

SMART STINGLESS BEEHIVE INTERNET BASED MONITORING SYSTEM

N. S. Ahmad Kamal.

Instrumentation and Control Engineering, Universiti Kuala Lumpur, Malaysian Institute of Industrial Technology, 81750 Masai, Johor, Malaysia.
noor.shafinaz98@gmail.com

S. I. Safie.

Instrumentation and Control Engineering, Universiti Kuala Lumpur, Malaysian Institute of Industrial Technology, 81750 Masai, Johor, Malaysia.
sairulizwan@unikl.edu.my

E. M. Mohd Yusof.

Instrumentation and Control Engineering, Universiti Kuala Lumpur, Malaysian Institute of Industrial Technology, 81750 Masai, Johor, Malaysia.
erniemazuin@unikl.edu.my

* noor.shafinaz98@gmail.com

ABSTRACT

Australia, South America, Africa, and Malaysia tropical and subtropical terrain can locate over 500 species of stingless bee including Apidae, Hymenoptera, and Meliponini. There are two genera most commonly subdue across the board which are Melipona and Trigona. More familiar called as 'Lebah Kelulut', Malaysia reportedly has 33 species of stingless bees. **Problem statement:** Due to the lack of monitoring, and traditional management of beekeeping is one of the main reasons why the stingless bee's beekeeper faced several difficulties in the industry. **Methodology:** To monitor the parameter of the stingless bee's hives using MATLAB software is one of the purposes for this research. The parameters that are focused on this research is height between camera and entrance. Also, the background colour of the base. Beekeepers may acquire real-time information from their hives and keep them healthy by monitoring them using the system. Other than that, the research focuses to investigate the method on how to keep track of the number of fly-in and fly-out of the stingless bee at the entrance of the hive. It is due to monitor whether the activeness of the stingless bee which effect the production of the colony. **Results:** The users able to detect the number of fly-in and fly-out of the stingless bee at the entrance of the hive. Also, able to monitor the stingless beehive real time and recording mode. Last but not least, able to monitor and control the parameter that affected the accuracy of the object detection.

Keywords: *Stingless Bees; Object Detection; MATLAB; Real-time*

1.0 Introduction

The Stingless bee is natural type of bee that exists in almost every continent [1]. Frequently found in the tropical and subtropical regions of the world, including Southeast Asia and tropical America, the stingless bees are small, all black life [2,3]. Australia, South America, Africa, and Malaysia tropical and subtropical terrain can locate over 500 species of stingless bee including Apidae, Hymenoptera, and Meliponini. There are two genera most commonly subdue across the board which are Melipona and Trigona [4]. More familiar called as ‘Lebah Kelulut’, Malaysia reportedly has 33 species of stingless bees. According to [5,6], stingless bees are significant pollinators for many wild and cultivated tropical plants, and they serve an important role in ecology, economy, and culture of the world. According to research officer in the Malaysian Agricultural Research and Development Institute (MARDI), because of their small size, stingless bees are uniquely suited to pollinate small flowers, something that honeybees cannot do [1]. Due to the environmental conditions surrounding the beehives and traditional management of beekeeping is one of the main reasons why the stingless bee’s beekeeper faced several difficulties in the industry as stated by [7].

There is a need to develop a system called Smart Stingless Beehives Internet Based Monitoring System in order to solve the problems faced by the beekeeper. The project strives to design real time monitoring system which can be used to monitor the number of fly-in and fly-out stingless bees (*Heterotrigona Itama*) at the entrance of the hive. Also, to monitor the stingless beehive real time and recording mode. Moreover, the system also able to monitor the number of fly-in and fly-out stingless bees at the entrance of help the detector learn to predict the boxes the hive. In order to do that, the system use video processing using MATLAB software. The system will detect each of the stingless bees in the video. If the number of stingless bees is more than 20 in one minute, then the system will appear active on the system’s layout. On the other, if it detects less than 20, then the system will turn in the buzzer and alert the user by sending email.

2.0 Literature Review

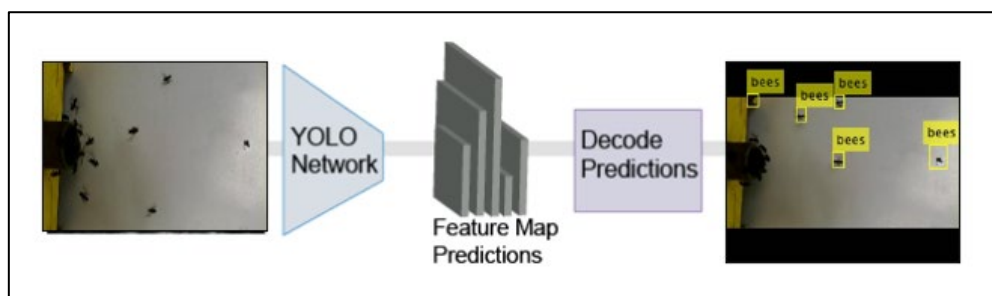


Figure 1. Image of YOLO v3 object detection flow.

Referring to Figure 1, you-only-look-once (YOLO) v3 object detector is a multi-scale object detection network that makes predictions at multiple scales by utilizing a feature extraction network and multiple detection heads [8]. To generate network predictions from multiple feature maps, the YOLO v3 object detection model employs a deep learning convolutional neural network (CNN) on an input image. To generate the bounding boxes, the object detector collects and decodes predictions. The YOLO v3 network observed in the YOLO v3 detector is represented in the Figure 2 below.

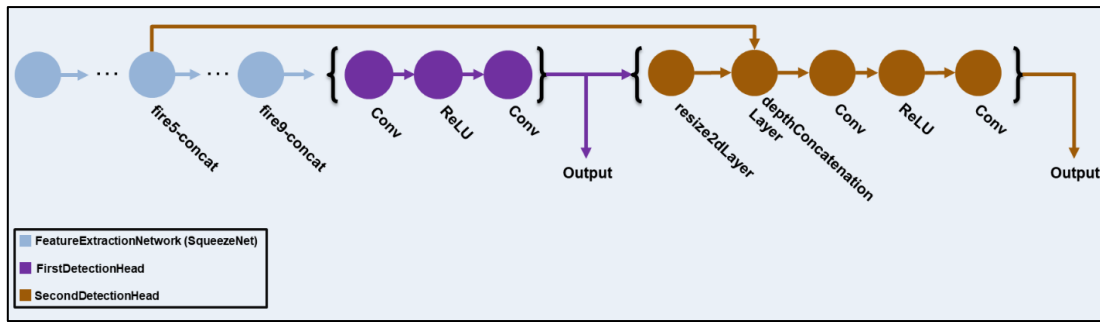


Figure 2. Image of YOLO v3 network.

Based on Figure 2, YOLO v3 detector is based on SqueezeNet (the type of CNN used in this project) and employs SqueezeNet’s feature extraction network, with the addition of two detection heads at the end [9]. Because the second detection head is twice the size of the first, it can detect smaller objects. It is worth noting that it can specify an unlimited number of detection heads of varying sizes based on the size of the objects that want to detect. To have better initial priors corresponding to the type of data set and to accurately, the YOLO v3 detector uses anchor boxes estimated using training data. SqueezeNet is an 18- layer deep convolutional neural network. A pretrained version of the network trained on over a million images from the ImageNet database can be loaded. The pretrained network can classify images into 1000 different object categories, including keyboards, mice, pencils, and various animals. As a result, the network has learned detailed feature representations for a diverse set of images [9,10].

3.0 Methodology

3.1 Block Diagram

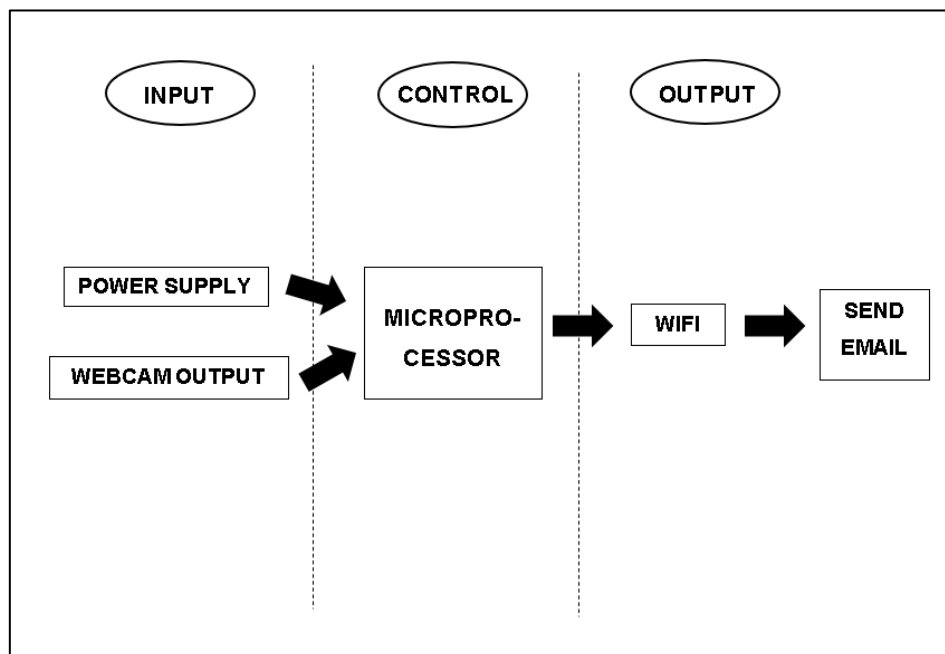


Figure 3. Image of block diagram of the system.

Figure 3 shows the image of block diagram of the system which consists of input, control, and output components of the parameter to be monitored are separated into three pieces. A power supply will deliver power to the microprocessor at the input section, allowing the

microprocessor which is laptop to operate. Also, webcam output which is the number of fly-in and fly-out of stingless bee. The measured data will be transferred to the microprocessor, which will process it. The microprocessor will display the output on the system. The system will then generate a graph of the number fly-in and fly-out of stingless bee at the entrance. Wi-Fi allows devices within the range of a wireless network with an Internet connection to connect to the Internet. After the laptop is connected to the Wi-Fi, the system will send email to the user email account if there are less than 20 stingless bees entering and exiting the entrance in one minute.

3.2 Flowchart

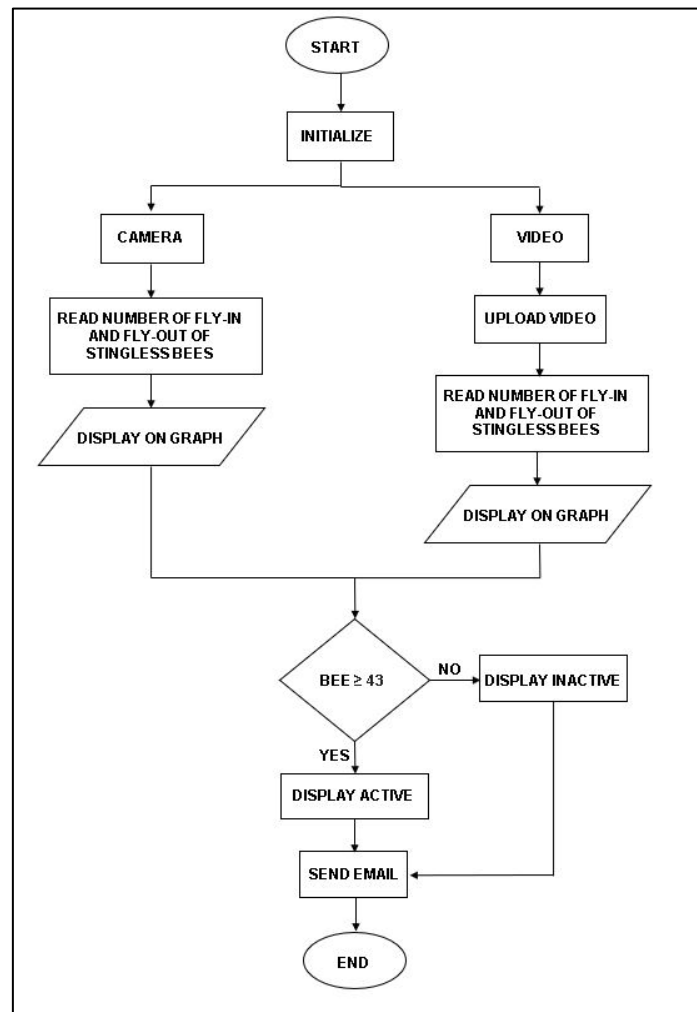


Figure 4. Image of flowchart of the system.

The flowchart in Figure 4 starts with the user select camera button for real-time mode or video button for offline mode. After that, the sequence of work is the same between real-time and offline mode which the camera detects the number of fly-in and fly-out of stingless bee at the entrance of the beehive. Then, the number will be uploaded and displayed on the history graph. If the number of stingless bees equal and more than 20, the system will display “ACTIVE” which means the colony hive is active. On the other hand, is less than 20, the system will display “INACTIVE” indicate the colony hive is not active and need further observation. Both of the situation will require the system to send email to the user.

4.0 Result and Discussion

4.1 System Layout

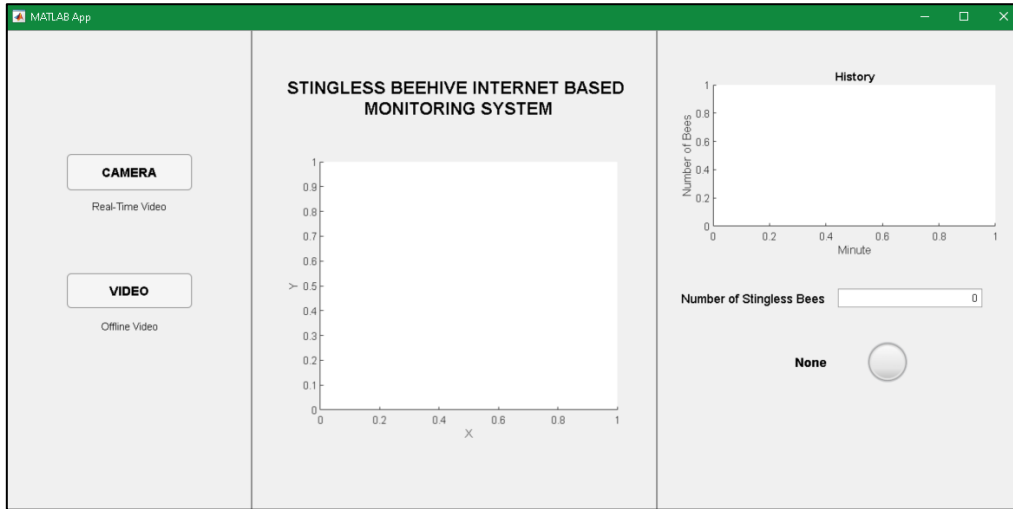


Figure 5. Image of system layout.

The system layout consists of three sections in Figure 5. The right section comprises of the “camera” button and “video” button. The “camera” button is for the real-time mode. When clicking the button, it will display the current view of the camera. On the other hand, a window will pop out when clicking “video” button. The user can upload the save stingless bees video on computer through the system to detect the number of stingless bees. As for the middle section, the graph displayed the video. Finally, the last section, the history graph will generate graph depending on the number of stingless bees detected in the video. If the number detected is more than 20 then the lamp will turn green, and the system display active while less than 20, the lamp turned red, and buzzer will turn on.

4.2 Experimental Setup



Figure 6. Image of experimental setup at stingless bee farm.

The experimental setup at the beehive by placing the webcam with background underneath the beehive’s entrance. The setup was shown in the Figure 6.

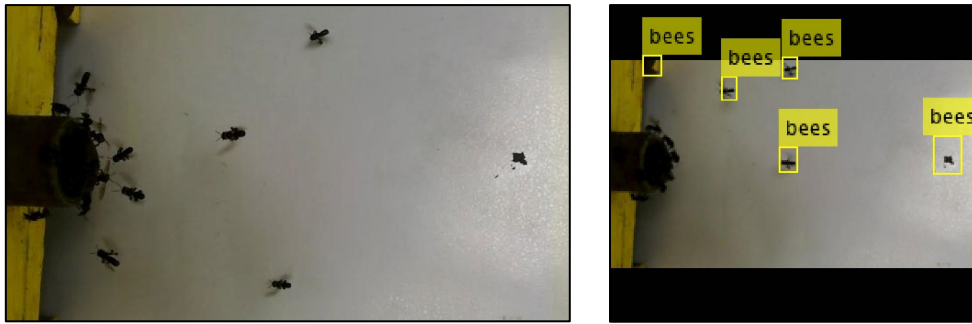


Figure 7. Image capture from video of stingless bees (a) on the left and stingless bees' detection using system (b) in the right.

Based on Figure 7, a series of testing for image obtained from the video taken real-time at the stingless bee farm. There are 20 pictures were used for every variable except for dark brown background which used only 7 pictures of 10cm height and 10 pictures for 20 and 30 cm height.

4.3 Discussion

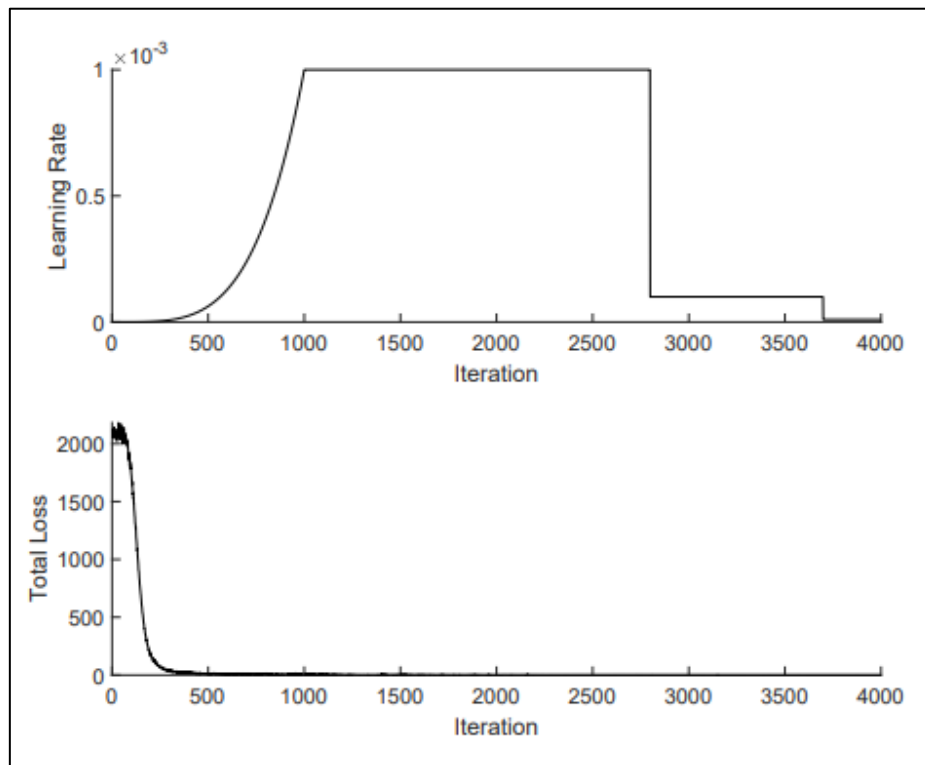


Figure 8. Image of learning rate and total loss graph

Referring to the Figure 8, the learning rate is a hyperparameter used in the training of the neural network that has a very small positive value. The range value is between 0.0 up to 0.1. The good learning rate is 0.001 which is shown in the graph starts on iteration 1000 to 2700. Next, the total loss means the result of a bad prediction. The loss value implies of how poorly or well a model behave after each iteration of optimization. If the value for total loss is more than 1 than the accuracy graph will not be generated.

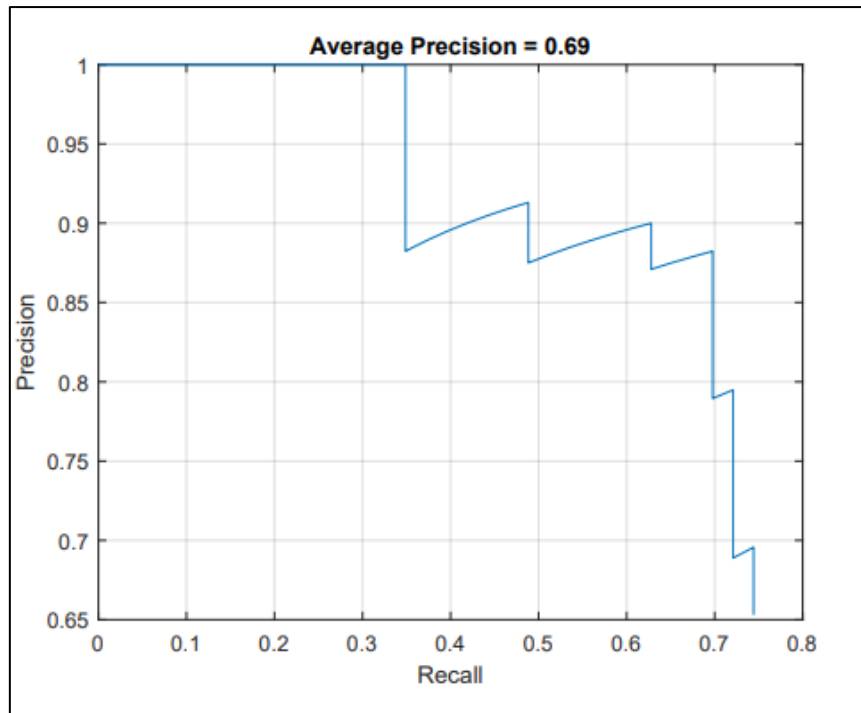


Figure 9. Image of average precision graph.

Based on the Figure 9, the average precision is equal to percentage of positives in the class. The value is 0.69 meaning there are 69% of positives examples in the class.

A series of testing is conducted to evaluate the accuracy of the system classification. The images were taken from a several heights. The first height is 10 cm from the camera to the base.

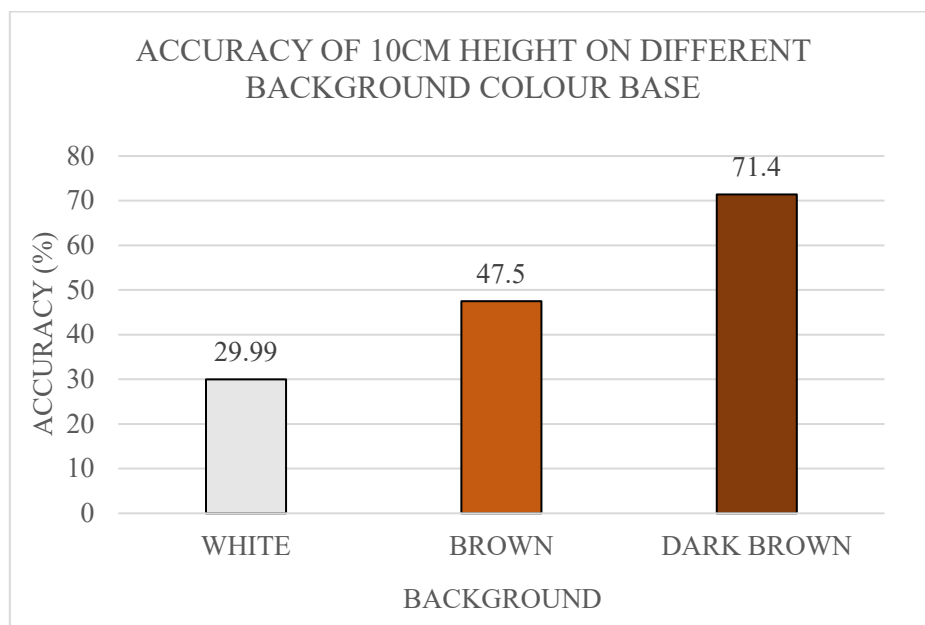


Figure 10. Graph accuracy of 10cm height on different background colour base.

Based on Figure 10, it shows the accuracy of 10cm height on different background colour base. The best among all 3 background colour is dark brown with 71.4%. Although the accuracy is quite high, the height of 10cm is too near to the base and all of the stingless bees cannot fit onto one frame. The value might be inaccurate.

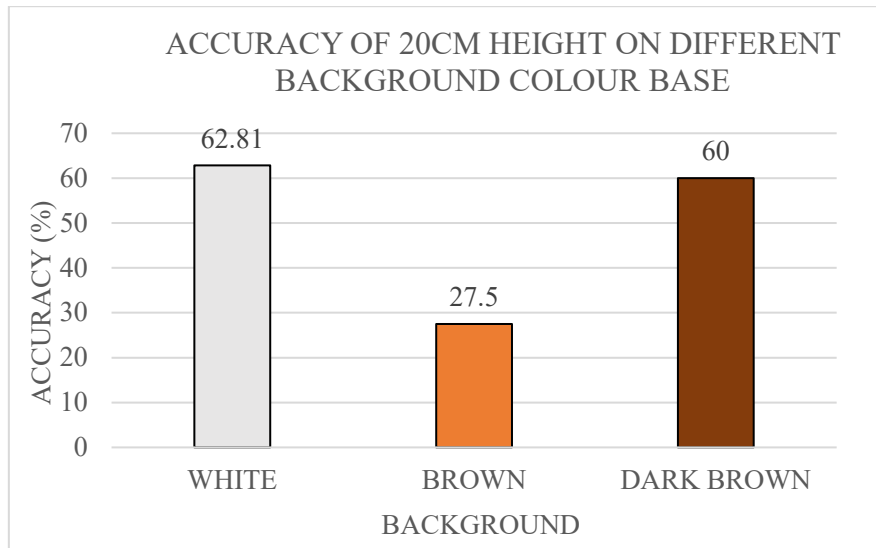


Figure 11. Graph accuracy of 20cm height on different background colour base.

Based on Figure 11, it shows the accuracy of 20cm height on different background colour base. The best among all 3 background colour is white with 62.81% followed by dark brown with 60% and lastly brown with 27.5%

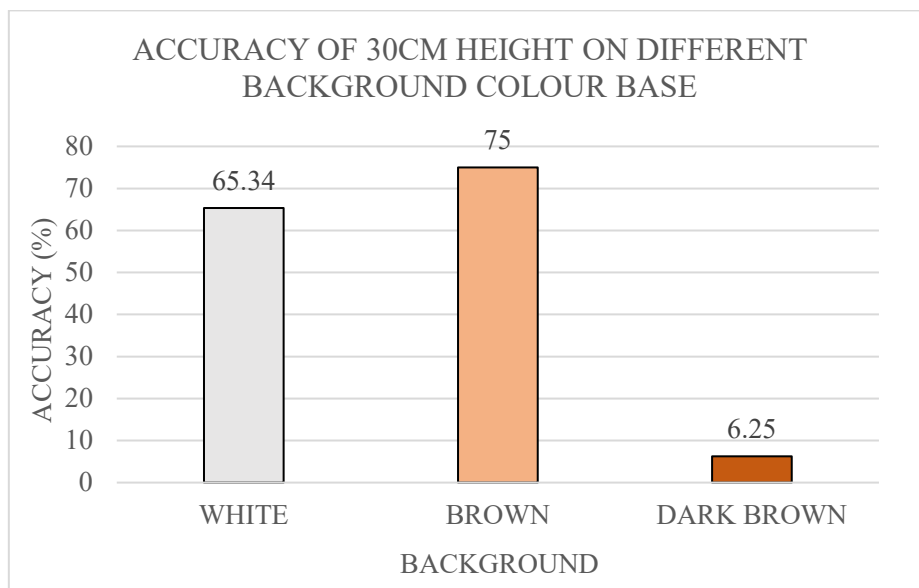


Figure 12. Graph accuracy of 30cm height on different background colour base.

Based on figure above, it shows the accuracy of 30cm height on different background colour base. The best among all 3 background colour is brown with 75% followed by white with 65.34% and lastly dark brown with 6.25%.

The final result is height of 30cm and brown colour background. This can be proven with the accuracy of 75% which is the highest among all parameters. The reason why I choose 30cm of height is because all of the stingless bees can be fit into the frame. Also, any higher, then the camera sharpness will decrease, and it is affecting the accuracy of the system. The colour of the base is also as important as the height of the camera. I choose the colour brown because among those three colours, the brown has the highest accuracy, 75%.

5.0 Conclusion and Recommendation

5.1 Conclusion

In conclusion, it has been demonstrated that the Smart Stingless Beehive Internet Based Monitoring System is successfully developed and operational but there is always a room for improvement. I have achieved the objectives of the project which is to design internet-based monitoring system which can be used to monitor the number of fly-in and fly-out stingless bees (*Heterotrigona Itama*) at the entrance of the hive. Furthermore, managed to monitor the stingless beehive through online and offline mode. Last but not least, successfully send email from the system to the user. The assistance of the Convolutional Neural Network (CNN) demonstrates how much can be accomplished in the real-world applications. The CNN discover new way or methods, which is just some of many amazing examples of how artificial neural networks are improving the world.

5.2 Recommendation

There are some recommendations for the Smart Stingless Beehive Internet Based Monitoring System that can be improved. Firstly, enhance the accuracy of CNN model. The number of images and epoch used for training the system should be increased so that the system can train a lot more patterns. Originally, this project used laptop as the microprocessor which it needs a power source after a certain of time. So, a better alternative is using a solar panel or lithium battery to supply power source to the microprocessor. Last but not least, the resolution of the camera can be improved with a higher resolution. The project used a camera with resolution of 640x480 pixels which is a good size image for image processing, to view on a monitor or email to a user but the more pixels in the image file, the higher the resolution. Thus, it is not optimal because the image not as detailed as it would be on a higher resolution camera.

6.0 Acknowledgement

This project was partially financial supported by the Majlis Amanah Rakyat (MARA) and Universiti Kuala Lumpur Malaysian Institute of Industrial Technology (UniKL MITEC). I thank Assoc.Prof.Ts.Dr. Sairul Izwan Safie for providing invaluable guidance throughout this research. Big thank to Persatuan Usahawan Lebah Kelulut (JBEEES)for letting me do the data collection at the farm.

6.0 References

- [1] Abd Jalil, M., Kasmuri, A. and Hadi, H., 2017. Stingless Bee Honey, the Natural Wound Healer: A Review. *Skin Pharmacology and Physiology*, 30(2), pp.66-75.

- [2] Julika, W., Ajit, A., Sulaiman, A. and Naila, A., 2019. Physicochemical and Microbiological Analysis of Stingless Bees Honey Collected from Local Market in Malaysia. *Indonesian Journal of Chemistry*, 19(2), p.522.
- [3] F. Sgolastra, S. Hinarejos, T. L. Pitts-Singer, N. K. Boyle, T. Joseph, J. Lückmann, N. E. Raine, R. Singh, N. M. Williams, and J. Bosch, “Pesticide Exposure Assessment Paradigm for solitary bees,” *Environmental Entomology*, vol. 48, no. 1, pp. 22–35, 2018.
- [4] Shamsudin, S., Selamat, J., Sanny, M., Abd. Razak, S., Jambari, N., Mian, Z. and Khatib, A., 2019. Influence of origins and bee species on physicochemical, antioxidant properties and botanical discrimination of stingless bee honey. *International Journal of Food Properties*, 22(1), pp.239-264.
- [5] Slaa, E., Sánchez Chaves, L., Malagodi-Braga, K. and Hofstede, F., 2006. Stingless bees in applied pollination: practice and perspectives. *Apidologie*, 37(2), pp.293-315.
- [6] N. C. Soh, N. S. Samsuddin, and M. M. Ismail, “Economic efficiency of stingless bee farms in Peninsular Malaysia estimated by data envelopment analysis (DEA),” *Pertanika Journal of Social Sciences and Humanities*, vol. 29, no. 1, 2021.
- [7] Ntawuzumunsi, E., Kumaran, S. and Sibomana, L., 2021. Self-Powered Smart Beehive Monitoring and Control System (SBMaCS). *Sensors*, 21(10), p.3522.
- [8] “Object Detection Using YOLO v3 Deep Learning,” *MATLAB & Simulink*. [Online]. Available: https://www.mathworks.com/help/vision/ug/object-detection-using-yolo-v3-deep-learning.html?s_tid=mwa_osa_a. [Accessed: 27-Jul-2022].
- [9] “SqueezeNet,” *SqueezeNet convolutional neural network - MATLAB*. [Online]. Available: <https://www.mathworks.com/help/deeplearning/ref/squeezenet.html>. [Accessed: 27-Jul-2022].
- [10] B. Baranidharan, S. Srivastava, and R. Khatoria, “A study on using convolution neural networks to predict nitrogen deficiency in rice plants,” *2022 International Conference on Electronics and Renewable Systems (ICEARS)*, 2022.