SIZE CLASSIFICATION OF MD2 PINEAPPLE USING DEEP LEARNING

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ABSTRACT

Determining pineapple size is crucial for assessing yield quality, typically measured by weight on a scale. However, manual measurement is labour-intensive, time-consuming, and prone to errors. To address this, leveraging deep learning techniques to automate size detection is envisioned as a viable solution. This study aims to elucidate the ability and performance of Convolutional Neural Networks (CNNs) for pineapple size detection and classification. A dataset comprising 1100 pineapple images of various weights was collected and annotated. Seventy percent of the annotated images were utilized to train a pineapple sizing classification model using the pre-trained YOLOv5 model, while 15% were allocated for validation and testing, respectively. The results demonstrate that the proposed method achieved an average validation accuracy of 0.988, indicating its ability to accurately classify MD2 pineapple sizes.

Keywords: deep learning, pineapple size classification, convolution neural network

INTRODUCTION

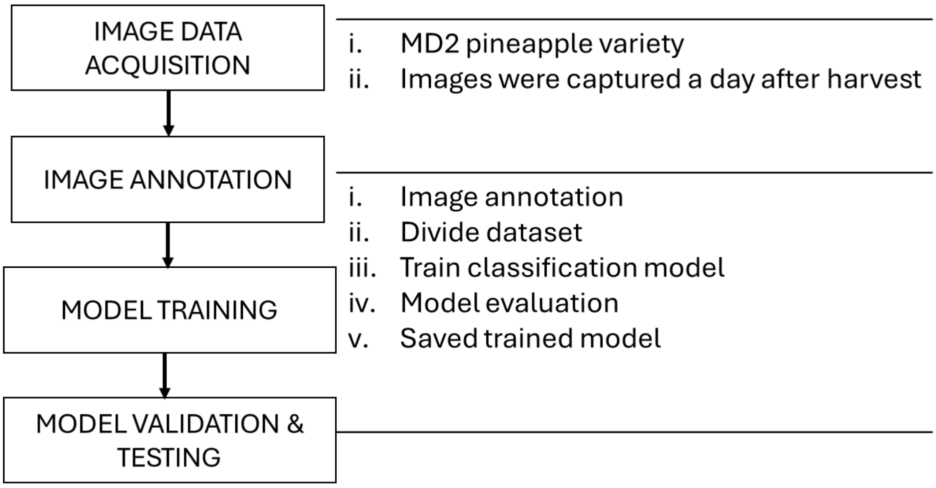
Estimating pineapple size holds significant importance in contemporary agriculture, impacting multiple facets of production, ranging from resource allocation to market forecasting. Size is typically characterized by weight or various dimensional parameters such as length, diameter, volume, circumference, projected area, or a combination thereof. Malaysian Pineapple Industry Board (MPIB) has issued a classification standard for pineapple fruit size based on the varieties. For the export premium varieties like the MD2, the size is classified as large (L) for weight more than 1.6 kg, medium (M) for weight of 1.3 to 1.5 kg and small (S) for weight below 1.2 kg (MPIB, 2020). In the manual process of classifying pineapple sizes, each fruit is individually placed on a weighing scale, manually recorded by the person conducting the measurement, and sorted into respective bins based on their weight categories. Although this practice is a straightforward method, it is a meticulously tedious process that may have limitations in terms of labour usage, time consumption and accuracy. For this reason, an automated or technology-driven approach is expected to replace the manual practice of pineapple size classification.

In recent years, the application of deep learning techniques, a subset of machine learning, has gained traction in agriculture due to its ability to process large datasets and extract intricate patterns. This feature makes the deep learning technique well-suited for tasks involving spatial patterns such as fruit quality properties determination including variety, maturity, freshness, defective and size (Katarzyna et al. 2019; Chang et al. 2022; Harsh et al. 2020; Jahanbakshi et al. 2020; Harris 2022). The Convolution Neural Network (CNN) which is the most popular model in deep learning has been explored by Harris, (2022) for the size determination of pineapple and reported that the distributions of the predicted fruit dimensions were found to be equal to the manually measured fruits. The author used Mask R-CNN to identify the instances of pineapples and subsequently extract fruit dimensions using the OpenCV library. If the model is used in situ, for instance, at a farm or on a harvester machine, a high performance of edge computing solution is required to complete both detection and classification tasks. Therefore, the objective of this study is to develop a simpler pineapple sizing classification model using a pre-trained CNN model that involves classification tasks only and elucidate its performance. The developed model is mainly focused on providing a simple and direct solution for the end users.

MATERIALS AND METHODS

The overall process for the development of the pineapple sizing model can be divided into two main sections which include image data acquisition and development of the pineapple sizing model. Figure 1 shows the overall flowchart for this study

Figure 1. Overall flowchart



Weight and image data acquisition

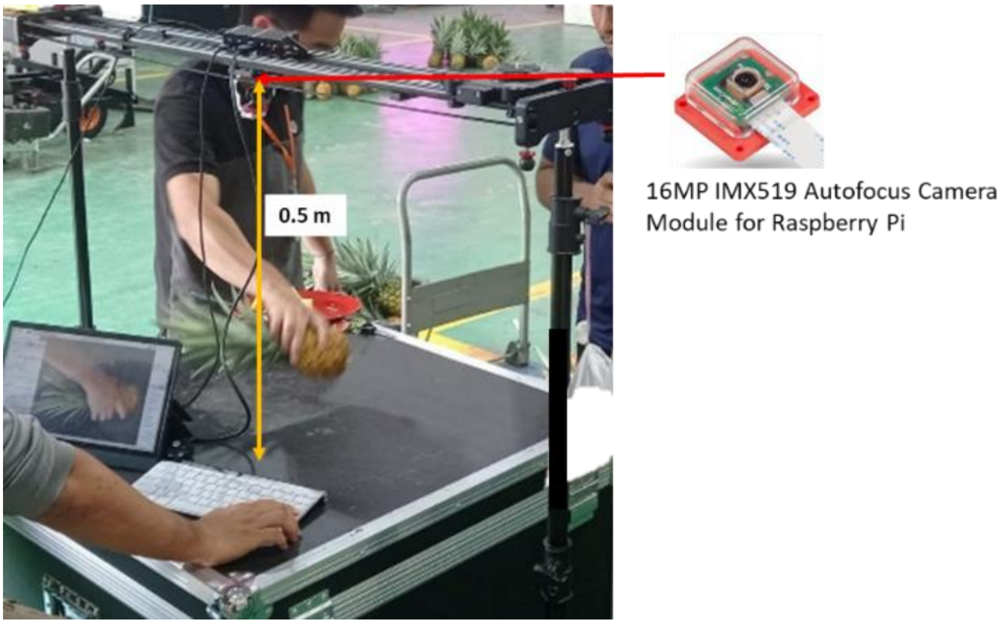
The MD2 pineapple variety which is the highest market demand pineapple variety recently, was selected for this study. Prior to the image acquisition, 600 MD2 pineapples were weighed one by one using a digital weighing scale and the size class of each sample was labeled according to the three size classes established by MPIB specifically for the MD2 variety (Table 1). According to Ahmad et al (2023), the pineapple weight is highly correlated with the circumference and diameter of the fruit with a coefficient of regression (R^2) of 0.997. This means that the weight of the pineapple can be used as a reference parameter to classify the size.

Table 1. MD2 pineapple size classification established by MPIB (MPIB, 2020)

Class	MD2 pineapple weight (kg)
Large, L	>1.6
Medium, M	1.3 – 1.5
Small, S	<1.2

For the image acquisition, the samples were then placed one by one on a black platform as exhibited in Figure 2. The images were captured using ArduCam 16 megapixels lP IMX519 autofocus camera module for Raspberry Pi minicomputer. The camera was mounted on a holder at a height of 0.5 m from the platform. Some of the pineapples were rotated randomly to capture images at several different positions. Finally, 1100 images were captured in total, with a resolution of 1280 x 980 pixels. The captured images were then saved in JPG file format in three different folders according to their respective weight namely L for large, M for medium and S for small. These image datasets were then used for further analysis.

Figure 2. Set up for the pineapple image acquisition

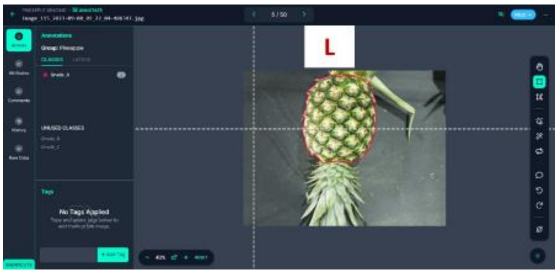


Development of the pineapple classification model

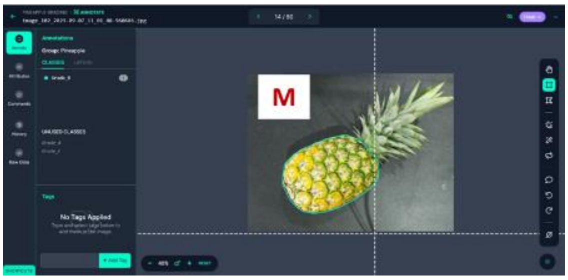
The original images were annotated using Roboflow, a platform for processing computer vision and machine learning models. During the annotation process, the pineapple images were annotated based on the shape of the pineapple (excluding the crown) using the smart polygon annotation as depicted in Figure 3. The annotated dataset was then divided into three datasets namely the training dataset, validation dataset and testing dataset with a ratio of 70:15:15. To develop the pineapple sizing classification model, the training dataset was used to train a pre-trained model namely YOLOv5. The hyperparameters set for the training were 640 for image segmentation, 100 for the number of epochs and 16 for the batch size. The validation dataset and testing dataset were then used to evaluate the model performances based on the confusion matrix of the classification. All the training, validation, and testing processes were performed on Google Colaboratory, a cloud-based platform provided by Google that offers free access for computing resources in machine learning and data science tasks.

Figure 3. Examples of images annotated using the smart polygon annotation and classified as (a) L (large), (b) M (medium) and (c) S (small).

(a)



(b)



(c)

The quantitative evaluation of the developed model was performed using the testing dataset and measured five performance metrics listed in equations (1) to (5). The parameters involved in the calculation of these performance metrics were derived from the confusion matrix of the classification. Table 2 describes the confusion matrix that consists of actual and predicted information (Cho et al. 2022). Based on this table, TP is a positive value that has been predicted as true by the classifier and FP is defined as a positive value that has been predicted as false by the classifier. On the other hand, TN is defined as a negative value that has been predicted as true by the classifier whilst FP is defined as a negative value that has been defined as false by the classifier. Thus, the model performance parameter of the model can be defined in equation (1) to (5).

$$\textit{Mean average precision, mAP} = \frac{1}{n}\sum_{k=1}^{k=n} AP_k \tag{1}$$

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \times 100\% \tag{2}$$

$$Precision = \frac{TP}{TP+FP} \tag{3}$$

$$Recall = \frac{TP}{TP+FP} \tag{4}$$

$$F1\ Score = \frac{2\ x\ Recall\ x\ Precision}{Recall+Precision} \tag{5}$$

where TP is the number of true positives, FP is the number of false positives, TN is the number of true negatives, FN is the number of false negatives, n is the number of thresholds and AP_k is the average precision of class k.

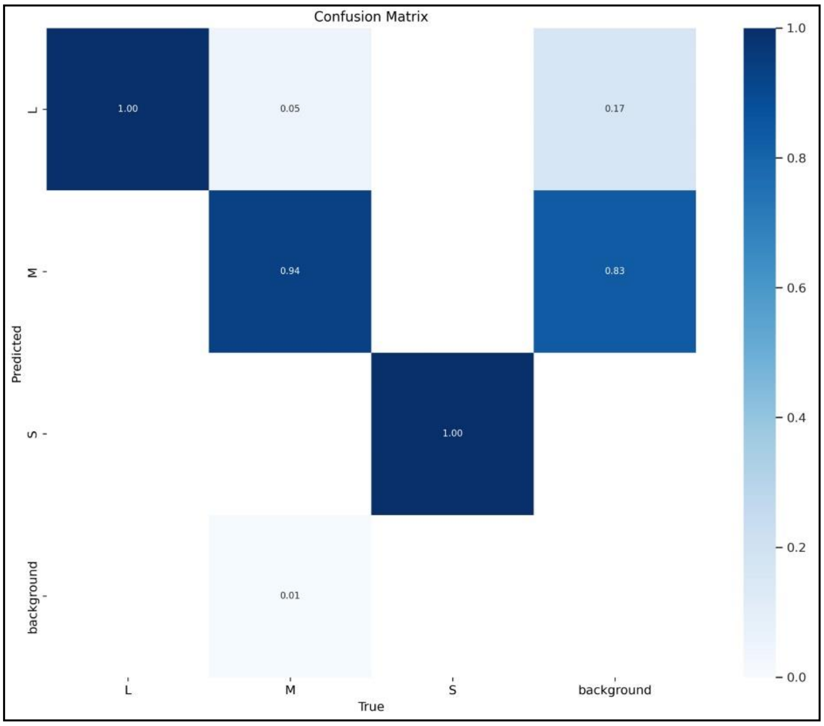
Table 2. Confusion table

		Predicted	
		Positive	Negative
Actual	Positive	True Positive, TP	False Negative, FN
	Negative	False Positive, FP	True Negative, TN

RESULTS AND DISCUSSION

The confusion matrix table of the developed model is exhibited in Figure 3. Referring to this table, all L-size image samples from the test dataset were correctly classified as L size. A similar result was obtained for the classification of S-size image samples. On the other hand, 5% of the M-size image samples were mistakenly classified as L size. The "background" class in a confusion matrix for object detection acts as a sentinel. It helps identify both missed objects (a low value on the background diagonal means objects are missed) and false alarms (high values in other background cells mean the model is incorrectly seeing objects where there are none). This way, it ensures the model's accuracy by revealing where it is struggling to differentiate between actual objects and empty space.

Figure 3. The confusion matrix of the pineapple sizing classification model

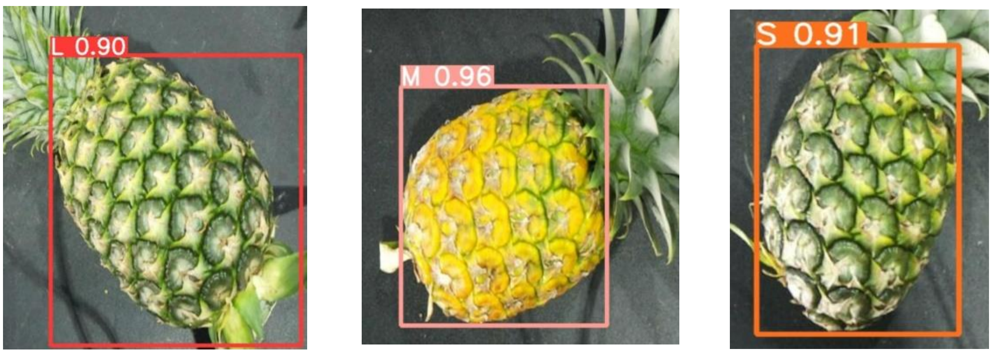


Based on the confusion matrix, the model performance parameter was computed using equation (1) – (5) and tabulated in Table 3. S-size attained 100.00% of accuracy as the group did not have misclassification. On the other hand, both L-size and M-size achieved 98.32% accuracy. Overall, the average accuracy for this model is 98.88% with the number of epochs equal to 100, the batch size equal to 16 and 640 image segmentation. Figure 4 depicted examples of pineapple images that were classified using the pineapple sizing classification model with confidence score of above 0.9.

Table 3. Performance result of pineapple sizing classification model

Class	mAP	Accuracy	Precision	Recall	F1 score
L (large)	0.987	0.983	0.952	1.000	0.976
(M) (medium)	0.974	0.983	1.000	0.950	0.974
S (small)	0.923	1.000	1.000	1.000	1.000
Average	0.961	0.988	0.984	0.983	0.983

Figure 4. Examples of the images that have been classified using the pineapple sizing classification model.



The high performance of the sizing classification model is expected as the smart polygon was used for annotating the images. This is because the smart polygon annotates the image exactly following the shape of the pineapple. However, this type of annotation generates a large number of dotted points of data that need to be analysed during the size classification process. In this case, the performance of the edge computer processor that will be used to execute the size classification task needs to be considered before the model can be fully deployed in real-time. Other types of annotation which involve less dotted points data to be analysed with good performance of model accuracy could be considered in the future study.

CONCLUSION

The MD2 pineapple sizing classification model has been developed using CNN technique. The validation and test results indicate that the developed model is able to classify the size of MD2 pineapple with excellent accuracy. The proposed technique that uses an edge computing solution for on-device inference is capable of being integrated with an IoT system, thereby making it possible to mount the size classification system on a mechanized pineapple harvester. The integration of sophisticated models with practical farming systems holds the potential to revolutionize the precision and efficiency of size estimation processes in pineapple cultivation. This revolution contributes to enhanced decision-making processes, optimized resource allocation, and more accessibility to farmers in resource-constrained environments.

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