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# Automated image identification, detection and fruit counting of top-view pineapple crown using machine learning

**Wan Nurazwin Syazwani R.** [a], **Muhammad Asraf H.** [b,*], **Megat Syahirul Amin M.A.** [c], **Nur Dalila K.A.** [b]

[a] *College of Engineering, Universiti Teknologi MARA, Shah Alam Selangor, Malaysia*
[b] *College of Engineering, Universiti Teknologi MARA, Cawangan Johor, Kampus Pasir Gudang, Malaysia*
[c] *Microwave Research Institute, Universiti Teknologi MARA, Shah Alam, Malaysia*

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**Abstract** Automated fruit identification or recognition using image processing is a key element in precision agriculture for performing object detection in large crop plots. Automation of fruit recognition for the captured top-view of RGB based images using an unmanned aerial vehicle (UAV) is a challenge. Image analysis demonstrated the difficulty of processing the captured image under variant illumination in natural environment and with textured objects of non-ideal geometric shapes. However, this is subjected to certain consideration settings and image-processing algorithms. The study presents an automatic method for identifying and recognising the pineapple's crown images in the designated plot using image processing and further counts the detected images using machine learning classifiers namely artificial neural network (ANN), support vector machine (SVM), random forest (RF), naive Bayes (NB), decision trees (DT) and k-nearest neighbours (KNN). The high spatial-resolution aerial images were pre-processed and segmented, and its extracted features were analysed according to shape, colour and texture for recognising the pineapple crown before classifying it as fruit or non-fruit. Feature fusion using one-way analysis of variance (ANOVA) was incorporated in this study to optimise the performance of machine learning classifier. The algorithm was quantitatively analysed and validated for performance via accuracy, specificity, sensitivity and precision. The detection for the pineapple's crown images with ANN-GDX classification has demonstrated best performance fruit counting with accuracy of 94.4% and has thus demonstrated clear potential application of an effective RGB images analysis for the pineapple industry.



* Corresponding author.
E-mail address: masraf@uitm.edu.my (H. Muhammad Asraf).

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## 1. Introduction

Precision agriculture has recently received attention by implementing a computational analysis using image processing to assist the agricultural management team in monitoring, measuring and responding to crop variability for improving farm-level management. Image processing in precision farming or agricultural applications for different crops using automatic detection and fruit yield counting during harvesting season could be of great benefit to farmers. Many technologies with immense potential in agriculture exist, specifically for satellites[1,2],ground-based vehicles [3,4] and unmanned aerial vehicles (UAV) [5,6]. However, applying these technologies depends on the crop types, size of the plantation area, desired image quality and resolution. The processing of images captured by UAV at a certain height requires pre-processing, segmentation and classification for enhancing image representation or object detection. Studies have investigated the applicability of image processing for crops to cater to yield maximisation and productivity management, including image processing based on automated disease detection [7], crop stress monitoring [8], yield prediction [9] and counting via machine [10]. The reason for pertinence in various branches of agricultural sector is the rapid development of computer processing technologies which provides benefits in terms of quick deployment, low-cost and accurate processing outcome for large in-field area.

The emergence of UAV technology as part of unmanned aerial systems for pineapple detection can be implemented at low-flying heights for extremely high spatial resolutions. These technologies are essential for improving the process or crop output. In the agricultural sector, automatic identification using image-processing techniques in the plantation area makes it challenging to obtain accurate detection results because of environmental factors contributed by the variant illumination during daytime that consistently vary from time-to-time and images with non-ideal geometric shapes and textured object processing. These drawbacks have posed significant challenges when the images are retrieved from a distance in addition to illumination levels; hence, the crop detection of the target crop area can be misidentified accurately. Other issues include unstructured, cluttered environments and a lack of distinguishing features on the fruit surface. Results are poor when different models and conditions were used for estimating the number of fruits in trees of different canopy shapes. Imaging at night under artificial illumination or selection of timely environment under cloudy lighting has commonly recommended maintaining of constant illumination levels.

To address these issues, several studies have been benchmarked to investigate the use of image analysis in high spatial resolution of RGB images from UAV. Current studies to introduce the spatial resolution of RGB images analysis have been implemented for several crops including broccoli [11], maize[12], citrus[13], banana[14], potato[15] and cotton ball [16]. However, to the best of the authors' knowledge this is the first study to specifically analyse pineapple image information using UAV based image analysis. Since limited research exists to automatically recognise and classify the fruit crown, this analysis provides advances in understanding image analysis for such crops because its morphological of depicting irregular geometric shape (i.e., non-circular). Based on the current issues, the algorithm should have considered the ability of overcoming irregular illumination, discrimination between the crop morphology and complex background, overlapping, occlusions and colour similarities between the fruits and leaves.

All previous studies have been incorporated as benchmark to demonstrate good performance capability for specific crops in recognising the desired region of interest; however, similar algorithm approaches cannot be easily applied to others because of their morphology characteristics. By understanding the crop's information related to its features and characteristics, necessary suitable approach for image analysis can be considered for detecting the pineapple crown images. For example, [11,13] have employed specific image analysis of spherical object recognition under illuminated in-field environment for broccoli heads and citrus. Segmentation issue due to the effect of inconsistency of illumination has been proposed to analyse colour and texture-based segmentation, low-pass filter, texture energy feature and median filter, and further classify the crop using expert system. To gain low false positive detection due to colour similarities between region of interest (ROI) and the background, these methods using colour conversion, thresholding, histogram equalisation, spatial filtering with Laplace and Sobel masks, and Gaussian blurt to combine with SVM classification are useful to improve detection of green fruit which are easily confused with the leaves of the tree. Sun [16] claimed that the shadow effect has contributed to reduced detection performance for cotton ball, and therefore implemented the image analysis namely colour thresholding with RGB and HSV, Circular Hough Transform and merging and splitting operation. Sun investigated the feature vector, including colour and texture features, to train a random forest classifier for boll segmentation, achieving an average accuracy of 99.4%. The area and elongation ratio between major and minor axes were used to separate bolls in overlapping clusters. Therefore, object detection algorithms should separate individual objects in clusters and connect disjointed regions as a single object. Another study showed that appropriate classification with BPNN[12], SVM and ANN[14], and RF[15] have enhanced the study, by remote sensing, machine learning and high spatial-resolution RGB images, and therefore could result in accurate image recognition and detection.

Machine learning method has a significant potential for the timely and accurate performance which will be evaluated with appropriate features using analysis of variance (ANOVA) to increase the efficiency of the designed algorithm. The quality images with well-illuminated backgrounds and proper segmentation approach are required to improve the detection process. This confirmed that the potential for processing RGB images from the in-field crops using UAV and analysis to highlight its features is possible. With that, the contributions of this paper are (1) to develop a pipeline for detecting, classifying and counting the top-view pineapple crown based on RGB based images of UAV (2) to perform fruit crown recognition using comparison of traditional machine learning classifiers with various training algorithms for discriminating between fruit and non-fruit, and (3) to reduce data dimensionality while improving and optimising the classification accuracy using feature selection via ANOVA. The rest of the paper is arranged as follows: Section 2 outlines the methodology and discusses pre-processing images, features extraction, feature selection and the classification strategy using machine learning classifiers to detect the pineapple crown. In this study, we compared six types of classifiers to obtain the most accurate algorithm for classifying the pineapple crown which possess non-ideal of geometric shape from the background noise. The experiment results and discussion are presented in detail in Section 3 and Section 4 concludes the findings.

## 2. Materials and methods

### 2.1. UAV data collection and instrument set-up

The top-view of N36-variant pineapple images were captured with the UAV (DJI Phantom 3 Advanced quadcopter) at the pineapple plantation which is located at the Southern part of Malaysia depicted in Fig. 1. The UAV is equipped with 3-axis gimbal stabiliser and a Sony ø0.3-inch CMOS digital camera sensor. The images were acquired during harvesting season in March 2019 using a 12 M−effective resolution of RGB camera and the videos were recorded line-by-line from the ground level at 3 m height above the ground covering the pineapple in 110 rows out of 1.44 acres. From the entire plantation area with many rows, this research limits the area specific on one division to contain 1300 image frames of 2,704 × 1,520 pixels per frame as preliminary investigation work. The flights were automatically set as speed of 16 m/s, and they fly on the designated row of pineapples. An Image Composite Editor software was used to join the overlapping aerial images of a plantation division to form a video in a standard colour format (RGB) that seamlessly combines the original images. Twenty sample images were randomly selected and manually annotated to evaluate the algorithm capability in extracting the pineapple images, comprising pre-processing, extraction of features and object classification to be described. From the 20 sample images, 360 pineapple crowns were detected, consisting of 180 pineapples and 180 background noises of leaves, grasses and the ground. The data were divided into training and testing data consisting of 90 pineapples and 90 background noises.

### 2.2. Image analysis workflow and methodology pipeline

This section explains the overall methodology pipeline to automate the pineapple crown detection and counting from RGB images as shown in Fig. 2. It starts by collecting data at the plantation, pre-processing image, feature extraction, ANN classification, feature selection using ANOVA algorithm and yield counting. Analysis of the UAV images was performed using a personal computer with a 2.6 GHz Intel Core i7-4720HQ CPU, 16 GB RAM, NVIDIA GeForce GTX 960 M and MATLAB R2019a (Mathworks, 2019). The computational analysis for the overall algorithm execution from image processing is used to detect, classify and estimate pineapple yield based on the detected fruit crown. The data images from the UAV were obtained by image processing to enhance the brightness of each image. Twenty images were selected randomly to develop a detection system consisting of 6–10 pineapples for each sample image in which the algorithm capability of showing the bounding box to detect object was cropped to extract the features.

### 2.3. Image pre-processing for identifying the fruit crowns

Pre-processing removes unwanted background images, such as the ground, leaves and grasses from the RGB images captured by UAV. Mathematically, the captured frame images can be represented by Equation (1) whereas $f(x,y)$ represents the function that retrieves the pixels in both x- and y-coordinates, respectively for R-, G- and B-components; $N$ represents maximum dimension row and $n$ represents maximum dimension column [17].

$$f(x,y) = \begin{bmatrix} R \\ G \\ B \end{bmatrix} = \begin{bmatrix} f_{0,0} & f_{1,0} & \cdots & f_{N-1,0} \\ f_{0,1} & f_{1,1} & \cdots & f_{N-1,1} \\ f_{0,n-1} & f_{1,n-1} & \cdots & f_{N-1,n-1} \end{bmatrix} \quad (1)$$

Extraction of the pineapple crowns from the background noise was conducted by converting the R, G and B channels to enhance colour contrast in images. Image enhancement was included to improve the image representation with the contrast-limited adaptive enhancement (CLAHE) technique [18,19] which was used to enhance the contrast and robust-to-background noise. Extracting the target crown detection with colour thresholding was performed in the HSV colour spaces to construct the most effective mask for removing the background noise. Separation of each of fruit crown was most difficult due to complex background noise, and therefore V-component is required to increase the brightness information.


**Fig. 1** Pineapple plantation and experimental set-up using DJI Phantom 3 Advanced quadcopter.

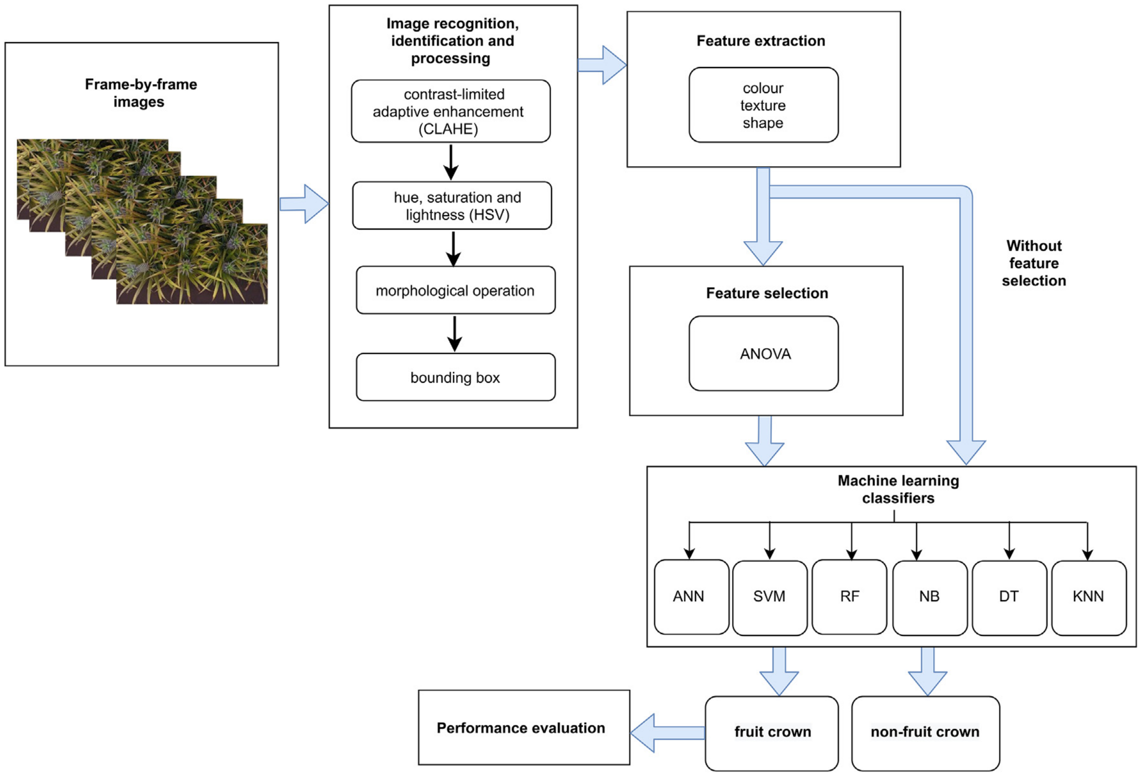


**Fig. 2** Flow diagram of proposed methodology of detection and yield counting pineapple fruits.

Threshold for both H- and S-component was then assigned to further isolate non-crown element. Remaining dotted noise was eliminated with morphological operation of dilation, fill, open, and close. Bounding box technique was performed to detect the ROI which may include pineapple crown or non-pineapple crown. Nevertheless, pre-processing is insufficient due to background noise detected as a result of misclassification. In this case, machine learning classification will distinguish between the pineapple crowns and background noise.

### *2.4. Feature extraction*

In this section, the extracted features are selected subsequently to the segmentation process. This research uses colour features to represent the appearance of the pineapple crown images and geometric characteristics to extract shape and texture features. An analysis of these features is then performed to differentiate the fruit's crown and background noise. Based on the sample images of this framework, three principal feature vectors were determined and identified as

- Colour features

Extraction of the shape features of the pineapple crown from the segmentation process used a colour histogram on the pineapple crown that was calculated for the three matrices of R, G and B. Three main features to be evaluated are namely mean R, mean B and mean G. Background noise may demonstrate colour similarities between pineapple crowns, and therefore slight differences existed.

- Shape features

Shape features are used to quantify the size and shape of each pineapple crown and background noise. Components of the shape feature to be evaluated are the area, centroid $x$, centroid $y$, major axis length, minor axis length, orientation, solidity, eccentricity and perimeter.

- Texture features

Texture extraction investigates the use of LBP and GLCM features to comprise of mean LBP, standard deviation LBP, contrast, correlation, energy, mean GLCM, standard deviation GLCM, entropy, variance, kurtosis, smoothness, homogeneity, root mean square and skewness. LBP feature as in Eqs. (2) and (3) operate the texture descriptors based on the difference between the central pixels and adjacent or neighbouring pixel on the pineapple crown and background noise. The LBP operator [20] is denoted by $t_i$ is the neighbour value, $t_c$ is the central pixel grey value, $N$ is the total number of involved neighbours and $R$ is the radius of the neighbourhood. At a central pixel $t_c$, each adjacent pixel $t_i$ obtains a binary label that can either be 0 or 1, depending on whether the centre pixel has a higher intensity value than the adjacent pixel.

$$LBP_{N,R} = \sum_{p=0}^{N-1} S(t_i - t_c)2^p \tag{2}$$

where

$$S(t) = \begin{cases} 1, t \geq 0; \textit{neighbour pixel is greater than central pixel} \\ 0, t < 0; \textit{others} \end{cases} \tag{3}$$

GLCM features are used to generate a matrix describing the occurrence of two pixels beside each other from the right in a greyscale image. The GLCM features compute in four orientations, namely 0°, 45°, 90° and 135°. The GLCMs are stored in an $i \times j \times n$ matrix, where $n$ is the number of GLCMs normally determined because of the different orientations and displacement of the algorithm. After extracting the GLCM matrix, some features were calculated [21,22], namely contrast, correlation, entropy, energy, homogeneity, variance, skewness and smoothness.

### 2.5. Feature selection using one-way ANOVA

One-way ANOVA demonstrated the capability of analysing redundant feature subsets by reducing the dimensionality of data. Several features can degrade classification performance even when all features are irrelevant and contain information about the response variable. If too many features are applied in the system, it can degrade prediction performance even when all features are relevant and contain information about the response variable. This study used a multi-comparison analysis testing in one-way ANOVA for feature selection with $p$-values less than 0.05 and mean separation was computed using Tukey's honestly significant difference test which demonstrated that one or more features are significantly different [23]. Feature selection reduces the dimensionality of data by selecting only a subset of measured features to create the machine learning classifier model for optimising classification performance.

### 2.6. Object classification with machine learning

In general, classification imposes a computational model inspired by the central nervous system in computer science and related fields to solve non-linear problems corresponding to noisy or complex data [24], including image analysis. Machine learning classifiers estimate the pineapple crown's number within the bounding box through learning from morphological features by counting the number of fruit crowns in multiple frames of images[25] shown in Equation (4). Assume that the bounding box of the $i\text{-}th$ image is denoted by $bb_i$ and $N$ is the maximum number of the bounding box therefore total number of detected ROI are:

$$Total\ number\ of\ ROI = \sum_{n=i}^{N} (bb_i, bb_{i+1}, bb_{i+2}, \cdots .bb_N) \quad (4)$$

The classification algorithm using machine learning is needed to remove the true positive detection of the pineapple crown to identify it as a non-fruit crown. Pre-processing based on the image algorithm is not able to detect all the bounding boxes. Therefore by using classification algorithm, this indirectly enhances the performance of algorithm to correctly discriminate the crown and hence makes it useful during fruit counting process. This study involves 26 neurons representing the morphological feature numbers as input node, 2 neurons at output node representing desired crown. Specific architecture of hidden layers depends on the proposed classifiers architecture. To make the results more reliable in the automatic counting, training and testing data for each experimental training, testing and validating set are randomly generated by setting 70% of the data set as the training set, 15% as the testing set and 15% as the validating set. The 360 processed images with cropped sections of the bounding box specifically contain both pineapple crowns, and background noise are trained using the training images and tested with unseen images to see the accuracy for classification and counting.

#### 2.6.1. Artificial neural network

Fig. 3 shows the MLP NNs structure, comprising input layer neurons, hidden layer neurons, of which each input neuron in ANN is multiplied by a connection weight and output layer neurons. To generate the final output of pineapple crown with automatic counting, the product and biases are summed and transformed through a transfer function consisting of algebraic equations [26], and the correct output is used to calculate pineapple yields. In ANN classification, this research works by the training, testing and validation processes. During the training process of the ANN network, in order to classify the pineapple and some background noise detected during image processing, a feedforward backpropagation procedure will be used. The backpropagation algorithm is a commonly used ANN learning technique. Using gradient descent, it allows a network to find a state that minimises the amount of error by modifying the weights connecting the neurons. For an ANN, a number of predefined neurons form each layer of the MLP [27] which consists of 26 input neurons, 10 hidden neurons and 2 output neurons. The neurons, $j$, in the hidden layer receive the information from the input layer and sums the input signals, $x_i$, after weighting them with the strengths of the respective connections,$w_{ij}$ from the input layer. Then, its output is forwarded to the output layer, $y_i$, as a function $f$ of the sum as shown in Eq. (5)

$$y_i = f\left(\sum w_{i,j} x_i\right) \quad (5)$$

where $f$ is the activation function needed to transform the weighted amount of all signals affecting the neurons. The output is classified into pineapple and background noise. The equations show the formula to count the total yield of the pineapple fruits and background noise. From the confusion matrix, the number of pineapples and background noise is correctly classified. The algorithm is proficient in adapting to various types of data and is effective at learning patterns. The classification outcome was compared with four types of training algorithms namely Levenberg-Marquardt (LM), scaled conjugate gradient (SCG), variable learning rate backpropagation (GDX) and resilient backpropagation (RP) to select the best performance for the detection and classification of pineapple crown and background noise.

#### 2.6.2. Support vector machine

SVM is a simple data classification method that generates a model that predicts the goal value of data in the testing set. The model is constructed using training and testing data, which consists of a series of data instances, each of which includes one target value and many attributes. Recognised labels aid in specifying the correctness of the system's output by providing an indicator of the desired outcome and validating the system's accuracy, or by assisting the system in learning to operate correctly [28]. A support vector machine's aim is to find the best separating hyper plane that maximises the margin by optimisation[29]; shown in Eqs. (6)–(8)

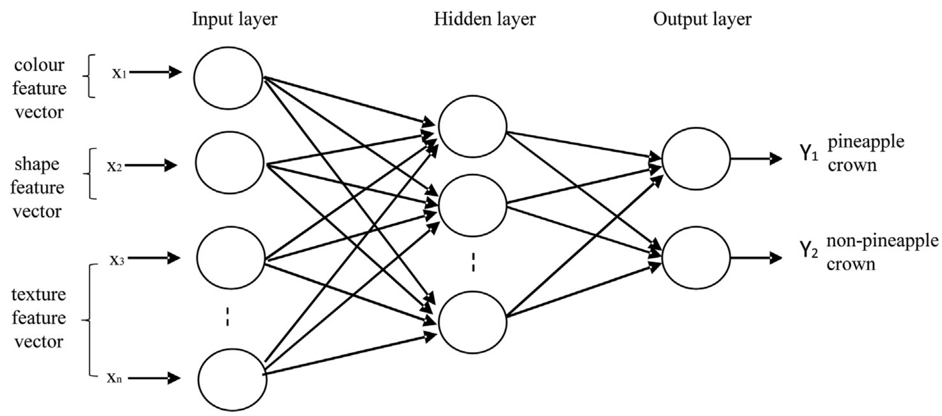


**Fig. 3** ANN-MLP structure.

$$\min_{w,b,\xi} J\left(\vec{w}, \vec{\xi}\right) = 1/2w^T w + C\sum_{n=1}^{N} \xi_n \tag{6}$$

$$y_n\left[w^T\varphi(x_n) + b\right] \geq 1 - \xi_{n'} \tag{7}$$

$$\xi_n \geq 0, n = 1, \cdots, N \tag{8}$$

where w,b and ξ are the weight vector, bias variable, and slack variable while φ is the non-linear kernel function, and C > 0 is a constant. Types of SVM include Linear, Quadratic, Cubic, Fine Gaussian, Medium Gaussian and Coarse Gaussian.

*2.6.3. Random forest*

The RF is one of the best classification and regression method that has the ability to classify a large dataset. This algorithm generates an ensemble of decision trees. The fundamental idea of ensemble techniques is to group weak learners together to create a strong learner. The input is entered at the top and as it descends to the tree; the original data is sampled at random, but with substitution, into smaller and smaller sets. The sample class is calculated using an arbitrary number of random forest trees. For classification, the predictions of the RFs are taken to be the majority votes of the predictions of all trees, and for regression, the predictions of all trees are taken to be the average of the predictions of all trees, as seen in Eq. (9) [30], where $S$ is the prediction of random forests while $K^{th}$ is a response of a tree and $K$ is the index runs over the individual trees in the forest.

$$S = 1/K\sum_{K=1}^{K} K^{th} \tag{9}$$

*2.6.4. Naïve Bayes*

Bayes' theorem is important for inferential statistics and several sophisticated machine learning models. Bayesian reasoning is a systematic method to adjust the probability of assumptions in light of recent evidence, and it therefore plays an important role in research[31]. The naive Bayes classifier is based on Bayes' theorem, which underpins a simple but efficient machine learning algorithm. The consequence of a variable value on a given class is assumed to be independent of the values of other variables by naive Bayes classifiers. This is known as class conditional independence. More complex classification approaches can often be outperformed by naive Bayes. It is particularly useful when the inputs have a high dimensionality. Models with predictive capabilities are created using naive Bayes [32]. The available types of Naïve Bayes are Gaussian Naïve Bayes and Kernel Naïve Bayes.

*2.6.5. Decision trees*

Decision trees (DT) is a well-known simple non-parametric supervised machine learning technique that has seen widespread use in data classification tasks. The main goal of DT is to learn some rules from the testing dataset to construct a model that predicts the class label of a test sample. A DT arrangement has two types of nodes: leaf nodes and internal nodes. A leaf is assigned a class label based on the majority vote of training examples that hit the leaf. Furthermore, each internal node is a function query, and it branches out based on the responses[29]. Types of DTs include Fine, Medium and Course DTs.

*2.6.6. K-nearest neighbours*

The k-nearest neighbours (KNN) classifier, which is a non-parametric method, is a well-known approach in the machine learning community. For assigning the class labels of the test samples, the KNN classifier takes into account the training samples, a distance parameter and the number of nearest neighbours (k). The Euclidean distance is a general solution for calculating distance. The majority vote of the labels of predetermined k-nearest neighbours determines the class labels of the test samples [29]. The KNN has several types namely fine, medium, course, cosine, cubic and weighted.

*2.7. Yield counting*

Conventional process of yield counting is based on the judgement by pineapple expert who decide the suitable fruit to be harvested. The pineapple will be harvested when demand from customer is received. Using manual process, the fruit will be counted for single plot and then multiplied with the number of plots to achieve the fruit target to be harvested. Differing with automatic counting, the algorithm learnt the counted ROI in the bounding box as fruit crown or non-fruit crown. Based on the total number of image frames, extraction of the bounding box will be accumulated to sum up the number of pineapple crowns to be counted into the yield of pineapple. In this study, the performance of automatic counting algorithm will be compared with the visual assessment made by a human inspector on a screen to yield a prediction using machine learning with and without feature selection.

### *2.8. Performance evaluation*

The performances of the pineapple crowns were compared with manual and machine classifier count. Evaluation regarding classification accuracy, sensitivity, specificity and precision was assessed as in Eqs. (10)–(13). The terms are defined as [33,34] True Positive (TP) is correctly classified positive cases of true fruit crown detection, True Negative (TN) is correctly classified negative cases of incorrect fruit crown detection, False Positive (FP) is incorrectly classified negative cases and False Negative (FN) is incorrectly classified the pineapple crowns as the positive cases. Sensitivity is defined as the probability that true fruit crown classification, specificity is the probability of classification as a noise detected from the background. Accuracy and precision describe how many classified pineapples are relevant, and the probability of the classification is correctly performed.

$$Sensitivity = \frac{TP}{(TP + FN)}\% \tag{10}$$

$$Specificity = \frac{TN}{(TN + FN)}\% \tag{11}$$

$$Precision = \frac{TP}{(TP + FP)}\% \tag{12}$$

$$Accuracy = \frac{(TP + TN)}{(TP + TN + FP + FN)}\% \tag{13}$$

## 3. Results and discussion

Image analysis for pineapple crown detection in open in-field environment requires systematic processing stages due to occlusions from background noise, in addition to colour similarities between leaf and crowns that contribute to the detection accuracy. Comparisons among classifiers demonstrated that FN and FP errors are still high to classify pineapple and noise which may be because of the features of pineapple and noise that seem similar especially from the colour and shape of pineapple leaves under these situations. The potential of desired ROI identification is high because the processing image algorithm is able to eliminate illumination and distinguish occlusions which are mandatory to image analysis in this stage shown in Fig. 4. Accurate pineapple crown detection is vital for fruit counting which is useful to estimate yield in each plot of pineapple plantation. The extraction of bounding box to retrieve the pineapple crown is shown in Fig. 5.

Features selection between colour, texture and shape has demonstrated better classification accuracy and yield better results using ANOVA. It can be seen that not all the extracted features were significant to proceed with the classification as clearly be seen in Fig. 6. Out of 26-features, there are 22-features selected by matching the significant differences of pineapple crown and the background noise could be reduced. Shape, colour and texture features were reduced into four significant features which demonstrated that the characteristic do not significantly differ for both pineapple and noise, namely eccentricity, homogeneity, root mean square and meanG. Fig. 6 illustrates the multiple comparison tests to examine the number of features that can be eliminated.

Table 1 shows the tabulated classifier accuracy performance of training and testing between training function for six classifiers algorithms with and without feature selection using the unseen tested images. This analysis focuses on discovering the feasibility detection of the pineapple crown in which the accuracy detection is most suitable to represent the outcome. The results before incorporating feature selection showed that the accuracy performance may be slightly improved or reduced when using one-way ANOVA for executing feature selection depending on the classifier type. Overall classification was able to classify accurately up to 90% identified crown. Least accuracy has been reported by coarse KNN to reduce by 36.02% from the maximum achieved accuracy. Moreover, the precision, specificity and sensitivity for ANN-GDX also showed that the performances exceeded above 90% which proved that the classifier was able to demonstrate high sensitivity to detect pineapple crown classification, high precision to recall the crown as a correctly identified pineapple crown and high specificity to confirm that the background noise image is correctly identified as background noise. Furthermore, the classification performance was optimised with ANOVA feature selection and have resulted in the increment of 2.94% in classification performance. Therefore, the feature selection process to eliminate non-informative features and select important features could improve the accuracy of the classification. Nevertheless, other classifiers follow an increased performance trend in KNN classifier to be optimised with ANOVA, except for DT, NB, SVM and RF which may be due to the network architecture, training function and its learning rate which was able to segregate between pineapple crown and background noise. This can be observed from Quadratic SVM classifier which was able to demonstrate comparable performance as ANN-GDX without performing feature selection with ANOVA.

Detail comparison between metric parameters in ANN learning algorithms was extracted from the confusion matrix as a measure of classification performance using one-way ANOVA for pineapple and background noise. As previously discussed, TP number represents the images to be correctly classified as pineapple crown, TN represent the number of images incorrectly classified as pineapple crown, or in other words to be detected as background noise, FP is incorrectly classified as pineapple crown and FN is incorrectly classified as background noise. The metric parameters were recorded in numbers of images. During training phase, ANN-LM without and with feature selection is TP = 90, TN = 84, FP = 0, FN = 6 and TP = 90, TN = 87, FP = 3, FN = 0. ANN-SCG for both without and with feature selection is TP = 89, TN = 89, FP = 1, FN = 1 and TP = 85, TN = 81, FP = 5, FN = 9. ANN-RP for both without and with feature selection is TP = 90, TN = 89, FP = 0, FN = 1 and TP = 84, TN = 81, FP = 6, FN = 9. ANN-GDX for both with and without feature selection is TP = 89, TN = 89, FP = 1, FN = 1 and TP = 85, TN = 83, FP = 5, FN = 7.

During testing phase, the performance metrics for classification between different training function and with/without one-way ANOVA of pineapple crown and the noise dataset was performed. The value of all confusion matrix for the

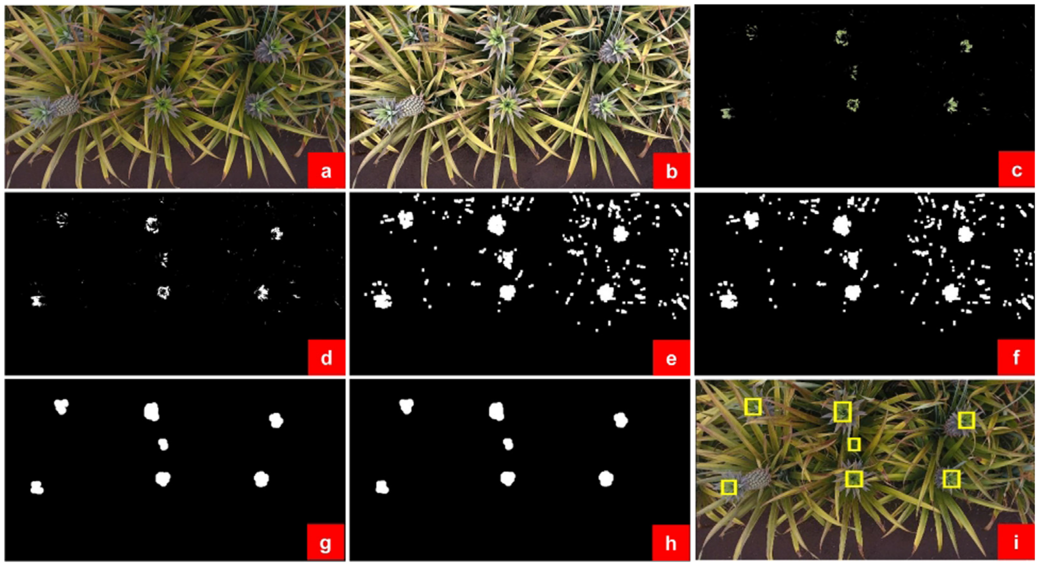


**Fig. 4** Crop image of (a) original image, (b) contrast enhancement (CLAHE technique), (c) background removal (HSV colour space), (d) binary image, (e) dilate process, (f) fill process, (g) open process, (h) close process and (i) bounding box technique.

**Fig. 5** Extracted pineapple crowns and noise from bounding box images.

ANN-LM with and without feature selection is TP = 79, TN = 82, FP = 8, FN = 11 and TP = 80, TN = 80, FP = 10, FN = 10. ANN-SCG for both with and without feature selection is TP = 84, TN = 79, FP = 11, FN = 6 and TP = 83, TN = 82, FP = 8, FN = 7. ANN-RP for both without and with feature selection is TP = 84, TN = 77, FP = 13, FN = 6 and TP = 83, TN = 86, FP = 4, FN = 7. ANN-GDX for both with and without feature selection is TP = 84, TN = 81, FP = 9, FN = 6 and TP = 87, TN = 83, FP = 7, FN = 3. Confusion matrix compares the actual and predicted fruit crowns detected within the images by providing its features into classification between different training function and with/without one-way ANOVA for the best represented classifier namely ANN-GDX and Quadratic SVM (see Fig. 7). The approach developed using multilayer perceptron without/with feature selection (see Fig. 8) indicates that the accuracy of the ANN-GDX achieved maximum percentage from overall performances which indicates that the classifier is more sensitive and accurate compared to ANN-LM, ANN-SCG and ANN-RP algorithm. Comparable to other algorithms, the ANN-GDX values are sensitive and accurate such that 94.4% of accuracy, 92.6% of precision, 96.5% specificity and 96.7% of sensitivity has been achieved. Meanwhile the performance of the precision reveals that ANN-RP algorithm achieves high value in dataset parameters of precision compared to all algorithms. Different training algorithm demonstrated performance metrics to vary, however the highest accuracy selection is the most preferable to indicate the capability of classifier of accurately classifying between pineapple crown and background noise.

For yield counting, it compares to the exact total pineapples detected in the image processing from the bounding box. Comparison between manual counting and automated counting by classifier were compared to test the learning ability of the proposed algorithms. Fig. 9 shows the results of fruit counting performance measure for overall training function

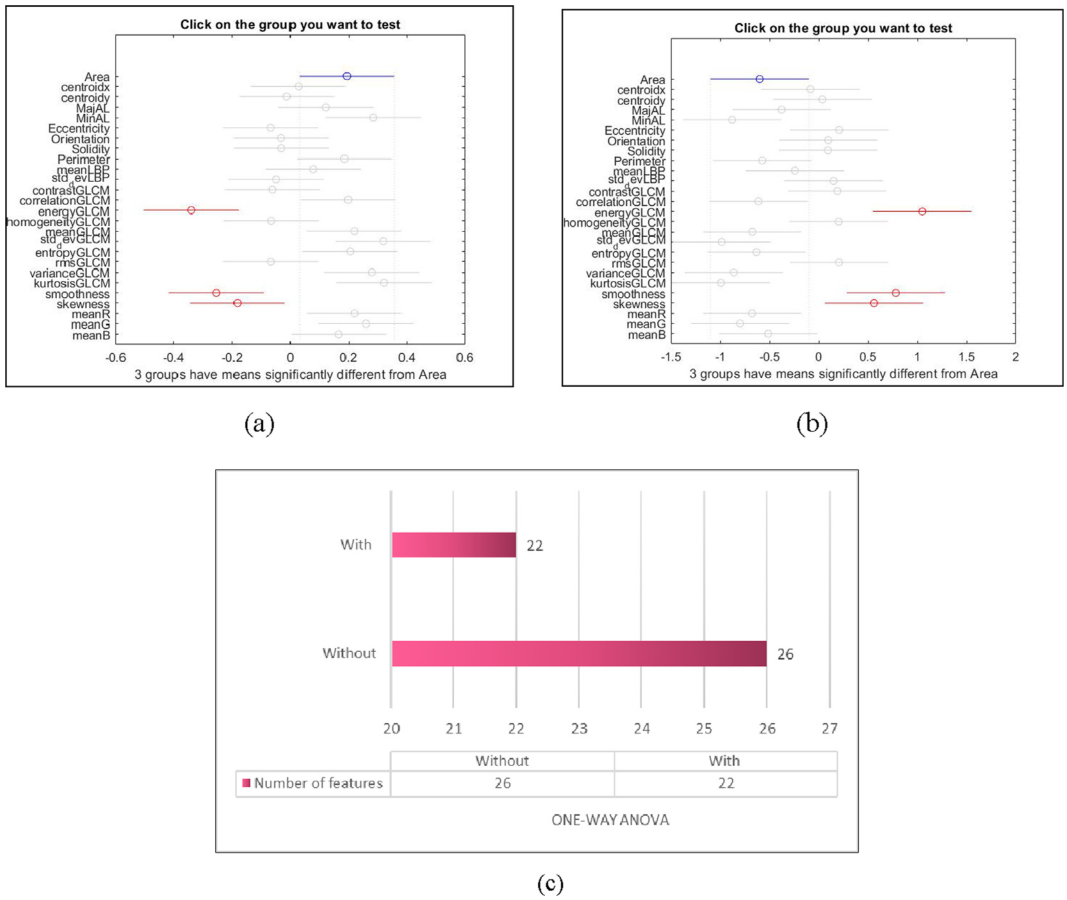


**Fig. 6** Illustration of multiple comparison tests to demonstrate (a) the significant difference among area feature (represented by blue line) and similar number of features namely energy, smoothness and skewness (represented by red line; p-value $< 0.05$) for pineapple crown (b) the significant difference among area feature with same number features namely energy, smoothness and skewness (represented by red line; p-value $< 0.05$) for background noise (c) the number of features comparison between with and without feature selection using one-way ANOVA.

algorithms and shows the detailed results of the experiment with and without implementation of ANOVA feature selection. Exact total number of pineapple crowns and background noise were recorded during the experiment. The automatic fruit counting was taken into account in the case of the total number detection of pineapple crown using machine learning has successfully classified the pineapple crown. Comparison between automatic counting and manual counting was compared in which selection of training function of classifier is selected such that ground truth image computed during automatic counting is the nearest to the manual counting.

The automatic counting approach developed using ANN-GDX with ANOVA feature selection indicates that the highest detection number of images, 87/90 able to be counted as pineapple crown. Similar to Quadratic SVM, comparable number of pineapple crown and background noise could be counted both at 86/90 and 87/90 respectively. Nevertheless, the worst counting algorithm demonstrated that learning algorithm of RF and DT were not suitable for counting algorithm due to low capability in producing accurate counting (exactly 76/90 and 69/90 respectively for pineapple and background noise). As result, RGB images can be processed and computed as automatic fruit counting based on aerial images with UAV and is shown to be effective method with 87/90 of correct pineapple crown detection. Digital image processing in highlighting the functionality and ability to accurate detection can be seen as alternative method to automate the counting process of the fruit prior harvesting.

## 4. Conclusion

A system with drone DJI Phantom 3 Advanced quadcopter and MATLAB software was used for real-time automatic crop recognition, detection and counting of pineapples using machine learning approaches. The density count of the pineapple in the selected area is determined in real-time. This study proposes an image-processing and machine learning method to detect and count the pineapple crown accurately. The proposed method consists of several steps. Firstly, enhance the data image to improve the quality and detect the pineapple crown using morphological operations. Secondly, extract the features of colour, shape, and texture features as input in machine learning classifier to classify between pineapple crown and background noise such as leaves, grass and ground. Optimisation with ANOVA aims to further improve the

**Table 1** Comparison of performance metrics for classification between different training function and feature selection with and without one way ANOVA in testing data.

| Classifier type | Training function | Without one-way ANOVA | | | | With one-way ANOVA | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | Pre (%) | Spe (%) | Sen (%) | Acc (%) | Pre (%) | Spe (%) | Sen (%) | Acc (%) |
| ANN | LM | 90.8 | 88.2 | 87.8 | 89.44 | 88.89 | 88.89 | 88.89 | 88.9 |
| | SCG | 88.4 | 92.9 | 93.3 | 90.56 | 91.2 | 92.1 | 92.2 | 91.7 |
| | GDX | 90.3 | 93.1 | 93.3 | 91.70 | 92.6 | 96.5 | 96.7 | 94.4 |
| | RP | 86.6 | 92.77 | 93.3 | 89.14 | 95.4 | 92.47 | 92.2 | 93.9 |
| DT | Fine Tree | 90.0 | 92.2 | 92.0 | 91.1 | 91.1 | 84.4 | 85.42 | 87.8 |
| | Medium Tree | 90.0 | 92.2 | 92.0 | 91.1 | 91.1 | 84.4 | 85.42 | 87.8 |
| | Coarse Tree | 90.0 | 93.3 | 93.1 | 91.7 | 91.1 | 76.7 | 79.62 | 83.9 |
| Naïve Bayes | Gaussian Naïve Bayes | 90.0 | 91.1 | 91.0 | 90.6 | 91.1 | 87.8 | 88.17 | 89.4 |
| | Kernel Naïve Bayes | 91.1 | 92.2 | 92.1 | 91.7 | 93.3 | 87.8 | 88.42 | 90.6 |
| SVM | Linear SVM | 91.1 | 93.3 | 93.2 | 92.2 | 98.9 | 85.6 | 87.25 | 92.2 |
| | Quadratic SVM | 90.0 | 96.7 | 96.4 | 93.3 | 95.6 | 85.6 | 86.9 | 90.6 |
| | Cubic SVM | 88.9 | 95.6 | 95.2 | 92.2 | 95.6 | 87.8 | 88.7 | 91.7 |
| | Fine Gaussian SVM | 72.2 | 100.0 | 100.0 | 86.1 | 70.0 | 100.0 | 100.0 | 85.0 |
| | Medium Gaussian SVM | 90.0 | 95.6 | 95.3 | 92.8 | 93.3 | 88.9 | 89.4 | 91.1 |
| | Coarse Gaussian SVM | 93.3 | 91.1 | 91.3 | 92.2 | 97.8 | 84.4 | 86.3 | 91.1 |
| KNN | Fine KNN | 92.2 | 92.2 | 92.2 | 92.2 | 94.4 | 90 | 90.4 | 92.2 |
| | Medium KNN | 96.7 | 86.7 | 87.9 | 91.7 | 96.7 | 82.2 | 84.5 | 89.4 |
| | Coarse KNN | 100.0 | 45.6 | 64.7 | 72.8 | 100.0 | 38.9 | 62.1 | 69.4 |
| | Cosine KNN | 91.1 | 91.1 | 91.1 | 91.1 | 94.4 | 88.9 | 89.5 | 91.7 |
| | Cubic KNN | 96.7 | 83.3 | 85.3 | 90.0 | 97.8 | 76.7 | 80.7 | 87.2 |
| | Weighted KNN | 94.4 | 92.2 | 92.4 | 93.3 | 95.6 | 84.4 | 86.0 | 90.0 |
| RF | Bagged Trees | 94.4 | 93.3 | 93.4 | 91.7 | 84.4 | 91.0 | 90.5 | 87.8 |

Pre = Precision; Spe = Specificity; Sen = Sensitivity; Acc = Accuracy.

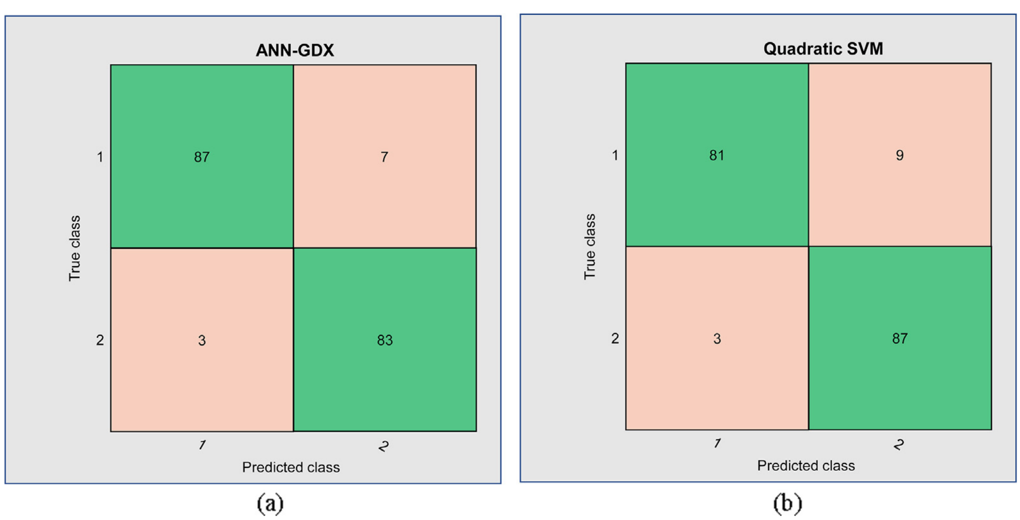


**Fig. 7** Confusion metrics to demonstrate the classification capability using the most accurate machine learning classifier (a) ANN-GDX classifier; notation of 1 = pineapple, 2 = noise and (b) Quadratic SVM classifier; notation of 1 = pineapple, 2 = noise.

classification performance, and lastly the pineapple fruits based on its detected crown through automatic counting algorithm must be counted to show pineapple yield in which the feasibility of the method is confirmed with testing of unseen images and ability to overcome issue of varied illumination and occlusion due to background noise ANN-GDX machine learning algorithm result up to 94.4% accuracy as the best classification as compared to other classifier algorithms. Future extension would focus on improving the robust detection to eliminate noise and increase counting precisely by increasing more features to be evaluated and provide make the decision of classification more accurate.

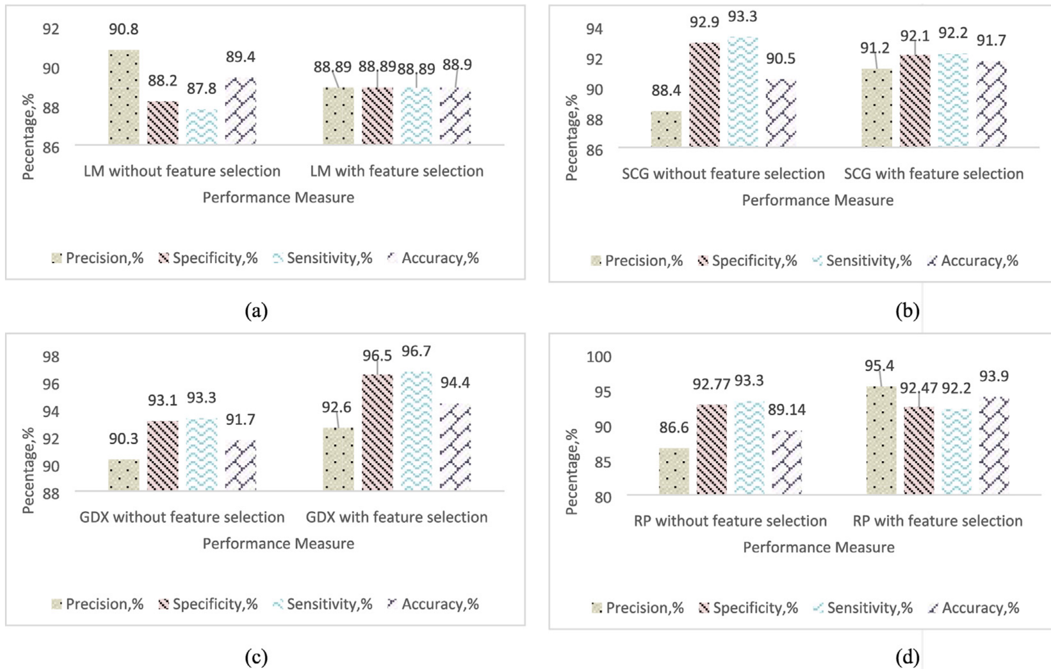


**Fig. 8** Comparison performance between classifiers with various training function (a) ANN-LM (b) ANN-SCG (c) ANN- GDX and, (d) ANN-RP algorithms of testing.

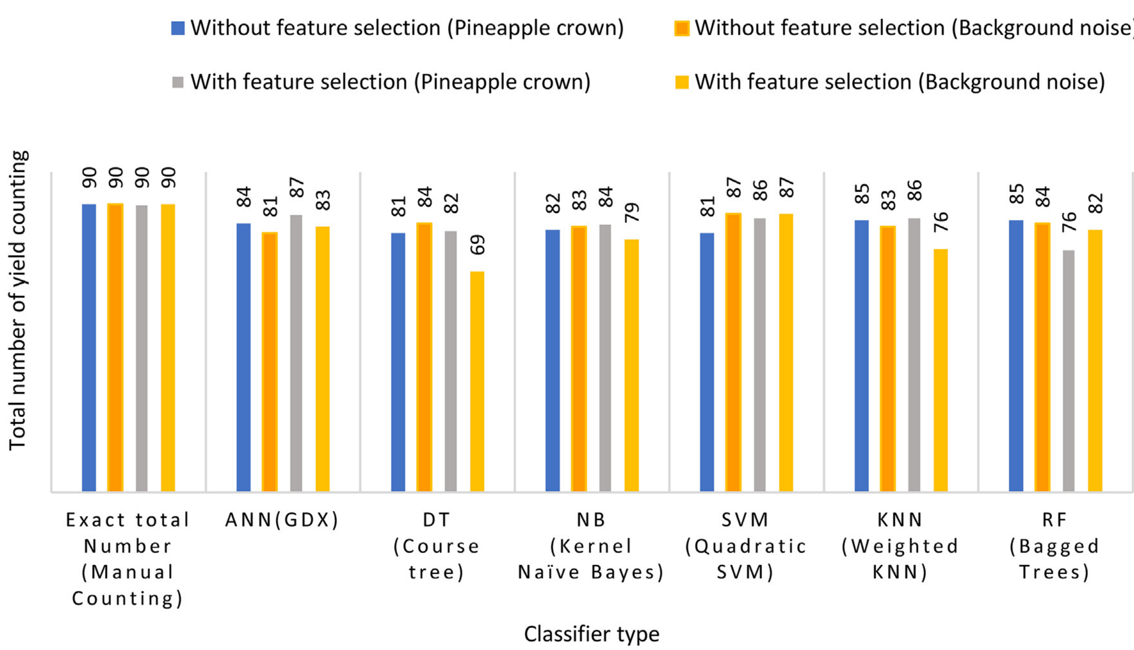


**Fig. 9** The comparison of yield counting of pineapple crown between manual counting and automatic counting using machine learning.

## Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.


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