JOURNAL OF CRITICAL REVIEWS

ISSN- 2394-5125 VOL 07, ISSUE 15, 2020

DESIGN AND DEVELOPMENT OF A STATIONARY PEST INFESTATION MONITORING DEVICE FOR RICE INSECT PESTS USING CONVOLUTIONAL NEURAL NETWORK AND RASPBERRY PI

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Article History: Received xxxxx; Revised xxxx; Accepted xxxx

ABSTRACT: The Agricultural Comprehensive Assessment of Landscape and Modeling for Sustainability Analysis and Forecasting Events Program (CALM-SAFE Agriculture) aims to design and develop an adult flying-stage insects for monitoring using Deep Convolutional Neural Network and Raspberry Pi since the main problem of the study includes the decrease of the rice production caused by destructive pest in the rice plants and lack of monitoring device that can automatically detect and classify pest. The other objective of this study is to automate the process of insect pests monitoring. The process involves data acquisition, labeling, training the CNN model, object detection, and classification until data stored on a JSON format. As observed, using Raspberry Pi paired with the SSD-MobileNet model is suitable despite its computing power, it performs well in the detection and classification of insects in a real-time scenario. Furthermore, this study has shown that using the SSD-MobileNet, has performed well on initial tests in the detection and classification of rice adult-flying insects. The trained model achieves a rate of 78.4 % accuracy, compared with 74.0 % accuracy in the previous study. The device will use on data gathering for the Decision Support System platform of the CALM-SAFE Agriculture program.

KEYWORDS:*Insect Classification;Insect Monitoring;Monitoring System;Insect Infestation.*

1.0 INTRODUCTION

The most popular agricultural food widely used in Asian countries is Rice (Oryza

ISSN- 2394-5125 VOL 07, ISSUE 15, 2020

sativa). To meet the needs ofthe growing demand for rice in the Philippines is to provide proper maintenance and fertilization, which is essential for contributing to high-quality production. Hindrances on achieving high yield are through adverse weather (floods, drought, typhoons) and pest epidemics [1]. According to local experts and farmers in Mindanao, many factors are contributing to the decrease in rice production, and as they observed, rice insect pests are the most significant in hindering the production process through destroying even the rice seedlings. Anygrowth stages of insects destroy rice plants by chewing the leaf and root tissues, boring, tunneling the stems,and sucking fluid sap from stems and grains. The attacks of these insects lead to severe damage of defoliated leaves, dead hearts, whiteheads, stunted and withered plants as well as unfilled or pecky grains [2]. Ultimately insects affect the quality and quantity of the harvest.

In order to take grasp of the pest problems of every farmer before it becomes too severe, proper knowledge of these rice pests and crop pests monitoring is essential. The traditional ways of monitoring by the local farmers are using sweep nets, shaking-off insects in the plants, and close examination. Sweep nets are proper for all insect stages except eggs. It is useful for aphids, budworms, pea weevils, and other insects found in the crop when the crop is knee-high or taller [3]. Next is by shaking off insects in the plants which are done by vigorously shaking or beating the plants over a bag or a sweep net then collect the insects for identification and counting. The close examination method includes assessments of small insects, especially those that live on or near the ground. This inspection is useful for insects such as red-legged earth mites, webworms, aphids, and vegetable weevils. However, Farmers have difficulty in applying traditional monitoring of insects because of the vast area of rice fields that needed to look. It is time-consuming to examine hectares of land by manually examined it one by one. That is why modern-day farmers are looking for very effective ways of monitoring insect pests. Seedlings and podding crops are one of the highest risks for damage by insects throughout the growing season. It is also essential to assess any crop damage as soon as observed to prevent further damage.

Applying pesticides is another way of protecting rice from pests, but it cuts rice productivity instead of improving it when the associated health costs counted as a production cost [4].Rice pesticides are among the most toxic agrochemicals. That is why spraying pesticidesis not recommended in the early stages of crop growth within 0−40 days after planting (0-40 DAP) because plants can recover from the insectinfestation damage without any loss to yield [2]. About 20% of more than 90% average yield loss of the world's rice produced is due to the various insect pests in Asia [5]. Improper scheduling of pesticides and its improper handling is increasingly problematic in the Philippines. Insect classification if one of the vital steps for pest management. With proper identification of an insect and its life cycle, control and

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prevention can apply when the pest is in its most susceptible stage of development [6].

Monitoring strategies [7] [8] [9] empowers experts and farmers to catch complications about their rice fields before they become problematic. A monitoring system is one way to increase yield and can minimize fertilizer and pesticide applications.It serves as an assistant in making informed decisions that serve as input to the automation of infrastructures, and most importantly, it is an indispensable learning tool[10]. One that is most suitable for monitoring rice insect pests is the Stationary Pest Infestation Monitoring Device for Rice Insect Pests using Convolutional Neural Network and Raspberry Piin a Wireless Sensor Network.Due to its high ability to classify images, Convolutional Neural Network (CNN) has been widely used in visual recognition since 2012[11] [12] [13]. The authors show a remarkable improvement in the accuracy of image classification in the Image Net Large Scale Visual Recognition Challenge (ILSVRC). CNN is the preferable choice for solving image classification challenges. Besides image classification, researchers have extended the application of CNN to several other tasks in visual recognition as well as to object detection.

2.0 METHODOLOGY

In this paper, the researchers created a platform and a housing that contains Raspberry Pi 3.0 B+ with a Raspberry Pi camera module, power bank, LED, and other electronic components. The combined electronic modules used for taking videos for data gathering. The collected data is in the video format of the insects that enter within the platform area. After taking the video, it is then extracted into a frame by frame images. Only the best images picked to proceed for labeling. After selecting the best images for the training data, the researchers' will then label the insects captured in the image. This way is called Object Localization, where the objects presented in the images are labeled. This step performed before the researchers proceed to train the CNN model using Tensorflow API.

2.1 To create a platform using mini-computer Raspberry Pi 3 Model B+ with a Raspberry Pi camera module and formulate a prototype that acts as data acquisition for an insect classification

The researchers created a platform to gather insect data by the use of a Raspberry Pi 3 Model B+ with a Raspberry Pi camera attached to the platform. It records instances and movements of insects in the platform for the insect training data.

2.1.1 Hardware and Software Requirements

Raspberry Pi 3 Model B+ is the device used in this study, and it acts as the processing unit for all data processing (Speed, Memory management). The camera used in this study is the Raspberry Pi Camera Module v2 with a supported video resolution of 1080p30, 720p60, and 640 x 480p90 with photo resolution of 3280 x 2464 pixel. The

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material used for the housing and the platform is an Acrylic Glass. In the device, there is an insect luring system composed of Light Emitting Diodes (LED). The Raspberry Pi controlled the fade-blinking function of this luring system. The software used in this study includes the NOOBS operating system.

For the training requirements, Python 3.5, Tensorflow v1.5 with API through Anaconda virtual environment are the software requirements for the training. The CNN model used is an SSD_Mobilenet ver1 coco 2017-11-17[14] [15]provided from the Tensorflow model zoo Github repository. The system unit used for training the model has an NVIDIA GeForce GTX 960 with Intel Xeon CPU.

The housing and platform are shown in Figure 2 (A) is the position that we planned to put the raspberry pi and pi camera. (B) is the position in where the insects will land, (C) and (G) is the position that supports the base of the platform, (D) is the position that will protect the Raspberry Pi and Raspberry Pi camera module, (E) is the position that supports the power bank to make it fit and stand and lastly (F) is the position that supports the entire housing.

Figure1:Raspberry Pi with the Raspberry Pi Camera Module

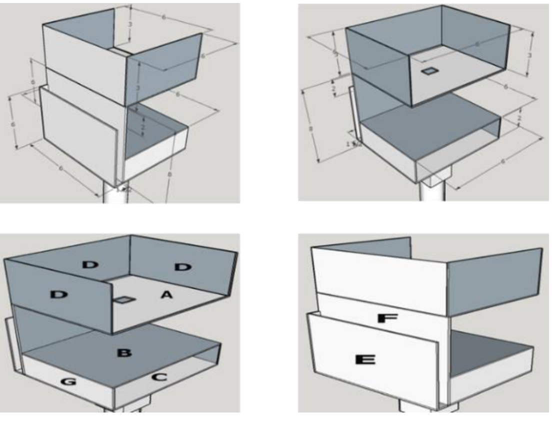

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Figure2:Platform Design

2.2 To design and develop an automated rice insect pest's detector that will act as a tool in detecting and classifying adult flying-stage insects within the area using convolutional neural network

2.2.1 Data Gathering

Our way of gathering data is by catching rice adult flying-stage insects in the rice field. As shown in Figure 3, insects recorded inside the platform. After taking a series of videos, the researchersextracted the gathered video to a frame by frame images. After the extraction, the researchers choose only the best images to proceed for the labeling data shown in Figure 4.

2.2.2 Labeling

The researchers use a LabelImg, a python program application that is efficient to use for labeling.With all the pictures gathered, it will then proceed to labelling. We will then put a square box in the best pictures from the gathered data. The researchers can quickly identify and label the gathered data of insects with the help of the International Rice Research Institute (IRRI). For now, the rice

Figure3:Sample insect video file

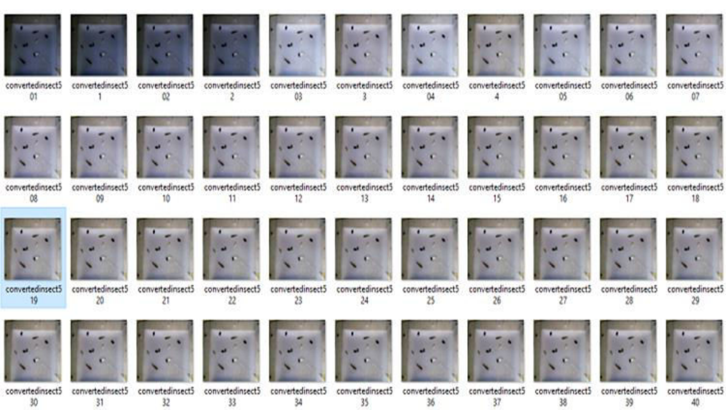

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Figure4:Result of extraction from video to images

2.3 To test the accuracy of detection and classification of adult flying-stage insects within the area

The goal of the researchers is to assess the accuracy of the model and to interpret the effectiveness of the classification of the device to the experts and farmers. The researchers use Accuracy Metrics, which is to determine the different ways to look at the thematic accuracy of the classification of the model in this study shown in Table 1. Accuracy Metrics is composed of Overall accuracy shown in equation 1, User's Accuracy shown in equation 2, and the Producer's Accuracy shown in equation 3.

$$ACCURACY_{Total} = \frac{Number of correct plots}{Total number plots} \times 100 \quad (1)$$

$$ACCURACY_{User} = \frac{Number of correct}{Number\ claimed\ in\ map} \times 100 \quad (2)$$

$$ACCURACY_{Total} = \frac{Correct\ identified\ in\ the\ given\ class}{Total number plots} \times 100 \quad (3)$$

Table1:Accuracy Metrics

		REFERENCE DATA				
		BLACK BUG	STEMBORER	GALL-MIDGE	NO CLASS	TOTAL
CLASSIFIED DATA	BLACK BUG					
	STEMBORER					
	GALL-MIDGE					
	NO CLASS					
	TOTAL					
User's Accuracy						
Producer's Accuracy						
Overall Accuracy						

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3.0 EXPERIMENTAL RESULTS AND DISCUSSIONS

3.1 The Platform

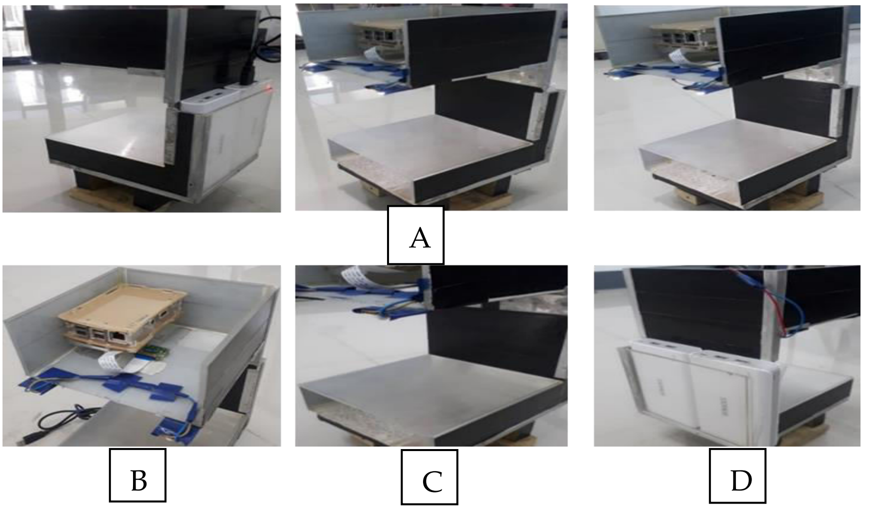
Figure 7 (A) shows the complete housing of the electronic system. Figure 7 (B) in the upper part of the platform where the Raspberry Pi 3 Model B+, Raspberry Pi camera, and the Luring System are in place. Figure 7 (C) is the base of the platform in which the insects expected to land. Lastly, Figure 7 (D) is where the power bank placed to supply power to the Raspberry Pi. The black color in the platform is the duct tape to avoid glare in recording videos.

3.2Labeling

Figure 8 shows that we used the LabelImg python program for labeling the gathered insects' data. We put a square box in the best pictures from the gathered data and label it with a proper name with the help of IRRI for the insects' classification since the IRRI provides the information of all the insects found in the rice field.

3.3Training Loss

In Figure 9 shows the overall loss of the model classifier overtime of the training, Tensorflow will initialize the training and reports of the loss in each training iteration. For example, 143333 steps, the loss is about 1.7752 shown in Figure 10. Using the Tensorboard, the user can view the whole progress of the training. The Tensorboard local webpage provides informative graphs that describe if the training is in progress.



A

B C D

Figure7:The Complete Housing for the Electronic Components

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Figure8:The Complete Housing for the Electronic Components

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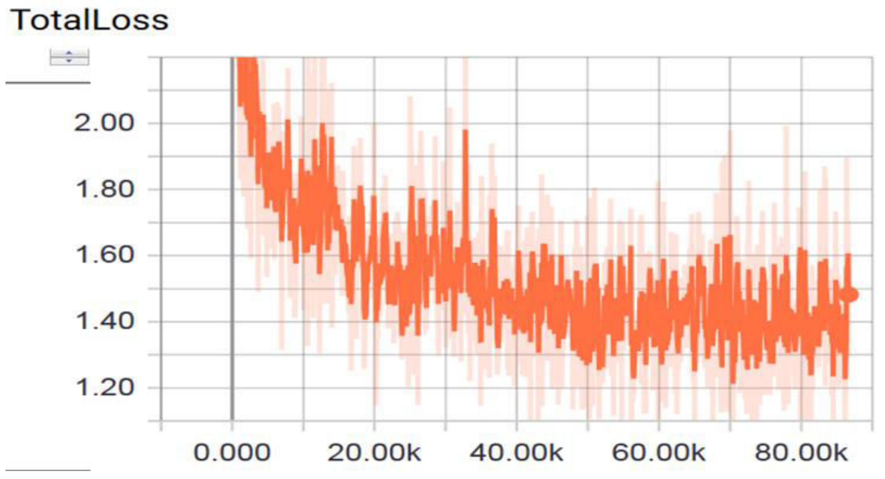

Figure9:Training Loss graph in Tensorboard

3.4Insect Detection and Classification and Storing Data

By applying the trained model using the SSD_Mobilenet-Ver1_coco_2017_11_17 model, we come up with the following results. Figure 11 shows that it detects and classifies the insects that touch down within the platform. Figure 12shows the JSON file format. The saving of the JSON file is also real-time, which means the detection process is running the JSON file is saving at the same time

3.5Testing the Accuracy

In Table 2, the researchers use the user's accuracy, producer's accuracy, and the overall accuracy for testing the accuracy of the model. In solving the classified black bug using the user's accuracy (solved by row), it came up with a 90 % accuracy, followed by the stem borer with 93.33%, gall midge with 56.7%, and the no class with 30 % accuracy. Also, in solving the classified black bug using producer's accuracy (solved by column), it came up with 87.80% accuracy, followed by stem borer with 91.30%, gall midge with 80.97% and the no class with 17.65%. Overall the SSD-MobileNet classifier came up with a 78.4% accuracy.

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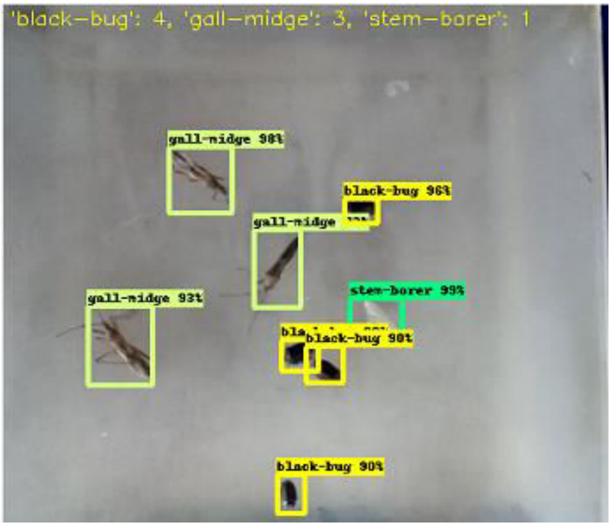

Figure11:Detection and Classification of Rice Adult Flying insects

trying.json
1. { "insect_pest": [{"name": "black-bug", "count": 2}, {"name": "black-bug", "count": 1}]}

Figure12: JSON file format for saving insect data

4.0 CONCLUSION

The researchers concluded that using Raspberry Pi for data gathering is not a bad idea at all. Despite its credit card-sized and small RAM capacity, it still performs well in detecting and classifying insects inreal-time scenarios. Furthermore, the researchers find it suitable and comfortable to use in this study. In the training part, the researcher faces difficulty in the Tensorflow version and installing libraries because the updated Tensorflow has many changes; with this, the researchers need to install the old version of Tensorflow in order to set up everything. Also, the researchers find labeling as a challenging part in this study because the researchers needed much data, but overall training experiences are good. This study has shown that using the SSD-MobileNet model, has performed well on initial tests in the detection and classification of rice adult-flying insects. The objective of designing and develop a stationary pest infestation monitoring device using a convolutional neural network and Raspberry Pi was successfully meet based on the output acquired by the researchers. Although we can meet our

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desired output, this study requires a lot of thorough research and testing to enhance more of its accuracy. Furthermore, the researchers suggest that it is much better to use a mobilenet v2 feature extractor to enhance more the accuracy of the result.

Table2:Accuracy Metrics of the CNN model

		REFERENCE DATA				
		BLACK BUG	STEMBORER	GALL-MIDGE	NO CLASS	TOTAL
CLASSIFIED DATA	BLACK BUG	36	0	0	4	40
	STEMBORER	0	42	0	3	45
	GALL-MIDGE	4	3	17	7	30
	NO CLASS	2	2	3	3	10
	TOTAL	41	46	21	17	125
User's Accuracy		90%	93.33%	56.70%	30%	
Producer's Accuracy		87.80%	91.33%	80.85%	17.65%	
Overall Accuracy		78.40%				

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