A HIGH ACCURACY PEST DETECTION METHOD USING NAÏVE MACHINE LEARNING

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ABSTRACT: Agriculture is one of the biggest economic activities in a developing country such as Malaysia. However, pest attacks are inevitable. This problem incurs loss due to profligate pesticide spray after farmers fail to detect pests accurately. For a developing country, a simple and low-cost pest detection system is indispensable. Here, we introduce naïve machine learning into the detection method and obtained high-accuracy pest detection results. We studied and explored the effect of k-means clustering value and segmentation number parameters on detection accuracy. Our method achieved 95% accuracy in pest detection, a competitive accuracy compared to other complex machine learning methods such as convolutional neural networks (CNN) and k-nearest neighbors' algorithm (kNN).

1.0   INTRODUCTION

Agriculture is one of the largest activities of a developing country's economy. In agriculture, pest attack is a significant problem in the

agriculture sector that results in the degradation of crop quality and output. Conventionally, in developing countries, pest detection is done through observation which is time-consuming, inefficient, and costly [1]. However, this option is the fastest and easiest method but less accurate. Therefore, an intelligent agriculture pest detection system using machine learning is required to boost production and maximize agriculture yields. This approach should help farmers appropriately quantify the type and quantity of pesticides for their farms. It should be meticulous, which can help the farmers to design the pesticide liquid solution specific for a particular area or lanes on the farm. This type of technology in agriculture can lower plant production costs while improving the reliability of farmer operations [2].

Machine learning has grown its popularity due to big data and high-performance computers. The advancements in computers have helped us innovatively deal with practical problems, especially in agriculture. According to Business Intelligence Research, global expenditure on agricultural technologies, artificial intelligence, and machine learning is expected to quadruple to $15.3 billion by 2025 [3]. In recent years, there has been an increasing interest in developing new methods for unraveling, quantifying, and comprehending data-intensive processes in agricultural systems contexts. For instance, [2] use a robotic model to identify, monitor, and detect crop diseases. The study shows that up to 61% of pesticides are reduced when designated spray mixtures are used for the disease.

From a developing country's point of view, a system with machine learning should be low-cost and highly efficient. Here, we studied such demand by exploring the naïve k-means clustering algorithm by looking at two different parameters - segmentation number and k-value. We adopted a study by [4] that proposed image segmentation using the k-means clustering technique for pest detection. However, the study on pest detection accuracy at a different segmentation number of the work is unknown. In our work, we study the effects of pest detection accuracy by changing the two parameters' values. We reveal competitive results to other complex machine learning approaches such as CNN and KNN. We implement the algorithm to color image segmentation and compute the confusion matrix to measure the accuracy. The algorithm is implemented in Python, and we use the TensorFlow library to analyze, classify, and detect the pests.

The paper is organized as follows: First, we discuss the prior works on machine learning in agriculture. Second, we describe our methodology and techniques for identifying pests. Third, we describe the experimental design and analysis of the data. Lastly, we conclude the research and discuss the limitation and recommend several future works.

2.0   RELATED WORKS

Here we describe prior works that incorporate machine learning algorithm for pest detection and control. Some works detect disease on leave, soil and weed pattern to control pest. Table 1 shows the prior works that incorporate machine learning methods. The detection algorithm for pest control can be classified into three main methods – CNN, KNN and k-means clustering.

Table 1: Comparison of Machine Learning Methods Used for Pest Detection and Control

Author	Technique used	Training dataset used	Result
[16]	K-means	Texture features of around 70 images of 3 different classes	The Feed Forward Neural Network gives the 96.7% result
[1]	K-means	Database with ANN	94% effectiveness verified pest
[5]	CNN	Real time images	A precision of 91.1% for carrot field images
[7]	CNN	150 images for training sets and 50 images is the testing set	Highly accurate of 84% and 86%
[23]	CNN	38 categories with more than 20,000 images as image datasets	High detection accuracy with 98.48%
[14]	K-proximate Neighbor (KNN)	200 leaf images of 5 disease classes for training of the KNN classifier	Detect and recognize with 96.76% accuracy
[11]	CNN, YOLOv3	12,000 images for training YOLOv3 and 4,000 images for training Xception	78% of the output represented overdetection
[13]	CNN	SVM training	The highest classification rate is 83.08%
[2]	CNN	KNN algorithm is used	Robot works 98% accurately as per proposed system

2.1 Convolutional Neural Networks (CNN)

[5] proposed a system that utilizes deep learning convolutional neural networks (CNN) for feature extraction, classification, and detection of leaf diseases. It also detects the type and location of weed in the farm image. The system works in real-time without segmenting plants or leaves. It also achieved a precision of 91.1%. This method is popular for pest detection. Previous research uses an advanced deep learning technique for detection known as mask region-based convolutional neural networks (R-CNN) [1, 6, 7, 8, 9]. The work carried out a comprehensive evaluation and is capable to outperform state-of-the-art models with a higher F1 score of 90% and a detection time of 0.25 seconds per frame.

[6] put forward an anchor-free region CNN for precision recognition and classification of 24-classes pests. A feature fusion module is designed to extract sufficient feature information about agriculture pests. The approach has yielded good results for general object detection where the highest classification rate is 91.5%.

Some work uses the CNN method and detects pests of YOLOv3 images with a low detection threshold. [11] uses the CNN method but detects pests of YOLOv3 image with a low detection threshold. This method detects precisely tiny pests. The prototype uses a Logicool C920r camera positioned sufficiently close without escaping insect pests from plants. [12] also use similar method with YOLOv3 to classify and detect pests for instance whiteflies and fruit flies. The researchers use a Raspberry Pi camera to gather images. The method obtained an overall accuracy of 83% in classifying and detecting whiteflies and fruit flies.

Other works use the Synthetic Minority Over-sampling technique and focal loss with CNN to obtain a higher accuracy score, 93% to be exact [8, 9]. Meanwhile, [7] use a single shot detector (SSD) method for localizing and classifying objects while using only one feed-forward neural network. But the CNN-based methods method requires a large dataset of pest detection. A large dataset will incur heavy computation costs. The higher detection rate relies on a large number of training data. A large number of data will increase similarities, hence reducing the detection rate [13].

2.2   K-nearest Neighbor (KNN)

There is also a method that uses a K-nearest neighbor (KNN) classifier but mainly to control pests by disease detection on leaves [14]. Some works utilize KNN to detect disease through the soil and its color. For instance, Maniyath et al., 2018 use KNN to classify disease images based on RGB values and label the images using Munsell soil notation.

Other works use KNN to detect pests through audio [15]. In this work, KNN and Support Vector Machine (SVM) is applied to the feature vector set. The process starts with data collection through Avisoft Bioacoustics ultrasound measurement. Then, the SVM method is used to classify the pests. This method obtained 83% detection accuracy.

2.3   K-Means

[16] identified the disease portion on the leaves by using K-means clustering and feedforward neural network. The k-means is used to extracted features while the feedforward is used to classify the disease on leaves. The work reported to obtain 96.7% accuracy. Similarly, [17] designed work detects the diseases in the plant in the initial stage by preprocessing the image using K-means clustering. Then, the features are required by extracted and the green masking pixel is done using thresholding.

[18] proposed image processing techniques for detecting the shape of insects in sugarcane crops using the k-means clustering method. The shape-based feature vector is designed to detect the form of the sugarcane crop. The input images are transformed into greyscale and segmented for k-means classification [16].

Some other works combine the k-means method with other methods. For instance, [19] and propose a convolution-based modified adaptive K-means approach for pest detection. Those work, an automatic window size generation approach has been designed to get the central value for every convolution step. The mean of these values is assigned as the initial seed point. Meanwhile, [1] extracted features by using Discrete Cosine Transform (DCT) and classified the pest with a combination of k-means and Artificial Neural Network (ANN) and managed to solve the color issue by

classifying five colors in which the image is segmented into a few segments. The method was tested on five pests and found 94% effectiveness.

From all the methods above, k-means clustering methods are less complex yet show promising results compared to the other two methods – CNN and KNN. Figure 1 show some works propose a combination of k-means with other methods, works that explored the effects of segmentation number and k-means value without any method combination are respectively limited. A combination of methods will only increase the complexity of the algorithm. Instead, we use the naïve k-means clustering algorithm and studied the effect of image segmentation and k-value on the pest detection accuracy. Our method reduces algorithm complexity thus contributing to a greener algorithm. Besides the number of datasets is high in CNN while our method requires a small number of datasets, yet the accuracy remains high. Some of the works above detect diseases as an alternative solution for pest detection: disease detection on leaves [2, 17, 16, 20] ; on soil [21, 22] ; and weed [5]. However, the earlier yet crucial stage of pest control is the pest detection. It not only can improve crop output but also preclude diseases from spreading to nearby crops in the field. In our work, we focus only the early-stage detection i.e., pest detection.
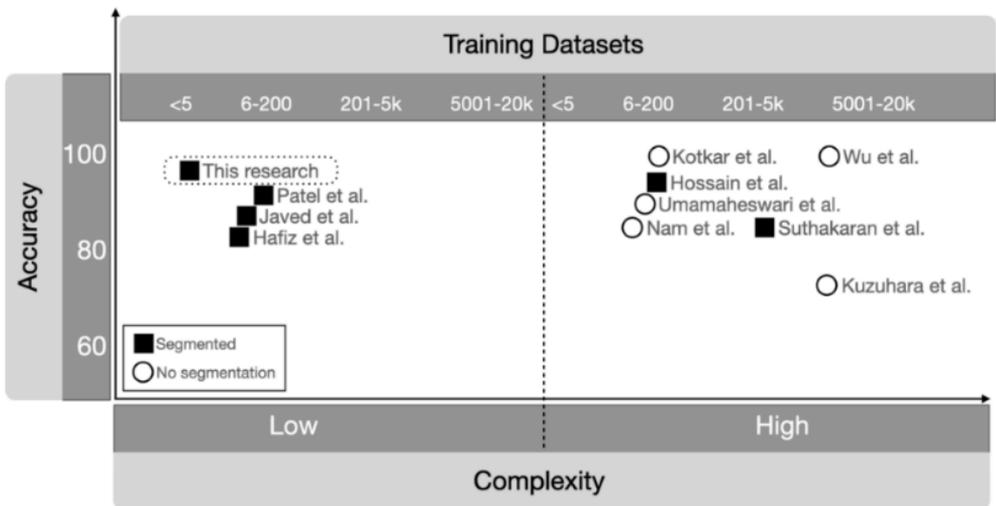

Figure 1: Synthesis previous work using machine learning in agriculture

3.0   METHODOLOGY

We introduce the general workflow of our proposed as can be seen in Figure 2. It consists of three procedures: training, testing, and experiment. Within these procedures, there are six phases involved: input, pre-processing, segmentation, k-means clustering, detection and confusion matrix. We prepared two sets of datasets in our proposed method: 1) Training dataset, and 2) Experiment dataset.
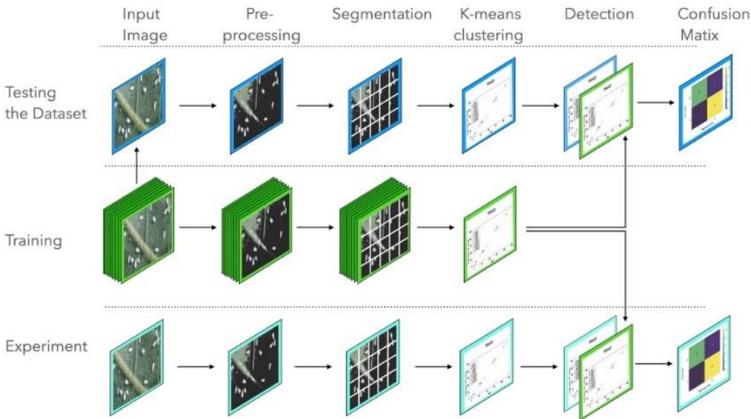

Figure 2: General Workflow of the Proposed Method

3.1   Training procedure

Firstly, we run the training procedure where the goal is to generate only one k-means signature of a particular pest (e.g., whiteflies, aphids) resulting from many k-means clusters of many images. This k-means signature is for the detection phase reference image. To achieve this, we clean up those training images through green color removal and noise removal algorithms. Then we divide each image into a 3 x 3 grid (i.e., nine equal segments). Each division will have its own k-means cluster known as k-means seeds. After that, we place those k-means in a single graph, our method run 60 iterations to produce the k-means cluster signature known as centroids.

3.2   Testing procedure

Secondly, we test the validity of the signature. We first find k-means centroids (using equation 1 with 60 iterations) of each training dataset

image after it has been cleaned and segmented. Then we compare the centroids of each image with the signature centroids. The result then is compiled in a confusion matrix table.

The objective of K-means clustering is to minimize the sum of squared

$$D(x,y) = ||x - y||^2 \qquad (1)$$

distances between all points and the cluster centroids as in equation (1):

The algorithm of the k-means clustering are as follows:

- i. Choose the number of k cluster
- ii. Select at random k points, which are the centroids
- iii. Assign each data point to the closet centroid that forms k clusters
- iv. Compute and place the new centroid of each cluster
- v. Reassign each data point to the new closest centroid

K-means is one of the simplest for generating an area of interest. The execution time of K-means increases linearly with the number of data objects. Therefore, the less training data, the less time required for creating the signature centroids.

3.3 Experiment procedure

Finally, we run an experiment. The procedures are the same as the testing procedure, except the test images were taken from the experiment datasets. We store the results in the confusion matrix table as in Table 5. The matrix will show the validity and performance of our proposed method. The confusion matrix is in Tables 3 and 4 below:

Table 2: Prediction classification

Prediction case (N=4)	1	2	3	4
Prediction classification	1	0	1	0
Actual classification	1	1	0	0
Result	T_P	F_N	F_P	T_N

Where the correct image predicted of the actual image that contains pest (1,1) is referred to as True Positive (TP), the correct image predicted of the actual image that precludes pest (0,0) is True Negative (TN), and the incorrectly predicted image of the actual image that contains pest (0,1) is False Positive (FP), and the incorrectly predicted image of the actual image that precludes pest (1,0) is False Negative (FN).

Table 3: Confusion matrix table

N=100	Predicted: Positive	Predicted: Negative
Actual: Positive	$\sum T_P$	$\sum F_N$
Actual: Negative	$\sum F_P$	$\sum T_N$

From the confusion matrix, we calculate the accuracy and precision. Table 4 shows the information required for accuracy and precision calculation. The accuracy represents the rate for the proposed method to predict correctly (i.e., classifier strength). The accuracy equation is defined as equation (2) and (3) where A = $(0 \leq A \leq 1)$ and 1 is the highest accuracy rate.

$$Accuracy\ (A) = \frac{total\ of\ correct\ predictions}{total\ of\ predictions} \tag{2}$$

$$A = \frac{\sum T_P + \sum T_N}{\sum T_P + \sum T_N + \sum F_P + \sum F_N} \tag{3}$$

We then measure the precision of the method which is described as the rate of correct positive predictions. The precision is written as equation (4) and (5).

$$Precision = \frac{total\ of\ correct\ positive\ predictions}{total\ of\ predicted\ positive} \tag{4}$$

$$Precision = \frac{\sum T_P}{\sum T_P + \sum F_P} \tag{5}$$

Recall is described as the rate for the proposed method to predict the actual positive image correctly. We calculate the recall by using equation (6) and (7):

$$Recall = \frac{total\ of\ correct\ positive\ predictions}{total\ of\ predictions\ for\ actual\ positive\ classification} \tag{6}$$

$$Recall = \frac{\sum T_P}{\sum T_P + \sum F_N} \tag{7}$$

4.0   EXPERIMENTAL METHODS

In this experiment, we used Python programming language (version 3.7) with Scikit-learn library and TensorFlow framework. The program run on i7 processor (64-bit) with 16GB RAM. Figure 2 summarizes the experimental methods. We present the measured accuracy, precision, and recall in the experimental result section.

4.1   Input image

In this works, we tested for two types of pests: (1) whitefly; and (2) aphid. We prepared two image datasets for each pest: (1) dataset for training; and (2) dataset for experiment. Each image has a fixed resolution of 275 pixels x 183 pixels. The image format is either *.jpeg or *.png file format of 24-bit depth RGB.

4.2   Pre-processing

In the pre-processing, we removed the image's green pixels using the green removal algorithm. This method will remove the green leaf and noises in the pixels. It also helps to segregate pests out of the chili leaves. We do this by firstly reshaping the image into a 2D vector. Secondly, we transform its RGB color space into HSI color space. Finally, we replace the intensity with hue to decrease the illumination effects and remove the green pixels.

4.3   Segmentation

In segmentation, we divide the image into equal blocks: 20, 40, 60, 80, and 100 blocks.

4.4   K-means Clustering

In this phase, first, we flatten the image into single vector pixels based on RGB colors, and, for each segmented block, we find the k-means clusters, known as seeds (for training purposes). After we obtained the seeds, we trained the data to find the signature centroids. We fixed the k-means iteration to 60 since we have discovered that the centroid stays constant after 50 iterations. We also try three other k-means values, 2, 3, and 4, and the centroids centroid remains constant. We assigned the centroid created after 60 iterations as the signature centroids.

4.5   Detection

The signature centroid later is used in this phase to detect the pest. The pest will be decided based on the closest distance between the experiment image's centroid and the signature centroid.

5.0   EXPERIMENTAL RESULTS

This section presents the experimental results that were obtained in this study. Figure 3 shows the example of seeds and signature centroids generated from images, particularly for 20 segmentations.
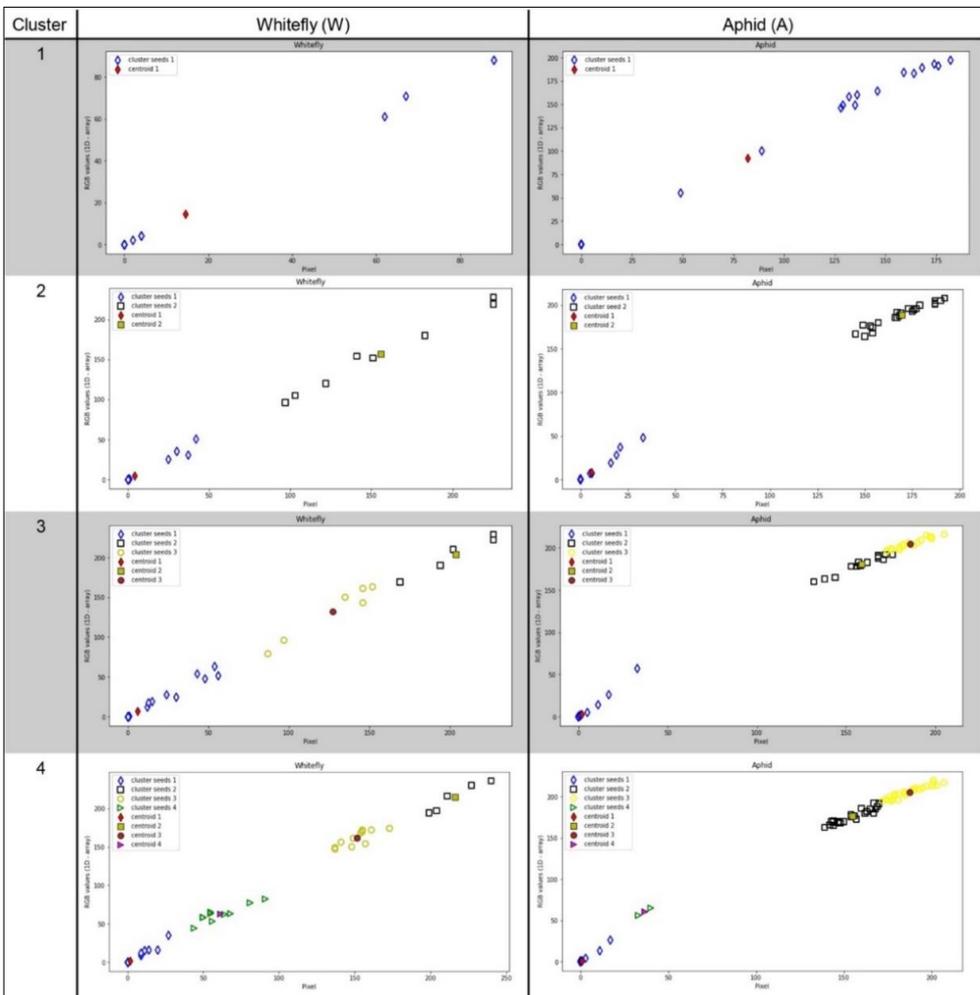

Figure 3: General Workflow of the Proposed Method

The signatures are produced for two types of pests, whiteflies, and aphids. In fact, the signature centroids in the figure are separated based on the k-means value. The k number defines the number of clusters for the pixels in each image. To quickly test the proposed method, we quantized the pixels according to the signature centroids value and recreate the image. Table 4 shows the image after the quantization for image with and without segmentation.

For the non-segmentation group (see Table 4), when the k-means = 2 or 3, all items in the image, including pests, dust, and leaves, were grouped into one cluster. This result is confounding and makes the prediction system less efficient and accurate due to overfitting. Meanwhile, when k-value = 4, one pest, for example, whitefly, is quantized into two clusters: outline and fill. This result is also confounding.

For segmented images, when the k-means = 2 or 3, we discovered that the method can separate the pests, background, and leaves. Meanwhile, when the k-value = 4, all items in the image can be in the same cluster. This result will cause overfitting. Therefore, we decided to make the confusion matrix only for segmented images.
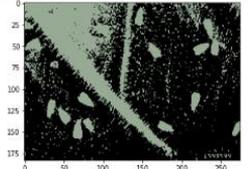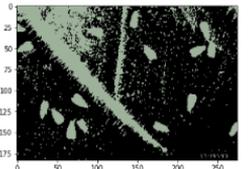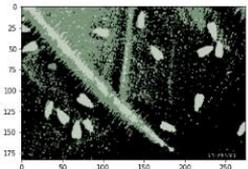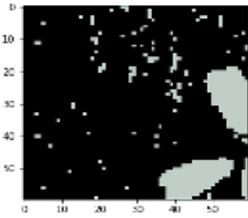
Table 4: Images Reproduced After Quatization

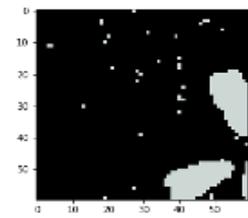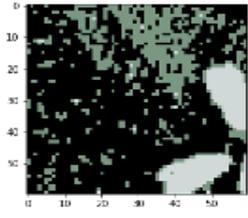| K-value	2	3	4
Before segments			
After segments			

Figure 4 shows the confusion matrix result of 20 whiteflies and aphids. It shows the best result when the k-value = 2 and 3 since the total value for TP and TN are the highest. i.e., out of 5 cases, 5 cases are correctly identified. The poor result is when the k-value = 1. It is because 1 cluster is unable to separate between background and foreground. This case is similar with a k-value = 4. We found that when the clusters are more than 3, the prediction is less accurate due to overfitting after cluster incrementation. This incrementation will result in pests grouped into more than one group.

N = 20	K value	TP	TN	FP	FN
Whitefly	1	0	0	2	3
	2	4	1	0	0
	3	3	2	0	0
	4	3	1	1	0

N = 20	K value	TP	TN	FP	FN
Aphid	1	1	0	0	4
	2	4	0	0	1
	3	4	1	0	0
	4	3	2	1	0

Figure 4: Confusion matrix result for whiteflies and aphid

We then calculate the precision, recall and f1-measure by using mean average precision (mAP) as shown in Table 5. In general, the precision, recall and f1-score is high since the results are greater than 90% except for precision of not detecting pest with 89% precision. However, the difference is little and trivial compared to 90%.

Table 5: Experimental results of Precision, Recall and F-measure

Class	Precision (%)	Recall (%)	F1-score (%)
0: pest not detected	89	100	94
1: pest detected	100	92	96

It is important to note that, our method used only 3 images as the training dataset, a small amount of training data required for pest detection. Despite the small number of training datasets, the precision, recall, and f1-score of the detection are high. Figure 5 shows the accuracy score for different k-value and segmentation numbers (ranging from 0 – 100 segmentations, for each image) for the two pests: whitefly and aphid. Both graphs in the figure

show that the highest detection accuracy is when the k-value = 2 and when the segmentation is less than 80. We found that, when the segmentation is greater than 80, the image will be less meaningful to our pest detection system. This is because the image will be divided into a tiny image that is unable to resemble any object.
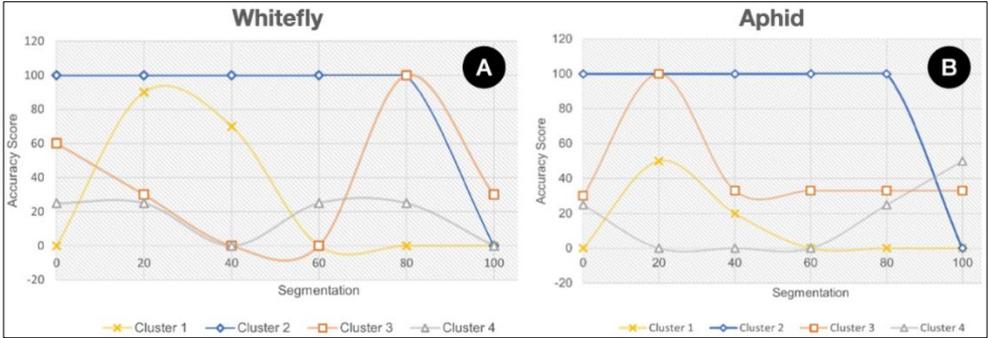

Figure 5: The graph of accuracy of different k-value and segmentation; (a) whitefly (b) aphid

6.0   DISCUSSION

Our results imply that our pest detection method is simple and can produce high-accuracy pest detection. Our proposed method manifests a high detection accuracy even with only three images for the training dataset. This small dataset requirement outperforms the works that require a higher number of training datasets [4]. We connote that our method is multifactorial since one should incorporate the k-value and segmentation number to achieve high pest accuracy detection. The k-value should be either 2 or 3, and the segmentation should be less than 80 (see Figure 5). If we separate an image into more than 81 or more equal blocks, the pixels value will be misleading and not be used to resemble a good centroid.

In this work, the method requires a less complex computation algorithm, and it can be applied for real-time pest detection. The cheap cost would also allow the system to be implemented in a small form factor and as a modular unit. The small form factor enables a highly compact sensing unit on an intelligent autonomous robot for farm management. Our less complex computation algorithm can be applied not only in farms but also in other

areas for instance, in factories, traffics, and shipping warehouses, an advantage that can unlock new avenue in that field.

Moreover, we tested only two types of pests, whitefly, and aphid. However, other pests can be found on a farm, particularly on chili farms, for example, thrips, leaf hoppers, mites, fleas, and beetles. Extending the training dataset to cater to these pests with our method is relatively easy and nuanced since our method requires only 3 images per pest for the training dataset.

This work deals only with the image pixel's RGB values as the feature for the detection, but one can extrapolate it with a combination of edges or outline feature. Researcher can also use edge as a standalone feature for the detection. We also tested the method with a fixed image resolution (i.e., 275 x 183 pixels, 24-bit depth). However, other researchers can experiment with various images. For instance, image with different resolutions, different lenses (e.g., wide, telephoto, prime, standard), and different focal lengths (e.g., 35 mm, 80 mm, 135 mm).

7.0   CONCLUSION

Pest detection has been challenging for the past few years. Numerous works discuss pest detection with different styles and approaches. In this paper, we have attempted to simplify, and reduce the complexity while maintaining the high quality of pest detection. We have investigated and described the specification required for such a simple yet high-accuracy method. To our knowledge, the proposed method outperforms prior work where we use a small number of images compared to the previous research (i.e., only three data required) as a training dataset and produce high pest detection accuracy. Our analysis demonstrates the veracity of the return. Depending on the application requirements, there is no need for expensive computing. Furthermore, researchers can improve the computing acceleration and accuracy by introducing other features (e.g., outline, edge detection) in the detection method. We hope our proposed method in this paper can expedite future research to support the advancement of object detection applications in different fields and areas.

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