

Brown Planthopper Detection System

Izanoordina Ahmad^{1,*}, Nurul Hidayah Han Mohd Fauzan¹, Nur Amirah Sabrina Luqman¹, Zuhanis Mansor¹, Noorazlina Mohamid Salih², Radial Anwar³, Hasanah Putri³, Alfin Hikmaturokhman⁴

¹ Intelligence Embedded Research Lab, Electronic Technology Section, Universiti Kuala Lumpur British Malaysian Institute, 53100 Gombak, Selangor, Malaysia

² Marine and Electrical Engineering Technology Section, Universiti Kuala Lumpur Malaysian Institute of Marine Engineering Technology, 32200 Lumut, Perak, Malaysia

³ Gedung Bangkit, Telkom University, Bandung, Jawa Barat 40257, Indonesia

⁴ Department of Electrical Engineering, Telkom Institute of Technology Purwokerto, Banyumas, Jawa Tengah 53147, Indonesia

ARTICLE INFO

Article history:

Received 21 January 2025

Received in revised form 11 March 2025

Accepted 23 September 2025

Available online 15 October 2025

Keywords:

Internet of things (IoT); computer vision;
deep learning; YOLOv8; agriculture;
brown planthopper detection system

ABSTRACT

This research is to revolutionize the pest control methods in a paddy field farming industry. This project develops a computer vision and Artificial Intelligence (AI) system for accurate and efficient way of detecting pest attacks in paddy field. In this paper, the focus is on Nilaparvata Lugens or more commonly known as Brown Planthopper a high-risk pest in the paddy farming industry. This pest has been the main contribute to paddy plant diseases in Malaysia. A recoded loss as much as 12% was recorded in the time span of 2015-2021 and this percentage has been growing as year passes. Currently, the process of detecting this pest in paddy field is only by manual labour which is labour intensive and a time-consuming process. Moreover, this pest infests the paddy field without any early warning signs. Therefore, this project was conducted to help farmers detect this pest for early pest control. This project uses image recognition to identify brown planthoppers and the YOLOv8 algorithm to train a model to detect and count the number of brown planthoppers on sticky traps. A camera-type C-mount lens has been used to get a clearer image. The images that have been collected for this project are as many as 800 images. In addition, the Internet of Things (IoT) system also successfully sends messages to its users. This project has achieved an accuracy of 85% for the detection and counting of the Brown Planthopper with the used of 6000 images for the learning process. Which is considered 23% more accurate compared to other experiments conducted.

1. Introduction

The growth of the agricultural sector has been related in recent years to a rising number of pest attacks, especially those of the brown planthopper, which harm crop production and growth, as shown in Figure 1 [1,2]. Brown planthoppers, scientifically known as Nilaparvata Lugens, are one of the most economically dangerous pests and pose a threat to paddy production throughout Asia, including Malaysia [2,3].

* Corresponding author

E-mail address: izanoordina@unikl.edu.my

<https://doi.org/10.37934/ard.145.1.110121>

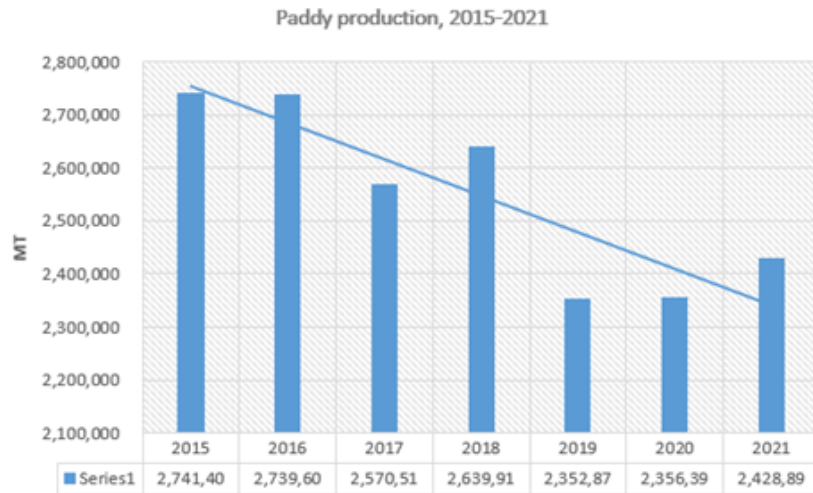


Fig. 1. The statistics for paddy production in Malaysia [1]

These brown planthoppers damage various plants by eating plant nutrients and cause the plants to become yellowish-brown and dry due to the attack of brown planthoppers, as shown in Figure 2. Therefore, the demand for an effective brown planthopper detection system increases with the increase in brown planthopper attacks. This is important to ensure the production of quality crops in the agricultural industry [4].



Fig. 2. The paddy plants died due to the brown planthopper insect attack

The recent expansion of agriculture has led to a corresponding rise in harmful pests, particularly brown planthoppers. These pests can damage crops, complicating the cultivation of nutritious food and impacting both agricultural producers and consumers. Consequently, the early detection employing a machine learning approach can identify brown planthoppers on sticky traps and enhance the precision in recognizing this pest [2-4]. The precise identification of brown planthoppers is essential for efficient pest management. This system concentrates on brown planthoppers, a prevalent and deleterious species. The deployment of image recognition technology and machine learning offers a dependable method for identifying and quantifying brown planthoppers, enabling farmers to initiate prompt actions and strategize subsequent measures post-detection [5-9].

The research based on image recognition systems can outperform traditional methods in several ways. The research allows early detection of pests, reduces the amount of manual work required and increases the ability to plan and manage pest control more effectively. This method can control the use of a lot of pesticides and protect the environment. Real-time monitoring with image recognition allows farmers to monitor brown planthopper populations and other pest species, prevent infestations from spreading and save crops. By acting early, farmers can save their money and ensure sustainable food production. Another research also comprehensively explores the current state and future of integrating image recognition into the detection of brown planthoppers [11-21].

1.1 Existing Methods and Limitations

In previous research, a deep convolutional neural network (CNN) was used for automated brown planthopper detection on sticky pads and this project got an accuracy of 95%. However, the shortcoming of this project is that it is based on grayscale images built from Euclidean Distance Maps (EDM), unable to capture all the features of the brown planthopper form with confidence [3].

Apart from that, there is also a technology that detects the results using YOLO algorithms [9,10,20,21] in detecting the condition of plant and also pest such as brown planthoppers. The two-layer Faster R-CNN employed in this project [14] exhibits instability, as the two layers interfacing the Faster R-CNN algorithm and YOLOv3 are unable to ascertain whether the brown planthopper population is excessive or insufficient or whether its size deviates from the tested dimensions.

Next, the technology uses convolutional neural networks (CNN) and CNN-Long Short-Term Memory (LSTM) learning models for classifying, detecting and predicting infestation patterns. By knowing the wind speed, humidity and temperature of the environment, the use of pesticides can predict the spread of brown planthopper attacks. This project process is challenging due to the prolonged duration required to obtain information regarding the presence of brown planthoppers and there is an absence of data on their population to assess the level of infestation [11].

Instead of detecting brown planthoppers, there is a system that detects damage to rice plants from brown planthoppers by using synthetic aperture radar (SAR) imagery, a convolutional neural network (CNN) to identify the area of paddy fields planted and a support vector machine (SVM) to detect brown planthoppers. The test results found that 96.20% were able to detect rice fields and 96.31% detected brown planthopper attacks. In addition, the use of remote satellites is used for large rice paddy areas. However, in this system, it is only able to detect or capture images twice, which may happen at contrasting times. Apart from that, the weather plays a crucial role in this project; if the clouds are covered by the satellite view, it will produce inaccurate results [12].

The research by Aquino [14] involved the use of the Faster Region-Convolutional Neural Network (FR-CNN) to detect brown planthoppers and collect brown planthopper images for pre-processing and use in model training. The model of this project reached 94.01%, but this project only made a software system and did not implement hardware in the paddy fields and there was no real-time detection of brown planthoppers.

1.2 Contribution of the Project

Based on the existing project by other researchers, a new hardware prototype of the brown planthopper detection system is designed to identify the existing of BPH. A system software has been built that utilises the YOLOv8 and Roboflow models to accurately detect and quantify the presence of brown planthoppers on sticky traps. The enhancements to this system incorporate the Internet of Things (IoT) to streamline usability for farmers or users and expedite access to information regarding

the presence of brown planthoppers in paddy fields. The Internet of Things (IoT) solution utilised the Telegram application to securely store data without causing excessive strain on the user's phone. Hence, this system has the capability to identify, quantify and notify farmers about the invasion of the brown planthopper.

2. Methodology

The methodology described involves the use of block diagrams and flowcharts. The details of each component and the operating system of the Brown Planthopper Project System are presented sequentially.

2.1 Block Diagram

Figure 3 shows the block diagram of the brown planthopper detection system, consisting of three main components: input, process and output. The system employs a manually focused C-mount lens camera to capture images of brown planthoppers on sticky traps. The use of a C-mount lens camera is immensely helpful in obtaining insect images, such as brown planthoppers. The press button on the system enables manual image capture, facilitating maintenance and operation even when a phone is not available in the paddy fields. The project also includes an Internet of Things (IoT) system, which provides instructions or status updates to users. A Raspberry Pi 4 Model B (8GB RAM) processes the images taken by the C-Mount lens camera, which is suitable for supporting the use of the Yolov8 algorithm for deep learning to create a model.

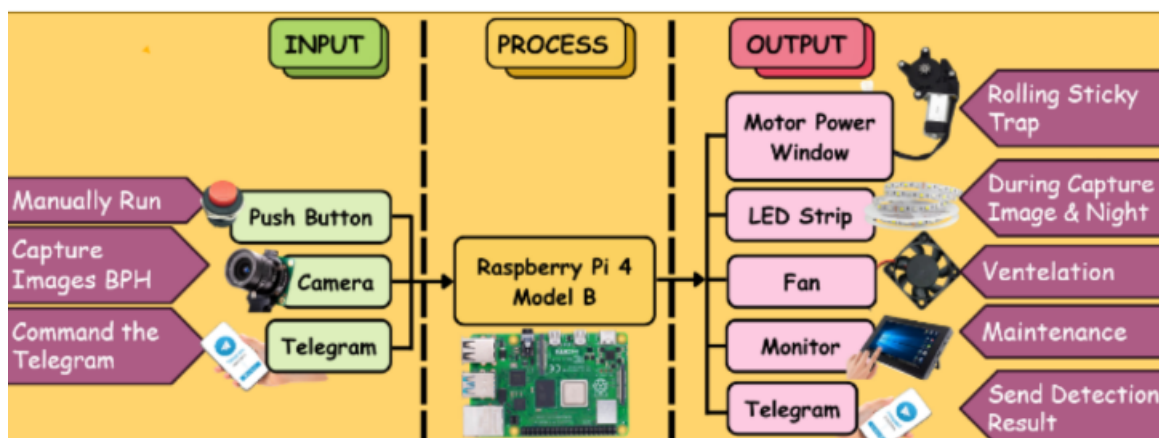


Fig. 3. Block diagram of the Brown Planthopper detection system

This project uses a power window motor to roll the sticky trap, which is activated a few seconds after image capture. The LED strip could light up when the C-mount lens camera is turned on. It turns off after 5 seconds to provide good lighting during image capture. The LED strip is also turned on at night according to the set time. A fan is necessary to prevent overheating of the circuit due to heat from other components. The monitor is used solely for maintenance monitoring purposes. Upon capturing an image, the Telegram application dispatches a notification concerning the detection results to assist users in the early identification of brown planthoppers. Telegram is utilized for user convenience to conserve data and mitigate data loss. Currently, Telegram has emerged as an essential application on mobile devices.

2.2 Flowchart

Figure 4 shows the flowchart for the brown planthopper detection system process, which consists of two parts: software development and hardware development. The software development process involves training the YOLOv8 deep learning model. In order to obtain the model, more than 800 images of Brown Planthopper were collected independently at Tanjung Karang, Perak and Sekinchan, Selangor. Each image underwent an annotation process to manually mark and label the brown planthopper with a bounding box. Additional image data was incorporated to iteratively train the model, enhancing the process through preprocessing and augmentation with filter selection. The data was split into 80% for training and 20% for testing sets to improve the model's performance. The training process continued until loss convergence was achieved, indicating that the model had reached a state where further training would not improve its performance. Finally, the trained model was obtained.

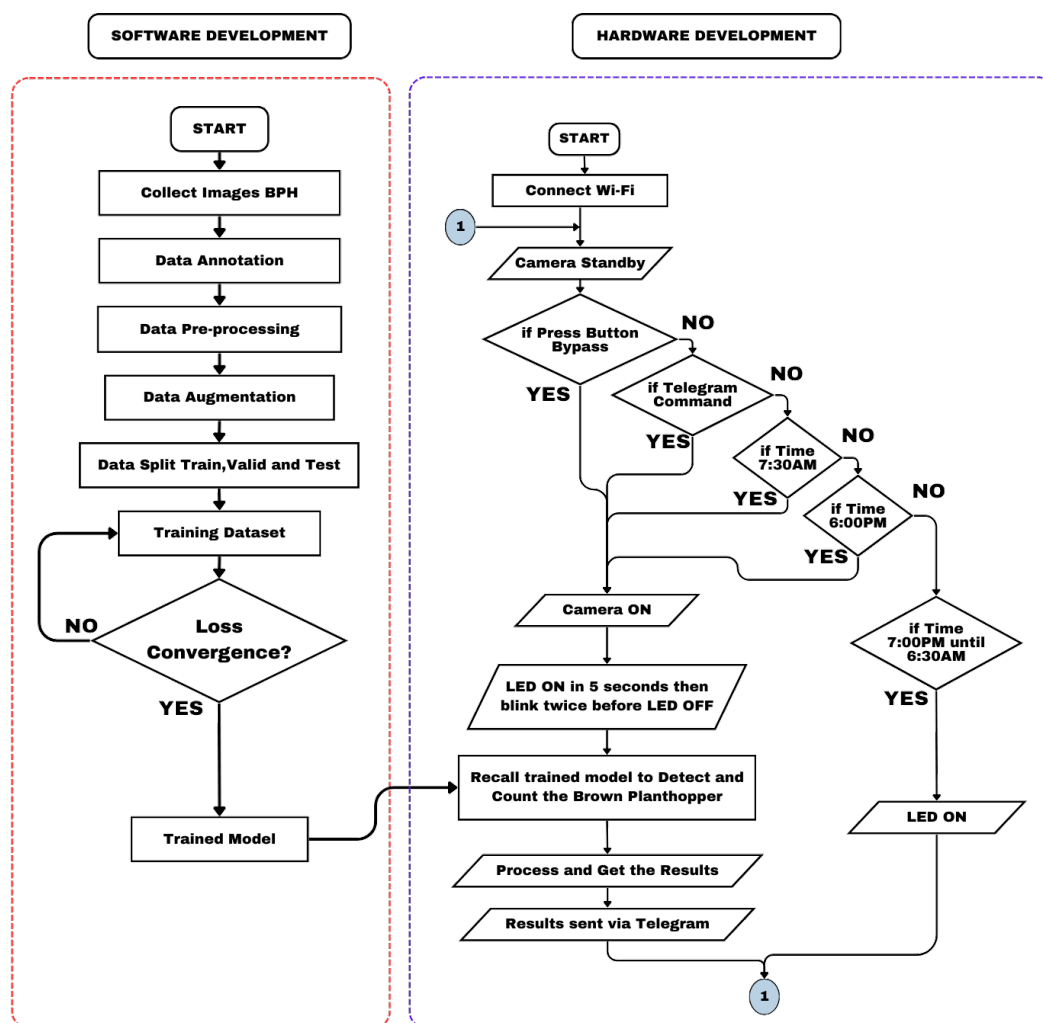


Fig. 4. Flowchart of the Brown Planthopper detection system

Table 1

Summary of software development process

Software development	Process:
Training YOLOv8 deep learning model:	• More than 800 images have been collected. • Each image undergoes an annotation process (manually mark and label BPH with bounding box).
Improving:	Additional image data added to train model, process undergoes: • Image Preprocessing • Image augmentation with filter. All data was split into training, validation and testing sets to improve performance. The training process continued until loss convergence is achieved.

The hardware development section describes how this project will operate as desired. The hardware system requires a Wi-Fi connection to operate and deliver project status updates. The system can be activated by pressing the push button, receiving an instruction from Telegram or at a scheduled time, as shown in Figure 5.

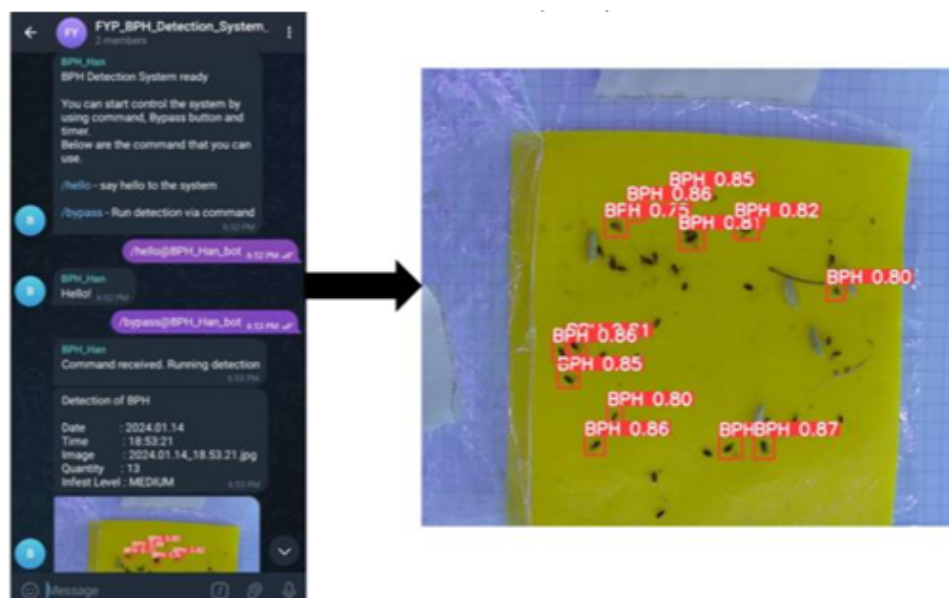


Fig. 5. IoT implementation (Telegram)

Upon activation, the camera will capture an image and the LED will illuminate within 5 seconds to ensure the system operates efficiently and conserves power. The LED will flash twice to signify the midpoint of the brown planthopper detection project before extinguishing. Otherwise, the system will remain inactive and await from 7:30 p.m. to 6:30 a.m. for the illumination to activate at night, thereby attracting brown planthoppers to the adhesive trap. This occurs because Brown Planthoppers are typically drawn to lights at night, specifically from 7:30 PM (sunset) to 6:30 AM (sunrise).

Table 2

Summary of hardware development process

Hardware development	Process:
Wi-Fi function:	• Provide project status via Telegram. • Turning on project via Telegram. • Provide the number of BPH after each image captured.
Other Hardware:	• Bypassed button on the prototype (to bypass telegram activation) • Camera to capture the BPH via scheduled time, bypass button or via telegram activation • LED to ensure the light exposure is enough when capturing BPH images. • At night from 7:30 pm till 6:30 am LED will remain 'ON' to attract BPH. • Solar and battery as main power sources.

This system captures and processes images to detect and quantify brown planthoppers utilizing the trained model. Upon completion of detection and counting, the system autonomously dispatches notifications to users through Telegram. The system operates on a 24-hour cycle to facilitate the early detection of brown planthoppers.

2.3 Internet of Things (IoT)

This project employs the Internet of Things (IoT) framework and the Telegram application to facilitate automatic notifications and results delivery to users' mobile devices. Upon initial activation, a notification will be dispatched via Telegram to confirm that the project has successfully connected to Wi-Fi and is functioning correctly.

The instruction in Telegram notification has two types of instructions: “/hello” and “bypass.” The “/hello” instruction is utilized to verify the operational status of the project. If the user presses “/hello” and gets a response, it means that the system is functioning properly and is in optimal condition.

The subsequent directive is “/bypass.” This activates the C-mount lens camera for image capture and the LED strip for illumination during the process. Shortly, the user will receive a response from Telegram containing the date, time, file name, number of brown planthoppers identified and infestation severity in paddy fields.

According to the flowchart in Figure 4, users receive notifications at 7:30 a.m. and 6:00 p.m. This application aims to enable users to remotely monitor paddy fields and store data solely via their mobile devices. Telegram was chosen for its extensive utilization and resilience against data loss. No data from the past will be lost if consumers change the device.

3. Results

3.1 Experiment 1: Build a Dataset and Obtain a Model

The experiment depicted in Figure 6 involves the creation of the dataset and the model's training to facilitate image recognition for detecting and counting brown planthoppers. Samples of the brown planthopper were collected from paddy fields in Tanjung Karang, Selangor, to serve as a data set.

Figure 5 and Figure 6 are also illustrating the resolution quality achievable by the camera utilized for data collection. Dimensions and proximity are critical factors in identifying brown planthoppers. Over 800 images have been gathered and adhering to the procedure can enhance the YOLOv8 model's learning, resulting in increased accuracy and confidence in the precise detection and enumeration of the brown planthopper.



Fig. 6. The samples of Brown Planthopper

This system employs image recognition to identify the brown planthopper from the images presented in Figure 7. The acquired image has been input into the Roboflow software to initiate the annotation process for each image. The system will be trained to recognize brown planthopper insects by annotating images with bounding boxes. The technique is challenging as it necessitates manual human instruction in the YOLOv8 system via bounding boxes in Roboflow.

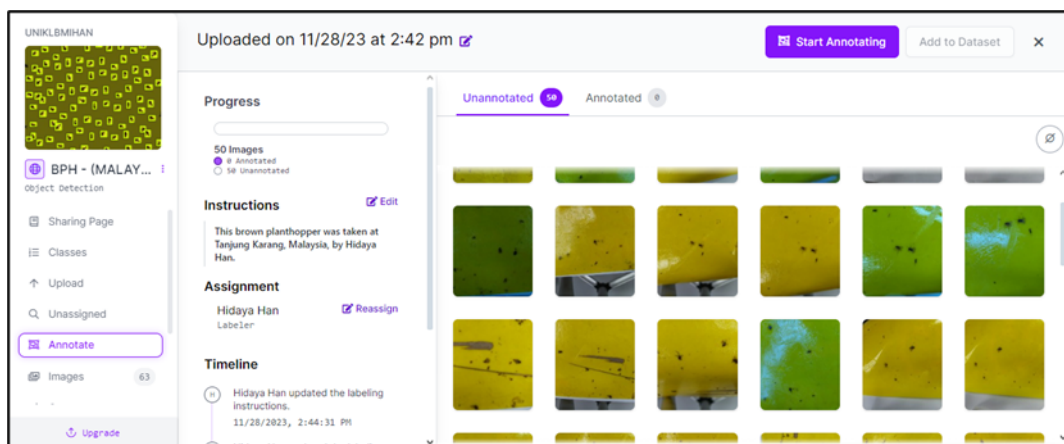


Fig. 7. The process of image collection for BPH dataset

Figure 8 shows the final software process to develop a deep learning model of the YOLOv8 algorithm, which is trained on a high-performance computer. The project collected about 6,000 images from a data set and it took around 4 to 5 days to get the performance results. In this case, 6,000 images are considered low image data but sufficient to undergo image processing.

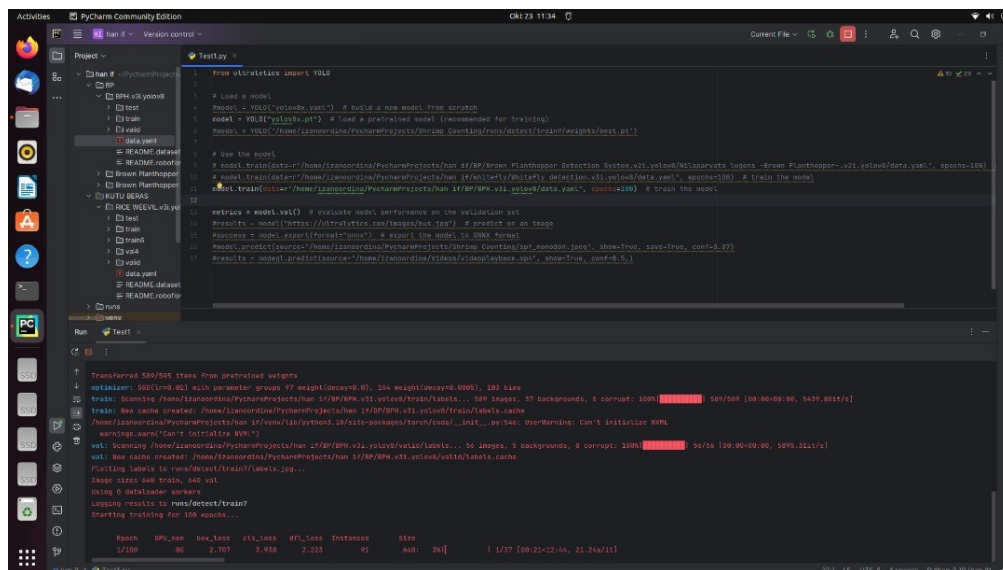


Fig. 8. The process of training a model using a high-performance computer

3.2 Experiment 2: Create a Prototype Project

In the experiment depicted in Figure 9, a prototype project consisting of a shaped project, a main circuit and a display of results was created. The design was inspired by a previous project and insights gained about the brown planthopper's attraction to light. This feature enables users to capture and obtain information via the Telegram application, which notifies them of detection results. All components of the main circuit are housed in one PVC box to protect them from water exposure or overheating and facilitate maintenance due to its lightweight and compact size. Results are obtained using the Internet of Things (IoT) system. features: was chosen for its popularity and data retention features; data remains accessible if users retain their phone number even if it is changed or lost on Telegram or deleted from the phone gallery.

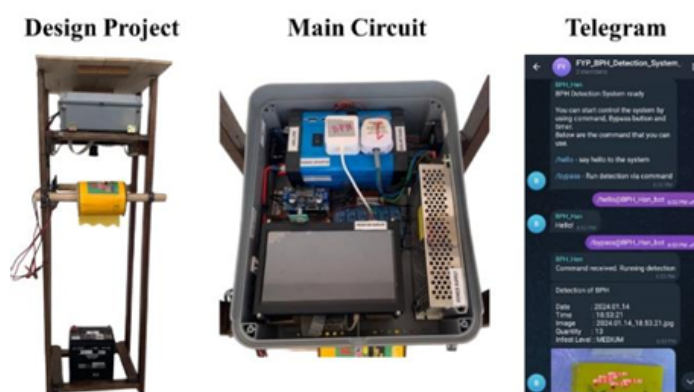


Fig. 9. Development prototype project for the Brown Planthopper detection system

3.3 Experiment 3: Test the Prototype and Performance of a Model

In the experiment depicted in Figure 10, a prototype project was tested to evaluate the performance of a model and determine its effectiveness in detecting the presence of brown planthoppers. The results indicate that the brown planthopper detection system project is efficient, as the model has a high detection and prediction rate.

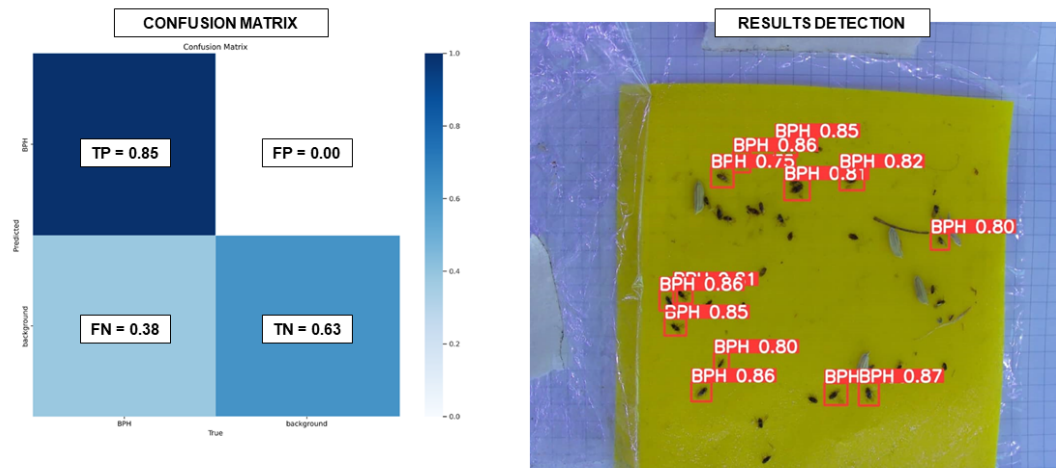


Fig. 10. The results performance model

Table 3 shows a summary of a confusion matrix for a model's performance in identifying brown planthoppers. The model has an 85% True Positive rate, meaning it correctly identifies brown planthoppers 85% of the time. However, it has a 38% False Negative rate, indicating that it incorrectly fails to identify brown planthoppers in 38% of cases. The True Negative rate is 63%, showing the model's accuracy in identifying non-brown planthoppers. There are no False Positives, meaning the model does not mistakenly identify other objects as brown planthoppers.

Table 3

Summary of the confusion matrix

Measure the performance	Meaning
True Positive (TP): 0.85	The model predicts the positive class correctly because it can identify 85% the brown planthoppers correctly.
False Negative (FN): 0.38	The model incorrectly predicted the negative class because it misidentified 38% of false brown planthoppers instead of true brown planthoppers.
True Negative (TN): 0.63	The model correctly predicts the negative class because it can correctly identify 63% of non-brown planthoppers.
False Positive (FP): 0.00	The model incorrectly predicted the positive class. In this system, there are no instance where the model identifies something as a brown planthopper.

4. Conclusions

The Brown Planthopper Detection System project was developed to detect and count brown planthoppers using deep learning. This project employs the YOLOv8 deep learning model and uses 800 images captured with a C-mount lens camera. The dataset was created using the same camera to maintain consistent resolution and size. The YOLOv8 model was trained through a process of image collection, annotation, marking and labelling of brown planthoppers with bounding boxes, preprocessing, augmentation and image splitting for training, validation and testing sets. The performance of this project is evaluated based on the confusion matrix, as shown in Figure 10. The objective of the Brown Planthopper Detection System, which is to detect and count brown planthoppers to help farmers prevent early insect infestations, has been achieved. The system's accuracy and confidence level reached 85%, as indicated in the section results above. These results show the project's capability to detect small objects, such as brown planthopper insects. As for the future work, more experiments and the comparison between Faster RCNN will be implemented.

Acknowledgement

The author wanted to express appreciations for the support that received from UniKL BMI, Intelligence Embedded Research Lab (IERL) research cluster for providing the lab throughout the project and paddy plant districts of Seberang Perak, Perak and Tanjung Karang, Selangor in completing this project.

References

- [1] Zainol Abidin, Ahmad Zairy and Abu Dardak, Rozhan. "Sociological Issues and Challenges of Rice Production in Malaysia." *Food and Fertilizer Technology Center for the Asian and Pacific Region*, (2023). <https://ap.fttc.org.tw/article/3473>
- [2] Narayana, S., S. Chander, S. Doddachowdappa, S. Sabtharishi and P. Divekar. "Seasonal variation in population and biochemical contents of brown planthopper, *Nilaparvata lugens* (Stål)." *Journal of Environmental Biology* 43, no. 1 (2022): 52-58. <https://doi.org/10.22438/jeb/43/1/MRN-1983>
- [3] Nazri, Azree, Norida Mazlan and Farrah Muharam. "PENYEK: Automated brown planthopper detection from imperfect sticky pad images using deep convolutional neural network." *PloS one* 13, no. 12 (2018): e0208501. <https://doi.org/10.1371/journal.pone.0208501>
- [4] Fadhil, J. A., K. T. Wei and K. S. Na. "Artificial intelligence for software engineering: an initial review on software bug detection and prediction." *Journal of Computer Science* 16, no. 12 (2020): 1709-1717. <https://doi.org/10.3844/jcssp.2020.1709.1717>
- [5] Shah, Nur Atiqah Nasser, Muhammad Khusairi Osman, Nor Azlan Othman, Fadzil Ahmad and Abdul Rahim Ahmad. "Identification and counting of brown planthopper in paddy field using image processing techniques." *Procedia Computer Science* 163 (2019): 580-590. <https://doi.org/10.1016/j.procs.2019.12.140>
- [6] Kasinathan, Thenmozhi, Dakshayani Singaraju and Srinivasulu Reddy Uyyala. "Insect classification and detection in field crops using modern machine learning techniques." *Information Processing in Agriculture* 8, no. 3 (2021): 446-457. <https://doi.org/10.1016/j.inpa.2020.09.006>
- [7] Sani Haliru, Bello, Mohd Y. Rafii, Norida Mazlan, Shairul Izan Ramlee, Isma'ila Muhammad, Ibrahim Silas Akos, Jamilu Halidu, Senesie Swaray and Yusuf Rini Bashir. "Recent strategies for detection and improvement of brown planthopper resistance genes in rice: A review." *Plants* 9, no. 9 (2020): 1202. <https://doi.org/10.3390/plants9091202>
- [8] Arshad, Muhammad Ali and Huang Zhiqiu. "Using CNN to Predict the Resolution Status of Bug Reports." In *Journal of Physics: Conference Series*, vol. 1828, no. 1, p. 012106. IOP Publishing, 2021. <https://doi.org/10.1088/1742-6596/1828/1/012106>
- [9] Ahmad, Izanoordina, Syed Harith Aidid Aljamalullil Syed Khair, Azmir Jamalulil, Nor Hidayah Abdul Kahar, Noorazlina Mohamid Salih, Danial Md Noor and Indrarini Dyah Irawati. "Crop Classification System in Agriculture." *Journal of Advanced Research in Applied Sciences and Engineering Technology* (2024): 201-212. <https://doi.org/10.37934/araset.63.2.201212>
- [10] Amiruddin, Khaidir, Nor Hidayah Abdul Kahar, Izanoordina Ahmad, Julie Roslita Rusli, Hasanah Putri and Ibrahim Alhamrouni. "Automated Mushroom Classification System using Machine Learning." *Journal of Advanced Research in Applied Sciences and Engineering Technology* (2024): 193-204.
- [11] He, Yue, Zhiyan Zhou, Luhong Tian, Youfu Liu and Xiwen Luo. "Brown rice planthopper (*Nilaparvata lugens* Stal) detection based on deep learning." *Precision Agriculture* 21, no. 6 (2020): 1385-1402. <https://doi.org/10.1007/s11119-020-09726-2>
- [12] Harris, Christopher and Y. Andi Trisyono. "Classifying, detecting and predicting infestation patterns of the brown planthopper in rice paddies." In *2019 18th IEEE International Conference On Machine Learning And Applications (ICMLA)*, pp. 246-251. IEEE, 2019. <https://doi.org/10.1109/ICMLA.2019.00046>
- [13] Lakmal, Dimuthu, Kumaran Kugathanan, Vishaka Nanayakkara, Suranga Jayasena, Amal Shehan Perera and Lasantha Fernando. "Brown planthopper damage detection using remote sensing and machine learning." In *2019 18th IEEE international conference on machine learning and applications (ICMLA)*, pp. 97-104. IEEE, 2019. <https://doi.org/10.1109/ICMLA.2019.00024>
- [14] Aquino, Jet. "Brown Planthopper Detection Using Faster Region-Convolutional Neural Network." *vol. 5*, no. 4 (2019): 44-47.
- [15] Widiarta, I. Nyoman, Etty Pratiwi, I. Putu Wardana and Oky Dwi Purwanto. "Population Development and Disease Incidence of Virus Disease Transmitted by Brown Planthopper on the Paddy Field Applied with Biofertilizers and Biopesticides." In *E3S Web of Conferences*, vol. 374, p. 00017. EDP Sciences, 2023. <https://doi.org/10.1051/e3sconf/202337400017>

- [16] Rahman, Chowdhury R., Preetom S. Arko, Mohammed E. Ali, Mohammad A. Iqbal Khan, Sajid H. Apon, Farzana Nowrin and Abu Wasif. "Identification and recognition of rice diseases and pests using convolutional neural networks." *Biosystems Engineering* 194 (2020): 112-120. <https://doi.org/10.1016/j.biosystemseng.2020.03.020>
- [17] Tamil Selvi, T., Abinanthan S., Manikandan, R. Nadesh and Nandheeswaran. S. "Image processing based motion sensor with telegram." *International Research Journal of Modernization in Engineering Technology and Science*, no.05, (2020):5656–5659.
- [18] Bernama. "Perak paddy farmers suffer losses due to pests, diseases." *Bernama*, (2021). <https://www.bernama.com/en/news.php?id=1924315>
- [19] Narayana, S., S. Chander, S. Doddachowdappa, S. Sabtharishi and P. Divekar. "Seasonal variation in population and biochemical contents of brown planthopper, *Nilaparvata lugens* (Stål)." *Journal of Environmental Biology* 43, no. 1 (2022): 52-58. <https://doi.org/10.22438/jeb/43/1/MRN-1983>
- [20] Terven, Juan, Diana-Margarita Córdova-Esparza and Julio-Alejandro Romero-González. "A comprehensive review of yolo architectures in computer vision: From yolov1 to yolov8 and yolo-nas." *Machine Learning and Knowledge Extraction* 5, no. 4 (2023): 1680-1716. <https://doi.org/10.3390/make5040083>
- [21] F. Jacob Solawetz. "What is YOLOv8? The Ultimate Guide." *Roboflow*, (2023). <https://blog.roboflow.com/whats-new-in-yolov8>