Available online at
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e-ISSN: 2689-4934

ESTEEM Academic Journal Vol 20, September 2024, 183-199

ESTEEM
Academic Journal
(EAJ)

Development of fig fruit ripeness classification using convolutional neural network

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ARTICLE INFO

Article history:
Received 26 June 2024
Revised 21 August 2024
Accepted 26 August 2024
Online first
Published 30 September 2024

Keywords:
Convolutional neural network
Figs
Fruit ripeness
Fruit classification
Performance evaluation

DOI:
10.24191/esteem.v20iSeptember.1837.g1829

ABSTRACT

This study presents the design and evaluation of a deep convolutional neural network (CNN) model for accurately classifying fig ripeness stages. Traditionally, fruit ripeness classification has been conducted manually, which presents several drawbacks, including heavy reliance on human labor and inconsistencies in determining fruit ripeness. By leveraging advanced deep learning techniques, specifically CNNs, this research aims to automate the fig ripeness classification process. The CNN architecture was developed and trained using MATLAB software, targeting three ripeness categories: ripe, half-ripe, and unripe. The methodology involved pre-processing the fig images and configuring the CNN model with multiple convolutional, batch normalization, and max pooling layers specifically for fig classification tasks. The final CNN model achieved an impressive accuracy rate of 94.44%, significantly surpassing results from previously reported studies. The developed model is a promising tool for automating fig ripeness classification, contributing to advancements in precision agriculture and smart farming technologies.

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https://doi.org/10.24191/esteem.v20iSeptember.1837.g1829

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1. INTRODUCTION

Agriculture plays a significant role in Malaysia's economy, where the demand for high-quality food is steadily rising. Current agrotechnology trends that use modern technology in agriculture enhance both yield and efficiency. With the advancement of digital technology nowadays, fruit production specifically can be produced effectively. Various technologies contribute to achieving optimal outcomes, including blockchain technology for supply chain management systems, machine learning (ML), greenhouse and controlled environment agriculture systems, and many more. Notably, machine learning (ML), deep learning (DL), and artificial intelligence technologies are key contributors to produce optimal agriculture output.

In today's market, consumers place great emphasis on fruit quality, particularly its ripeness. Over time, researchers have developed various methods to address the issue of fruit ripeness classification, which has had a significant impact on farmers [1-4]. In agriculture, the classification of fruit ripeness is important because it directly affects both consumer health and fruit quality.

This study focuses on the fig fruit, specifically *Ficus carisa* L. Figs are highly nutritious, providing a rich source of dietary fiber, vitamins, and minerals. They also contain a variety of amino acids, are high in fat, and are free of cholesterol. Like other fruits, figs contain organic acids and sugars that affect their quality, similar to other fruit species [5]. To meet the high demand for fig production, a breeding program is necessary to select new fig cultivars with good qualities for fresh fruit consumption, such as rich flavor, an acceptable balance of sweetness and sourness, and good post-harvest performance [6].

Traditionally, fruit ripeness has been assessed manually, a method that presents several limitations. Manual assessment relies heavily on human labor, often resulting in inconsistencies [7]. It requires significant time and effort, as each fruit must be visually assessed, touched, and sometimes even cut or squeezed to evaluate its ripeness. This process can become particularly burdensome when dealing with large quantities of fruits. Moreover, the subjective nature of manual assessment introduces variability, as different individuals may have different interpretations of fruit ripeness [8]. This subjectivity can lead to human error, with factors such as perception biases, personal judgment, and individual experience influencing the assessment [9].

There are two methods for assessing fruit ripeness: destructive and non-destructive [10]. The destructive method involves manually opening the fruit to assess ripeness, which damages the fruit and renders it unsellable. As a result, farmers prefer non-destructive methods that enable accurate ripeness assessment without damaging the fruit.

Consequently, there is a growing demand for non-destructive methods that can determine the ripeness without damaging the fruit. As interest in non-destructive methods for fruit ripeness classification increases, researchers have proposed automated approaches. For instance, studies such as [11-15] explore automated fruit ripeness classification, acknowledging that traditional methods may lead to inconsistencies.

Various automated approaches using ML and image processing (IP) techniques have been developed to classify the ripeness of different fruit samples. However, integrating IP with ML often requires considerable effort and human intervention for accurate ripeness classification.

Additionally, the results produced from IP techniques can also be inconsistent. To overcome the problem, researchers are exploring deep learning-based approaches based on convolutional neural networks (CNN) for fruit ripeness classification. Despite significant research on common fruits such as apples, mangoes, and strawberries, little attention has been given to exotic fruits like figs.

To the best of the authors' knowledge, studies focusing specifically on fig ripeness classification using CNNs remain scarce. This research aims to bridge the gap by using a CNN model to classify the ripeness of figs. The paper is organized as follows: Section 2 reviews related studies on ML and DL CNN models for fruit ripeness classification. Section 3 outlines the methodology of the study. Section 4 presents and

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discusses the results. Finally, Section 5 concludes the study and proposes potential future research directions.

2. RELATED WORKS

To address the challenge of determining fruit ripeness, researchers have developed various solutions utilizing advanced technologies. These solutions incorporate IP, ML, and DL techniques to effectively classify fruit ripeness. Image processing encompasses operations such as image acquisition, pre-processing, segmentation, and feature extraction to enhance image quality or extract valuable information. These techniques aim to improve visual appearance and enable the extraction of specific features for further evaluation. The next subsection presents related works on fruit ripeness classification using these approaches.

2.1 Machine learning

In the past, determining the ripeness of fruits relied on manual inspection. This process was not only time-consuming and labor-intensive but also subjective. To overcome these issues, researchers have increasingly turned to advanced technologies. For example, Castro et al. [12] employed ML techniques to classify the ripeness of cape gooseberry fruit. These methods increase the accuracy of ripeness classifications by employing several color spaces and IP techniques. Some promising methods applied in this field involve artificial neural networks (ANNs), K-nearest neighbor (KNN), support vector machines (SVMs), and decision trees. The study evaluated three color spaces (RGB, Lab, and hue saturate value (HSV)) for assessing the ripeness of cape gooseberry. Their findings indicated that the combination of SVM and the Lab color space outperformed other methods in terms of accuracy.

Worasawate et al. [11] employed ML techniques to classify the ripeness of mangoesThey applied four ML techniques: k-means, naïve Bayes, SVM, and feed-forward artificial neural network (FANN). The performance of these models was evaluated using four-fold cross-validation. Consequently, the FANN classifier achieved the highest mean accuracy of 89.6% across categories of unripe, ripe, and overripe mangoes.

A fuzzy classification method based on color cues was examined in the work by Hamza and Chtourou [16] to categorize the maturity of apples. Their system classified apples into three categories: unripe, ripe, and mature.. The fruit images were divided into four parts using the KNN algorithm: the background, the green area, the yellow area, and the red area. The results indicated that the trained fuzzy classifier outperformed ANN (98.33%), OAO multi-SVM (96.66%), and OAA multi-SVM (96.66%), with an accuracy rate of almost 99.33%. This demonstrates that the trained fuzzy classifier outperforms other current techniques in terms of accuracy and execution time.

Sudana et al. [12] proposed KNN classification for the identification of coffee fruit maturity. They implemented a mobile application using digital IP, where the HSV color space was used to obtain color features of the coffee fruits. The maturity of the coffee fruits was classified into three categories: ripe, half-ripe, and unripe. The results obtained from the testing demonstrated an accuracy of 95.56%.

Wang and Chai [17] introduced a novel feature extraction method aimed at improving the accuracy of pineapple ripeness classification through the application of fuzzy logic. Their research used three categories of ripeness: unripe, ripe, and fully ripe. Consequently, the system achieved an accuracy of 86.05%. Kamelia et al. [18] developed a system that classifies the ripeness level of bananas using the KNN algorithm based on the HSV color space. Their classification system also comprises three categories: unripe, ripe, and rotten. As a result, this system attained an accuracy of 93.333%.

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While ML approaches have been extensively used in fruit classification, they come with limitations related to feature dependence and complexity. As a result, DL techniques, particularly convolutional neural networks (CNNs), have gained popularity for improving fruit classification accuracy by allowing automatic feature extraction from raw image data.

2.2 Deep learning approach

MacEachern et al. [19] proposed a DL CNN to assess the ripeness and estimate the yield of wild blueberry fruit. The study utilized two distinct classification models: a 3-class model that categorized red berries, green berries, and blueberries, and a 2-class model that differentiated between unripe and ripe berries. Six networks were used in their research, including YOLOv3-Tiny, YOLOv3- SPP, YOLOv3, YOLOv4-Tiny, YOLOv4- Small, and YOLOv4. The results indicated that YOLOv4 outperformed other models, achieving a mean of 79.79% and an average precision of 88.12%. This result was further validated by YOLOv4, which attained the highest F1-score of 0.82.

Vasumathi and Kamarasan [20] proposed a methodology that combines CNN and long short-term memory (LSTM) DL to classify pomegranates into two categories: normal and abnormal. In this work, CNNs were utilized for deep feature extraction, while LSTM networks were employed to classify the extracted features. The proposed system attained an accuracy of 98.17%, a specificity of 98.65%, a sensitivity of 97.77%, and an F1-score of 98.39%.

Palakodati et al. [13] applied a DL approach to classify fresh and rotten fruits using CNN for apples, bananas and oranges. The work focused on three types of fruits: apples, bananas, and oranges. A CNN was utilized to extract features from the input fruit images, while the SoftMax function was applied to categorize the images as either fresh or rotten. The proposed model achieved an accuracy of 97.82%, with its performance evaluated on a dataset downloaded from Kaggle. In the study by Hamza and Chtourou [16], a fuzzy classification approach based on color features was investigated to classify fruit ripeness.

Sari et al. [21] developed a CNN integrated with augmented reality to innovate fruit quality classification. This study focused on classifying fruits using augmented reality combined with a CNN. The system could recognize seven types of fruits: apples, bananas, mangoes, oranges, pears, pineapples, and strawberries. The application works by scanning real fruits with a smartphone, subsequently providing information on fruit quality along with three-dimensional images for comparison. This functionality assists farmers to easily distinguish between high- and low-quality produce. The fruit dataset used comprises 1,260 images across seven categories, with 85% of the images designated for training and 15% for testing. The proposed model achieved an accuracy rate of 98.74%.

Pachon-Suescun et al. [22] proposed the use of a CNN with a Directed Acyclic Graph (DAG)structure for the identification and quality detection of fruits. In their study, they examined eight types of fruits: bananas, lemons, lulos, mangoes, oranges, strawberries, tamarillos, and tomatoes, to determine the type of fruit and its condition. As a result, they achieved approximate processing times of 45–55 ms, with an accuracy of 94.43% in classifying 1,600 test images.

Cho et al. [14] proposed a prediction system that combines deep neural networks and ML to automatically classify the ripeness of fruits. For data collection, they manually collected image data of strawberries and tomatoes from a website, which included four ripening stages: unripe, partially ripe, ripe, and overripe. The results indicated a classification rate of 84% for the combination of MobileNet v2 and a multi-layer perceptron (MLP), which is a model with a combination of DL and ML, respectively.

Sitohang et al. [23] presented a presented a CNN with transfer learning using the VGG16 model for fruit ripeness detection. Instead, the MLP block was added to replace the top-layer VGG16. The study classified the ripeness of four types of fruits (mangoes, tomatoes, oranges, and apples), which were categorized into two classes: ripe and unripe. Consequently, the VGG16 transfer learning architecture

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achieved performance accuracies of 0.90, 0.84, and 0.76, when employing dropout, batch normalization, and regularization kernel, respectively.

Gill et al. [24] developed a multi-model fruit image identification system utilizing CNN, recurrent neural network, and LSTM DL techniques to identify various fruit species. The types of fruits used in their study were red apples, green apples, golden apples, guavas, and oranges, with respective accuracies of 98.51%, 98.54%, 98.56%, 98.03%, and 98.23%. In addition, the average accuracy achieved was 98.37%.

Huang et al. [25] proposed a fuzzy mask R-CNN model to automatically classify the ripeness levels of tomatoes. The tomatoes were divided into four categories based on their harvestability: immature (completely green), breaker (green to tannish), preharvest (light red surface), and harvest (fully colored tomato). They used 100 tomato images for sample detection, achieving an accuracy of 98.00%. For the ripeness classification of tomatoes, the overall recall rates and weighted precision were 0.9591 and 0.9614, respectively, using 98 tomatoes.

Although various methods have been developed for fruit ripeness classification across different fruit types, there is a significant gap in studies specifically focused on fig ripeness classification. Furthermore, the application of CNN in this context has yet to be unexplored. This study aims to fill this research gap by employing a CNN approach to classify the ripeness of figs. The following section presents the methodology used to develop the proposed CNN model for fig ripeness classification.

3. METHODOLOGY

This section outlines the methodology developed for classifying fig ripeness using a CNN. The process begins with data processing, which includes data collection and image pre-processing, followed by the development, training, and validation of the CNN model. Finally, the performance of the system is evaluated. Fig. 1 depicts the process of the entire system. In this study, MATLAB software was employed, particularly for constructing and training the CNN. MATLAB's interface facilitates the definition of the CNN architecture, including the specification of the number and types of layers, as well as the setting of relevant hyperparameters. Furthermore, this software also provides tools for evaluating the performance of the trained CNN model.

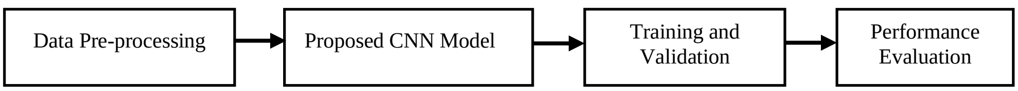

Fig. 1. Steps involved in the development of fig classification using CNN

3.1 Data processing

In this project, the fig variety being classified is the Super Red Hybrid. The datasets used in this study were obtained from [26]. The datasets comprise 150 images, which are further divided into three sets as follows: stage S1 with 50 images of unripe figs (S1), stage S2 with 50 images of half-ripe figs (S2), and stage S3 with 50 images of ripe figs (S3).

Table 1 shows a sample of images of the datasets from these three different categories. Each fig sample was captured from different angles, including the front, back, left, bottom, and top, ensuring a diverse range of viewpoints. This comprehensive approach facilitates a thorough examination of the physical characteristics of the fruits, thereby increasing the accuracy and comprehensiveness of the analysis.

Table 1, Table 2, and Table 3 present the samples from the datasets for S1, S2, and S3, respectively. It can be observed that different stages of ripeness and maturity in figs exhibit distinct color variations,

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transitioning from green to purple based on their ripeness level. In Stage 1, as exemplified in Table 1, the figs are unripe and predominantly green with hints of red. In Stage 2, as depicted in Table 2, the fruits are half ripe, becoming more reddish with less green coloration. Finally, in Stage 3, as shown in Table 3, the figs reach full ripeness, showing a deep red or purple hue. Most farmers consider harvesting figs at stages S2 and S3, which are considered the edible stages [10].

Before developing the CNN model, the datasets undergo image pre-processing. This process involves techniques such as resizing and cropping to improve the quality of the acquired sample images, making them suitable for analysis by the CNN model. Resizing ensures all dataset images have consistent sizes and dimensions, facilitating efficient batch processing. Cropping extracts the region of interest of the figs, allowing the model to focus on the relevant parts of the image for accurate fig ripeness classification.

Table 1. Sample dataset for unripe figs (Stage 1) from various viewpoints

Category	**Front**	**Left**	**Right**	**Back**	**Bottom**
S1 Sample 1					
S1 Sample 2					
S1 Sample 3					

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Table 2. Sample dataset for half-ripe figs (Stage 2) from various viewpoints

Category	Front	Left	Right	Back	Bottom
S2 Sample 1					
S2 Sample 2					
S2 Sample 3					

Each image in the dataset for this study was resized to a standard size of 100 pixels by 100 pixels. This resizing guarantees consistency and suitability for the training and evaluation processes. By resizing the images to a smaller size, it reduces the computational process, which can be beneficial for training large datasets and optimizing the performance of CNN model. The resized images were then fed into the CNN architecture, enabling the model to learn and extract significant features from the fig images for accurate ripeness classification. Additionally, the images were processed using the RGB color model, which is commonly used in IP. This model represents colors through three primary colors of red, green, and blue. Each image was segmented into three separate color channels, which were then used in the training process to calculate the accuracy of the model. By integrating color information from the RGB channels, the model can effectively capture and utilize color-related features for accurate classification of fig ripeness

The dataset utilized for this study comprised a training set and a validation set. Accordingly, 30% of the images were allocated for validation, while the remaining 70% were used for training. The training set is necessary to train the CNN model to classify images according to their level of ripeness. During training, the CNN gradually adjusted its internal parameters to reduce classification errors as it learned to identify and extract relevant characteristics from the images. Conversely, the performance of the trained model was assessed using the validation set. The trained CNN receives images from the validation set and uses them to provide predictions for the ripeness categories. The subsequent subsection discusses the development of the CNN for determining the maturity of figs.

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Table 3. Sample dataset for ripe figs (Stage 3) from various viewpoints

Category	Front	Left	Right	Back	Bottom
S3 Sample 1					
S3 Sample 2					
S3 Sample 3					

3.2 Proposed CNN model

The CNN architecture, as depicted in Fig. 2, consists of multiple convolutional layers, followed by several fully connected layers. The CNN model can be divided into two main blocks: feature extraction and classification. During feature extraction, the network performs a series of convolutional and pooling operations to identify relevant features. The initial layer serves as the input layer, containing various images of figs depending on their ripeness. These captured images undergo filtering and pre-processing before image extraction, which relies on the fig color. The model also includes convolutional layers and batch normalization layers, which are also known as hidden layers. Furthermore, the pooling layer, responsible for reducing input image dimensions (such as image features), plays a crucial role in this process. Lastly, the fully connected layer categorizes the pre-processed fig images into three ripeness categories, performing as the output in this study.

As illustrated in Fig. 3, building the proposed CNN model comprises several essential components: convolutional layers, rectified linear unit (ReLU) activation function, and pooling layers. The convolutional layer applies convolution operations to the input data to extract features such as textures and shapes. Its primary function is to detect spatial hierarchies in the data. Next, the ReLu introduces non-linearity to the model, enabling it to learn more complex patterns by replacing negative values with zero while keeping positive values unchanged.

Next, the pooling layer—commonly referred to as max pooling or average pooling—is employed to reduce the spatial dimensions of the features. This down-samples the input image, reduces computational load, and retains important features. After passing through several convolutional and pooling layers, the network reaches the fully connected layers, where high-level reasoning is performed. These layers combine all the extracted features to make final classification decisions. Lastly, the SoftMax function, which serves as the final layer in a classification CNN, converts the output into probabilities for each class, allowing the network to make definitive classifications.

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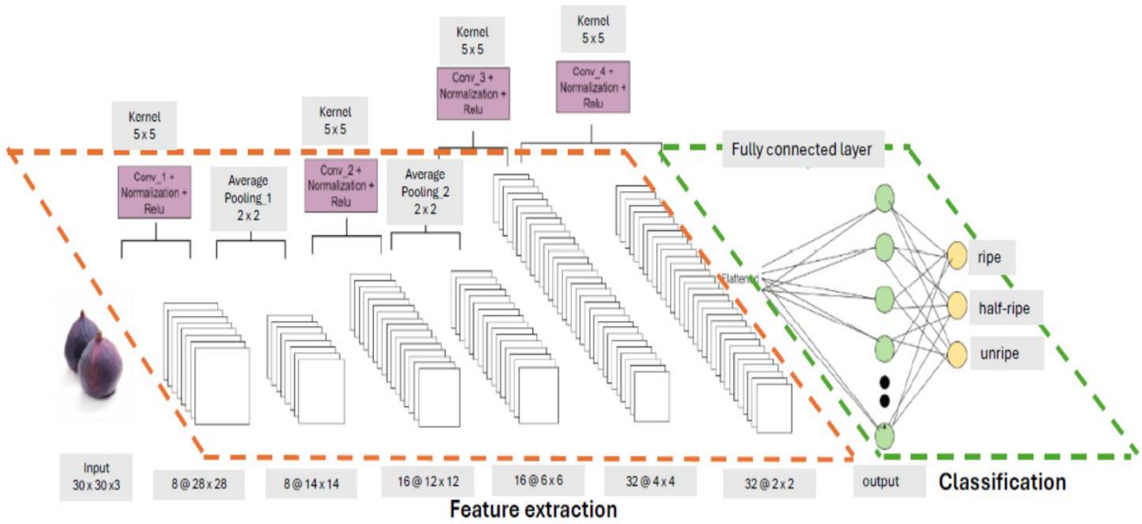

Fig. 2. General architecture of a CNN

In this study, the proposed architecture of the CNN for fig classification is illustrated in Fig. 3. The CNN comprises 22 layers, allowing it to capture complex and abstract features from the input data, thereby enhancing performance in tasks like image classification. The architecture starts with an input layer that defines the image dimensions at 100 × 100 pixels. Convolutional layers with 32, 64, 128, and 256 filters extract spatial patterns and produce feature maps. Four batch normalization layers were included to improve accuracy.

Additionally, four max pooling layers were used instead of average pooling layers due to the ability of max pooling to preserve important features while reducing spatial dimensions, which is beneficial for detecting visual cues related to fig ripeness. Max pooling selects the maximum value within each region, helping to retain essential features like color variations and textural details that are crucial for distinguishing between ripe, half-ripe, and unripe figs. Following this, a fully connected layer with 512 neurons was added. The SoftMax layer produces class probabilities for classification, and lastly, the final classification layer determines the predicted class (ripe, half-ripe, or unripe). The final parameters used in the proposed CNN are listed in Table 4.

In addition to the proposed CNN method, its performance was compared with common CNN models, such as Inception [27], SqueezeNet [28], VGG16 [29], and VGG19 [29]. This comparison serves as a guideline to evaluate the effectiveness of the proposed method.

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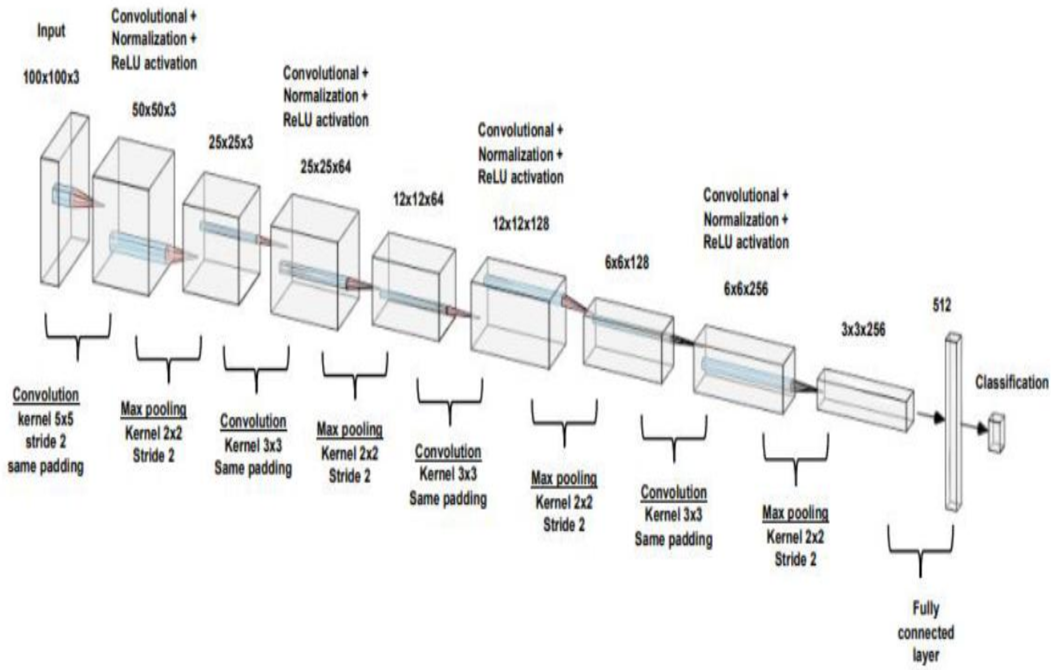

Fig. 3. The proposed CNN model with varying layers

Table 4. The parameters of the proposed CNN layer

The Proposed CNN Layers	CNN Layers
• 1 image input layer	imageInputLayer
• 4 convolutional 2D layers	convolution2dLayer(filter size=5x5, # of filter = 32, stride=2, same padding)
• 4 batch normalization layers	batchNormalizationLayer
• 4 maximum pooling layers	reluLayer
• 5 ReLU layers	maxPooling2dLayer(pooling size = 2x2, stride =2)
• 2 fully connected layers	convolution2dLayer(filter size=3x3, # of filter = 64, stride=2, same padding)
• 1 SoftMax layer	batchNormalizationLayer
• 1 classification layer	reluLayer
• Total: 22 layers	maxPooling2dLayer(pooling size = 2x2, stride = 2)
	convolution2dLayer(filter size=3x3, # of filter = 128, stride=2, same padding)
	batchNormalizationLayer
	reluLayer
	maxPooling2dLayer(pooling size = 2x2, stride =2)
	convolution2dLayer(filter size=3x3, # of filter = 256, stride=2, same padding)
	batchNormalizationLayer
	reluLayer
	maxPooling2dLayer(pooling size = 2x2, stride =2)
	fullyConnectedLayer(# of neuron = 512)
	reluLayer
	fullyConnectedLayer(# of neuron = numClasses)
	softmaxLayer
	classificationLayer

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3.3 Testing and validation process

During the training process in fig ripeness classification using CNN, the model engages in iterative learning to recognize and extract meaningful features from the input images. The process begins with the random initialization of the weights and biases of the CNN. The model was then exposed to the training dataset, and forward propagation was performed to generate predictions for the ripeness categories. These predictions were compared to the ground truth labels, and the performance of the model was assessed using a loss function that measures the classification error. Backpropagation, an optimization algorithm, computes the gradient of the loss function with respect to the parameters of the CNN. This gradient was used to update the weights and biases of the network in a way that minimizes the classification error. By iteratively repeating this process across different batches of the training dataset, the CNN gradually fine-tunes its parameters and improves its ability to classify accurately the ripeness of figs.

The training process aims to optimize the performance of the CNN and enable it to automatically learn discriminative features for effective ripeness classification. If the performance does not reach the desired value, the model needs to be modified again by either adjusting the parameters in the CNN algorithm or varying the architecture layers of the CNN. However, if the performance is already satisfied, it will proceed to the next step, which is the performance evaluation of the CNN model.

3.4 Performance evaluation

After training the CNN using the labeled dataset and optimizing its parameters, the performance of the model was evaluated using the validation dataset. The images from the validation set were fed into the trained CNN, and the model generated predictions for the ripeness categories. These predictions were then compared to the ground truth labels of the images. Performance metrics such as precision (Eq. 1), recall (Eq. 2), F1-score (Eq. 3), and accuracy (Eq. 4) were calculated to measure the classification performance of the model. Accuracy reflects the overall correctness of the prediction of the model, while precision measures the proportion of correctly classified positive instances (ripe, half-ripe, or unripe fruits) out of all instances predicted as positive. Recall, also known as sensitivity, represents the proportion of actual positive instances that the model correctly classifies. The F1-score is a balanced metric that combines precision and recall. These metrics provide valuable insights into the ability of the model to correctly classify fig ripeness levels.

$$Precision = \frac{TP}{TP + FP} \tag{1}$$

$$Recall = \frac{TP}{TP + FN} \tag{2}$$

$$F1\ score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{3}$$

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$$Accuracy = \frac{TP - TN}{TP + TN\,FP + FN} \tag{4}$$

Where *TP*, *FP*, *TN*, and *FN* stand for true positive, false positive, true negative, and false negative, respectively. These metrics are derived from the confusion matrix, which reflects the classification performance of the model. By analyzing these evaluation metrics, necessary adjustments can be made to the CNN model or the training process to enhance its performance and improve the accuracy of fig ripeness classification. In this study, the evaluation of the performance of the model focused on the accuracy score. Accuracy provides a comprehensive assessment of the overall correctness of the classification results, taking into account both true positives and true negatives.

4. RESULTS AND DISCUSSION

In this work, prior to assessing the accuracy of fig ripeness using the proposed method, the initial results were evaluated. Utilizing the same dataset, several common CNN models, Inception v3, SqueezeNet, VGG-16, and VGG-19 were assessed based on the performance evaluation metrics. The results obtained from these models are summarized in Table 5. Various evaluation metrics were employed, including accuracy, F1-score, precision, and recall. Accuracy measures overall performance, while precision and recall assess the ability of the model to correctly predict positive instances. The F1-score provides a balanced perspective by considering both precision and recall, enabling informed judgments regarding the effectiveness of the model.

From the results, both SqueezeNet and VGG-16 achieved the highest accuracy at 88.7%, followed by VGG-19 at 88.0% and Inception v3 at 87.3%. The confusion matrices obtained for these models are shown in Fig. 4 for Inception v3, SqueezeNet, VGG-16, and VGG-19 respectively. In the figure, the classes S1, S2, and S3 correspond to the unripe, half-ripe, and ripe categories, respectively. The diagonal numbers highlighted in the figures represent correct predictions, which can be used to calculate metrics such as accuracy, precision, and recall for each model.

In this study, the highest accuracy of 94.44% was achieved using the CNN architecture as proposed in Fig. 3. This accuracy was obtained using the final modified MATLAB code for the CNN architecture layers, as listed in Table 4. When compared to the previous work by Ikmal et al. [26], which did not employ a CNN approach, our proposed CNN model significantly outperformed theirs while using the same dataset of figs. While the method of Ikmal et al. achieved an accuracy of 91.67%, our approach reached 94.44% in classifying fig ripeness. Additionally, when comparing this result with the initial results summarized in Table 5, it is evident that the proposed method surpassed other established CNN models, such as Inception v3 (87.3%), SqueezeNet (88.7%), VGG-16 (88.7%), and VGG-19 (88%). This highlights the success of the approach in automating and enhancing the accuracy of fruit ripeness classification.

Table 5. Performance evaluation of fig ripeness using various common CNN approaches

CNN Model	Accuracy	F1-Score	Precision	Recall
Inception v3	87.3	87.4	87.6	87.3
SqueezeNet	88.7	88.6	88.6	88.7
VGG-16	88.7	88.8	89.6	88.7
VGG-19	88.0	88.1	88.5	88.0

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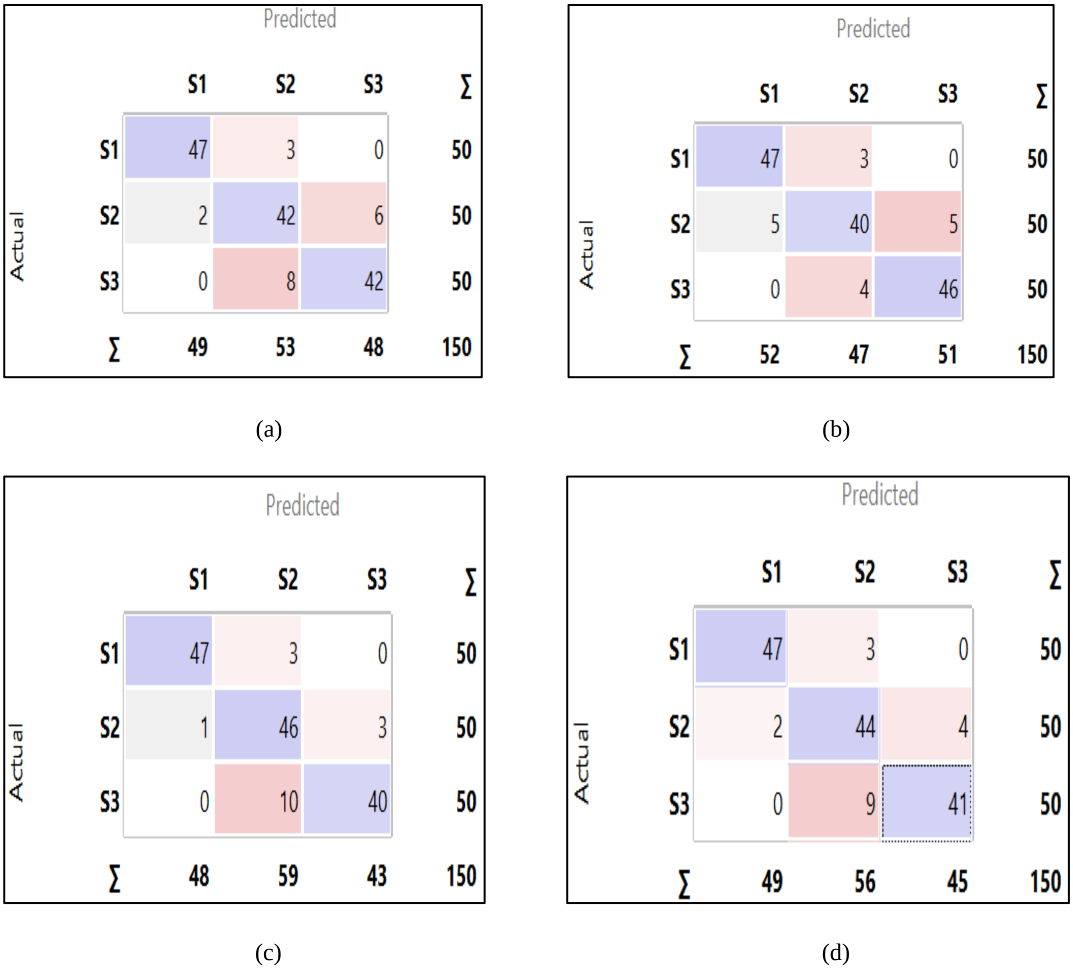

Fig. 4. Confusion matrix for (a) figs using Inception v3, (b) figs using SqueezeNet, (c) figs using VGG-16 , and (d) figs using VGG-19

Furthermore, the study examines the effect of different CNN layers on accuracy. Several experiments were conducted to assess the effectiveness of these layers. Table 6 summarizes the results, demonstrating how the addition of batch normalization and average pooling layers influences accuracy. The findings highlight that variations in layer architectures can significantly affect accuracy. Adjusting the layers helps prevent overfitting, which occurs when the network becomes too complex and memorizes the training data rather than generalizing to new examples. Experimenting with various layer configurations allows for a balance between complexity and generalization. The conclusion drawn from this analysis is that altering the CNN layer architecture has a substantial effect on overall accuracy.

These findings highlight the significance of selecting an appropriate number of layers and designing an optimal CNN architecture to maximize accuracy in fruit ripeness classification. The study demonstrates the effectiveness of the DL approach in accurately determining fig ripeness. The developed CNN architecture serves as a reliable tool for automating and improving the accuracy of fruit ripeness assessment, specifically in the context of figs.

https://doi.org/10.24191/esteem.v20iSeptember.1837.g1829

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Table 6. Experimental results on varying CNN layers

Changes Made to CNN Layers	CNN Layers	Accuracy (%)
Adding one layer of batch normalization	convolution2dLayer(5,20) batchNormalizationLayer reluLayer fullyConnectedLayer(numClasses) softmaxLayer classification layer;	70.37
Adding one layer of batch normalization and one layer of average pooling	imageInputLayer(inputSize) convolution2dLayer(filter size=5x5) batchNormalizationLayer reluLayer averagePooling2dLayer(5, Stride= 2, Padding 1x 0 convolution2dLayer(filter size=5x5) reluLayer fullyConnectedLayer(numClasses) softmaxLayer classificationLayer;	83.33
Adding two layers of batch normalization and one layer of average pooling	imageInputLayer(inputSize) convolution2dLayer(filter size=5x5) batchNormalizationLayer reluLayer averagePooling2dLayer(5, Stride= 2, Padding 1x 0 convolution2dLayer(filter size=5x5) batchNormalizationLayer reluLayer fullyConnectedLayer(numClasses) softmaxLayer classificationLayer;	90.74

5. CONCLUSION

This study successfully developed a deep cnn model to reliably classify the ripeness stages of figs. By employing modified cnn techniques, the study showed that the traditional categorization process could be automated. The cnn model achieved a high accuracy of 94.44% using matlab software, showcasing the effectiveness of this deep learning (DL) technique and surpassing previous studies on fig maturity classification. The outcomes indicate the potential of cnn architecture as a reliable tool for automating and enhancing the evaluation of fruit maturity, particularly for figs. The successful application of this cnn technique paves the way for advancements in fruit quality management and streamlining the harvesting procedure. Future research could explore different network architectures, including different layer configurations and network depths, to identify more effective models for classifying fig ripeness. Additionally, optimizing hyperparameters such as learning rate and batch size may further enhance the accuracy of the model.

6. ACKNOWLEDGMENT

The authors would like to thank Universiti Teknologi MARA, Cawangan Pulau Pinang, especially the members of the Machine Learning Research Group (MLRG), Electrical Engineering Studies, College of Engineering for their support and assistance in completing this research work.

https://doi.org/10.24191/esteem.v20iSeptember.1837.g1829

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7. CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest regarding the publication of this paper.

8. AUTHORS' CONTRIBUTIONS

Siti Juliana: Conceptualization, data collection, data analysis, technical paper writing, and editing format; **Hanis Raihana Musa**: Conceptualization, investigation, methodology, data collection, data analysis, report writing; **Mohamed Syazwan Osman**: Dataset collection; **Mohamed Mydin M Abdul Kader**: Conceptualization; **Denis Eka Chayani**: Conceptualization; **Samsul Setumin**: Supervision and validation.

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