



UNIVERSITI PUTRA MALAYSIA

***PADDY INSECT PEST IDENTIFICATION USING ARTIFICIAL
INTELLIGENCE AND MACHINE LEARNING***

LAI ZHI YONG

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INTELLIGENCE AND MACHINE LEARNING**

**LAI ZHI YONG
187028**

**BACHELOR OF AGRICULTURAL AND BIOSYSTEMS
ENGINEERING WITH HONOURS
FACULTY OF ENGINEERING
UNIVERSITI PUTRA MALAYSIA
SERDANG, SELANGOR**

SEPTEMBER 2020

Approval

The Project report entitled “**PADDY INSECT PEST IDENTIFICATION USING ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING**” prepared and submitted by **LAI ZHI YONG** in partial fulfilment of the requirement for degree in Bachelor of Agricultural and biosystems Engineering with Honours at Universiti Putra Malaysia is hereby accepted.

Approved by:

.....

Assoc. Prof. Dr. Samsuzana Abd Aziz

(Project Supervisor)

Date:

.....

Prof. Sr. Gs. Dr. Abdul Rashid b. Mohamed Shariff, CEng

(Project Examiner)

Date:

.....

Dr. Nurulhuda bt. Khairudin

(Project Examiner)

Date:

Acknowledgement

It would not be possible to finish the project without the help of those around me; therefore, I would like to take this opportunity to express my gratitude to some of them who lend me their hands while I was doing the project.

First of all, I would like to thank my supervisor, Assoc. Prof. Dr. Samsuzana Abd Aziz who provided me help and guidance to finish the work, holding the Machine Learning Workshop as well as helping to contact the authority of MARDI for visitation to collect data.

Besides, I would also like to thank the coordinator of EAB 4949, Dr. Mohd Nazren b. Radzuan who has provided me help for thesis writing and holding seminar for research methodology.

Last but not least, I would like to thank MARDI for allowing me to collect data and to use the amenities such as the sticky pad light trap to capture the insects.

Abstract

The trend of paddy harvested area in Malaysia has a -0.2% growth rate where the government has to import about 0.9 million metric tonnes (MT) of rice from neighboring countries per year. The government strives to achieve 100% self-sufficiency level of rice in 2020. Pest has been a critical challenge in paddy plantation as it can cause up to 37% loss in yield. This project developed an insect pest detection model that can detect the species of insect pest as well as counting the insects according to their species using Faster Recurrent Convolutional Neural Network (Faster R-CNN). The insects were captured at MARDI with a sticky pad light trap, and the images of the insects were taken using a smartphone camera which was set at a shutter speed of 1/50 second, lens aperture of f/2 and a focal length, $f = 3.5\text{mm}$. The images were taken in a black box with 6 LED light bulb. The model was trained with 1460 RGB images of 3 classes of insects including Zig Zag brown planthopper (Zig Zag BPH), green leafhopper (GLH) and a class for a mixture of other insects. The model was trained for 23200 iterations and the accuracy of classification of Zig Zag BPH, GLH and others were 0.98, 1 and 0.97 respectively, while the F1 score for the respective species were 0.92, 1 and 0.98. The model was able to achieve a mean average precision (mAP) of 0.93 and an average recall (AR) of 0.60.

Abstrak

Trend kawasan penuaian padi di Malaysia mempunyai kadar pertumbuhan -0.2% di mana kerajaan perlu mengimport kira-kira 0.9 juta ton metrik beras dari negara jiran setiap tahun. Kerajaan berusaha mencapai tahap 100% kadar kemampuan diri beras pada 2020. Perosak telah menjadi cabaran kritikal dalam perladangan padi kerana ia boleh menyebabkan kerugian sehingga 37% dalam hasil. Projek ini membangunkan model pengesanan serangga perosak serangga yang boleh mengesan spesies serangga perosak serta mengira serangga mengikut spesies mereka menggunakan *Faster Recurrent Convolutional Neural Network* (Faster R-CNN). Serangga-serangga ditangkap di MARDI dengan perangkap lampu pad melekit, dan imej serangga diambil menggunakan kamera telefon pintar yang ditetapkan pada kelajuan pengatup = 1/50 saat, kanta aperture = $f/2$ dan panjang fokal, $f = 3.5\text{mm}$. Imej-imej itu diambil dalam kotak hitam dengan 6 mentol lampu LED. Model ini dilatih dengan 1460 imej RGB daripada 3 kelas serangga termasuk benah perang Zig Zag (Zig Zag BPH), lelompap daun hijau (GLH) dan satu lagi kelas untuk campuran serangga yang lain. Model ini dilatih untuk 23200 leran dan ketepatan klasifikasi Zig Zag BPH, GLH dan 'lain-lain' adalah 0.98, 1 dan 0.97 masing-masing, manakala skor F1 bagi spesies masing-masing adalah 0.92, 1 dan 0.98. Model ini mampu mencapai min purata ketepatan (mAP) 0.93 dan purata ingat kembali (AR) sebanyak 0.60.

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Chapter 1 Introduction

1.1 Background

Oryza sativa or more commonly known as paddy is a type of semiaquatic grass that belongs to a family of plants that includes other cereals such as wheat and corn. It is grown across the world and has successfully fed more than 3 billion people worldwide. In tropical climate, paddy is a perennial where it can produce new tillers from nodes after harvesting. At maturity, the plant has a main stem and several tillers; each one of them bears a terminal flowering panicle. Paddy plant can grow up to between 0.4m to 5m high depending on the environment (Phatak & Khan, 1994). The growth duration of the plant is 3 to 6 months, according to variety and environment.

Rice is a staple food in Malaysia; however, the Government of Malaysia has revealed that the production of rice does not meet its demand. According to Harun and Ariff (2017), the trend of paddy harvested area has a -0.2% growth rate where the government has to import about 0.9 million metric tonnes of rice from other countries such as Myanmar and Thailand. In the 11th Malaysia Plan, the government has aimed to increase the average annual growth of harvested area and reached the self-sufficiency level of rice to 100% in 2020 (Rajamoorthy et al., 2015a).

Insect pests have been a critical concern that all farmers face. According to the International Rice Research Institute (IRRI, 2016), insect pest attack can cause up to 37% loss of paddy yield. Therefore, there is a need to detect insect pest to help decrease yield loss. Pest detection is traditionally done by human inspection. According to Gondal and Khan (2015), farmers analyze and detect pests aided by traps such as black light traps and sticky traps. These methods require manpower for wide field and can be time consuming as well as expensive. Therefore, studies have been done to scour new technologies to help farmers to detect pest on field at the early stage before further serious outbreak.

Agriculture sector has joined the Industrial Revolution 4.0 that aimed to fully automate and digitize the industry; thus, technologies such as the Internet of Things (IoT), big data management and machine learning have come to place in this past decades in agriculture sector. These technologies are different and more advanced compare to the technologies before, where machine can learn by themselves through experience from observations of data. The application of these technologies aligns with the 4th National Agrofood Policy (NAP4), where its 1st objective is to modernize and boost agricultural production to ensure sustainable supply and stabilize the nation's food prices by stressing the paddy, ruminant and fishery subsectors. To achieve the objective, the authorities have strategized to modernize agricultural practices through application of technology where they stress on the mechanization and automation in agriculture (Bakar et al., 2012). The contribution of big data and machine learning is the precursor of modernizing agriculture sector; therefore, it is reasonable to speculate that machine learning to bring great advancement in agriculture sector.

Machine learning is an application of artificial intelligence that provides systems the ability to automatically learn and improve from experience without being explicitly programmed. There are different methods used in machine learning including supervised machine learning, unsupervised machine learning and the list goes on. Machine learning has earned its place in agriculture sector for crop health monitoring, soil defect detection and even weather prediction (Feng et al., 2019; Suchithra & Pai, 2019). Since its invention, researchers tried to utilize machine learning to fully automate the industry to meet the need of labor. As pest detection is one of the most concerned issue in paddy field, several studies have proposed the application of machine learning for pest detection in paddy field (Cheng et al., 2017)

1.2 Problem Statement

There are more than 100 species of insect pest that attacks paddy. However, only about 20 species of them cause economic damage. These insects include rice leaffolder, ant, armyworm, black bug, cutworm, field cricket, grasshopper, locust, green leafhopper, etc. These insects grow in different environment, in different country. According to Ooi (2015), the major pests in paddy field of Malaysia include stem borer *Chilo polychrysus*, rice armyworm (*Spodoptera mauritia*), Malayan black bug (*Scotinophora coarctata*), caseworm (*Nymphula depunctalis*), rice leaf folder (*Cnopalocrocis medinalis*), green leafhopper (*Nephotettix virescens*), rice ear bug (*Leptocorisa oratorius*), rice brown planthopper (*Nilaparvata lugens*) and white-backed planthopper (*Sogatella furcifera*).

Studies have estimated that there is an annual loss of rice grain between 120 to

200 million tonnes in tropical Asia caused by pest, diseases and weed. In Malaysia, these attacks do not only cause the grain loss on farm but also bring a further decrease in farmers revenue as factories will impose high reduction rates for lower grade paddy. According to Mohamed et al. (2016), as there is a premium attached to unblemished-looking produce, farmers often over-apply pesticides to prevent pest attacks. This causes a high residue of pesticides in paddy.

Besides, the traditional methods of sampling techniques; the light trap, which involves various size sample is good for comparing seasonal and yearly catches of insects; however, the catches depend on the behavior of the insects. Carino, Kenmore and Dyck (1979) also claims that manual technique; the sweep net is fast and economical as well as effective, but it is prone to human error due to variability and poor catch at the base of the plant (Miranda et al., 2014).

Furthermore, the manual technique of estimating pest density captured on a sticky trap do not only give inefficient result but also proved to be harmful to the environment as farmers take preventative measure to spray pesticides in bulk (Gondal & Khan, 2015). From the literature, it was also stated that the manual technique for pest analysis is time consuming and less effective, it also requires availability of experts, thereby, increasing the cost. Since then, automatic pest detection techniques using image processing and classification algorithm have been proposed. It was also shown that by using computer vision, the detection can be three times faster. Studies have shown that machine learning generally gives better result than traditional image processing algorithm (Liu & Wang, 2020). Therefore, this project focused on developing a paddy insect pest identification system with machine learning and

artificial intelligence.

1.3 Objective

The main objective is to develop an insect pest detection model for paddy insect pest with Faster Recurrent Convolutional Neural Network (Faster R-CNN). The specific objectives are:

1. To develop a machine learning algorithm to detect Zig Zag Brown Plant Hopper (Zig Zag BPH) and Green Leaf Hopper (GLH) using Faster R-CNN.
2. To develop an algorithm for insect pest counting based the result of the Faster R-CNN detection model.

Chapter 2 Literature Review

This chapter includes research into the paddy plant and its economic values in Malaysia, the insect pest common to paddy plant, current insect pest control methods and machine learning algorithms used to detect pest.

2.1 Paddy in Malaysia

Rice is the second most important crop in the world after wheat, with Asia being the biggest producer and consumer (Rajamoorthy et al., 2015b). There are 31 million people in Malaysia consuming rice daily. In 2016, Malaysia's consumption of rice was at 2.7 million MT and according to projections by the Organization for Economic Co-operation and Development (OECD), the consumption is expected to skyrocket as the population grows (Omar et al., 2019).

2.1.1 Physiology of Paddy Plant

Paddy or *Oryza sativa* is a type of semiaquatic grass that belongs to the family of Poaceae which include other cereals such as wheat and corn. Rice is grown all over the world, and there are many varieties of rice, cultivated in different ways. However, they share some common features and go through three main stages of growth, i.e., vegetative, reproductive, and ripening before the seeds are harvested.

At maturity, paddy has a main stem and several tillers. Each tiller bears a terminal flowering head or panicle. The height of paddy plant ranges from 0.4m to 5m, depending on the variety, the environment condition, etc. After harvesting, the paddy will be dried before selling to customers.

2.1.2 The Economic Stand of Paddy

Undoubtedly, rice has been a staple food for all Malaysians; however, the supply of paddy failed to meet its demand in this few decades. Harun and Ariff (2017) revealed that the trend of paddy harvested area shows a -0.2% growth rate where the Government of Malaysia have import around 0.9 million MT of rice from other countries such as Thailand and Myanmar.

In the previous 10th Malaysian Plan (MP), the government has achieved its target of a -2.4% average annual growth rate of the paddy harvested area, where it strives to achieve a -1.4% growth rate in the 11th MP. Besides, the 4th National Agrofood Policy (NAP4), also aims to increase the self-sufficiency level of rice to 100% in 2020. The 1st objective of NAP4 is to modernize and boost agricultural production to ensure sustainable supply and stabilize the nation's food prices by stressing the paddy, ruminant and fishery subsectors. In order to achieve the objectives, the authorities have strategized to modernize agricultural practices through application of technology where they stress on the mechanization and automation in agriculture, development of new model of modern agriculture and the development of National databased for agrofood (AGF). NAP4 also strives to increase production of paddy subsector by managing the greenery area efficiently (Bakar et al., 2012).

2.2 Insect Pest of Paddy

To achieve the goals set in the NAP4, insect pest is one of the most important element to tackle as it can bring a loss up to 37% in paddy yield (Phatak & Khan, 1994). There are more than 100 species of insect pest that attack paddy plant; however, only about 20 species of them bring significant economic loss. These attacks display different symptoms, depending on the species of insect pest that infest the plant. In this section, only insect pest that is common in Malaysia will be discussed.

2.2.1 Black Bug

Black bug or *Scotinophara sp.* is a nasty smelling insect pest in paddy field. There are 2 main species of black bugs, the Malayan rice black bug *Scotinophara coarctata* (Fabricius) and the Japanese rice black bug *Scotinophara lurida* (Burmeister). The first encounter of *Scotinophara coarctata* in Malaysia is traced back to the 1918, right after the first record of *Scotinophara coarctata* in Indonesia in 1903. Since 1983, it started to increase its number in the region of Philippine, Indonesia and Malaysia (Phatak & Khan, 1994).

It was found that black bugs attack paddy plant at various growth stages, from seedling to maturity. Large populations of black bugs are more common in continuous irrigated, continuously rice-cropped field rather than rainfed, single-cropped field (Phatak & Khan, 1994).

The adult black bug (as shown in Figure 2.1) has a black head, collar and cicatrices; yellowish brown antenna; reddish to dark brown abdomen; reddish brown

legs with yellowish tibiae and tarsi. The average size of a black bug is 9mm from the anterior margin to the apex of the abdomen and is 4.5mm across the prothorax (Phatak & Khan, 1994).

Black bugs are active in the early hour of the day and at night, when the sunlight intensity is low. They often seen in flight and feed on the plant continuously at night (Phatak & Khan, 1994).



Figure 2.1 Adult Malayan Black Bug

2.2.2 Rice Stem Borers

Rice stem borer or *Chilo polychrysus*. is one of the most common rice insects in Malaysia. It bore into the paddy stem, damaging it. However, at low level attack, paddy can compensate the loss by growing more tiller (Ooi, 2015). According to Ooi (2015), a full-grown caterpillar can be up to 22cm long and it becomes pupa in the damaged stem for about six to nine days as shown in Figure 2.



Figure 2.2 The Rice Stem Borer caterpillar

2.2.3 Rice Armyworm

Full grown caterpillar of armyworm or *Spodoptera mauritia* often have a low population in paddy field as most of the caterpillars die from fungus infection (Ooi, 2015). Although small in numbers, a nearly full-grown caterpillar can cause very serious damage at the heading. It can rapidly consume a large amount of foliage in a short period of time and detach the panicle (the heading). The caterpillar of armyworm is shown in Figure 2.3.



Figure 2.3 The caterpillar of Armyworm

According to Phatak and Khan (1994), the fully-grown larva of the armyworm hibernates, and the period of hibernation depends on the surrounding temperature. The armyworm can produce 5 generations of offspring per year.

The armyworm has a habit of pupating in the soil, limits their reproduction in the lowland rice fields. Therefore, the adult or moth of the armyworm multiply in other area before migrating to the paddy field, either in swarm of caterpillar or moths. The moths rest on the paddy plant (as shown in Figure 2.4), and most of the damage are caused by the caterpillar and most of the time it is hard to detect before the paddy are damaged (Phatak & Khan,1994).



Figure 2.4 The Moth of Armyworm

2.2.4 Caseworm

Caseworm or *Nymphula depunctalis* is also a common paddy insect in Malaysia. Caseworm usually occurs in low population in paddy field. However, occasionally, they build up in a small area and cause severe defoliation. Caseworm larvae are in pale cream color, about 1.2mm long and 0.2mm across the head (Figure 2.6). They form tubes with the leaves and enclose themselves to protect themselves from natural enemies. The tubes also act as floats to help them travel from one plant to another (Figure 2.5). Caseworm causes damage at the seedling and vegetative stages of paddy.



Figure 2.6 Larva of Caseworm



Figure 2.5 Larva of Caseworm in tube of paddy leaf

The adult moths are white in color. They are about 6mm long and have a wingspan of about 15mm. The wings have some light brown or black speckles and two to three submarginal fulvous bands (Figure 2.7).



Figure 2.7 The Adult Moth of Caseworm

The caseworm may build up at paddy field with standing water. It also increases in number during the rainy season (Haq et al., 1970). No record of hibernation is recorded because the insect occurs in overlapping generations.

2.2.5 Leaffolder

Rice leaffolder or *Cnaphalocrocis medinalis* is one of the best known leaffolder species in Asia. A new-born larva is translucent but after feeding the leaves, the leaffolder turns green. A full-grown larva is yellowish green in color, with a dark brown head and its average size is 20- 25mm long and 1.5-2mm wide. The larva pupates inside the leaf roll in loosely woven strands of silk thread as shown in Figure 2.8 (Phatak & Khan, 1994).



Figure 2.8 The caterpillar inside the leaf roll woven with silk

The adult *Cnaphalocrocis medinalis* are usually confused with *Marasmia patnalis* (also a type of leaffolder). The morphological characteristics of the insects are shown in Figure 2.10 and Figure 2.9 respectively. The adult moths are 10-12mm long and have a wingspan of 13-15mm. They are light brown in color and have shiny, brownish yellow wings with dark, broad margin and 2-3 dark vertical strips.



Figure 2.10 *Cnaphalocrocis medinalis* adult



Figure 2.9 *Marasmia patnalis* adult

During high insect population density, the paddy plants dry up and appear scorched. The larvae roll the leaves and feed on the mesophyll in the folded leaves. Feeding greatly reduces the general vigor and photosynthesis of paddy plant.

2.2.6 Green Leafhopper

The green leafhopper (GLH) or *Nephotettix virescens* is a vector of tungro or more notoriously known as “penyakit merah”. Besides the virus disease, GLH also feed on the plant. Therefore, even a sparse population of GLH cause significant yield loss.

The average size of leafhoppers is up to 15mm. They inject a toxin into the plant when they feed on it (Britannica Online Encyclopedia, 2018). The adult of GLH is shown in Figure 2.11.



Figure 2.11 Green Leafhopper

The infected paddy will demonstrate symptoms of stunted growth, and hopperburn, as shown in Figure 2.12.



Figure 2.12 Hopperburn in paddy field

2.2.7 The Rice Ear Bug

Rice ear bug or rice bug (Figure 2.13) is one of the most important insect pests for paddy especially in the tropical and subtropical area. It belongs to the genus of *Leptocorisa*. The most common species of rice bug in Malaysia is *Leptocorisa oratorius*. They feed on developing rice grain resulting empty grain (Ooi, 2015).

The adult rice bug is long and slender, about 14-17mm long and 3-4mm wide. They are most active during the early morning and evening when the sunlight is not

strong. The nymphs are small and green, but become brown eventually, as they grow. They blend in very well in the foliage and often escape from detection. The adults and the nymphs camouflage in the paddy field and are very hard to detect. They are abundant during the flowering season of paddy (Serrano et al., 2017).



Figure 2.13 Rice ear bug camouflage in rice grain

2.2.8 Brown Riceplanthopper

The brown planthopper (BPH) or *Nilaparvata lugens* exist in two forms, the long-winged form (macropterous form) and the short-winged form (brachypterous form). The first invasion will usually by macropterous but after a generation, most of the BPH will be brachypterous. BPH are small, about 5mm long and they feed near the base of the paddy plant, allowing them to escape from detection (Ooi, 2015). The two forms of BPH are shown in Figure 2.14 and Figure 2.15.



Figure 2.14 Macropterous form



Figure 2.15 Brachypterous form

2.2.9 White Backed Planthopper

White-backed planthopper or *Sogatella furcifera* is a common insect pest during the early crop stages, unlike BPH it does not have brachypterous form. They share similar life cycle and life history pattern with BPH. The moth of white-backed planthopper is shown in Figure 2.16.



Figure 2.16 The white-backed planthopper

2.3 The Severity of Paddy Insect Pest in Malaysia

The condition of paddy field in Malaysia is not deeply investigate; however, according to Hafizal and Idris (2014), the severity of insect pest depends on the crop stages. The study shows that planthopper is in abundance at maturity of paddy plant. Besides, Chang (1980) also claims that the population of insect pest is also affected by the cultivating methods and variety of paddy plant.

Outbreak of insect pest in Malaysia is comparatively rare. However, there are some outbreak of insect pest recorded in 1925 and 1929 in Krian followed by 1967 in Terengganu (Lim, 1969). Since then, Malaysia have no records of serious outbreaks.

2.4 The Status of Pest Control and Monitoring in Malaysia

Since the 1960's, there aren't any record on serious outbreaks. However, this doesn't mean that the pest control in Malaysia is done correctly according to standards. The pest control method has evolved in the past few years. The purpose of pest control is not only to catch the pest but also to monitor them.

2.4.1 Methods of Pest Control

The use of nonpesticide methods to control agricultural pests in Malaysia has a very long history. Biological control can be an alternative to pesticides when comes to pest control. However, it is still a norm in the agriculture industry that pesticides are the go-to solution of insect pest. According to Mohamed et al. (2016), the paddy industry in Malaysia have a premium attached to unblemished looking produce; therefore, farmers often over-apply pesticides to prevent pest attacks. This causes a high residue of pesticides in paddy.

The study also found that about 80% of the farmers in the sample space practices unsustainable practices of paddy farming. They over-apply chemicals resulting chemical residue even the paddy reaches the market.

2.4.2 Methods of Pest Monitoring

According to Gondal and Khan (2015), the traditional methods of monitoring pest in paddy field include black light and sticky trap, which will be then analyse by human. This method can be cost and labour intensive in wide field where more people are hired to monitor the pest. Malaysian Agricultural and Development Institute (MARDI), have done a research on the surveillance technique between light trap and manual sampling (Masarudin et al., 2019). Masaeudin et al. (2019) stated that manual methods by visual scoring is labor intensive and does not illustrate the real condition of the field. On the contrary, light trap sampling is one of the most effective methods to manage past as it trapped numerous specimens with minimum efforts; however, manual counting and human inspection is still needed. According to the study, this methods

can study the real condition of the field and can help field supervisor to monitor and estimate BHP population before taking measures to spray; thereby, reducing loss in crop and reduce the cost for excess pest control. Several studies had been done to automate pest detection using technology such as acoustic sensing, remote sensing, machine vision, artificial nose (E-nose), etc.

2.4.2.1 Acoustic Sensing

According to Liu (2017), acoustic sensing can be used to detect invertebrate on crops. She stated that, accelerometers, piezoelectric sensors and acoustic probes are attractive to detect pests inside plant tissue, soil, or stored grains. All these sensors detect sounds and vibration of insect. The research shows promising result. However, this method is prone to affected by background noises which limit the types of sensors that can be used. Besides, the exact numbers of larvae are unknown and the applications to detect and identify insects through some of the vibrometers are very limited and need further study.

2.4.2.2 Remote Sensing

According to Zhang et al. (2019), remote sensing (RS) can be used to monitor plant diseases and pests. The sensing systems are classified that include visible & near-infrared spectral sensors (VIS-NIR); fluorescence and thermal sensors; and synthetic aperture radar (SAR) and light detection and ranging (Lidar) systems.

The used of RS allow data acquisition ranging from gamma ray to microwave to detect the symptoms of infections, physiological responses of plants to infection and

the structural changes such as canopy structure caused by plant diseases and pests (Zhang et al., 2019). There are limitation and disadvantages of each RS systems. For instance, VIS-NIR system might provide reliable result; however, it performs poorly on early detection; fluorescence and thermal system have high potential to provide pre-symptoms detection but it is difficult to apply in wide area; SAR and Lidar may indicate structural changes but the case studies are scarce.

2.4.2.3 *Machine Learning*

Machine learning (ML) has been studied to allow pest identification in agriculture sector. Machine learning is an application of artificial intelligence that provides systems the ability to automatically learn and improve from experience without being explicitly programmed (MathWorks, 2016). There are different methods used in machine learning including supervised machine learning, unsupervised machine learning and the list goes on. Machine learning has earned its place in agriculture sector for crop health monitoring, soil defect detection and even weather prediction. Since its invention, researchers tried to utilize machine learning to fully automate the industry to meet the need of labor. As pest detection is one of the most concerned issue in paddy field, several studies have proposed the application of machine learning for pest detection in paddy field.

Support Vector Machine (SVM) is a supervised machine learning model. SVM can be used for classification and regression analysis. Several studies have proposed SVM for pest detections. According to Gondal and Khan (2015), SVM allows simpler implementation yet give accurate result for detection of white flies. The proposed

algorithm involves 2 major steps which are data preprocessing and model training. The RGB images were converted to grayscale and the image were resized. Image noise removal algorithm and segmentation algorithm where used to enhance the image and to segment out the insects. The feature used to train the SVM is the Gray Level Cooccurrence Matrix (GLCM). After the data were preprocessed, the GLCM is used to train the SVM. The proposed algorithm was proven to perform well with overlapped flies. The algorithm also was able to detect the shape of the flies. The accuracy of the proposed model is 97%.

Besides, Agnihotri (2019), also proposed a pest detection system that integrate thermal imaging with SVM. Through the study, it was proven that the system can detect larger pest such as rat as well as small pest like insects. Several other research papers also proposed SVM to detect pest. By integrating remote sensing technologies such as Thermal infrared and florescence system, SVM can accurately detect pest and diseases such as wheat leaf rust at 93% of accuracy (Zhang et al., 2019).

According to Cui et al. (2018), an artificial nose (E-nose) can be used to detect pests. In the study, Cui et al. (2018) stated that volatile organic compound (VOC) can be used identify pests as plant will excrete VOC to combat with infection. From the literatures, it was shown that E-Nose combined with Artificial Neural Network (ANN) can classify healthy and unhealthy plant at an accuracy of 94%. Besides with E-Nose and ANN, the level of infection of oak wilt can be detected at an accuracy of 78.65%. The reliability of E-nose technology has been confirmed in rice plant diagnosis. Infected rice plants attacked by the rice stem borer and the BPH can be easily discriminated from healthy plants. E-Nose with ANN can detect age and number of BPH at an accuracy of 100% and 48.93% respectively.

Besides SVM and ANN, Johannes et al. (2017) proposed using Random Forest and Naïve Bayes to detect pest and diseases in wheat. From the literature, the data were preprocessed by means of color constancy algorithm to reduce the effect of illumination. The leaf images were segmented from the background. The shape and color of the image were used as features to train the model. The model was able to achieve accuracy of 0.78 for early detection of wheat rust.

According to Islam et al. (2017), potato diseases can be detected using image segmentation and SVM. Plant Village dataset were used to train the model. The model was able to detect late blight, early blight and healthy potato plant with an average precision of 95%, average recall of 95% and average F1 score of 95%.

Hlaing and Zaw, (2018) proposed a tomato plant disease classification with a model-based statistical features for mobile phone image. From the literature, it was found that the texture of leaves was used to train a SVM to detect tomato diseases with Plant Village database. The model was able to achieve an accuracy of 84.7% after training for 12000 iterations.

With the advancement of machine learning, researchers have started to incorporate deep learning into their studies, including pest detection. With deep residual learning, pest can be identified in a complex background and the classification accuracy can be up to 98.67% for 10 class of crop pests (Cheng et al., 2017). The deep convolution neural network (CNN) also have to ability to extract features automatically without explicit human interference. As residual deep learning allows pest detection in complex background, it is more practical for agricultural task compare to the previous

research. Besides, deep learning also allows accurate discrimination of highly similar insect between inter-class and interclass species. It also allows effective identification of different phenotypes of the same insect species in different growth periods (Xia et al., 2018). From the literature, Xia et al. proposed an improved CNN to detect insects using images from the internet. The model was able to achieve a mean average precision (mAP) of 0.8922 after training the model for 11.2 hours.

According to Agnihotri (2019), pests can be detected using thermal camera aided with machine learning. From the literature a total of 55 images were used to train 3 CNN including the AlexNet, ResNet-50 and ResNet-101. The models were trained for 2000 iterations and he reported that ResNet-101 with deep residual learning achieved 98.67% accuracy for 10 class of pest.

Fuentes et al. (2017) proposed using Faster R-CNN to detect insect pest and infection status of tomato plant. The model was trained with a total of 5000 images and the model achieved a mAP of 0.8306. Besides, Liu and Wang (2020) also proposed using an Improved YOLO V3 to detect tomato diseases and pest. The model was trained with 15000 images and the model was able to achieve mAP of 96.91% with high resolution images (1024 pixels).

DeChant et al. (2017), proposed using CNN to detect Northern Leaf Blight (NLB) infected maize. The CNN model was trained with 1786 field-acquired images. The model consists of 3 stages. In the 1st stage, CNNs were used to detect the presence of NLB lesion, the 2nd stage used CNNs to produce heat maps which indicated the probability of the infection of each region in the images. The 3rd stage used the heat

map to classify the full images. The model was able to achieve an accuracy of 96.7% on the test set images.

Jiang et al. (2019) proposed using improved CNN to detect apple leaf diseases. Apple leaf disease dataset (ALDD) of 26377 images was used to train the CNN. The proposed model, Single Shot Detection with Inception module and Rainbow concatenation (INAR-SSD) was able to achieve a mAP of 78.70% on the ALDD.

In paddy, several research papers had study the application of deep learning model to detect pest and disease. Lu et al. (2017) proposed a custom CNN to detect rice disease. The structure of the CNN is shown in Figure 2.17. The CNN consisted of 6 hidden layers where each convolutional layer was followed by a polling layer. At the end of the model there was a fully connected layer which was activated with a softmax function. The model was trained with a total of 500 images for 10 class of common rice diseases. The model achieved an accuracy of 95.48%.

Layer name	Function	Weight filter sizes	Output tensor
Input			$3 \times 512 \times 512$
Conv1	Convolutional	16×16	$3 \times 224 \times 224$
Pool1	Stochastic pooling	5×5	$32 \times 112 \times 112$
Conv2	Convolutional	9×9	$64 \times 112 \times 112$
Pool2	Stochastic pooling	5×5	$64 \times 56 \times 56$
Conv3	Convolutional	5×5	$128 \times 28 \times 28$
Pool3	Stochastic pooling	5×5	$128 \times 14 \times 14$
Output	Softmax regression		$10 \times 1 \times 1$

Figure 2.17 The Structure of the Convolutional Neural Network for rice disease detection

Besides, Atole and Park (2018) proposed a multiclass CNN classifier to detect common rice plant anomalies. A CNN was trained to classify rice plant into normal, unhealthy and snail infested. The CNN model used was a pretrained AlexNet. The model was trained with 600 images and it achieved an accuracy of 91.23%.

Furthermore, Ramesh and Vydeki (2020) proposed using Deep Neural Network with Jaya Optimization Algorithm (DNN-JOA) to detect paddy leaf diseases. Unlike other DNN, DNN-JOA had a feedback loop after classification to make the model stable, the proposed flow of methodology was shown in Figure 2.18. The model was trained with a total of 650 images and the model achieved an accuracy of 98.9% for the blast affected paddy, 85.78% for bacterial blight, 92% for sheath rot, 94% for brown spot and 90.57% for normal paddy leaf image.

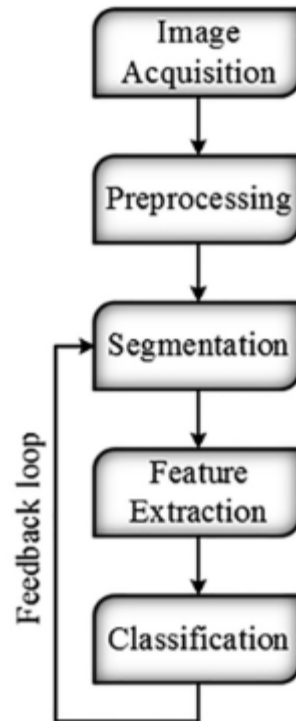


Figure 2.18 Flow chart of the Deep Neural Network with Jaya Optimization Algorithm

2.5 Summary of Literature Review

From the literature review, it is shown that insect pest contributes to a significant loss in paddy yield. Therefore, to achieve the target set in NAP4, this issue can be a key element to deal with. Besides, even though there are not any major pest breakout since the 1960's, studies have shown that most of the farmers over-apply pesticide to prevent insect pests. It is also shown that good surveillance technique can help field supervisor monitor and estimate the number of pests before taking control measures.

From the literature, it is also shown that the pest monitoring system in Malaysia is highly dependent on Entomologist where pest counting, and identification needed to be done manually. Some of the paddy insect pests shares similar phenotype where it may be hard to differentiate; however, by new computational intelligence technique such as machine learning, highly similar features can be accurately distinguished. It is also shown that machine learning can help to identify, and count insect pests and it is able to give promising result. Hence, this project focuses on the development of an insect pest detection system with machine learning algorithm.

Chapter 3 Methodology

This project focused to develop a machine learning algorithm to detect the species and to count the number of insect pest in paddy field with Python (Python Software Foundation. Python Language Reference, version 3.7. Available at <http://www.python.org>) and Tensorflow 1.15. The model was trained with ASUS ROG Strix SCAR III with NVIDIA RTX 2070 GPU and Intel Core i7 9th Generation CPU. To develop the model, several activities were done including study area selection, image data collection, image data preprocessing, insect pest detection model training and model evaluation. The process of developing the model is shown in Figure 3.1.

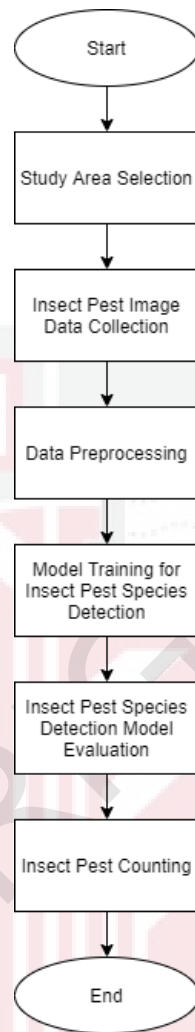


Figure 3.1 The process of developing of insect pest detection model

3.1 Study Area

The study area of this project was MARDI Seberang Perai, Pulau Penang. It is a paddy and rice research centre, located at Jalan Paya Keladi / Pinang Tunggal, Kampung Permatang Durian, 13200 Kepala Batas, Pulau Pinang, with 10 blocks of paddy field. The location of the area is shown Figure 3.2.



Figure 3.2 Location of Mardi Seberang Perai

3.2 Data Collection

Data was the heart of machine learning; therefore, data collection was a crucial part of developing a machine learning algorithm. To train a deep learning model through transfer learning, the insect pest image data were collected at MARDI Seberang Perai. To collect the data, an insect pest light trap was used to trap the insects on the sticky pad and an image acquisition system was built to capture the image in the lab. The sensor used to collect the data was a smartphone camera.

3.2.1 Insect Pest Light Trap

A light trap with sticky pad was set up to attract and catch the insect pests. The light trap consists of a 30W electrical bulb, a transparent box, an A3 plastic sheet sprayed with adhesive spray. The transparent box has many holes at each surface, this

is to control the size of the insects trapped on the sticky pad. The plastic sheet was sprayed with adhesive spray to make a sticky pad. The sticky pad was rolled into a cylinder with the sticky surface at the exterior. The light bulb was placed in the center of the plastic cylinder. The light bulb and the cylinder were placed in the transparent box and the light bulb was switched on to attract the insects. The design and setup of the insect pest sticky pad light trap was by MARDI. An image of the trap was shown in Figure 3.3.



Figure 3.3 Stick pad light trap by MARDI

The light bulb was switched on overnight to capture the insects. The trap was only able to capture insect pests with wings and were able to fly. The size of insect pest captured was controlled by the size of the holes where only the insects with size similar or smaller than the BPH can enter the trap. The data were collected for a week, and a

total of 7 sticky pad were collected.

3.2.2 Gridded Sticky Pad

To make sure all the insects on the sticky pads were captured, an A3 white paper was gridded with 21.0mm by 29.7mm each as shown in Figure 3.4. The sticky pads were clipped on the paper with paper clips to ensure the sticky pad was secure on the paper while taking picture of the insects. The grids were label 1 to 10 each row and A to J each column. The images were taken 8 grids at a time as shown in Figure 3.5.

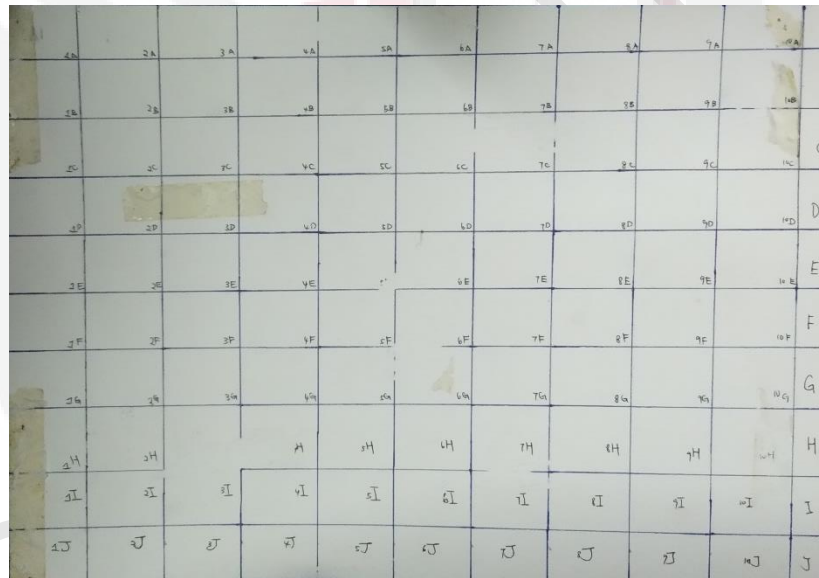


Figure 3.4 Gridded A3 paper to ensure all the insects on the sticky pad were captured.



Figure 3.5 The images were taken 8 grid at a time.

3.2.3 Image Acquisition

A smartphone was used to collect the data. The images were collected in a black box to ensure the illuminance was constant and 6 30W-White LED light bulbs were used to illuminate the black box. The images were collected at constant height of 12cm from the sticky pad. The shuttle speed of the camera is set at 1/50 second and lens aperture = $f/2$ and a focal length, $f = 3.5\text{mm}$. The dimension of the images taken is 2592x4608 pixels.

To ensure images were taken from the same height a platform was made to put the smartphone as shown in Figure 3.6 a schematic diagrams of the image acquisition setup were shown in Figure 3.7 and Figure 3.8. The platform was made with plywood and the platform was put in the black box with on the gridded sticky pad. The platform can move sideways, and the smartphone can move up and down. The lightbulbs were hung at the sides of the wall of black box to ensure the light distributed evenly. For every sticky pad, the number of images taken were around 13 images.



Figure 3.6 The image acquisition setup to collect the insect pest image.

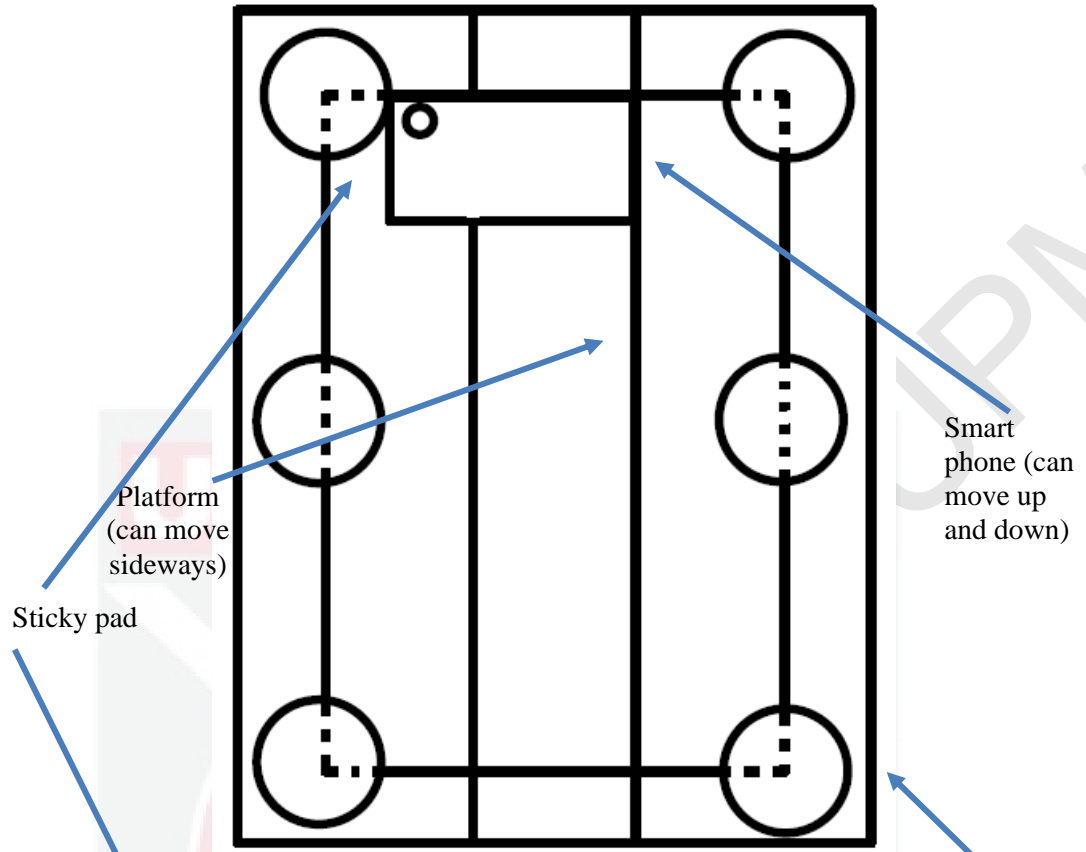


Figure 3.7 Plan of the image acquisition setup

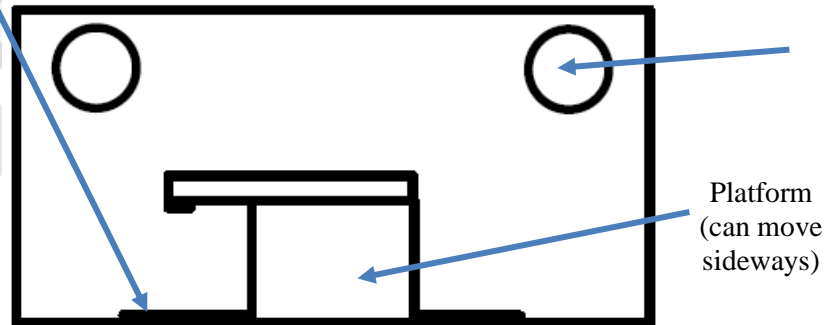


Figure 3.8 Side view of the image acquisition setup

3.3 Machine Learning Algorithm Development

The Machine Learning algorithm consist of 2 parts, the insect pest species detection and insect pest counting. For the insect pest species detection model, a pretrained Faster R-CNN model were retrained to fit the insect pest image data collected at MARDI. The insect pest counting algorithm depended on the insect pest species detection. The detected insect pests were counted according to each species.

To retrain the model, the data was preprocessed to format that were compatible with the Faster R-CNN. The Faster R-CNN was trained to detect the insect pest species. After the model was trained, an algorithm was developed to count the insect pest. The model was then evaluated to check the performance of the insect pest species detection. After the performance was checked, an algorithm was developed to count the detected insect pest.

3.3.1 Data Preprocessing

The images were preprocessed by cropping the images into several random pieces of same sizes of $1536 \times 1296 \times 3$ pixels. The images were randomly created using Python (Python Software Foundation. Python Language Reference, version 3.7. Available at <http://www.python.org>) and the generated images were saved according to time stamp to prevent the images to overwrite each other. This was to save the memory of the GPU to avoid Out of Memory (OOM) error during training. A total of 56 images were used to train the model. The images were then separate into validation and training data. 75% (42 images) of the images were used for training and 25% (14 images) were used for validation. The total number of insects in the training set was 1142. The number of zig

zag BPH was 178, the number of GLH was 13, the number of other insects was 951. For the validation set, the total number of insects used was 318. The number of zig zag BPH was 48, the number of GLH was 7, the number of other insects was 263. The images were then label using labellmg, an application in python, to annotate the bounding boxes of each insect pest on the sticky pad as shown in Figure 3.9.

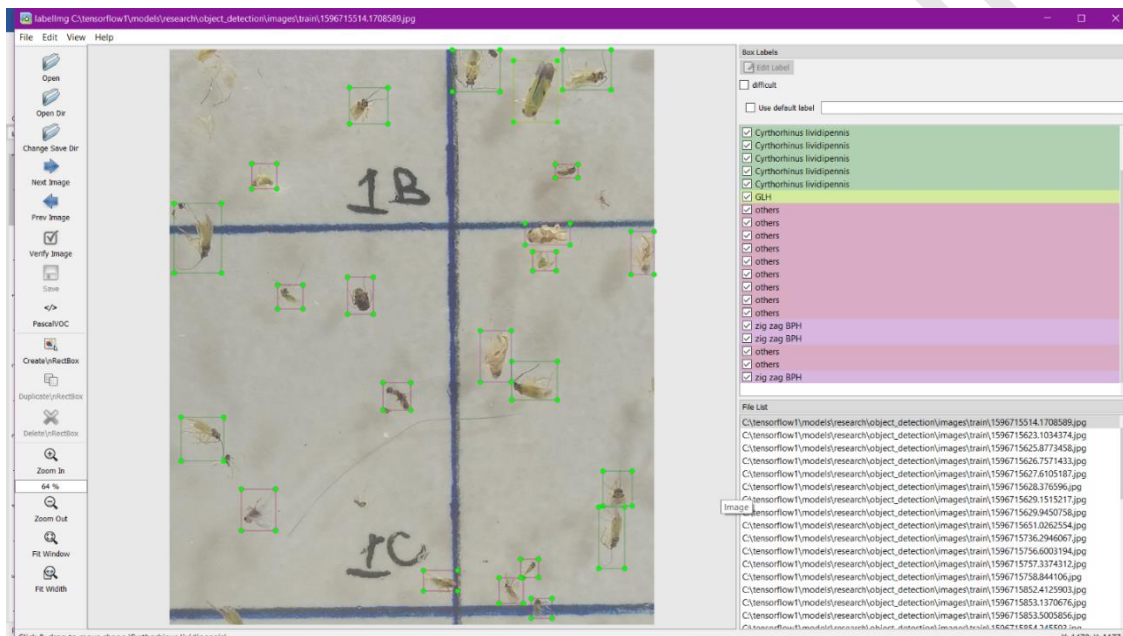


Figure 3.9 The labellmg user interface that were used to annotate the bounding box of the insect pests.

After the images were labeled, the .xml files were generated in Pattern Analysis, Statistical Modelling and Computational Learning Visual Object Classification (Pascal VOC) format for each image as shown in Figure 3.10. The .xml files contain information on the filename, the image dimensions, the class of each object on the image as well as the bounding boxes coordinates of each object in the image. The .xml files were compiled and converted into the .csv file as shown in Figure 3.11.

```

<?xml version="1.0"?>
- <annotation>
  <folder>train</folder>
  <filename>1596715514.1708589.jpg</filename>
  <path>C:\tensorflow1\models\research\object_detection\images\train\1596715514.1708589.jpg</path>
  <source>
    <database>Unknown</database>
  </source>
  <size>
    <width>1296</width>
    <height>1536</height>
    <depth>3</depth>
  </size>
  <segmented>0</segmented>
  <object>
    <name>Cyrthorhinus lividipennis</name>
    <pose>Unspecified</pose>
    <truncated>0</truncated>
    <difficult>0</difficult>
    <bndbox>
      <xmin>12</xmin>
      <ymin>411</ymin>
      <xmax>139</xmax>
      <ymax>597</ymax>
    </bndbox>
  </object>
  <object>
    <name>Cyrthorhinus lividipennis</name>
    <pose>Unspecified</pose>
    <truncated>0</truncated>
    <difficult>0</difficult>
    <bndbox>
      <xmin>915</xmin>
      <ymin>833</ymin>
      <xmax>1037</xmax>
      <ymax>936</ymax>
    </bndbox>
  </object>
  <object>
    <name>Cyrthorhinus lividipennis</name>
    <pose>Unspecified</pose>
    <truncated>1</truncated>
    <difficult>0</difficult>
    <bndbox>
      <xmin>756</xmin>
      <ymin>1</ymin>
      <xmax>RR4</xmax>

```

Figure 3.10 PASCAL VOC .xml file which consists of the information of each insects

A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V
1	filename	width	height	class	xmin	ymin	xmax	ymax													
2	15967155	1296	1536	GLH	920	30	1037	194													
3	15967155	1296	1536	zig zag BPH	951	465	1071	522													
4	15967155	1296	1536	zig zag BPH	1234	486	1296	601													
5	15967156	1296	1536	GLH	1246	24	1296	143													
6	15967156	1296	1536	zig zag BPH	1160	705	1239	838													
7	15967156	1296	1536	zig zag BPH	174	1108	257	1197													
8	15967156	1296	1536	zig zag BPH	1	1376	98	1460													
9	15967156	1296	1536	zig zag BPH	346	1338	434	1435													
10	15967156	1296	1536	zig zag BPH	14	2	121	101													
11	15967156	1296	1536	GLH	532	591	642	754													
12	15967156	1296	1536	zig zag BPH	554	1024	681	1085													
13	15967156	1296	1536	zig zag BPH	840	1041	917	1168													
14	15967156	1296	1536	zig zag BPH	764	90	885	207													
15	15967156	1296	1536	zig zag BPH	442	1311	523	1441													
16	15967156	1296	1536	zig zag BPH	665	497	787	621													
17	15967156	1296	1536	zig zag BPH	462	1429	581	1496													
18	15967156	1296	1536	zig zag BPH	756	1449	814	1536													
19	15967156	1296	1536	GLH	429	1001	553	1161													
20	15967156	1296	1536	zig zag BPH	496	72	617	179													
21	15967156	1296	1536	zig zag BPH	174	1288	256	1418													
22	15967156	1296	1536	zig zag BPH	284	1001	420	1068													
23	15967156	1296	1536	zig zag BPH	574	1019	653	1147													
24	15967156	1296	1536	GLH	262	558	384	733													
25	15967156	1296	1536	zig zag BPH	45	918	129	1013													
26	15967156	1296	1536	zig zag BPH	1026	519	1109	658													
27	15967156	1296	1536	zig zag BPH	1148	232	1264	293													
28	15967156	1296	1536	zig zag BPH	57	513	157	608													
29	15967156	1296	1536	GLH	998	736	1112	899													
30	15967156	1296	1536	zig zag BPH	1224	268	1296	357													
31	15967156	1296	1536	zig zag BPH	1031	1171	1149	1232													

Figure 3.11 .csv file generated by compiling the xml files which containing all the information in the xml files.

The .csv files were used to generate .record files (TFrecord files). The .record files contain

all the information of the image and store the image in sequence of binary records. The information was encoded into bytes using the UTF-8. The information was then able to feed into the Faster R-CNN system for training.

3.3.2 Insect Pest Species Detection Model Training

The Faster R-CNN consist of two modules. The first module is the deep fully convolutional network that proposes regions called the Region Proposal Network (RPN) and the second module is the Fast R-CNN system that uses the proposed regions to detect objects. The Fast R-CNN system consist of a VGG model that was created by Google for feature generation, classification, and bounding box. The structure of the Faster R-CNN system was shown in Figure 3.12.

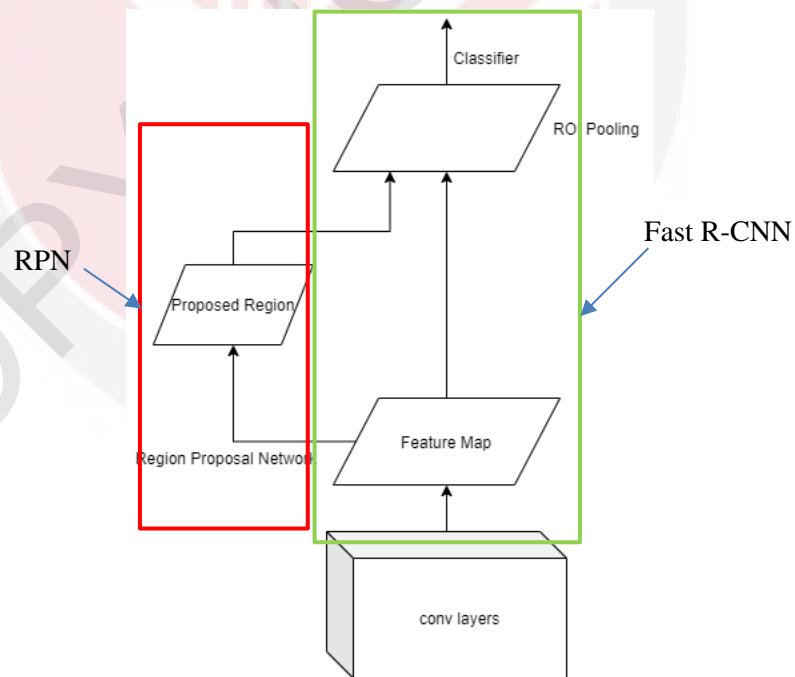


Figure 3.12 The structure of Faster R-CNN model which consist of Fast R-CNN detector and the Region Proposal Network

The feature generation stage was to obtain features of the objects using VGG16. At each layer, features were extracted by the model with filters. The filters of the VGG 16 model were some edge detector. There were 64 filters for each RGB channel. Some samples of the filters of VGG16 were shown in Figure 3.13. After the first convolution layer of the filters, the dimension of the image became $1536 \times 1296 \times 64$. The size of the image decreased by half after each block as there was a max pooling filter of a 2×2 kernel size of stride 2 were at the end of each block. The max pooling layer of conserve only the maximum pixel value in the 2 by 2 window, thereby, reducing the width and height of the image to half of its original size. Besides, the depth of the image was increased to 512 as there were 512 filters at the 5th convolutional block. Hence, the image dimension was $768 \times 648 \times 128$ at the beginning of the second block. As shown in Figure 3.14, there were 5 convolutional blocks, resulting of a final image dimension of $48 \times 40 \times 512$. As the image height and width decreases after each convolutional block, the features extracted were more abstract after each block. The samples of the feature map of some of the layers were shown in Figure 3.15, Figure 3.16, and Figure 3.17.

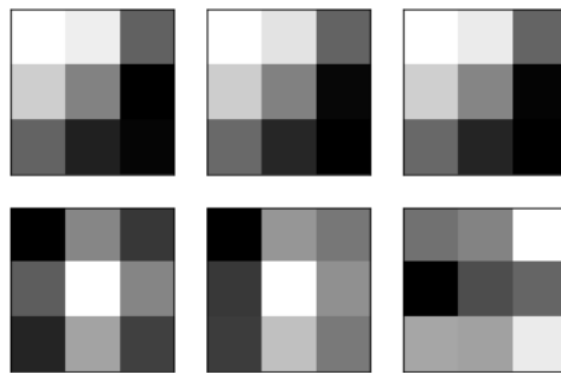


Figure 3.13 Samples of filters of the convolutional layers. These filters are edge detectors.

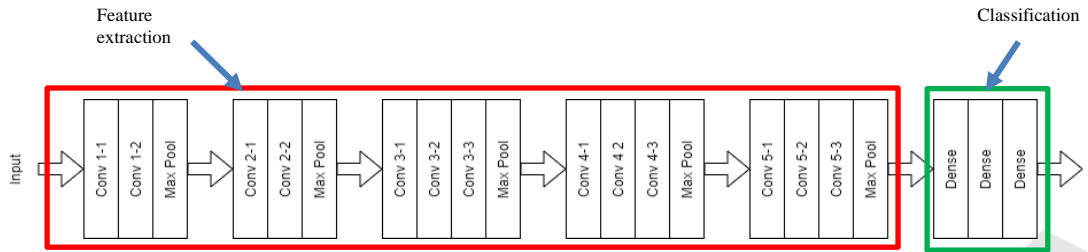


Figure 3.14 VGG16 model with 5 convolutional block for feature extraction and a dense layer block for classification.

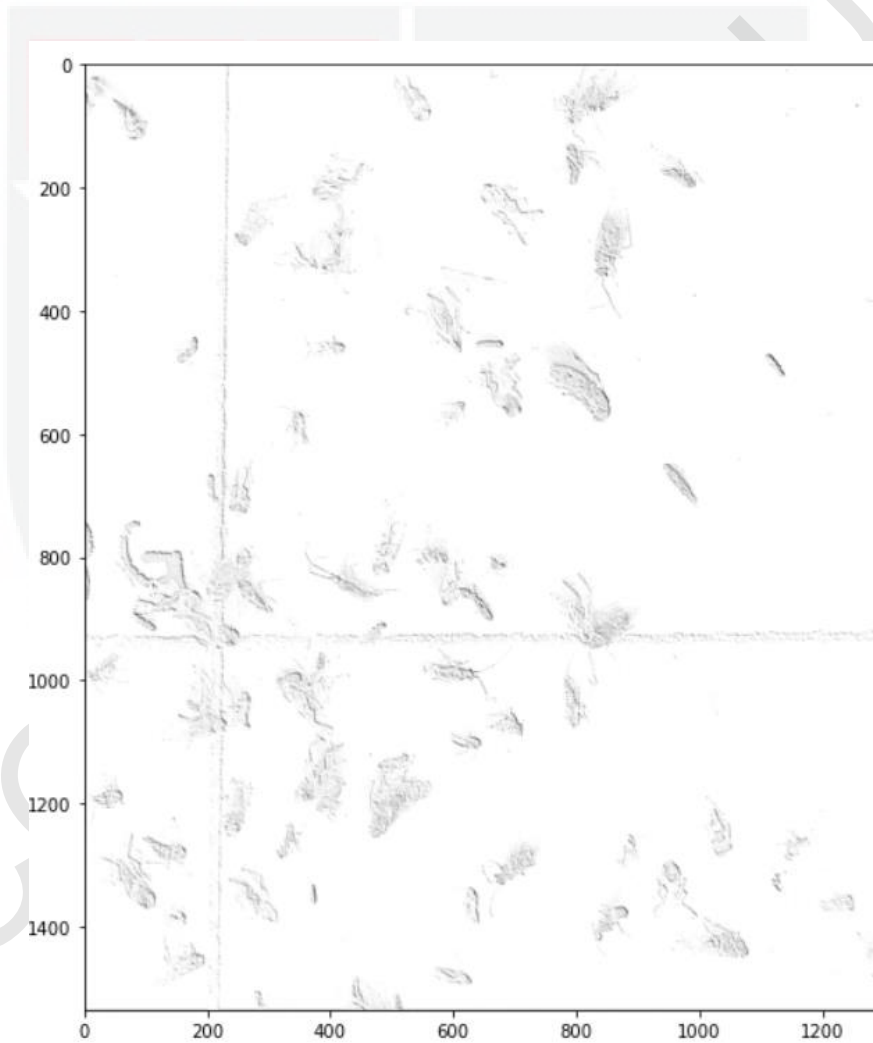


Figure 3.15 Feature map at the first convolutional layer of first convolutional block.

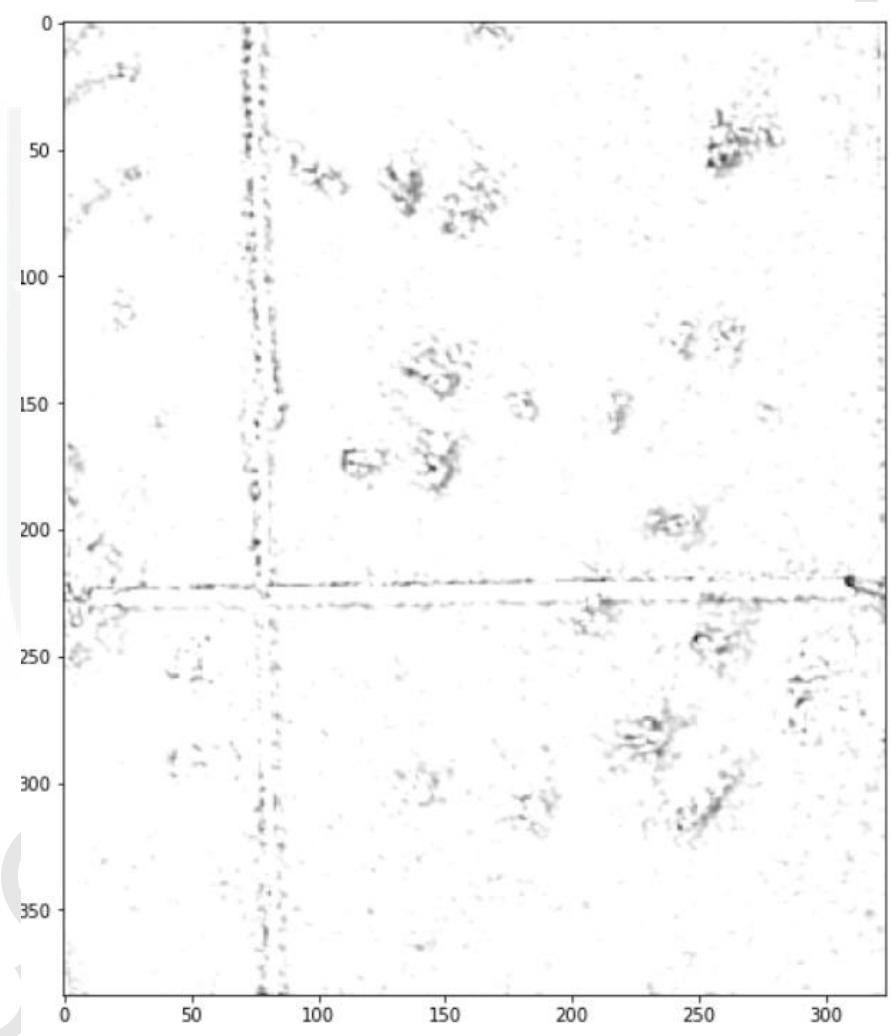


Figure 3.16 Feature map at the third convolutional layer of the third convolutional block. The feature become more abstract.

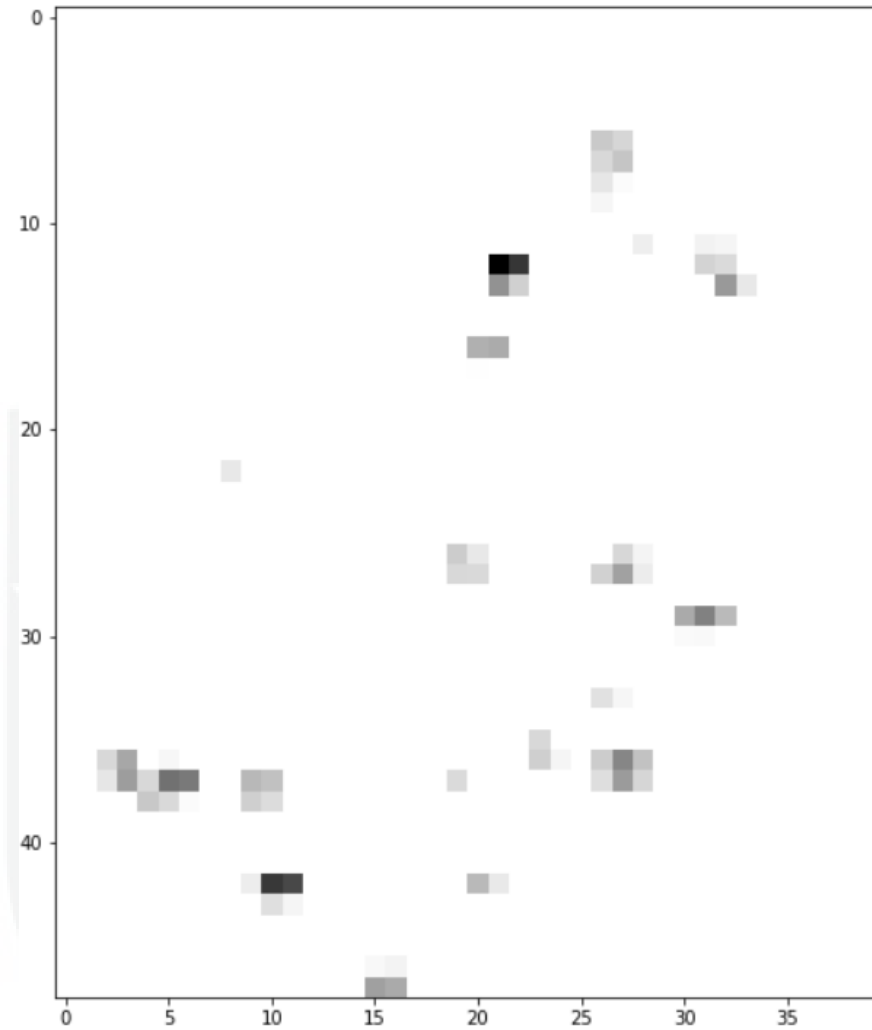


Figure 3.17 Feature map of the third convolutional layer of the fifth convolutional block. The feature became more abstract where it only consists of features that were important to the model.

The output of the convolutional block was used by the RPN to generate the proposals of the location of the insect pest. The RPN was a 3 by 3 kernel of convolutional layer that slide across the feature map followed by a pooling layer. Bounding boxes of several aspect ratios were drawn on the image. For the bounding boxes that had the Intersection of Union (IoU) of more than 0.7 with the ground truth bounding boxes, the regions were considered as object while the IoU of less than 0.3, the regions were

considered as background. The regions with IoU of between 0.3 and 0.7 were not involved in learning.

The classification stage is to predict the class of the proposed region. The classifier consists of 3 layers of fully connected dense layers as shown in Figure 3.14. The fully connected layers used the output of the max pooling layer of the last convolutional block to classify the objects. The output of the convolutional block was a tensor that contain the information of the crucial features of each insect pest. The dense layer contained 3 nodes at the output which represent each output class of the insect pest species. The image dimension at the end of the dense layer is 1 x 1 x 4, which represent the 4 outputs. The fully connected layers were Softmax activated to score each output with a confidence score and assign the class of the image according to the highest score. The Softmax function was defined as:

$$\text{Softmax}, \sigma(z)_i = \frac{e^{z_i}}{\sum_{i=1}^K e^{z_i}}$$

Where z_i is the i -th element of the vector of size 1 by 1 by K where $K = 3$

The softmax function ensured the sum of all the scores was equal to 1 and there was only one dominant score from all the output.

The regression stage of the Fast R-CNN system used the output of RPN to refine the bounding box of the insect pest (Ren et al., 2017). The regression stage produced 4 outputs which include the x and y coordinates of the top left corner of the bounding box and the x and y coordinates of the bottom right corner. The coordinates were the predicted location of the insect pest on the sticky pad.

The output of the Faster R-CNN was saved as a frozen inference graph in .pb format where the model can no longer be trained. It contained the weight of each nodes representing the importance of each features for the insect pest detection. The frozen was used to detect the species and the location of each insect pest. The sample of the insect pest detection was shown in Figure 3.18 where it showed the bounding box of each insect pest and a label of the insect pest species and the confidence level at the top of each box.

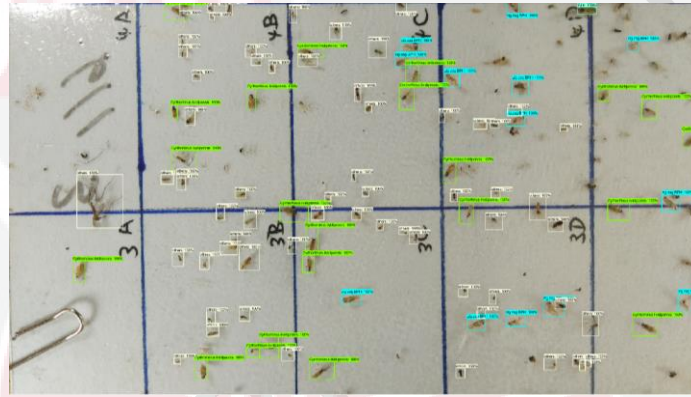


Figure 3.18 Example of detection output

3.4 Insect Pest Species Detection Model Evaluation

The performance of the insect pest Species Detection Model were evaluated with loss. The lower the loss the better the performance of the model. The training of the model was governed by the loss function. The loss function for the RPN of a Faster R-CNN was defined as (Ren et al., 2017):

$$\ell = \ell_{class} + \ell_{box}$$

$$\ell(\{p_i\}, \{t_i\}) = \frac{1}{N_{class}} \sum_i \ell_{class}(p_i, p_i^*) + \lambda \frac{1}{N_{box}} p_i^* \cdot L_1^{smooth}(t_i, t_i^*)$$

where ℓ is the loss

N_{class} is the number of mini batch size of 256,

N_{box} is the number of anchor (bounding box),

p_i is the predicted probability that the anchor i being an object,

p_i^* is the ground truth label whether the anchor is an object,

t_i is the predicted coordinates,

t_i^* is the ground truth coordinates,

λ is the balancing parameter, λ was set to 10

By using Tensorflow Object Detection API, the losses were calculated automatically, and the losses were visualized using Tensorboard. There were four losses visualized in tensorboard include RPN Localization Loss, RPN Objectness Loss, Box Classifier Localization Loss and Box Classifier Classification loss. The RPN Localization Loss was the loss caused by ℓ_{box} where there was a difference between the predicted coordinate and the ground truth coordinate. The sample of the graph generated in Tensorboard was shown in Figure 3.19.

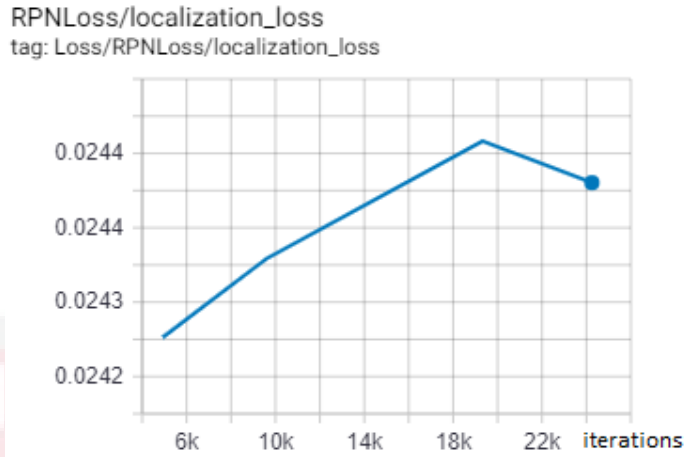


Figure 3.19 Region Proposal Network localization loss of each iterations

The RPN Objectness Loss was caused by ℓ_{class} where there some of the anchor predicted were not actual object (not insects), or some of the actual object (insects) were not predicted as objects. The sample of the graph generated in Tensorboard was shown in Figure 3.20.



Figure 3.20 Region Proposal Network Objectness loss of each iterations

The Box Classifier Localization loss had a loss function of a Mean Square Error, MSE as follow:

$$MSE = \frac{1}{N} \sum_i^n (t_i^* - t_i)^2$$

where N is the number of samples,

t_i is the predicted coordinates,

t_i^* is the ground truth coordinates

The loss function penalized the difference between the predicted coordinates and the ground truth coordinates. The sample of the graph generated in Tensorboard was shown in Figure 3.21.

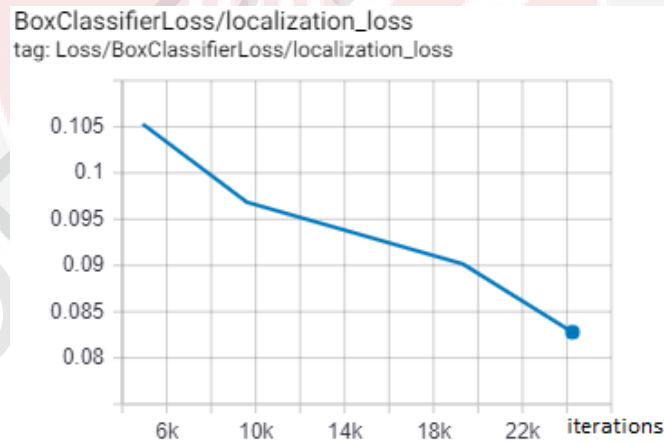


Figure 3.21 The Box Classifier Localization loss of each iterations

The Box Classifier Classification Loss is a categorical crossentropy loss, CCE with a loss function as:

$$CCE = -\sum_{c=1}^M p_{i,c}^* \log(p_{i,c})$$

where M is the number of classes,

$p_{i,c}^*$ is the binary indicator if class label c is correctly predicted,

$p_{i,c}$ is the predicted probability that the ground truth is of class c

As there were 4 categories of insect classes, the CCE can be express as follow:

$$CCE = -p_{i,1}^* \log(p_{i,1}) - p_{i,2}^* \log(p_{i,2}) - p_{i,3}^* \log(p_{i,3})$$

The CCE penalized the difference between the predicted class and the ground truth class.

The sample of the graph generated in Tensorboard was shown in Figure 3.22.

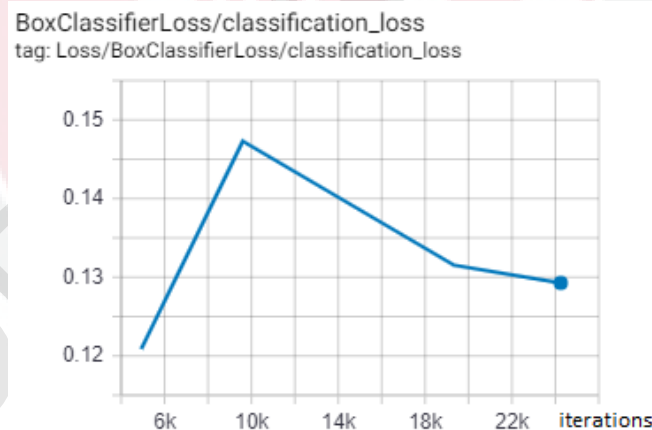


Figure 3.22 Box Classifier Classification loss of each iterations

Besides losses, a confusion matrix can be used to visualize the performance of the model. A matrix of row as ground truth, and column as predicted classes were used to display the number of true class and predicted class as well as to show the number of misclassifications. The sample of a confusion matrix was shown in Figure 3.23.

Zig Zag BPH	3	0	0
GLH	0	40	0
Others	0	0	4

Figure 3.23 Sample of Confusion Matrix.

With the numbers of correct classification and misclassification, the precision, recall, accuracy and F1 score were calculated where these metrics were also important means to evaluate the performance of the model. Precision were shown as follow:

$$Precision = \frac{TP}{TP + FP}$$

Precision measured the number of correctly predicted cases turned out to be positive. This metrics was useful when False Positive is more of a concern than False Negatives.

Recall was defined as follow:

$$Recall = \frac{TP}{TP + FN}$$

The recall measured the number of actual positive cases were able to predict correctly with the model. This metric was useful where False Negatives were more important than

False Positive.

Accuracy was defined as:

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN}$$

Accuracy summarized the overall performance of the model. Accuracy measured the number of true predictions.

F1 score was defined as:

$$F1 = \frac{2}{recall^{-1} + precision^{-1}}$$

This metric was a function of recall and precision. This metric took in account for both recall and precision where both will be emphasized. F1 score has a value between 0 and 1 where 1 will be the ideal score where recall and precision are 1.

After the precision and recall were calculated, the average precision and average recall were also used to evaluate the performance of the model. Average precision, AP was defined as:

$$AP_i = \frac{1}{GTP} \sum_k^n P_i \times Rel_i$$

where GTP was the number of ground truth positives,

P_i was the precision at class i ,

Rel_i was the relevance at i , $Rel_i := \begin{cases} 1 & \text{if } i \text{ is relevant} \\ 0 & \text{if } i \text{ is not relevant} \end{cases}$

Average recall, AR was defined as follow:

$$AR = 2 \int_{0.5}^1 R(IoU) dIoU$$

where R is the recall,

IoU is the intersect of union of t_i and t_i^*

The average recall described the area doubled under the recall versus IoU curve. Average recall is a summary of the distribution of recall across the range of 0.5 to 1. Only IoU greater than 0.5 were considered good prediction of bounding box; therefore, the integral started at 0.5 to 1.

After the average precision was calculated, the mean average precision was calculated. The mean average precision, mAP was defined as follow:

$$mAP = \frac{1}{N} \sum_{i=1}^N AP_i$$

where N is the number of class categories,

AP_i is the average precision of class i

The mAP was a mean of precision of all the classes.

3.5 Insect Pest Counting

The insect pest counting depended on the insect pest detection. The insect pest detection detects and localize the insects by bounding them in boxes. To count the number

of insects the information including the class index of the insects and the confidence score of each prediction were extracted. The confidence score to draw the bounding box were set to a minimum of 50% and the number of insects counted were also based on the number of bounding boxes drawn. A for loop with if-else statement was used to iterate the counting process till all the bounding boxes were count. The flow of the counting algorithm was shown in Figure 3.24.



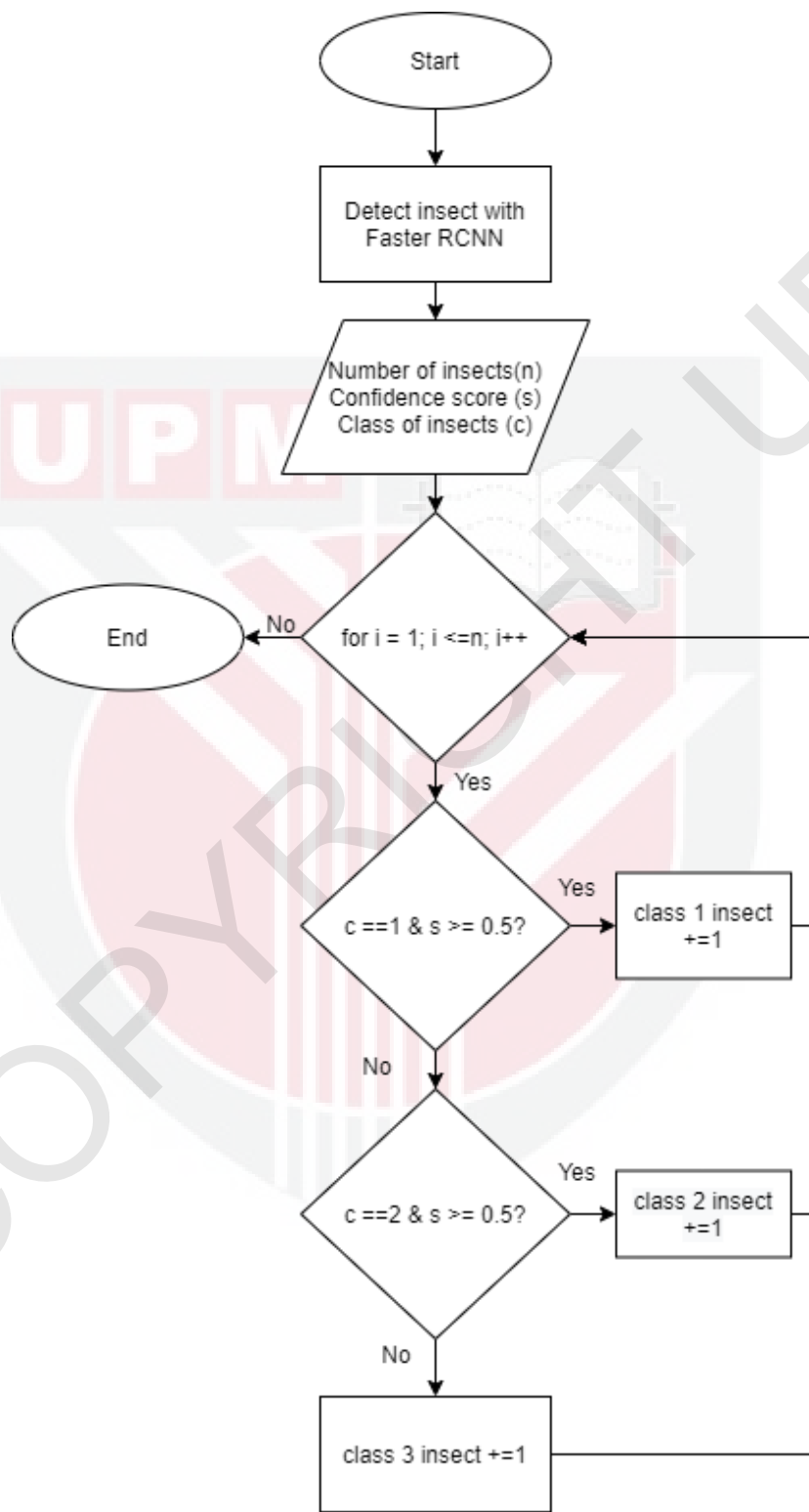


Figure 3.24 The flow of counting algorithm based on Faster R-CNN

Chapter 4 Result and Discussion

In this chapter, the performance of the model was described with RPN localization loss, RPN objectness loss, Classifier localization loss and Classifier classification loss. Besides, a confusion matrix of the model on the validation set was used to visualize the performance of the model. The precision, recall, accuracy F1 score, mean average precision and average precision were calculated based on the confusion matrix.

4.1 Localization Loss of the Region Proposal Network

The RPN localization loss described the performance of the model to create bounding boxes. The minimum RPN localization loss that was able to achieve by the model was 0.0052 at 23200th iteration. There was no other further improvement in lowering the RPN localization loss after this iteration. The trend of the RPN localization loss was shown in Figure 4.1. The loss fluctuated in the beginning and decreased drastically at the first 8000 iterations and the decrement decreased after 8000th iteration.

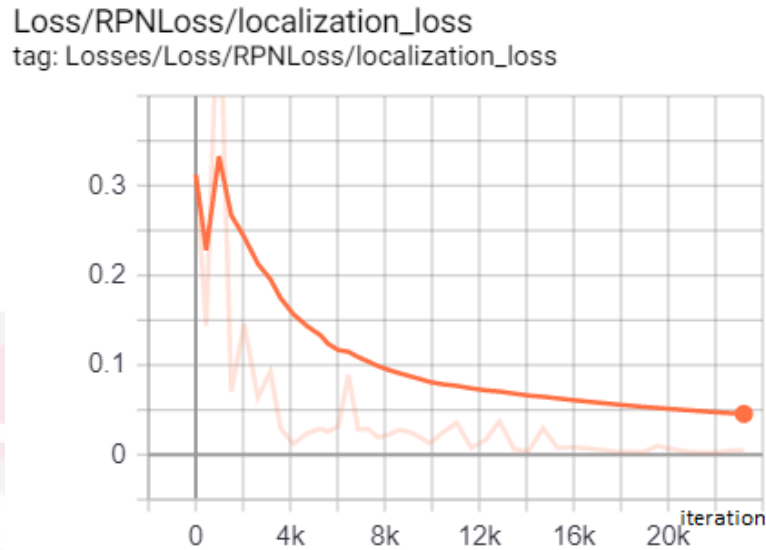


Figure 4.1 Region Proposal Network localization loss of each iterations

4.2 Objectness Loss of the Region Proposal Network

The objectness loss described the performance of RPN to differentiate object from background. The minimum RPN objectness loss that was able to achieve by the model was 0.0082 as the 23200th iteration and there was not improvement of the performance by further training the model. The trend of RPN objectness loss were shown in Figure 4.2. The loss fluctuated in the beginning with an overall decreasing trend and decreased drastically at the first 8000 iterations and the decrement decreased after 8000th iteration.

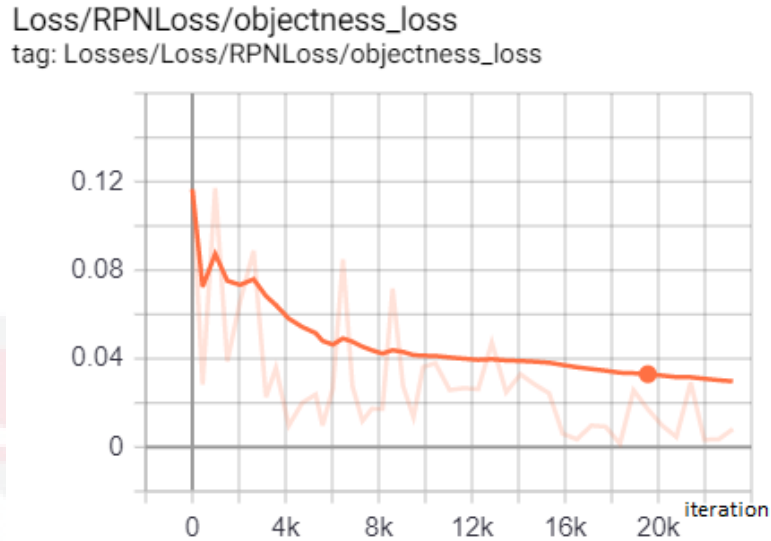


Figure 4.2 Region Proposal Network objectness loss of each iterations

4.3 Localization Loss of the Classifier

The localization loss of the classifier described the performance of model to determine the location of the insects. The minimum Classifier localization loss that was able to achieve was 0.0199 at the 23200th iteration. There was no improvement of the model performance after this iteration. The trend of the Classifier localization loss was shown in Figure 4.3. The loss decreased drastically at the first 6000 iterations and the decrement decreased after 6000th iteration.

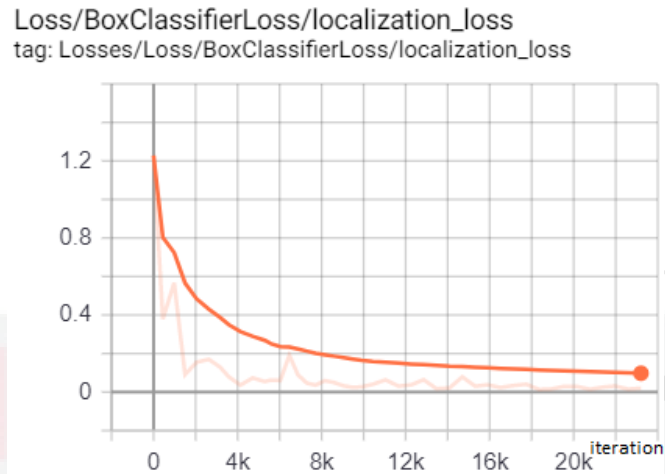


Figure 4.3 Classifier Localization Loss of each iterations

4.4 Classification Loss of the Classifier

The classification loss of the described the performance of the model to classify each type of insects. The minimum Classifier classification loss achieved by the morel was 0.0145 at the 23200th iteration. There was no improvement of performance after training for the 23200 iterations. The trend of the loss was shown in Figure 4.4. The loss decreased drastically at the first 6000 iterations and the decrement decreased after 6000th iteration.

Loss/BoxClassifierLoss/classification_loss
tag: Losses/Loss/BoxClassifierLoss/classification_loss

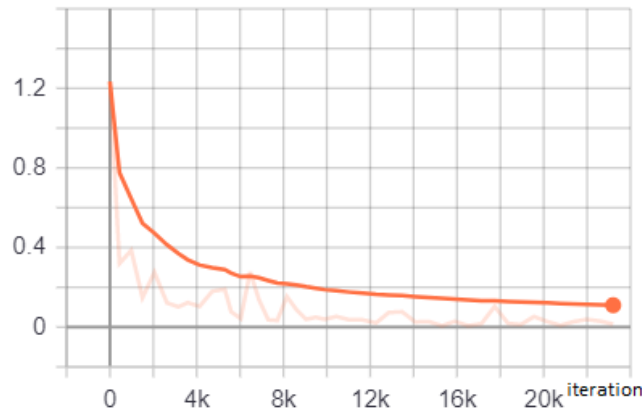


Figure 4.4 Classifier Classification loss of each iterations

4.5 Visualization of the Model Performance using Confusion Matrix

The performance of the model was visualized using a confusion matrix. There were 2 confusion matrices, one was for the performance of detection and another for classification. The confusion matrix for detection was shown in Figure 4.5.

Object	301	17
Not Object	17	0
	Object	Not Object

Figure 4.5 Visualization of the model performance to detect insect from background through confusion matrix.

From Figure 4.5, it was shown that 17 insects from the validation set (318 insects) were undetected. The model was not able to detect some of the smaller insects. Besides, the model also falsely detected some separated parts of body as insects. The accuracy, precision, recall and F1 score of object detection was shown in Table 4.1 Performance of the model to detect insects and background.

Table 4.1 Performance of the model to detect insects and background.

	Accuracy	Precision	Recall	F1
Object Detection	0.90	0.95	0.95	0.95

The confusion matrix for classification of insects was shown in Figure 4.6.

Zig zag BPH	39	0	7
GLH	0	7	0
others	0	0	248
	Zig zag BPH	GLH	others

Figure 4.6 The confusion matrix for classification of insects.

It was shown that the model was unable to classify 7 of the Zig Zag BPH. The 7 Zig Zag BPH was classified as others. The accuracy, precision, recall and F1 score were calculated from the confusion matrix and the result was tabulated as in Table 4.2:

Table 4.2 The performance of model according to each classes

Species	Accuracy	Precision	Recall	F1
Zig Zag BPH	0.98	1	0.85	0.92
GLH	1	1	1	1
Others	0.98	0.97	1	0.98

As shown in Table 4.2, the model was able to classify GLH and other insects accurately with no error. The model, however, did not classify the zig zag BPH without error. The zig zag BPH had an accuracy of 0.98 and a F1 score of 0.92. The accuracy was much higher than the F1 score because the True Negatives dominated the effect of accuracy, on the other hand, the precision for Zig Zag BPH was 1; however, the recall was 0.85 indicated that not all of the Zig Zag BPH detected were Zig Zag BPH but there were no Zig Zag BPH undetected. The 'others' had an accuracy of 0.98 and a F1 score of 0.98. As there were Zig Zag BPH classified as others. This caused the precision to decrease and hence, decreased the accuracy and F1 score.

4.6 Mean Average Precision and Average Recall of the Insect Species Detection

Model

The mAP described the overall performance of the model for classification. The mAP accounted for all the class of insects. The mAP that was able to achieve by the model

was 0.93. This indicated that the model was able to classify most of the insect correctly.

On the other hand, AR describe the overall performance of the model for classification and localization as AR considered the IoU of the detection. AR only considered the detection with IoU more than 0.5. The low AR might be caused by the undetected insects. The low AR also indicated that some of the IoU of the detection is less than 0.5. However, for model to detect insect pest on sticky pad, the IoU was not as important as there was not any requirement to meet for the location of the insects.

Chapter 5 Conclusion

To conclude, a machine learning algorithm using Faster R-CNN to detect the species of insect pest were developed with deep transfer learning using Tensorflow 1.15 and Python 3.7. The computer used for the training was ASUS ROG Strix SCAR III with NVIDIA RTX 2070 GPU and an Intel Core i7 9th Generation GPU.

The model was trained with 56, 1536 x 1296 x 3 RGB images which consist of a total number of 1460 insects. 1142 insects were used as training set and the other 318 insects were used as validation set for 3 class of insect which were Zig Zag BPH, GLH and others. The number of insects for each class is unbalanced where Zig Zag BPH only consist of 15% from the set, GLH consist of 1%, while the other 82% were for others.

The model was able to classify GLH accurately at an accuracy, precision, recall and F1 score of 1. However, for Zig Zag BPH, the model was only able to achieve an accuracy of 0.98, a recall of 0.85 and a F1 score of 0.92. The unbalance number of insects caused the accuracy to be higher than expected because the True Negative was much greater than the False Positive. Therefore, F1 score was more reliable in this case. Besides, for others, the model was able to achieve an accuracy of 0.98, a precision of 0.97 and an

F1 score of 0.98. The result of an image size of 1536 x 1296 x 3 was able to be generated within an average of 1 minute.

The overall performance that was achieved by the model was a mAP of 0.93. This indicated that most of the image predicted were classified correctly. The AR achieved by the model was 0.60. This indicated that some of the insect detected has IoU less than 0.5.

This model could be used to help entomologists to make decision faster on the pest control measures according to the economic threshold level of pest at different paddy growth stage by counting and classifying paddy insect pest on sticky pad more efficiently. However, the model has a low AR which might be caused by the low IoU, the model was unsuitable for highly precision task such as using it in robot, as the model lacks precision in the location of the insects.

Further work such as detection and counting of insects at different stages of life cycle, recognition separated body parts of insects and small insects could be done to improve the performance of the model.

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Appendices

Code: Pest Counting Algorithm Based on Faster R-CNN

```
# Import packages
import os
import cv2
import numpy as np
import tensorflow as tf
import sys
import time
# This is needed since the notebook is stored in the object_detection folder.
sys.path.append("..")

# Import utilites
from utils import label_map_util
from utils import visualization_utils as vis_util

# Name of the directory containing the object detection module we're using
MODEL_NAME = 'inference_13'
IMAGE_NAME =
r'C:\tensorflow1\models\research\object_detection\images\test\1596715624.9739103.jpg
'

# Grab path to current working directory
CWD_PATH = os.getcwd()

# Path to frozen detection graph .pb file, which contains the model that is used
# for object detection.
PATH_TO_CKPT =
os.path.join(CWD_PATH,MODEL_NAME,'frozen_inference_graph.pb')

# Path to label map file
PATH_TO_LABELS =
os.path.join(CWD_PATH,'inference_graph_model_main_fyp_12','labelmap.pbtxt')

# Path to image
PATH_TO_IMAGE = os.path.join(CWD_PATH,IMAGE_NAME)

# Number of classes the object detector can identify
NUM_CLASSES = 3

# Load the label map.
# Label maps map indices to category names, so that when our convolution
# network predicts `5`, we know that this corresponds to `king`.
# Here we use internal utility functions, but anything that returns a
# dictionary mapping integers to appropriate string labels would be fine
label_map = label_map_util.load_labelmap(PATH_TO_LABELS)
```

```

categories = label_map_util.convert_label_map_to_categories(label_map,
max_num_classes=NUM_CLASSES, use_display_name=True)
category_index = label_map_util.create_category_index(categories)

# Load the Tensorflow model into memory.
detection_graph = tf.Graph()
with detection_graph.as_default():
    od_graph_def = tf.GraphDef()
    with tf.gfile.GFile(PATH_TO_CKPT, 'rb') as fid:
        serialized_graph = fid.read()
        od_graph_def.ParseFromString(serialized_graph)
        tf.import_graph_def(od_graph_def, name='')

    sess = tf.Session(graph=detection_graph)

# Define input and output tensors (i.e. data) for the object detection classifier
# Input tensor is the image
image_tensor = detection_graph.get_tensor_by_name('image_tensor:0')

# Output tensors are the detection boxes, scores, and classes
# Each box represents a part of the image where a particular object was detected
detection_boxes = detection_graph.get_tensor_by_name('detection_boxes:0')

# Each score represents level of confidence for each of the objects.
# The score is shown on the result image, together with the class label.
detection_scores = detection_graph.get_tensor_by_name('detection_scores:0')
detection_classes = detection_graph.get_tensor_by_name('detection_classes:0')

# Number of objects detected
num_detections = detection_graph.get_tensor_by_name('num_detections:0')

# Load image using OpenCV and
# expand image dimensions to have shape: [1, None, None, 3]
# i.e. a single-column array, where each item in the column has the pixel RGB value

ts1 = time.time() # For measuring time for detection, Initial time stamp

image = cv2.imread(PATH_TO_IMAGE)
scale_percent = 50
width = int(image.shape[1]*scale_percent/100)
height = int(image.shape[0]*scale_percent/100)
dim = (width,height)
image = cv2.resize(image, dim, interpolation = cv2.INTER_AREA)
image_expanded = np.expand_dims(image, axis=0)

# Perform the actual detection by running the model with the image as input

```

```
(boxes, scores, classes, num) = sess.run(
    [detection_boxes, detection_scores, detection_classes, num_detections],
    feed_dict={image_tensor: image_expanded})
final_score = np.squeeze(scores)
```

```
# Counting Algorithm
```

```
count_total = 0
```

```
count_1 = 0
```

```
count_2 = 0
```

```
count_3 = 0
```

```
for i in range(100):
```

```
    if scores is None or final_score[i] >.5:
```

```
        count_total += 1
```

```
        if classes[0][i]==1. and final_score[i] >.5:
```

```
            count_1 += 1
```

```
        if classes[0][i]==2. and final_score[i] >.5:
```

```
            count_2 += 1
```

```
        if classes[0][i]==3. and final_score[i] >.5:
```

```
            count_3 += 1
```

```
ts2 = time.time() #final time stamp
```

```
time1 = round(ts2-ts1) # Time taken for detection
```

```
#Printing Result
```

```
print(f"
```

```
The numbers of each insects are as follows:
```

```
zig zag BPH    : {count_1}
```

```
GLH           : {count_2}
```

```
others        : {count_3}
```

```
Total        : {count_total}
```

```
Time taken for detection is {time1} seconds
```

```
")
```

```
# Draw the results of the detection
```

```
vis_util.visualize_boxes_and_labels_on_image_array(
```

```
    image,
```

```
    np.squeeze(boxes),
```

```
    np.squeeze(classes).astype(np.int32),
```

```
    np.squeeze(scores),
```

```
    category_index,
```

```
    use_normalized_coordinates=True,
```

```
    line_thickness=4,
```

```
    min_score_thresh=0.50)
```

```
# All the results have been drawn on image. Now display the image.  
cv2.imshow('Object detector', image)  
#cv2.imwrite('Insect Pest Detection.jpg', image)  
# Press any key to close the image  
cv2.waitKey(0)  
  
# Clean up  
cv2.destroyAllWindows()
```

