ADVANCES IN AGRICULTURAL AND FOOD RESEARCH JOURNAL

HH PUBLISHER

Original Research Article

Oto-BaC^{TM}: An Automated Artificial Intelligence (AI) Detector and Counter for Bagworm (*Lepidoptera*: *Psychidae*) Census

Mohd Najib Ahmad[1]*, Abdul Rashid Mohamed Shariff[2], Ishak Aris[3], Izhal Abdul Halin[3], Ramle Moslim[1]

[1]Malaysian Palm Oil Board, 6, Persiaran Institusi, Bandar Baru Bangi, 43600 Kajang, Selangor, Malaysia. mnajib@mpob.gov.my, ramle@mpob.gov.my

[2]Department of Biological and Agricultural Engineering, Faculty of Engineering, Universiti Putra Malaysia (UPM), 43400 Serdang, Selangor, Malaysia. rashidpls@upm.edu.my

[3]Department of Electrical and Electronic Engineering, Faculty of Engineering, Universiti Putra Malaysia (UPM), 43400 Serdang, Selangor, Malaysia ishak_ar@upm.edu.my, izhal@upm.edu.my

*Corresponding author: Mohd Najib Ahmad; Malaysian Palm Oil Board, 6, Persiaran Institusi, Bandar Baru Bangi, 43600 Kajang, Selangor, Malaysia; mnajib@mpob.gov.my

Abstract: The bagworm species of *Metisa plana*, is one of the major species of leaf-eating insect pest that attack oil palm in Peninsular Malaysia. Without any treatment, this situation may cause 43% yield loss from a moderate attack. In 2020, the economic loss due to the bagworm attack was recorded at around RM 180 million. Based on this scenario, it is necessary to closely monitor the bagworm outbreak at the infested areas. Accuracy and precise data collection is debatable, due to human errors such as miscounting, cheating and creating data. The objective of this technology is to design and develop a specific machine vision that incorporates image processing algorithm according to its functional modes. The device, Automated Bagworm Counter or Oto-BaC^{TM} is the first in the world to be developed. The software functions based on a graphic processing unit computation and used TensorFlow/Teano library set up for the trained dataset. The technology is based on the developed deep learning with Faster Regions with Convolutional Neural Networks technique towards real time object detection. The Oto-BaC^{TM} uses an ordinary camera. By using self-developed Deep Learning algorithms, a motion-tracking and false color analysis are applied to detect and count number of living and dead larvae and pupae population per frond, respectively, corresponding to three major groups or sizes classification. Initially, in the first trial, the Oto-BaC^{TM} has resulted in low percentages of detection accuracy for the living and dead G1 larvae (47.0% & 71.7%), G2 larvae (39.1 & 50.0%) and G3 pupae (30.1% & 20.9%). After some improvements on training dataset, the percentages increased in the next field trial, amount of 40.5% and 7.0% for the living and dead G1 larvae, 40.1% and 29.2% for the living and dead G2 larvae and 47.7% and 54.6% for the living and dead pupae. Furthermore, the development of the ground-based device is the pioneer in the oil palm industry, in which it reduces human error when conducting census while promoting precision agriculture practice.

Keywords: bagworm; automated counter; deep learning; census; accuracy

Received: 24th March 2021

Received in revised form: 17th June 2021

Accepted: 19th June 2021

Available Online: 2nd July 2021

Citation: Ahmad, M. N., Shariff, A. R. M., Aris, I. Oto-BaCTM: an automated artificial intelligence (AI) detector and counter for bagworm (Lepidoptera: Psychidae) Census. Adv Agri Food Res J 2021; 2(1): a0000218. https://doi.org/10.36877/aafrj.a0000218

1. Introduction

Bagworm is one of the main and serious leaf eating insect pest of oil palm plantation in Malaysia. The bagworm outbreaks in oil palm plantations were documented by Wood (1968) and Basri *et al*. (1988) whereby there are three major species of bagworms reported, namely *Metisa plana* Walker, *Pteroma pendula* Joannis and *Mahasena corbetti* Tams. In Standard Operating Procedure (SOP) for bagworm control (Malaysian Palm Oil Board, 2016; Najib *et al*., 2020), it is mentioned that the bagworm is gazetted as a dangerous pest (Federal Government Gazette, 15 November 2013, P.U. (B) 468) under the Plant Quarantine Act 1976 (Act 167, Section 2). It is an offence if the bagworm outbreak not controlled by the plantation owner which leads to a penalty under the Plant Quarantine Act 1976. Integrated pest management (IPM) is recommended for combating bagworm outbreaks in oil palm plantations. According to the outlined SOP, control actions should be taken when 90% of the bagworm population are recorded in the early larval instars and exceeds the economic threshold level. The limit for *M. plana* and *P. pendula* is fixed at 10 larvae per frond.

In order to control bagworm infestation in oil palm plantation effectively, it is vital to conduct a census. Census is a method to calculate number of insect pest unswervingly to allow effective control measures planned and implemented. Currently, census is done manually through naked eyes observation and counting method. Realizing the need for a better census operation and result, the objective of this paper is to present the design and development an automated counting device. First to be developed in the world is the device referred as Automated Bagworm Counter or in the short trademark name, Oto-BaCTM. It is embedded with software that is based on GPU computation and used TensorFlow/Teano library set up for the trained dataset. The Oto-BaCTM uses an ordinary camera and self-developed DL algorithms, consisting of motion-tracking and false color analysis to detect living and dead larvae and pupae of *M. plana* and to count number of living and dead larvae and pupae population per frond, respectively, corresponding to three major groups or sizes classification (Najib *et al*., 2020).

This paper was written to elaborate on the performance of Oto-BaCTM to detect and count the larval and pupal stage of *M. plana*. This validation work has been carried out in the field, with real time acquisition and measurement in actual surroundings of an oil palm.

2. Materials and Methods

The process flow for the development of Oto-BaC™ is illustrated as below in Figure 1.

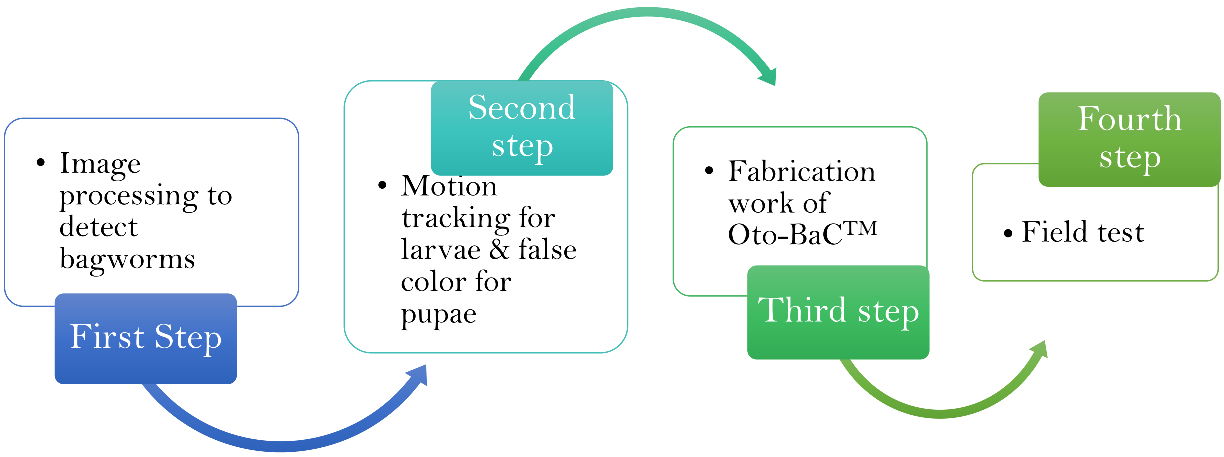

Figure 1. Overall flow of the development of Oto-BaC™

2.1 First Step

There were two methods being applied in the first step or image processing approach as follows: The **first method** involved development of image segmentation algorithm to localize/detect region of interest (RoI) in dataset based on color processing and to trace object (bagworms) and also to remove unnecessary background in the dataset. Then, it was continued with morphological operator method, which focused on extracting the object or bagworms corresponding to shape pattern, plus removing non-targeted regions in the dataset. Lastly, classification that applies supervised classifying algorithm based on trained data, specific to size and shape recognition-based and also to identify live and dead bagworms plus stages of the bagworms. The **second method** in this study focused on the detection of bagworms which employed a supervised classifying algorithm. This algorithm was based on trained data that include specific size and shape recognition to distinguish between stages of bagworm. Experiments were conducted on three groups of *M. plana* Walker, which were classified according to their stages (Figure 2). The first group contains the early larval stage, G1 which was the 1-3 stage. The second group was made up of the late larval stage, G2 of the 4-7 stage. The third group was the pupal stage (positioned at the bottom part of the oil palm fronds), G3. In this step, an algorithm was developed to detect bagworms and classify them into groups according to the stages. This was achieved by training the dataset from the images for object detection and recognition. A deep learning technique with Faster Regions with Convolutional Neural Networks (Faster R-CNN) coupled with a Region Proposal Network (RPN) (Ren *et al*., 2015) was used to predict the object bounds and object scores at each position. The software functions based on GPU computation and uses the TensorFlow/Teano library set up for trained datas

Figure 2. The bagworm, *Metisa plana* life cycle

The experiment was conducted in controlled condition and fixed camera distance to ensure good results and accurate detection of the bagworm features. The controlled conditions were planned and set as follows; a) fully close condition, b) half open condition and c) fully open condition (Figure 3). Meanwhile, the position of the camera from the targeted objects was set at 30 cm and 50 cm distance. This set up was planned and tested during experiment to consider changes in light condition, shadow, vibration and sudden object captured during recording such as other insect and hands.

Figure 3. Controlled condition during snapshot a) fully close, b) half open and c) fully open condition

2.2 Second Step

The second step involve methods to distinguish between the living, dead larvae and pupae.

2.2.1 Motion tracking for determination of the living and dead larvae

Motion analysis was used to detect dead and living larvae. It detects any movement of the larvae by subtracting the moving foreground from the static background. The following flowchart describes the motion analysis algorithm process (Figure 4).

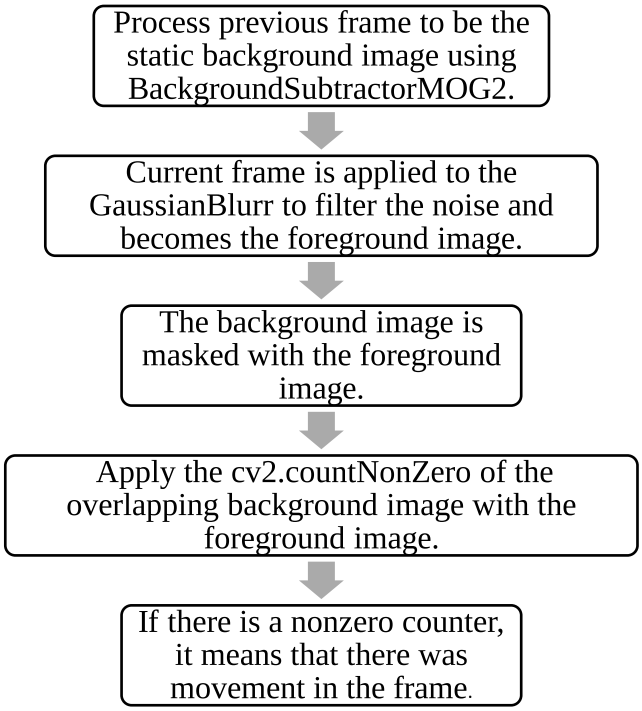

Figure 4. A flowchart describing the motion analysis algorithm

2.2.2 False color for determination of the living and dead pupae

Sixty samples of dead and living pupae were randomly placed on a black ground canvas. Two light sources were identified to be economical and practical, namely the 940 nm (IR) and 630 nm (red). These two wavelength points were selected based on the spectral reflectance properties of the living and dead pupae, which were significantly different between the 630 nm and the 940 nm (Najib *et al*., 2020). The data was achieved using a spectroradiometer in other experiments to find the reflectance percentage at specific wavelengths for the pupae. The images for 630 nm and 940 nm were then captured in the RGB format. The images were converted to grayscale form before an average of all the values of the pixels were picked within a boundary of the pupa. The average pixel values were collected for all samples.

The steps for pixel counting are explained as follows (Figure 5).

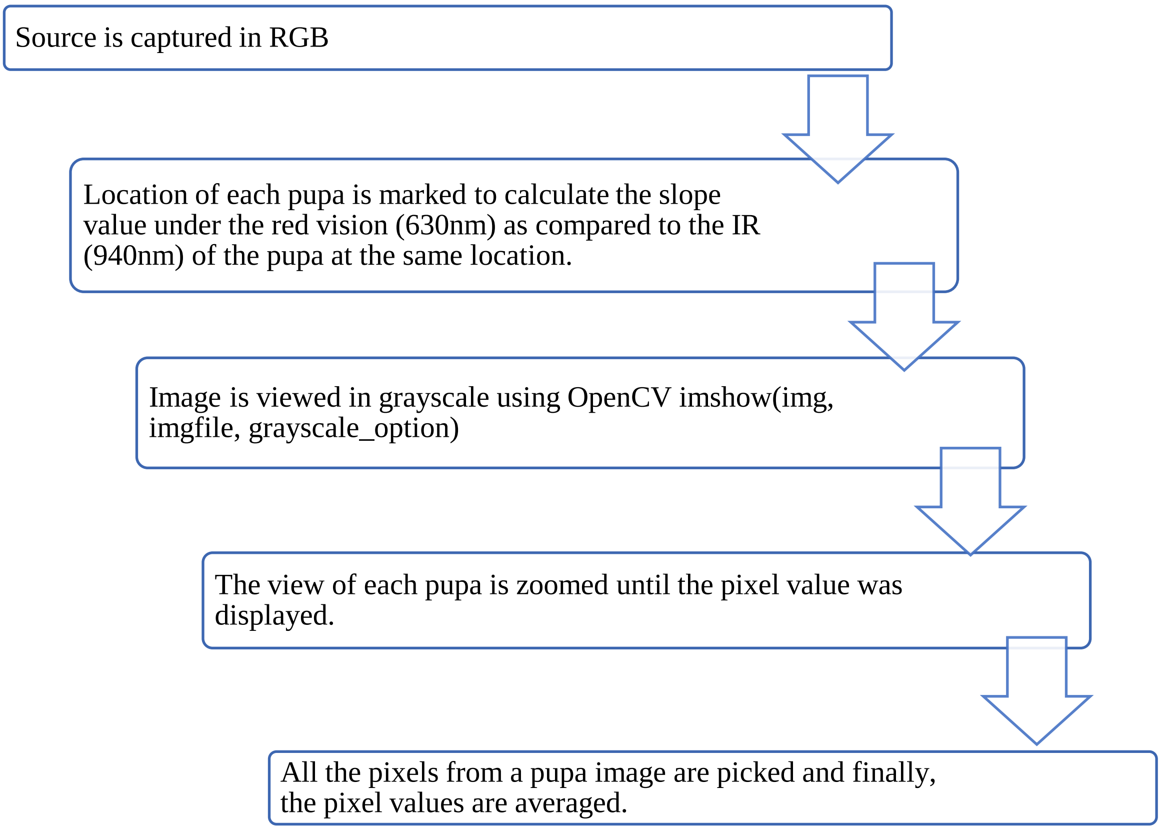

Figure 5. Pixel counting steps in false colour analysis.

2.3 Third Step

The third step involves fabrication of the prototype, Oto-BaC^{TM}, with several steps as follows;

2.3.1 Mechanical design

Mechanical design of the prototype was carried out using 3D CAD software, Inventor (Autodesk Inc., USA) to produce the enclosure nomenclature. The assembly was planned and set before the fabrication step, which was conducted by using Computer Numerical Control (CNC) machine, model HT710 (Hans Laser, China).

2.3.2 Device enclosure

The 3D Device enclosure was drawn in the 3D CAD software is shown in Figure 6. The design focuses on the comfort of the user and convenience of handling. The position of the LCD screen is tilted 15° to give a better view of the screen to the user without the need to tilt their heads down.

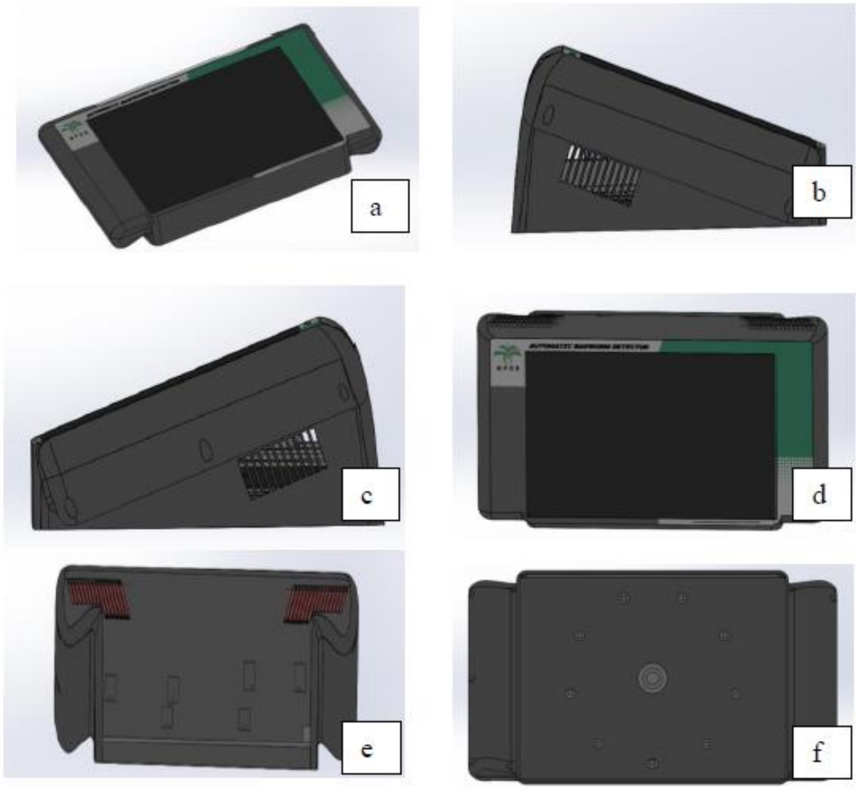

Figure 6. 3D design of the enclosure a) Isometric view b) Left view c) Right view d) Top View e) Front view f) Bottom view

2.3.3 Computing unit

The main processing unit from Dell Inspiron 7567 was explored and tested to search whether it fits all the sets of criteria. The specifications in the processing unit are shown in Table 1. Although the graphic module GeForce GTX 1050Ti has the 768 CUDA core which may be moderate in terms of specifications, it was able to handle the processing speed requirements.

2.3.4 Operating system (OS) and graphical user interface (GUI)

The fabricated device was installed with Ubuntu 16.04 64-bit Desktop mode. It is a Linux based operating system to run the Graphical User Interface (GUI) that became the primary medium of interaction between the user and the device. A graphical user interface (GUI) was developed using PyQT5 and Python 3.3. Since this GUI will call another Python file that will execute the AI detection algorithm of bagworm, the location of all files must be in the same location.

Table 1. Specification of processing unit by Dell Inspiron

Specifications	Hardware details
	Dell Inspiron 15 7567
GPU	NVIDIA GeForce GTX 1050Ti 4GB GDDRS 768 CUDA cores 1290MHz
CPU	7th Gen. Intel Core i7-7700HQ Quad Core
Memory	16GB 2400MHz DDR4 SDRAM
Storage	128GB PCle Gen3 SSD
Operational system	Ubuntu Linux x64 16.04
TensorFlow Builder Test (13 test)	TensorFlow-GPU (0.039s)

2.4 Fourth Step

The fourth step was conducted to validate performance of Oto-BaC™ in the real field environment.

2.4.1 Set up of field trial

The first field trial was conducted at Slim River, Perak on 17 June 2019 and 8 July 2019. The total infested area is approximately 1000 ha. The second field trial was carried out on 8 August 2019 at smallholder areas in Tapah, Perak, with a total infested area of 40 ha. The field trial was done by cutting down 10 oil palm fronds. The fronds with inclination of 45° or the upper fronds with sign of attack were cut for census (Malaysian Palm Oil Board, 2016). The field consists of mature oil palm with average age between 15 to 18 years. The experiment was replicated three times for each treatment in both fields and a plot size of 8 m × 8 m was used to collect the response data. One frond was separated into three main parts; top, middle and bottom. Before starting the test, a field of view (FoV) of the device per snapshot onto the frond was measured. Number of snapshots per frond was counted to cover up one whole frond census. It has the size of about 60 cm x 35 cm. During the snapshot, time duration was recorded for both techniques of Oto-BaC™ (Figure 7) and manual census. However, the time duration was also affected by density of bagworm population per FoV slot (automated counting) or area of interest (AoI) (manual counting).

Figure 7. An automated bagworm counter or Oto-BaC™ used during field trial

3. Results

The summary results of the Deep Learning (DL) approach with Faster R-CNN is illustrated in Table 2**.**

Table 2. DL performance to detect bagworms at different camera distances and frond areas

Camera distance	Condition	Algorithm detection	Human detection	% detection
30cm	Open	9	10	90 **a**
30cm	Closed	10	10	100 **b**
30cm	Half open	9	10	90 **a**
50cm	Open	8	10	80 **a**
50cm	Closed	9	10	90 **b**
50cm	Half open	8	10	80 **a**

Note: Rows with different letters were significantly different (P<0.05) after one-way ANOVA using the LSD test. Number of bagworms detected was depended on randomized leafspots, and the experiment was repeated three times for every condition.

From Table 2, it was proven that the DL with Faster R-CNN gave better results. There was a significant difference in terms of detection accuracy between the 30 and 50 cm camera distances, where p<0.05 for the closed condition, as compared to other conditions. It generated the highest detection accuracy, recorded at 100% and 90%, respectively (Figure 8). Whereas, there was a slightly lower detection at 30 cm and 50 cm camera distances for open and half open conditions, resulting in 90% and 80% detection. The wrong detection was observed, 10% and 20%, due to insufficiently strong trained data.

Based on Figure 8, the different image processing approaches gave different levels of detection accuracy and it was proven by the one-way ANOVA analysis with the Least Significant Difference (LSD) test at P<0.05. By using the colour processing technique, it was revealed that the percentage of the detection accuracy was low. The highest detection accuracy for the colour processing technique was recorded at 55% detection accuracy at 30 cm camera distance.

Meanwhile, by applying DL, the percentage of detection accuracy increased up to 100% at the 30 cm camera distance. From both stages techniques, it was revealed that the 30 cm camera distance resulted in better detection performance and showed more accurate feature details of the bagworms.

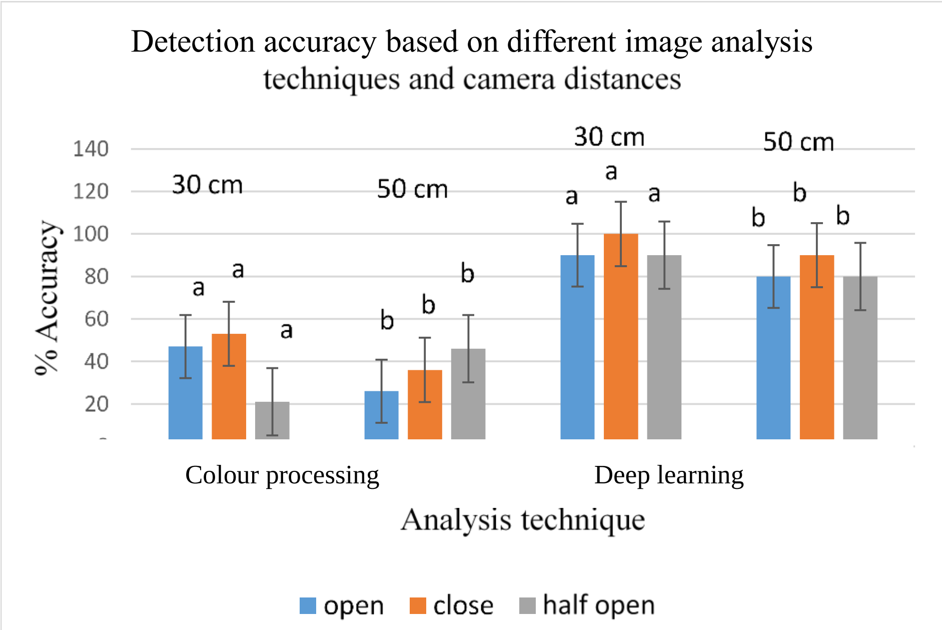

Figure 8. Detection accuracy based on different image analysis techniques at different camera distances. Note: Bars across a group with the different letters were significantly different (P<0.05) after the LSD test.

From the results of the false colour analysis, distinct differences in the pixel counts based on the slopes were observed for the dead and live pupae at 630 nm and 940 nm, following the spectral reflectance properties' trend, with the slopes recorded at 0.37 and 0.26, respectively. A positive result to distinguish between the living and dead pupae was achieved by using the image processing approach. This result was following the trend of the spectral reflectance data with slightly different slope values as shown in Table 3. The slope was calculated based on straight lines generated by the living and dead pupae in Figure 9. It is recommended that live samples are collected and the image will be instantly captured in the field.

Table 3. Measured slopes on reflectance of living and dead specimens using 630 nm and 940 nm wavelengths.

Descriptive statistics	Spectral reflectance		False colour imaging	
	Live	Dead	Live	Dead
Mean	0.26	0.38	0.26	0.37
Min	0.26	0.38	0.14	0.30
Max	0.27	0.38	0.29	0.50

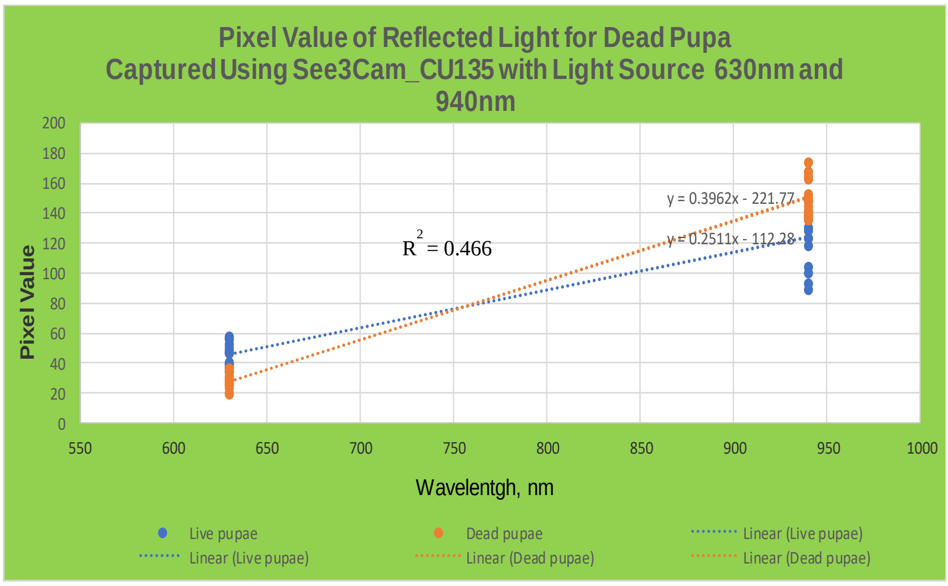

Figure 9. Observation of pixel value of grayscale image using See3Cam_CU135 camera using two different light sources at 630 nm and 940 nm to determine slopes of the living and dead pupae

From Figure 9, a significantly different slope value was indicated between the living and dead pupae. This result is supported by the means separation by Students *t*-Test at $p<0.05$.

In this study, the main focus to be highlighted is the validation of effectiveness and detection accuracy by Oto-BaC™. This was clarified through a series of field trials at two different oil palm plantations, which were attacked by the *M. plana* bagworms. Based on the results in Figure 10, it was revealed that the average percent of detection and classification accuracy for the larval G1 and G2 in trial 1, recorded around 48.6% and 41.9%, and 34.9%, respectively. The results showed that the detection and classification for these two groups still require improvement.

The second field trial was conducted to improve the detection accuracy for larval G1 and G2. From Figure 10, the result shows that the average percentage of the detection and classification accuracy for larval G1 was 87.5% and 66.7%, respectively. Meanwhile, the average percentage of the detection and classification accuracy for larval G2 was 79.2%, respectively. The results showed increasing percentage of detection and classification for the improved prototype as compared to the first field trial result, 38.9% and 24.8% for G1 larvae, and 44.3% (detection and classification) for the G1 and G2 larvae, respectively (Figure 10).

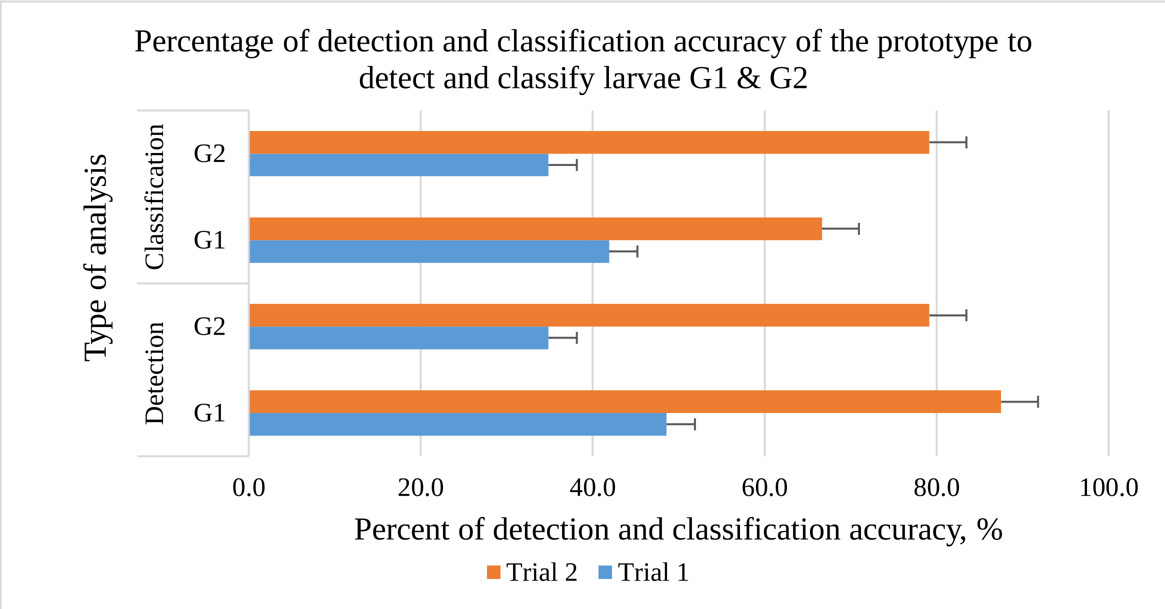

Figure 10. Summary of the prototype performance to detect and classify the living and dead larval G1 and G2 in Trials 1 and 2.

Based on Figure 11, the percentage of detection accuracy was increased with average detection of 87.5% and 78.7% for the living and dead G1 larvae, as compared to manual census, 100% accuracy. The results show that average percentage of the detection accuracy recorded was 79.2% for the living and dead G2 larvae. The result showed a positive result with 40.2% and 29.2% increment in the detection accuracy for the living and dead G2 larvae, respectively, as compared to the first trial result, 39% and 50% accuracy. The result showed that the average detection accuracy increased up to 77.8% and 75.5% for the living and dead pupae from 30% and 20.9% in the first trial (Figure 11), respectively. From the results, it was revealed that the difference on detection accuracy between manual and auto detection was approximately ranging from 12% to 25% for all groups.

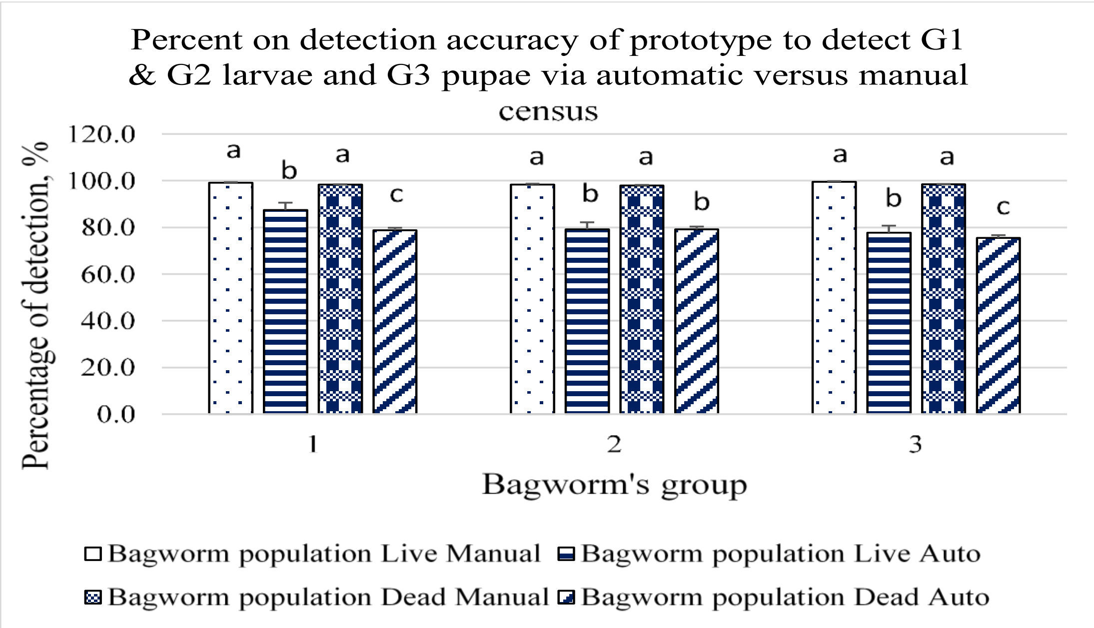

Figure 11. Overall performance of the improved prototype to detect living and dead bagworms through automatic census against manual census in second trial. Note: Bars in a group with the different letters are significantly different (P<0.05) after LSD test.

Overall, from the two trials conducted at two different locations, the results show a significant detection improvement, $p<0.05$ between the first and second trial after LSD test (Table 4).

Table 4. A summary of bagworm detection for G1-G3 groups in two trials

Group	% Detection in Trial 1		% Detection in Trial 2		% Improvement		Census duration, min/frond	
	Live	Dead	Live	Dead	Live	Dead	Automatic	Manual
1(larvae)	47.0**a**	71.7**a**	87.5**b**	78.7**b**	40.5	7.0	14.0	17.2
2(larvae)	39.1**a**	50.0**a**	79.2**b**	79.2**b**	40.1	29.2	13.9	17.0
3(pupae)	30.1**a**	20.9**a**	77.8**b**	75.5**b**	47.7	54.6	0.5	0.8

Note: Bars across a trial group with the different letters are significantly different (P<0.05) after LSD test.

Table 4 shows a significant difference in percentage of detection between first and the second trial for the living and dead bagworms. Group 3 shows a high percentage of improvement for the living and dead pupae (47.7% & 54.6%) because of the size effect of the pupae compared to G1 and G2 larvae. The obvious different on sizes and location on palm leaflet (bottom part) gave an advantage to the pupae group. These two factors are able to avoid overlapping detection by algorithm, subsequently generating high percentage of detection of G3 pupae. Census duration for one whole frond was recorded for G1 larvae, G2 larvae and G3 pupae by using prototype, Oto-BaC^{TM} and manual census. The census duration for G1 and G2 larvae was longer as compared to G3 because of the different technique of detection applied.

4. Discussion

Referring to Section 2.2.1 in Materials and Methods and results on detection accuracy for live G1 and G2 larvae, the larvae was considered alive when motion was detected in the processed frames. Motion was considered happening when there was a change in pixel of larvae contour in current frame comparing with the previous frame. Since the pixel changed was very minimal between two frames, a consecutive 100 frames of images that is equivalent to video with 4.16 seconds duration (24 frames per second) was used in the motion analysis. The device takes around 120 seconds (2 mins) to execute the whole larvae algorithm. When subtracting total time with 4 seconds used to capture frames, the algorithm takes 116 second/100frames, equivalent to 1.16 second per frame (detection + classification). The processing time can be further improved by reducing the total frame (shorten the video duration). However, it was difficult to ensure the larvae has movement in a shorter time. Meanwhile, the G3 pupae only took 0.5 minutes to process and transforming data into figures.

By using false color analysis, processing time was saved because this method involved applying pixel intensity of the images through slopes to classify between the living and dead pupae. From the test conducted, time taken was around 13 seconds. However, it can be fluctuated when switching the light source, due to stabilizing the lighting occasionally The time can be divided into time acquiring images (around 5s), identification (1s), subtracting infrared (IR) and red image with reference image and calculating slope (7s). Overall, the automatic detection was faster compared to manual census, by saving three minutes for G1 and G2 larvae and 0.3 minutes for G3 pupae, during census. From the results of the first field trial, it was revealed that the percentage of detection accuracy to distinguish between the living and dead bagworms were averaged, approximately to 47-72% for G1 larvae and 39-50% for G2 larvae. This part was the most challenging scope because the test on performance of the prototype was conducted at the field site of oil palm plantations, with bagworm outbreak record.

In terms of lighting effect from surrounding/sunlight, the prototype has been equipped with imaging chamber or set up in a closed system operation. This condition gave a better recognition on bagworm features or details. According to Shivang *et al*. (2019), up-scaling the image before detection can tackle low detection problems. However, a naive upscaling is not competent, due to the large sized images that are too large and heavy to fit into a GPU processor for training. Furthermore, when the detection was carried out at the field, flatness of the ground or ground surface level for operating the prototype was uncertain. The structure of the fronds contributed to different LED light intensity which came from the Red and IR light sources (630nm and 940nm), to detect the living and dead pupae. This irregular ground flatness could be part of the factor that contributed to low percentages of the detection accuracy. Furthermore, the deep learning with Faster R-CNN algorithm configuration could be one of the reasons on the lowered detection performance. Specificity of the model used must tally with the targeted object characteristic, corresponding to the configuration of TensorFlow. Further works on training dataset and developing codes are crucial to ensure that high accuracy of detection can be achieved. According to Zhou *et al*. (2018), a larger training data can improve the detection accuracy of the proposed detection model.

Based on the second field trial results, it was revealed that the percentages of detection increased up to 87.5% for the G1 larvae and 79.2% for the G2 larvae. Besides, the percentage of detection for pupal stage (G3) was also increased up to 77%. The increment was achieved after training more image datasets and changing of the algorithm to detect the living larvae. This was successfully done by setting the first frame of the captured images as living larvae, not averaging 100 frames per 3 second.

5. Conclusions

The prototype was successfully designed, fabricated and tested. The field test was conducted to validate the effectiveness of the prototype through series of field trial at the infested areas. The final developed and tested software was integrated with Dell Inspiron 7000 Series and NVIDIA GeForce 1050, CUDA A.I. processor as a platform to operate the function of the device. Design and fabrication of detector and counter was based on 3D imaging using an AutoCAD software. The design covered top and side view of the device to ensure high accuracy and precise image captured during image shooting. The fabrication of a detector and counter prototype involved the use of a specific and practical materials and was tested in the field. The results showed that the average percentage of the detection accuracy was recorded at average detection of 87.5% and 78.7% for the living and dead Group 1 larvae. Meanwhile, the average percentage of the detection accuracy for the living and dead Group 2 larvae was 79.2%, respectively. As for pupa in Group 3, the result showed that the average percentage of detection accuracy of the prototype to detect the living and dead pupae against manual census was 77.8% and 75.5%, respectively. From these trials, factors which contributed to low detection of larvae and pupae of *M. plana* were identified as follows;

1) Size of the bagworms (larvae and pupae)
2) Lighting effect from surrounding
3) Flatness of ground or ground surface level during snapshot
4) Amount of trained images in TensorFlow library
5) Specificity of DL algorithms to detect small objects
6) Camera FoV effectiveness during snapshot

6. Patents

There are several IP outputs that have been generated from this study, including; pending patent filing with PI No.: 2019006153, protecting copyright of the algorithm under Voluntary Notification of Copyright No. CRLY 00022664, protecting design of Oto-BaC^{TM} under Malaysia-Industrial Design Application with Application No. 19-01109-0101 under Class 10-05 and establishing trademark of Oto-BaC^{TM} with trademark filing for Oto-BaC with Trade Mark Number: TM2019033069 under Class 09.

Author Contributions: Conceptualization, Najib, M.A. and Rashid, A.M.S.; methodology, Najib, M.A., Ishak, A. and Rashid, A.M.S.; software, Najib, M.A. and Rashid, A.M.S.; validation, Najib, M.A., Rashid, A.M.S., Ishak, A. and Izhal, A.H..; formal analysis, Najib, M.A.; investigation, Najib, M.A..; resources, Najib, M.A..; data curation, Najib, M.A..; writing—original draft preparation, Najib, M.A.; writing—review and editing, Rashid, A.M.S., Izhal, A.H. and Ramle, M.

Funding: No external funding was provided for this research

Acknowledgments: The authors would like to thank the Director-General of the Malaysian Palm Oil Board (MPOB) for permission to publish this article, the financial support and patenting of all data. Much gratitude also goes to University Putra Malaysia (UPM), Selangor, Malaysia for technical and supervisory support throughout the study.

Conflicts of Interest: The authors declare no conflict of interest.

References

Basri, M. W., Abdul, H. H., Zulkifli, M. (1988). Bagworm (Lepidoptera: Psychidae) of oil palms in Malaysia. *Palm Oil Research Institute of Malaysia occasional paper*. pp 1–23.

Malaysian Palm Oil Board. (2016). Standard operating procedures (SoP) guidelines for bagworm control. *Malaysian Palm Oil Board (MPOB)*. Malaysia. ISBN 978-967-961-218-9.

Najib, M. A., Ramle, M., Rashid, A. M. S. (2020). An Automated Artificial Intelligence (A.I.) Counter for Bagworm (Lepidoptera: Psychidae) Census. Malaysian Palm Oil Board (MPOB) TT. 668.

Najib, M. A., Rashid, A. M. S., Ishak, A., *et al*. (2020). Identification and determination of the spectral reflectance properties of live and dead bagworms, *Metisa plana* Walker (Lepidoptera: Psychidae), using Vis/NIR spectroscopy. *Journal of Oil Palm Research*. doi.org/10.21894/jopr.2020

Ren, S., He, K., Girshick, R., *et al*. (2015). Faster R C-NN: Towards real-time object detection with region proposal networks. In: Advances in Neural Information Processing System 25. 24th International Conference (ICONIP) 2017, Guangzhou, China (2015). pp 91–99.

Shivang, A., Jean, O. D. T., Frédéric, J. (2019). Recent advances in object detection in the age of deep convolutional neural networks. ffhal-01869779v2f.

Wood, B. J. (1968). Pests of oil palm in Malaysia and their control. *The Incorporated Society of Planters* (1st ed.). Kuala Lumpur. Wiley Online Library.

Zhou, S., Xu, Z., Liu, L., *et al*. (2018). Towards Accurate Deceptive Opinions Detection Based on Word Order-Preserving CNN. *Mathematical Problems in Engineering*. doi.org/10.1155/2018/2410206.