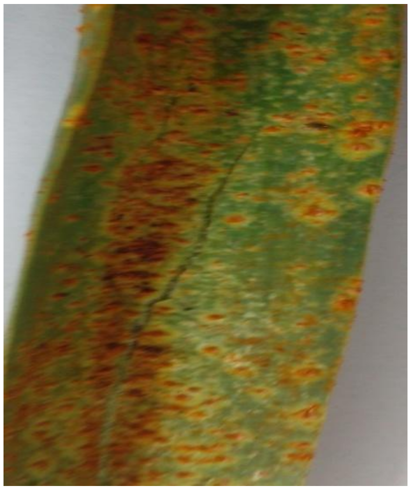
R2I1



R2I2

R2I3

R2I4


R2I5


R2I6


R2I7

Appendixc8: Original Infected Garlic Rust Images Round Three.

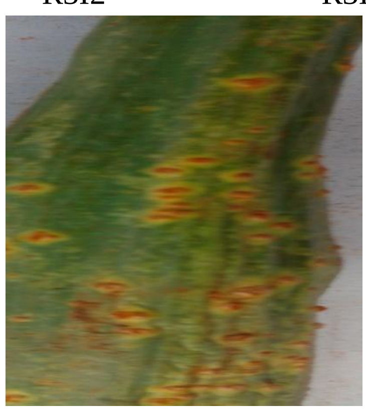

R3I1

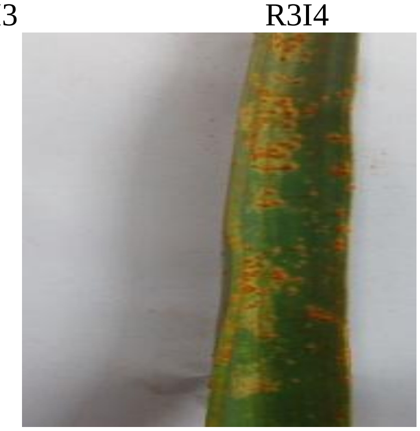

R3I2


R3I3


R3I4


R3I5


R3I6


R3I7

Appendix C9: Original Infected Garlic Rust Images Round Four.


R4I1


R4I2


R4I3


R4I4


R4I5


R4I6


R4I7