Chili fruits maturity estimation using various convolutional neural network architecture

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ABSTRACT

Agricultural robots recently become popular by helping the farmer to conduct their daily chores. A slow process of picking and grading will leads to an inaccurate result thus increasing the production cost. This study represents an innovative and economical alternative for farmers who require to undergone the process of estimating their maturity categories. A total of 1,200 chili images with 256×256 pixel are used, where 840 is used for training and the remaining 360 being served for testing. The maturity is determined by measuring the length of chili structure between the calyx and apex. Various convolutional neural network (CNN) architectures are applied to learn and recognize the chili fruits into three maturity categories; immature, moderately mature, and mature. ADAM and stochastic gradient descent with momentum (SGDM) optimizers with multiple CNN architectures is capable in recognising and classifying chilli fruits with an accuracy of above 85%.

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1. INTRODUCTION

Agriculture is regarded as one of the sectors that will contribute to the economic and social needs of humans [1]. Agriculture provides approximately $5 trillion in food, raw materials and employment opportunities to the global community. Thus, it certainly made significant contributions throughout the developing countries in growing their economy [2]. It is difficult for farmer or labourers to define chili maturity when using traditional picking and grading method. Small errors or missteps are almost always unavoidable when dealing with humans, especially when estimating grading based on maturity categories. This occurs because human eyes are prone to errors and tend to be inaccurate. Traditional harvesting processes are unable to recognise the object as well as humans due to changes in agricultural procedures and techniques. A sluggish process produces inaccurate and inefficient results while increasing production costs. Artificial intelligence (AI) can solve the aforementioned problem by substituting deep learning methods such as convolutional neural network (CNN) in the implementation of intelligence detection and classification. AI is a branch of computer science concerned with the creation of intelligent machines capable of working and responding in the same way that human do [3]. In 1950, Alan Turing claimed that a machine's intelligence could be determined by its ability to exhibit intelligent behaviour indistinguishable from an intelligent human [4]. AI technology is widely used in variety of industries, with significant impacts in healthcare, industry and agriculture. Agriculture is one of the most extreme sectors in the world with 30.7% of global population directly working on 2,781 million hectares of agricultural land [5]. An AI invention in agriculture sector outperforms in terms of accuracy and resilience. Agriculture is a dynamic domain where it is impossible to generalise situations in order to propose a standard response.

Dubey and Jalal [6] proposed an analysis of fruit and vegetable recognition using machine learning. In this work, two features, colour and texture, are extracted with an accuracy of more than 87%. Aside from colour and size, shape is one of the features that is commonly used to identify an object's characteristics [7]. As a result, Ishikawa *et al*. [8] conducted the study on classifying strawberry fruits based on shape. Using their proposed method, they obtained 70% accuracy. Deepika [9] created a work on estimating the maturity category based on the size of fruits using artificial neural networks (ANN) in order to recognise and select the fruits based on their maturity. Simultaneously, additional features such as shape have been implemented to improve the model's ability to recognise fruits. There are only a few works that have been discovered that are related to chilli fruits. Cruz-Dominguez *et al*. [10] have published their findings on the classification of dried chilli peppers based on their grading. ANN was used to extract size and colours from an image, and it achieved 82% accuracy. Taofik *et al*. [11] discovered another paper in which the K-means clustering method is used to estimate and detect the ripeness of tomatoes and chilis. A new data acquisition framework has been proposed to improve the fruit grading process.

Hubel and Wiesel's 1959 discovery laid the groundwork for the CNN [12]. Among the numerous deep learning architectures, CNN is a specific sort of multilayer neural network for spatial data. CNN architecture is inspired by the visual perception of living beings. CNN is primarily used for image recognition and has an excellent feature extraction capability [13]. LeNet, AlexNet, VGGNet, GoogleNet, ResNet and ZFNet are some of the CNN architectures that can be used [14]. Fofana *et. al* [15], uses 2D images of flames fed into learning model to recognize its categories. In comparison with stochastic gradient descent with momentum (SGDM), ADAM is capable of producing high accuracy performance in both categories. Align with the conjunction of their work, CNN with various architecture including AlexNet, Inception ResNet v2 and ResNet-50 with ADAM and SGDM optimizer is implemented. The purpose of this study is to examine the maturity category of chilli fruit using various CNN architectures. The length of chili fruit is measured using geometric coordinate based on two points cloud from its structure called as calyx and apex. The number of samples or chili images is collected from the farms located in Duyung, Melaka. The images will then be classified based on their size and colour. Following the classification of the maturity of chili fruits, further analysis is carried out to determine the classification accuracy for both categories.

A wide variety of studies have been reported that use of AI or machine learning resulted in high accuracy performance. Machine learning is a computer science technique that emerge from pattern recognition in AI and computational learning theory. It will analyse and implement an algorithms that will learn from data and make predictions. It has been used in a wide range of computational tasks where explicit algorithms cannot be designed or coded. While, the terms data mining and machine learning are frequently used interchangeably, data mining is primarily concerned with exploratory data processing [16]. When it comes to doing their jobs, the primary distinction between humans and machines is intelligence. The neural system transmits data to the human brain for perception and action. The data is then coordinated and recalled in the brain through comparison to previously recorded experiences before being processed during the perception phase [17]. As a result, this study proposed using CNN to analyse the maturity category of chilli fruits. A number of CNN architectures are being investigated and compared in terms of accuracy performance. Simultaneously, the performance of those architectures is compared to two optimizer algorithms: ADAM and SGDM. This article is divided into four sections: section 1 presents the background analysis, problem, and some literature works, section 2 explains the proposed method, section 3 describes the experimental results and discussion of the proposed work, and section 4 discusses the conclusion and future work.

2. METHOD

This section describes the framework comprising of methodology for completing this work. This work is continuing of our previously published preliminary work [18]. The proposed framework including the method used is explained in this article, and some preliminary analysis is also reported.

2.1. Proposed chili maturity framework

First, a sample of chili fruit images is collected. The various sizes and colours of chili fruits are also considered. Image pre-processing is conducted to resize images in order to make process classification easier while also reducing model complexity. The datasets were pre-processed, which included filtering, segmentation, and image resizing. Before proceeding with any further process, the noise or unwanted features are removed. Filtering is a technique for modifying or improving image representation. A filter, for example, is applied to an image to highlight specific elements while removing others [19]. Segmentation is a technique of separating an image into many pieces to represent an object, and it is widely used in digital photos to identify an item and pertinent information. Image segmentation is the process of dividing a digital image into several segments, or groups of pixels. The goal of image segmentation is to improve understanding of an image by simplifying or changing its representation [20]. The image pixel is then reduced from 4,160×3120 to 256×256. The feature extraction method is used to extract features by measuring the length and recognising the chili class based on its colour. Then, CNN is used as an algorithm to detect the size and colour of chilli fruit in order to classify the maturity category.

Finally, model performance is evaluated in terms of recognition accuracy and compared with different optimizer models in various CNN architectures. The other features such as colours can also be used to recognize the chili class. A small number of experiments are required to pursue the process of classifying the maturity category of chili fruit. The dataset is divided into two subsets; training and testing. To demonstrate this work, the desired accuracy is defined above 90%. The experimental work is measured and evaluated for all architectures. The optimal parameter must be chosen to ensure that the model converges well until the desired accuracy is obtained. Figure 1 depicts the framework of this work.

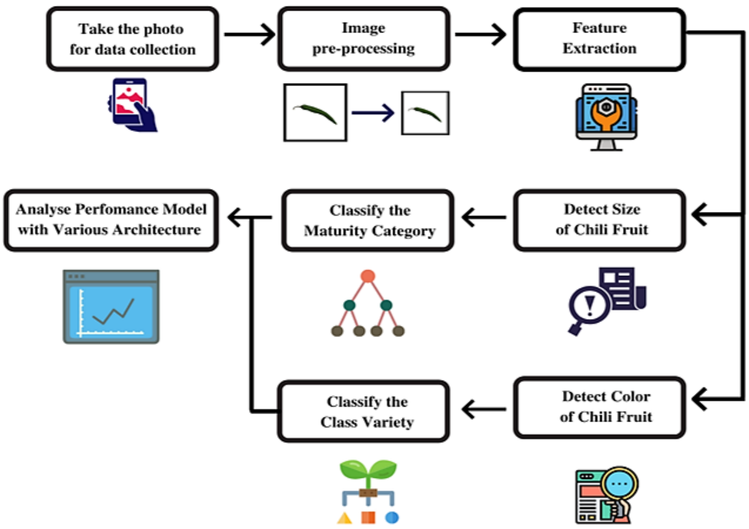


Figure 1. Proposed chili maturity framework

2.2. Data collection

There are 600 images in total, and the datasets are divided in a 70:30 ratio, with 420 images used for training and 180 images used for testing. All images are classified into three maturity levels based on their size: immature, moderately matured, and matured. The image is composed of frames whose positions have been rotated. Table 1 displays a sample of instances of each class to represent the size of the category.

Table 1. Maturity category of chili fruit

Maturity level	Size	Training sample	Testing sample
Immature 	<6 cm	140	60
Moderately mature 	7 cm-11 cm	140	60
Mature 	>12 cm	140	60

3. RESULTS AND DISCUSSION

This section provides a comprehensive and detailed explanation of the results derived from the conducted experiments. Additionally, it further explores the experimental setup, outlines the parameters employed, scrutinizes the analyses performed, and thoroughly discusses the implications and findings discovered throughout the process. The meticulous exploration of these elements contributes to a comprehensive understanding of the experimental process and its outcomes.

3.1. Data pre-processing

The size chili fruit is determined by measuring the length between its calyx and apex. The calyx is the part of the stem that connects to the top of the chili fruit, and the apex is the rounded point of the fruit. The structure of chili fruits is depicted in Figure 2.

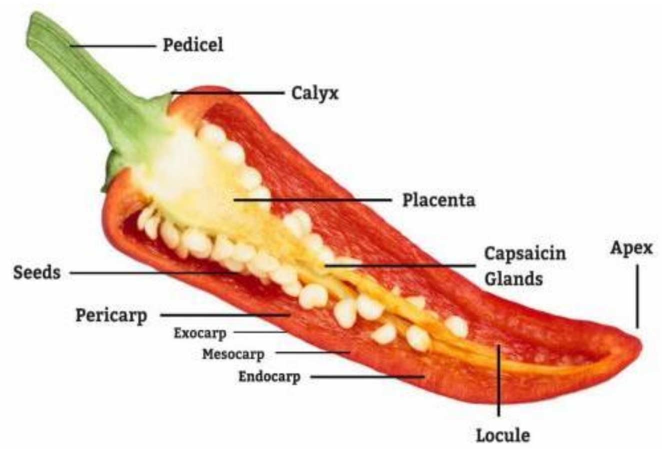


Figure 2. Structure of chili fruits [21]

Segmentation is necessary to measure length of the chili fruit. Thus, the points cloud defined based on the point position of calyx and apex. The segmented image is created by converting the original images in Figure 3 into a binary image in order to distinguish the background from the objects in Figure 4. The background is later removed to allow for further processing. A distance tool is used to measure the length between its calyx and apex, which consists of an interactive line superimposed on an image, along with a text label indicating the distance between the line endpoints, as shown in Figure 5. As a result, the length of chili images is calculated and represents the maturity category, which is divided into three classes; immature (estimation size less than 6 cm), moderate mature (estimation size 7 cm to 11 cm) and mature (estimation size greater than 12 cm). During data collection, an expert is consulted to select chili sizes based on their category. Because this work is being done in collaboration with our industrial partnership, the data was gathered at the Solok Fertigasi chili farms in Duyung, Melaka. As an expert, he was able to provide and ensure that the data was properly collected, as well as the size of the chili fruits was properly measured.

Figure 3. Original chili fruit image

Figure 4. Segmented chili fruit image

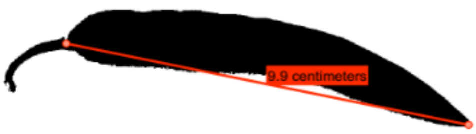


Figure 5. Measuring the length between two-point clouds (calyx and apex)

3.2. Experimental setup

In this experiment, 1,200 chili images with 256×256 pixel are used, with 840 serving as training and the remaining 360 serving as testing. For training and testing purposes, there are few number of parameters need to be defined. Table 2 tabulates the experiment parameter settings using three CNN architectures (AlexNet, Inception ResNet v2 and ResNet-50). The system is powered by a 3.11 GHz Intel i5-11300 H quad-core processor, 8 GB of RAM, and Windows 10. Figure 6 depicts the created graphical user interface (GUI) to serve as experiment's front end process. The image is chosen, and the extraction can begin once the image has been imported into the GUI. The original image has been reduced in size to 256×256 pixels.

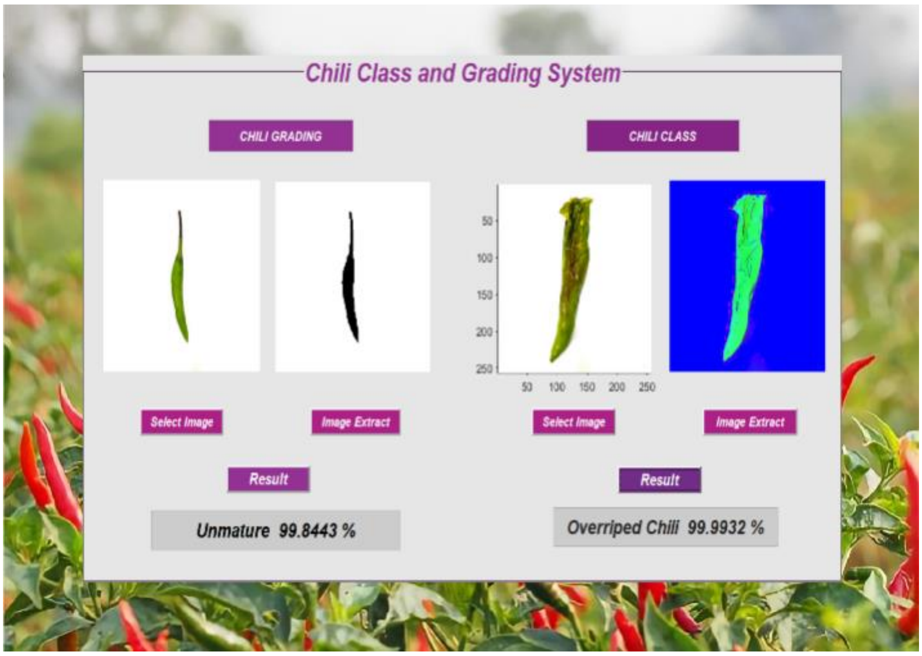


Figure 6. GUI chili maturity category and grading system

Table 2. CNN parameter setting

Parameter	Value
Training epoch	100
Learning rate	0.0001
Maximum iteration	400
Batch size	64

3.3. Classification of maturity category of chili fruits

After the chili images were segmented, they were classified based on their size and maturity stage. In a preliminary experiment, the accuracy of classifying the chili fruit into its maturity category using CNN was greater than 93%, as shown in Figure 7. Figure 8 depicts a sample of chili fruit recognition based on maturity classes.

3.4. Experimental analysis and discussion

CNN has recently gained popularity due to its ability to recognize 2D images at variety of circumferences. This method has also been shown to solve difficult problems quickly and accurately while minimizing error rates [22]. Despite the fact that different architectures are used, CNN is capable of estimating maturity of chilli fruit with high accuracy recognition. In order to broaden our analysis, different optimizers, such as SGDM and ADAM, were used in this experiment with varying learning rate values. Both optimizers have also been tested against three different CNN architectures: AlexNet, Inception ResNet v2, and ResNet-50. Figures 9 to 11 depict the training progress for each of the three architectures. An average of accuracy from AlexNet (80%) is obtained slightly lower than ADAM (95%) as show in Figures 9(a) and 9(b). The performance Inception ResNet version 2 and ResNet-50 also stated a comparatively accurary using both optimizers. However, the loss recorded from Inception ResNet version 2 is significantly differs as shown in

Figures 10(a) and 10(b). The performance recorded by ResNet-50 is highly similar when both optimizers; SGDM and ADAM was used as Figures 11(a) and 11(b). When compared to SGDM, AlexNet, Inception ResNet version 2, and ResNet-50 achieved high accuracy with low learning rates using ADAM. All architectures achieve greater than 95% accuracy with a training loss of less than 0.1.

Tables 3 to 5 displays the classification results for recognizing chili maturity using AlexNet, Inception ResNet v2 and ResNet-50 architectures with both SDGM and ADAM optimizers. The performance of different CNN architectures (AlexNet, Inception ResNet version 2 and ResNet-50) is analysed to determine the classifier's ability to recognise and differentiate the maturity category. Experiments on two optimization algorithms; ADAM and SDGM with various architectures are evaluated. As a result, ADAM and SGDM produced the greatest performance with learning rate of 0.0001. Hence, it is clear that ADAM optimizer is capable of producing an utmost performance on recognition for maturity of chili fruit. AlexNet with ADAM achieved the highest accuracy 97.88% with learning rate of 0.0001. However, using the same learning rate, the accuracy of SGDM with AlexNet was 85.89%. This is regarded as being slightly lower than ADAM. The performance is also measured in terms of run time, with the lowest run time recorded for ADAM being 2.42 minutes with learning rate of 0.0001 and the highest run time recorded by SGDM with AlexNet being 6.40 with 0.001 as their learning rate. To sum up, when a small number of learning rate is used, the model produces superior results.

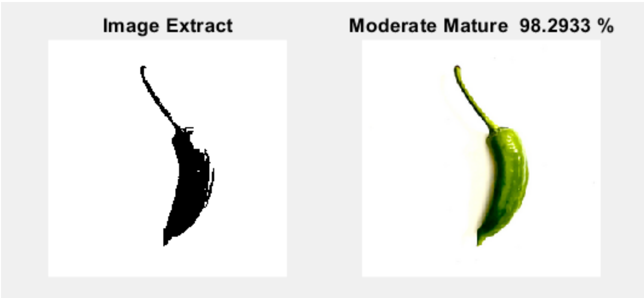


Figure 7. Accuracy of classification chili fruits maturity category

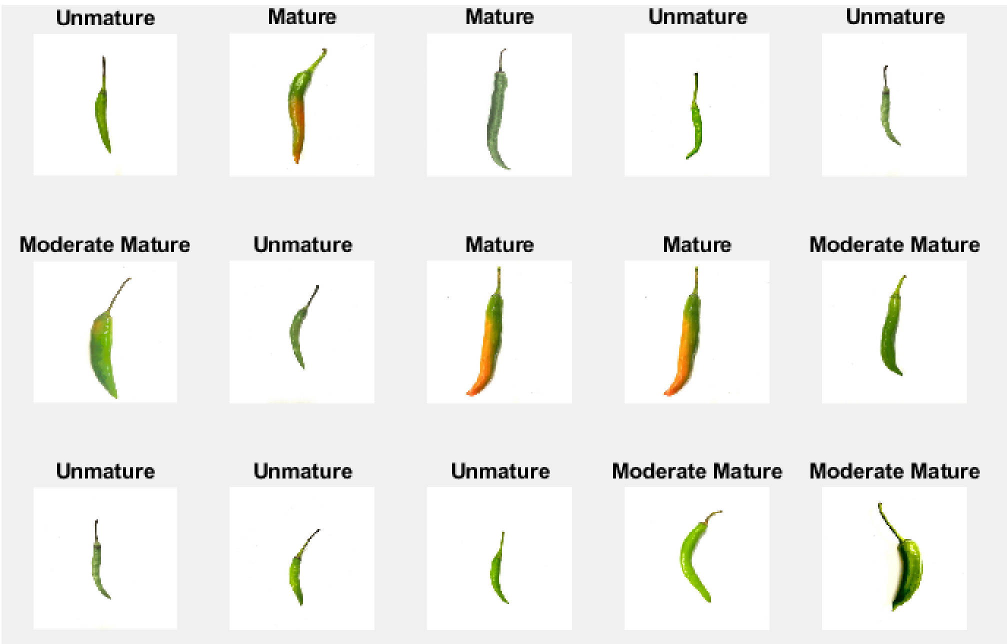
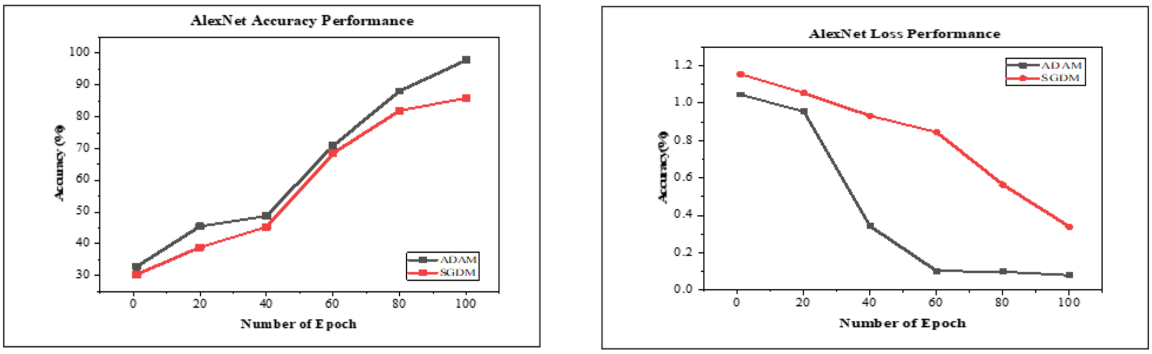
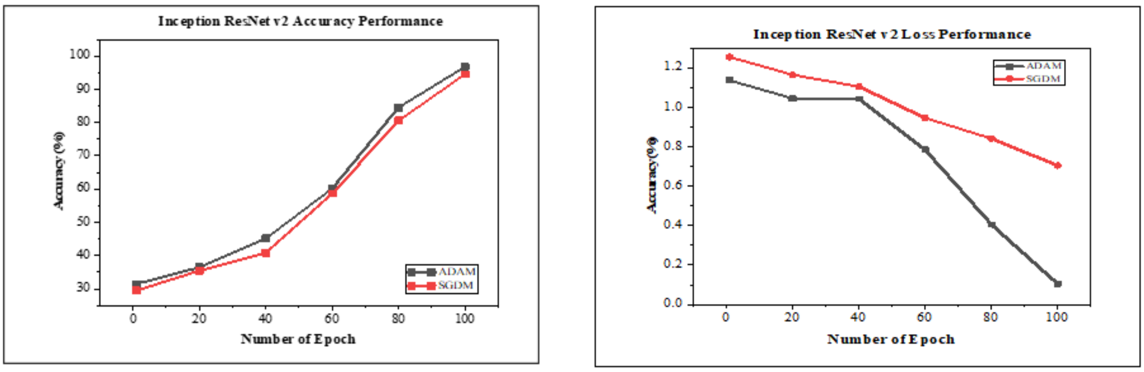


Figure 8. Classification sample of chili fruits maturity category



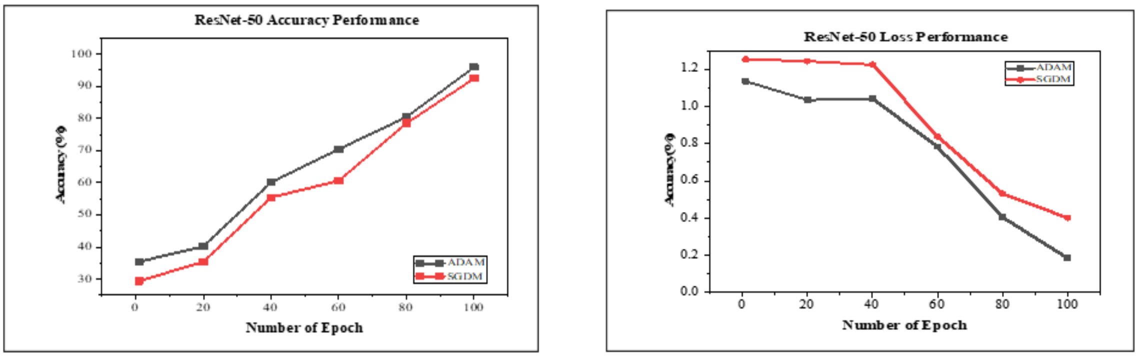
(a) (b)

Figure 9. Training curve of AlexNet with learning rate 0.0001 and 100 epoch (a) accuracy and (b) training loss



(a) (b)

Figure 10. Training curve of inception ResNet v2 with learning rate 0.0001 and 100 epoch (a) accuracy and (b) training loss



(a) (b)

Figure 11. Training curve of ResNet-50 with learning rate 0.0001 and 100 epoch (a) accuracy and (b) training loss

Table 3. Classification using AlexNet

Parameter	Training method	Learning rate			
		0.001		0.0001	
		Training	Testing	Training	Testing
Accuracy (%)	ADAM	95.88	94.12	97.88	95.85
Loss rate		0.1421	0.1414	0.0796	0.0615
Run time (minutes)		3.34		2.42	
Accuracy (%)	SGDM	81.89	80.88	85.89	83.33
Loss rate		0.5521	0.4411	0.3395	0.2395
Run time (minutes)		5.30		4.50	

Table 4. Classification using Inception ResNet v2

Parameter	Training method	Learning rate			
		0.001		0.0001	
		Training	Testing	Training	Testing
Accuracy (%)	ADAM	94.29	92.34	96.75	94.55
Loss rate		0.3943	0.2023	0.1047	0.1156
Run time (minutes)		2.59		2.51	
Accuracy (%)	SGDM	90.14	89.51	92.38	91.54
Loss rate		1.4584	1.2452	0.7450	0.8452
Run time (minutes)		5.12		4.55	

Otherwise, when large number of learning rate are used, the accuracy is slightly lower. Overall, the most outstanding performance was recorded using ADAM with greater than 93% accuracy across all architectures (AlexNet, Inception ResNet v2 and ResNet-50). In addition, less consumption time has been recorded when compared to SGDM. In comparison to ADAM, SGDM performs slightly worse because the model is unable to recognise the maturity category with high accuracy, as shown in Figure 12.

Overall, it is clear that the ADAM optimizer is capable of producing high accuracy performance in both categories when compared to the SGDM optimizer. In terms of model evaluation time, ADAM was found to be less time consuming than SGDM, which is thought to be more efficient for dealing with a wide range of image classification problems. This result is clearly proven by Rajakumari and Kalaivani [23], which shows that good performance can be achieved with different optimizers when training is evaluated on different image datasets. AlexNet has the best architecture, outperforming Inception ResNet v2 and ResNet-50 using the ADAM optimizer in terms of accuracy. With less processing time, this model is more effective and capable of detecting the size and colour of chili fruit with high accuracy. Furthermore, multi label classification is believe to be another suitable approach that might be used to distinguish various types of chili fruits (color, size, specises) in parallel [24]. This invention also helps farmers or agricultural practitioners to empowering the use of AI in algricultural autonomus robot [25]. In addition, we also had some experiment on recognition of ghost pepper and chili padi using an object detection in real-time detection [26], [27].

Table 5. Classification using ResNet-50

Parameter	Training method	Learning rate			
		0.001		0.0001	
		Training	Testing	Training	Testing
Accuracy (%)	ADAM	90.45	89.54	95.98	93.38
Loss rate		0.1654	0.2284	0.1856	0.2854
Run time (minutes)		4.21		3.32	
Accuracy (%)	SGDM	89.54	89.44	92.45	89.64
Loss rate		0.5421	0.4421	0.4021	0.4285
Run time (minutes)		4.45		4.38	

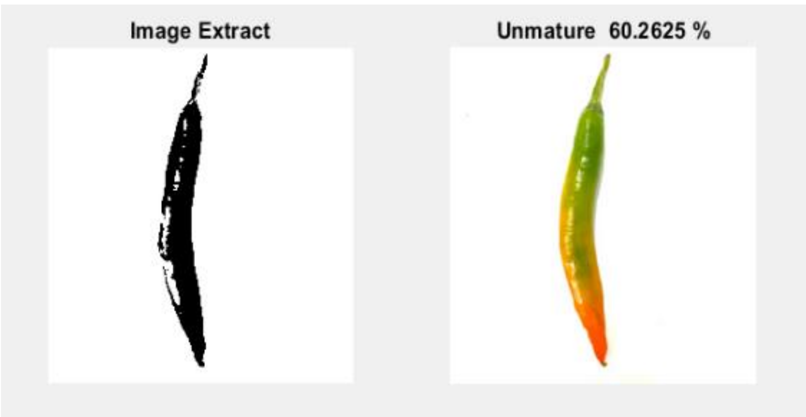


Figure 12. Testing performance using SGDM optimizer

4. CONCLUSION AND FUTURE WORK

The goal of this work which analyses the maturity and class variety of chili fruit using a CNN model. The length of chili fruits is calculated by calculating from two points: calyx and apex, and it is classified into three maturity categories: immature, moderate mature and mature. In this case, a deep learning CNN model is investigated and implemented. Simultaneously, various optimizers such as ADAM and SGDM are used with various CNN architectures to analyse recognition accuracy. We chose 90% as our benchmark, as stated in our desired performance. However, when it comes to recognising the size of a chili, ADAM outperforms SGDM by a significant margin. In terms of optimizer comparison, ADAM is considered as the best and most suitable for real-time when compared to SGDM. This is due to ADAM optimizer combines the features of stochastic gradient descent with momentum and RMSProp techniques to provide the best solution for sparse gradients. In terms of architecture, AlexNet is regarded as the best because it achieves high accuracy on average for whole experiments.

It would be ideal in projection if a dual or stereo camera was used to collect the dataset. Because stereo cameras can capture additional depth information than standard cameras, the position and exact size of an object can be estimated. This can also be applied to a proposed fruit picking robot, where depth information can be extracted to define the precise position of the fruits. The image is corrected, and the distance from a camera image can also be estimated. As a result, another point cloud in 3D perspective can be obtained, which is thought to be useful for estimating the size and maturity of the chili fruit based on its position. On the other hand, multi label classification would be used to define the maturity and category of chili fruits. As a result, using multi label classification problems where the algorithm is able to classify various type of classes at the same time in parallel, the proposed algorithm can classify and recognise the maturity of chili fruits as well as the class of chili fruits as green, red, or brownish. AI or machine learning can also be used to investigate or diagnose faults in machines or fruit picking robots.

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