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Spodoptera Litura Damage Severity Detection and Classification in Tomato Leaves

Sathesh. A

Research Scholar, Tianjin Key Laboratory of Process Measurement and Control, School of Electrical and Information Engineering, Tianjin University, Tianjin 300072, China

E-mail: sathesh4you@gmail.com

Abstract

Agriculture plays a key role in global economy. Tomato is India's third most prioritized crop after potato and onion, but it is the world's second most prioritized crop after potato. Worldwide, India ranks second in tomato production. However, Tomato crop is constantly threatened by different pest infections. The most significant pest infection that highly affects the tomato crop yield is *Spodoptera Litura.* Emerging from the family of Noctuidae with vigorous eating pattern, this insect primarily feed on leaves and fruits by leaving the entire crop completely destroyed. Monitoring the pest spread dynamics will reduce the probability of an outbreak. Early detection of pests can assist farmers in taking the required precautions to limit the spread of the infection. This paper provides a brief introduction to performs an assessment on the infection spread by *Spodoptera Litura* in the tomato plants. Here, the plants are classified as low, moderate and high pest infestation and further the severity of the damage is assessed by analyzing the number of S. Litura Larvae present in Tomato crop and also the percentage of pest infestation in tomato plants. The primary goal of this research study is to detect pests as early as possible and decline the usage of pesticides on the crops by taking early sustainable alternative measures.

Keywords: Spodoptera Litura, tomoto leaves, disease detection, pest dynamics, severity analysis

1. Introduction

With the increasing world population, the global food consumption tends to increase at an unprecedented rate. In 2040, the demand for food will increase by 2.5 times the demand raised in the year 2017. Agriculture remains as a major source for food production. In crop

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cultivation, India ranks second in producing different varieties of cotton, cereals, vegetables and fruits remaining as primary revenue generating occupation for 58% of the total population. Every year, a considerable amount of food production decline has been observed. The major cause for this decline is increasing number of pests. Spodoptera Litura is one such insects belonging to the Noctuidae family. Generally known as leafworm moth, which is spread across the tropical and sub-tropical areas of the world and widespread in India. Spodoptera Litura is considered a serious polyphagous pest with more than 87 identified species in Indian subcontinent. The Spodoptera Litura larvae attack a wide variety of crops, including tomatoes, cabbage, strawberries and soybeans and it has been officially reported on about 20% of cultivated plants. Spodoptera Litura may cause an economic loss in the range 27-80% The majorly affected crop is Tomato.

In the initial stages, the worms are dangerous as they completely scrape the chlorophyl content present in the tomato leaves leaving only a white and transparent leaf structure. In the later stages, these pests become more aggressive and proceeds towards making unusual holes and very high defoliation in the tomato leaves. Finally, the moths are gregarious and it leaves all the matured fruits with irregular holes in it. They usually consume on the leaflets, stems, and stalks of tomato plants and even slice them off by destroying the entire plant in no time. In severe infections, it might completely destroy the plant, causing inhibited growth and poor yield.

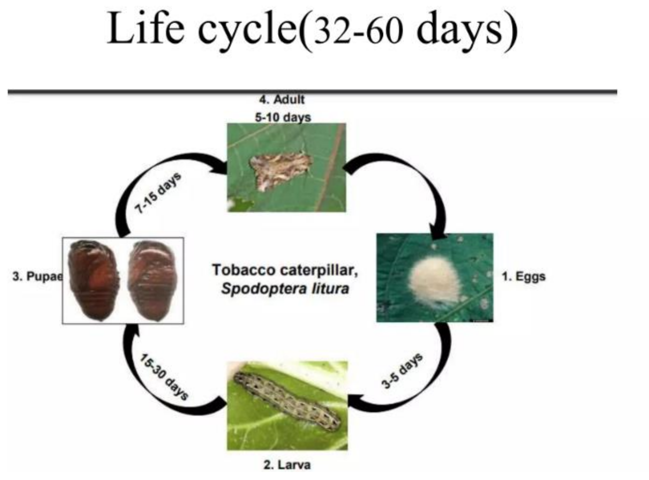

Figure 1. Life Cycle of Spodoptera Litura

To monitor these pests and its aftereffects on tomato, farmers solely depend on the manual inspection process. However, the unpredictability and inconsistency observed in the manual inspection remains as a potential barrier for farmers. This leads to a delay in administrating the pesticides. Pesticides used in excess pollute the soil, water and air. Pesticide suspensions carried by the wind can also contaminate agricultural fields / environment. This research study focuses on developing a novel early pest detection model, which can regularly observe the plants. The tomato plant images are acquired by using cameras. The acquired images will then be used to interpret the severity of the pest infestation and larvae population for the given area by using image processing techniques.

2. Literature Review

This section will discuss about different methods that are presently used in the early detection of pests in plants by considering both advantages and disadvantages.

Pest Detection using Image and Video Analysis

Thonnat et. al [1] have utilized image processing techniques to particularly detect the whiteflies in rose plants. This model has delivered a more accurate and reliable results when compared to the manual pest monitoring techniques. Since early-stage pest infection detection is considered as a complex process, they have selected to only detect the adult flies.

Ocampo et. al and Luna et. al [2,3] have discussed about how the pests and other plant diseases limits the plant growth and affect the production of crops. Here, researchers have used color textures to detect the infections.

Recently researchers are preferring to integrate the Artificial Intelligence (AI) and Computer Vision (CV) approaches to ease the process of early-stage pest detection.

Pest Detection using Sticky Traps

Martin et. al [4] have implemented a video camera network to detect the insects and pest infection on the plant leaves. The traditional pest infection detection method will consume more time and effort to detect as well as count the number of pests infested. The developed system based on video analysis utilized 5 wireless cameras and sticky traps are used to attract and monitor the pests. In order to detect insects, image segmentation algorithms are used.

The future scope is to develop more adaptive systems can be used to monitor the agricultural fields in any weather conditions.

In the literature study two significant challenges have been encountered, they are

1. Low Image/Video Quality: Due to the quality constraints and image transfer and analysing speed, most of the research works that exists in the literature becomes impractical [5].

2. Real-Time Inconsistencies: Inconsistencies emerge due to various factors, they are image illumination, fast movement of insects, existence of irrelevant objects in the focused area, existence of non-pest variety insects, and so on [6].

These challenges make it hard for the researchers to design an efficient rule-based system. This necessitates the need to develop a novel and efficient method, which should also be flexible to adapt to diverse factors like working with minimal manual effort and labelled data by performing daily pest monitoring. Aside from insect classification/detection, general visual object recognition and detection has been the long-term objective of computer vision. Various methods and datasets [7, 8] are recently proposed to advance this field. Convolutional Neural Networks (CNN) and its types have recently emerged as the most effective method for performing any type of object recognition and detection, achieving state-of-the-art performance [9, 10, 11] and overcoming various object recognition challenges [12, 13, 14].

3. Materials and Methods

Here, a study has been conducted to note down the extent of damage made by Spodoptera litura during the Rabi season from October, 2021 to March, 2022 at Coimbatore, India. Experiment was conducted on high-yielding hybrid tomato variety IIHR-2834 × IIHR-2833 with spacing 70cm × 60cm (Row × plant) and with plot size 20m × 50m.

Visual observations were made to determine the percentage of pest infestation and the extensiveness of tomato crop damage caused by S. litura. Totally, thirty heads were observed at fortnightly to estimate the average population of Spodoptera litura larvae per head. In addition to, sixty heads were observed based on various criteria such as low, moderate, and high pest infestation. The percentage of infection at different larvae populations was used to determine the extent of damage in tomato crops. Plant infestation percentage can be determined by using the following formulae:

$$Damage\ heads\ per\ field = \frac{No. of\ Plants\ Infested}{Total\ No. of\ Plants} \times 100$$

$$Yield\ Loss = \frac{Damaged\ Plant\ Yield}{Total\ Yield} \times 100$$

In this study, cutworms are particularly focused since this pest requires early pest detection and treatment to prevent its infection in tomato plants. Here, samples are collected by using a title camera and the data is acquired as shown in Fig 2.

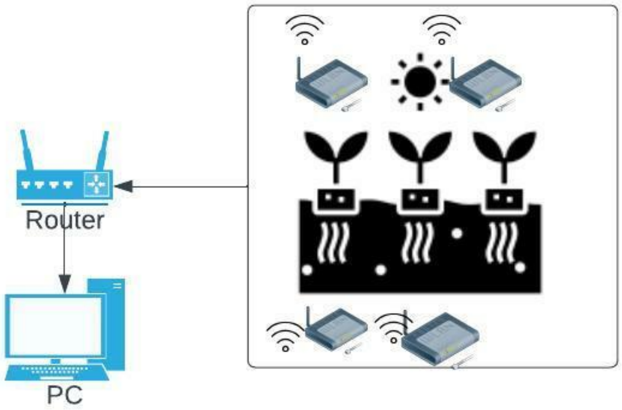

Figure 2. Proposed Architecture

Methodology

Image Collection:

The images of tomato leaves are captured by using a camera and the image will then be stored in a JPEG format an.332123d transferred to via Wi-Fi routers to the local PC.

Image Pre-Processing:

This step is used to enhance the final version of the capture image by performing the below-mentioned processes

(i) RGB-to-Grey Image Conversion

The storing of images with large pixels in the form of RGB requires more space and processing time. Hence, the images should be converted into grey format.

(ii) Image Resizing

The dimensions of the images will be resized to a standard form. Here, the nearest neighbourhood interpolation resizing method is used.

(iii) Image Filtering

In this phase, the unwanted portion of the image will be eliminated. This study has preferred to use a smoothening filter to reduce the noise in the captured image and enhance the visual quality.

Feature Extraction:

Some image properties are particularly considered in this phase, they are region properties and grey covariance matrix properties. Different properties like standard deviation, entropy, and contrast, are extracted and used to train the dataset into a binary classification based learning method, Support Vector Machine (SVM).

4. Results and Discussion

Detection and Classification:

Tomato Plants - Vegetative Stage	Tomato Plants - Fruit Formation Stage
Low Pest Infestation	Low Pest Infestation
	
Moderate Pest Infestation	Moderate Pest Infestation
	
High Pest Infestation	High Pest Infestation

Figure 3. Pest Infestation and Classification

Figure 3 represents the three major categories of pest infestation in tomato plants. The pest infestation in the field is divided into three categories as low, moderate and high.

The first infestation made by cutworm Spodoptera Liptura has been recorded in the fortnight of December with the average larvae population of 0.5 larvae/head with nearly 15 percent plant infestation as shown in Figure 4.

Maximum of 65% plant infestation were recorded during the mid-fortnight of January with a larvae population of about 3.9 larvae/head, out of which 12, 5, 10 percent tomato plants were moderately, less and highly infected. First fortnight of march there was a sudden decline in the larvae population, it was about 3.1 larvae/head, with 39% infection. In the second fortnight of March, it was abruptly reduced 30% with 3.5 larvae/head as illustrated in Figure 4 and 5.

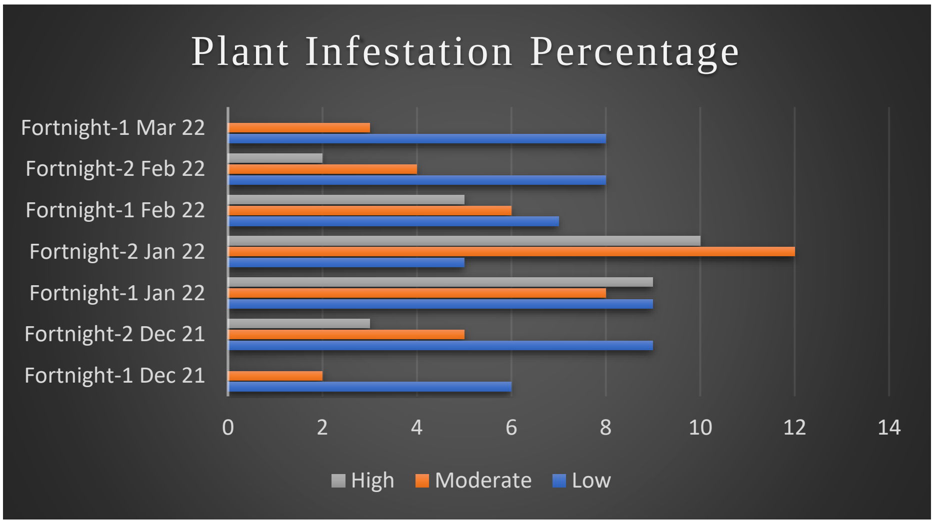

Figure 4. Plant Infestation Percentage at Different Durations (Months)

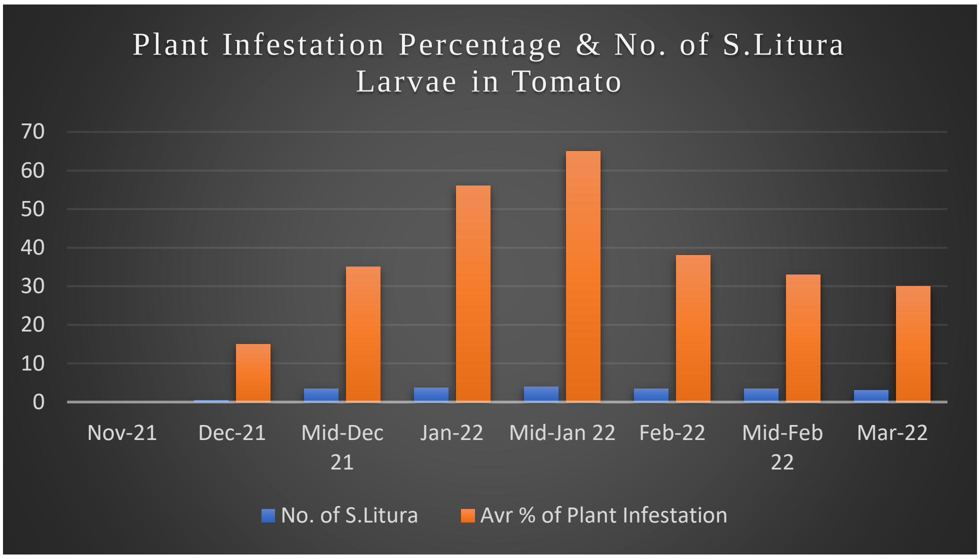

Figure 5. Plant Infestation Percentage & No. of S.Litura Larvae in Tomato

5. Conclusion

This study has actively recorded the images of the crop for about 3-6 months period. From November till the harvesting of the tomato crops. However, with the performed analysis a maximum of 65% pest infestation is recorded in January 2022. The corresponding information will help the farmers to analyse and determine the effect of S. Litura in tomato crop production. The proposed model has reported a highest pest damage in early January and a positive correlation has been observed between pest density and the plant damage. To detect pests, this study has used a camera connected with a Wi-Fi router for enabling a continuous monitoring. This process helps to capture and analyse the pest infestation without disturbing them. This prototype will help to obtain a complete and prolonged analysis on the pest infestation.

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