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Classification of Strawberry Ripeness Stages Using Deep Learning

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Abstract

The issues related with the labor-intensive, inflexible, and error-prone manual classification of strawberries in supply chain are the focus of this project. The objective of the project is to accurately classify different stages of strawberry ripeness based on color by creating an effective deep learning system using MATLAB. The procedure is gathering a sizable dataset of images of strawberries taken at different stages of ripeness, pre-processing the images, and then using the image processing toolbox in MATLAB to extract relevant features. The pre-processed dataset was used to train convolutional neural network (CNN) models, such as CNN in MATLAB and YOLOv5 in Google Colab. The mean average precision (mAP) of 0.922 (50%), recall of 0.939, and precision of 0.887 were all attained by the YOLOv5 mode which is equivalent to 92.2% accuracy. The CNN model trained over several epochs with up to 100% accuracy. In the end, this automated system increases agricultural productivity by minimizing errors and manual labor while guaranteeing product quality and consistency throughout the strawberry supply chain.

1. Introduction

In Malaysia's supply chain, the manual classification of strawberries is time-consuming, unspecific, and responsible to mistakes. These difficulties affect the effectiveness and precision of distinguishing between various stages of ripeness, which is essential for ensuring quality. This work, which focuses on strawberry ripeness based on color, uses deep learning techniques [1] to automate the classification process in order to address these problems. It used Google Colab's YOLOv5 and MATLAB to create an automated method. This system consists of gathering a sizable dataset of images of strawberries taken at different stages of ripeness, pre-processing each image, and using Convolutional Neural Networks (CNN) to classify the images. The objective is to develop an accurate model that can precisely identify the ripeness stage of strawberries through using deep learning. High accuracy has been shown by the models trained for this project, indicating that this approach has the potential to successfully replace conventional manual classification techniques. Deep learning has been the subject of several recent studies, with some noteworthy works investigating fruit classification using conventional machine learning techniques. For example, Ibba et al. (2021) [2] classified strawberries into binary categories based on bioimpedance data. Using sophisticated deep learning models, our method overcomes the shortcomings of the previous approaches in terms of accuracy and generalizability to different environments.

This project intends to create a deep learning-based system that uses color as the primary indicator to automatically classify strawberry ripeness stages in order to address these issues. The accuracy required for a reliable assessment of strawberry ripeness is lacking in conventional techniques, such as color detection using

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simple sensors or manual inspection. These techniques are inappropriate for large-scale farming, where quickness and accuracy are essential. The YOLOv5 model in Google Colab and convolutional neural networks (CNN) in MATLAB are used in this system to accurately classify strawberries into three ripeness stages: immature, nearly mature, and mature. The project's main goal is to assess these models' efficiency in terms of recall, accuracy, precision, and detection speed. The images are taken from Google Images and Kaggle, and they are enhanced using augmentation techniques like scaling, rotation, and resizing to increase variability and boost the capacity of the models to generalize. To maintain consistency, all of the images undergo pre-processing, which includes resizing each one to 256 by 256 pixels and applying color correction as needed.

For classification, Google Colab's YOLOv5 model is picked for its real-time object detection capability, which makes it appropriate for fast-paced environments, while MATLAB's CNN model is chosen for its high accuracy in intricate classification tasks. To maximize performance, both models are trained using different batch sizes and epochs on the pre-processed dataset. Then, measures like accuracy, precision, recall, F1-score, and detection speed are used to assess how effective these individuals have become. The one that is more suitable for practical uses in the strawberry supply chain can be identified through this comparison.

In order to guarantee that the classification system operates efficiently in the given environment, the project intends to incorporate particular regional requirements into the model. This entails modifying the models to take into consideration variations in strawberry growth and appearance brought on by various climatic circumstances. The project's ultimate goal is to optimize the supply chain procedure in addition to improving ripeness detection accuracy. The system is anticipated to decrease errors, eliminate manual labor, and guarantee a more consistent product quality by automating the classification. By using this method, strawberry farming and distribution operations should become much more efficient. It also offers a scalable solution that can be extended to other crops and agricultural industries in the future.

2. Methodology

The method used to categorize strawberries based on their level of ripeness is described by system design. Fig. 1 illustrates the block diagrams that each determine the project's implementation process. Using MATLAB software on the laptop, the general block diagram for the deep learning flow is shown in Fig. 1. The original input for the project is represented by the strawberry image. Subsequently, the strawberry image will be processed through a deep learning algorithm, resulting in a classified output image.

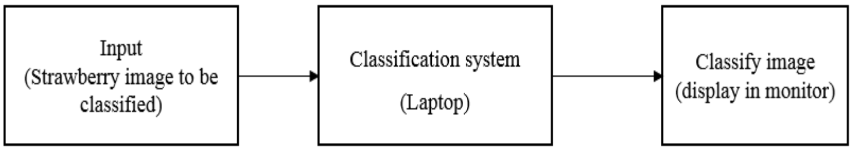


Fig. 1 *Block diagram of proposed system*

2.1 Development of the Proposed System

The image is trained through a step-by-step process as shown in Figure 1. First, information or a picture of the strawberry must be gathered. The collected image will first undergo pre-processing. Following that, the image will go through training to obtain accuracy. The image will be trained again until the best outcome is obtained if the accuracy of the training image is insufficient. The models are used to categorize fresh images of strawberries once they achieve an excellent level of accuracy. In order to identify the ripeness stage immature, nearly mature, or mature the pre-processed images must be given into the trained models in the final classification stage.

Loading the original, 256x256 pixel dataset images is the first step in the pre- processing process for strawberry classification (Fig. 2). To guarantee consistency in input dimensions for the model, these images are subsequently resized to a standard size. After the resizing process, an optional augmentation step is implemented, in which every image is multiplied to generate augmented versions. This enriches the dataset with transformations such as rotation, scale, and other variations, thereby improving the robustness of the model. By exposing the model to a greater range of data variations, this augmentation process lowers the risk of overfitting and helps in the model's learning of solid characteristics. After that, the final pre-processed photos are prepared for training. According to the flowchart (Fig. 3), the model starts a retraining phase (Fig. 4) during the training stages when it determines that an image does not accurately represent an immature, nearly mature, or mature stage. Based on misclassifications, this entails modifying the model's parameters, which are subsequently confirmed by more testing. Before being deployed finally, this iterative process makes sure the model gains more accuracy.

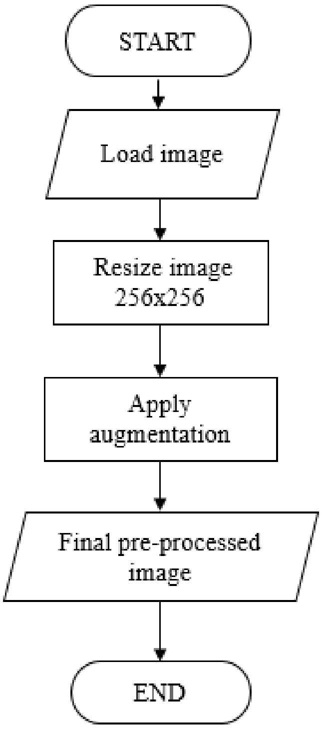


Fig. 2 *Flowchart of Training Stages*

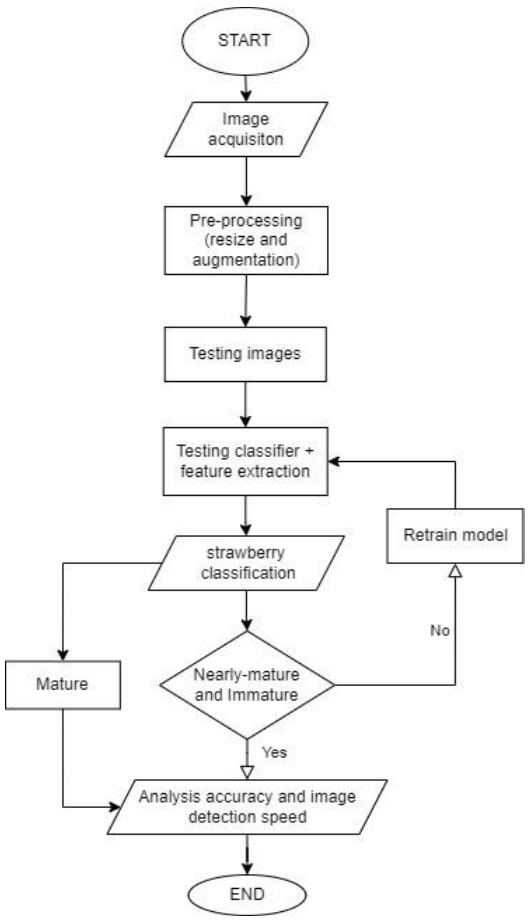


Fig. 3 *Flowchart of Testing Stages*

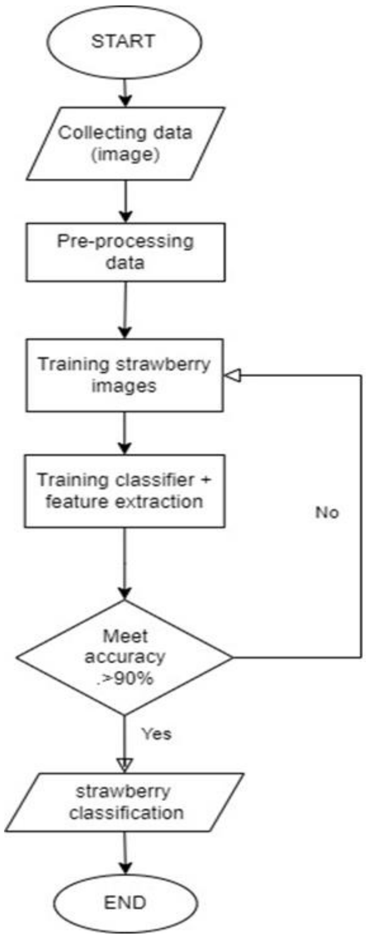


Fig. 4 *Flowchart of Training Stages*

2.2 Image Dataset and CNN Training

The training dataset included 245 images of mature strawberries, 220 images of immature strawberries, and 255 images of nearly mature strawberries, for a total of 720 training images. The model was tested on a dataset with 8 images for each ripeness class, or 24 test images. The images in the dataset were resized to 256 by 256 pixels, as shown in Fig. 5. These photos were taken from a variety of websites, but Kaggle offered the largest collection of accessible images [7]. CNN and YOLOv5 were selected due to their demonstrated ability to perform object detection and classification tasks. CNN's accuracy is appropriate for demanding classification tasks, while YOLOv5's real-time detection capability makes it perfect for deployment in hectic environments. The selection of parameters, including batch size and number of epochs, was based on their impact on the learning rate and overall performance of the model. For instance, a batch size of 64 made sure that generalization and training speed were balanced.

Fig. 5 *Images in the dataset that are used for training*

Convolutional Neural Networks (CNN) have significantly improved computer vision by frequently outperforming people in image classification tasks. CNNs automatically identify key characteristics that indicate different ripeness stages when classifying strawberries. The CNN model has the following layers.

- Activation Layers. These layers add non-linearity to help the network learn complex relationships.
- Max Pooling Layers: These layers reduce the spatial dimensions of feature maps without losing important information.
- Softmax Layer: This layer assigns a probability distribution across output classes, allowing the network to predict the ripeness stage with the highest probability.
- Image Input Layer: This layer specifies the input image dimensions and channels.
- Convolutional Layers: These layers identify features like edges and textures.

This convolutional neural network (CNN) architecture can handle images up to 256 x 256 pixels in size and three RGB color channels refer to Fig. 6. It consists of four convolutional layers, each of which is followed by ReLU activation to add non-linearity and batch normalization for stable training, thereby improving the model's capacity to learn complex patterns [6]. The feature maps are then down sampled using max-pooling layers with a 2x2 window and a stride of 2, which lowers computational complexity and increases translation invariance. A fully connected layer with 256 neurons is added after the convolutional layers in order to aggregate the learned features and carry out high-level reasoning.

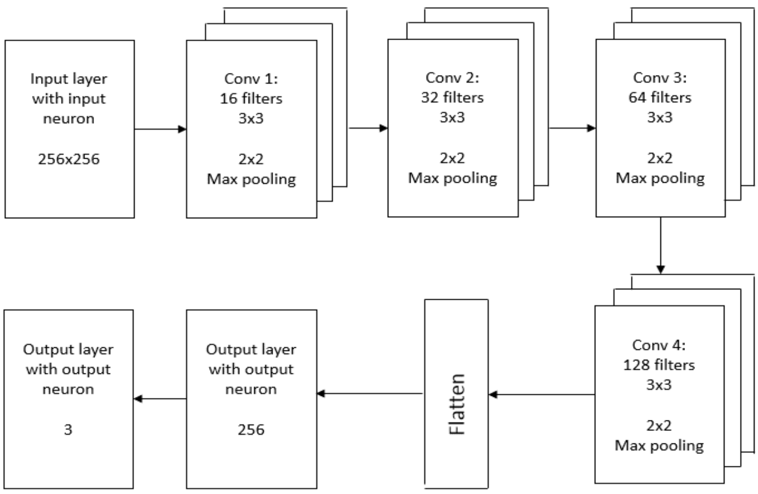


Fig. 6 *CNN model structure for strawberry ripeness classification*

2.3 Metrics for Performance Evaluation

Different metrics can be used to measure performance in a variety of domains, including object detection, image classification, and deep learning tasks.

A table called a confusion matrix is used to explain how well a classification model performs. It displays the total number of accurate and inaccurate predictions separated into by class. Accuracy is determined by dividing the number of correctly predicted situations by the total number of instances in the dataset.

$$\boldsymbol{Accuracy} = \frac{TP + TN}{TP + FP + TN + FN}$$

$$\boldsymbol{Precision} = \frac{TP}{TP + FP}$$

$$\boldsymbol{Recall} = \frac{TP}{TP + FN}$$

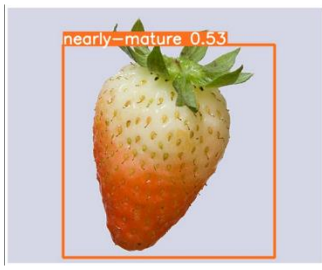
$$\boldsymbol{F1\ Score} = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

By figuring out what percentage of all predictions both positive and negative are accurate, accuracy assesses a model's overall correctness. Recall evaluates the model's capacity to recognize all true positive cases, while precision concentrates on the accuracy of positive predictions [5]. The F1 score, which combines recall and precision, offers a balanced metric. Elevated values in these metrics signify a dependable model that reliably distinguishes between various classes, accurately predicting outcomes and effectively identifying true positives.

3. Result and Discussion

3.1 Comparison MATLAB and YOLOv5

Table 1 *Comparison accuracy between MATLAB and YOLOv5*

	MATLAB	YOLOv5
Mature		
Nearly mature		
Immature		

The accuracy of MATLAB and YOLOv5 in divided strawberries into three ripeness categories mature, immature, and nearly mature is evaluated in Table 1. The same set of images was used to test MATLAB and YOLOv5, with each system trained to identify the designated ripeness stages. The YOLOv5 model's reduced elapsed time for image classification indicates that its optimized architecture for real-time object detection is the reason for its faster detection speed. On the other hand, CNN's deep-layered architecture, which enables more thorough feature extraction, is responsible for its higher accuracy.

According to Table 2's results, the trained model performs well as it comes to identifying the ripeness of new images of strawberries. Mature and immature strawberries achieve accuracy levels of 87.5% and 100%, respectively, while nearly mature strawberries achieve a 75% accuracy level. Eight newly acquired images that were not seen during training were used to test each ripeness category, suggesting the model's good expansion to new data. The model's sensitivity to edge cases is highlighted by an analysis of misclassifications that shows how frequently nearly mature strawberries were confused for mature ones, most likely because of minute color differences.

Table 2 *Detection Accuracy for Testing Images*

Class	Number of Testing images	Correct Detections	Incorrect Detections
Mature	8	7	1
Nearly mature	8	6	2
Immature	8	8	0
Total	24	21	3

The performance metrics for dividing strawberries into three ripeness stages mature, nearly mature, and immature are shown in Tables 3 and 4. The confusion matrix is displayed in Table 3 and includes a list of each class's true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN). The total accuracy is determined to be 99.54%. A thorough performance evaluation with precision, recall, and F1-score for every class is given in Table 4. With the mature category displayed the best performance and the nearly mature category showing slightly lower recall, the results show high precision and recall across all classes, pointing to an overall solid classification system.

Table 3 *Confusion matrix for 3 classes*

Class	True Positives (TP)	True Negatives (TN)	False Positives (FP)	False Negatives (FN)
Mature	49	95	0	0
Nearly mature	44	99	0	1
Immature	50	93	1	0
Total	143	287	1	1

$$\boldsymbol{Accuracy} = \frac{TP + TN}{TP + FP + TN + FN}$$

$$\boldsymbol{Accuracy} = \frac{143 + 287}{143 + 1 + 287 + 1}$$

$$\frac{430}{432} = 0.99537$$

Table 4 *Performance Evaluation According Two Detection Classes*

Class	Precision	Recall	F1-Score
Mature	1	1	1
Nearly mature	1	0.9778	0.9888
Immature	0.9804	1	0.99

3.2 Accuracy for the Training Process

The results of training a Convolutional Neural Network (CNN) to categorize strawberry ripeness at various epochs and batch sizes are shown in Table 5. The model, which took 6:39 minutes to train, produced a mini-batch accuracy of 96.88% and a validation accuracy of 97.92% in 5 epochs with a batch size of 32. On the other hand, a minor drop in validation accuracy to 95.83% over 12:44 minutes was observed when the number of epochs was increased to 10. The model maintained a lower mini-batch accuracy of 92.19% in 12:59 minutes, but a validation accuracy of 97.92% in 10 epochs when using a batch size of 64. The model with a batch size of 64 achieved 100% validation accuracy in 25:39 minutes, and perfect mini-batch accuracy in 20 epochs. This shows that longer training times and larger batch sizes improve model performance significantly.

Table 5 *The Result of the Comparison*

Epoch	Batch size	Mini-batch accuracy (%)	Validation accuracy (%)	Time elapsed (min)	Base learning rate
5	32	96.88	97.92	6:39	0.001
10	32	96.88	95.83	12:44	0.001
10	64	92.19	97.92	12:59	0.001
20	64	100	100	25:39	0.001

A Convolutional Neural Network (CNN) can be trained to classify various categories of strawberry ripeness, as shown in Fig. 7. It creates directories for every ripeness level, from fully ripe to almost ripe strawberries, and loads images from these directories into distinct image datastores. Based on the directory names, labels are assigned to create a unified image datastore with corresponding categorical labels. The data is shuffled in order to maintain randomness during training. After that, a CNN architecture is described, consisting of convolutional, batch normalization, max-pooling, and fully connected layers at the front, followed in order by softmax and classification layers. After that, the provided labels and image data are used to train the CNN.

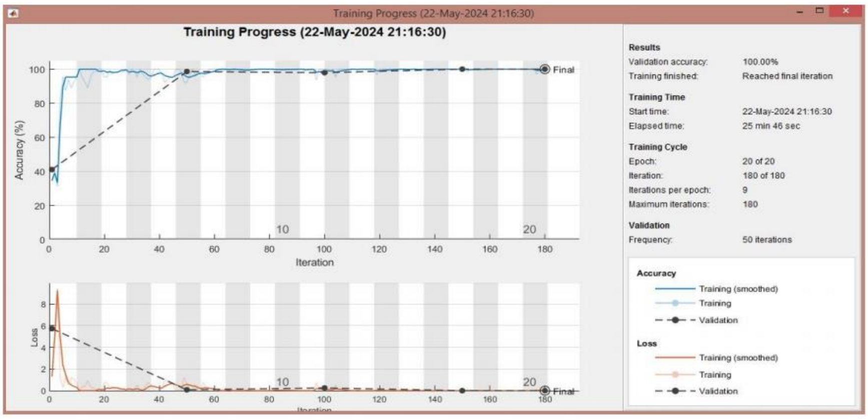


Fig. 7 *Training progress*

3.3 Detection Speed of Testing Images

To be able to classify strawberry ripeness into mature, nearly mature, and immature categories, Table 6 presents a comparison of the image detection speeds of MATLAB and YOLOv5. We used eight images per class. Using a speed of 1.90 images per second, MATLAB was able to identify mature strawberries in 4.2 seconds, nearly mature strawberries in 6.3 seconds, and immature strawberries in 7.8 seconds. While immature strawberries were identified in 5.8 seconds at 1.3 images per second, nearly mature strawberries were identified in 4.5 seconds at 1.73 images per second, and mature strawberries in 3.0 seconds at 2.67 images per second by YOLOv5. These findings suggest that YOLOv5 outperforms MATLAB in all categories for strawberry ripeness detection.

Faster image processing is provided by Google Colab, but there are some disadvantages as well, including limited resources, an internet connection requirement, and restricted software control. Although Google Colab offers more processing speed and cloud resource accessibility, MATLAB offers a more complete toolkit, optimized algorithms, offline usability, and a rich integrated development environment.

The proposed CNN and YOLOv5 models have demonstrated impressive results in identifying different stages of strawberry ripeness. As seen in Fig. 8, the MATLAB model obtained perfect training and validation accuracy at 15.1%, whereas the YOLOv5 model only managed 15% accuracy. By contrast, accuracy rates of 12% to 14% were usually reported for earlier techniques. These developments highlight how deep learning techniques can reliably and accurately classify strawberry ripeness, which makes them very useful for real-world agricultural applications. This accomplishment is consistent with the project's aim of creating an accurate and effective classification system.

4. Conclusion

This project effectively illustrates the use of convolutional neural networks (CNN) for strawberry ripeness classification. The CNN model's efficiency was greatly enhanced by the MATLAB-based pre-processing, resizing, and augmentation stages, which standardized and increased the diversity of the image dataset.

The model performed very well, as demonstrated by the training process results, which are shown in Table 5. For both metrics, the validation accuracy reached 100% and the mini-batch accuracy reached 100% at 20 epochs with a batch size of 64. When new images were used to validate the testing procedure, the results revealed an overall accuracy of 90% for almost mature strawberries and 100% for both mature and immature strawberries. The model's robustness and reliability were further confirmed by the confusion matrix and performance metrics (precision, recall, and F1 score).

There are certain limitations, even though the study's accuracy in determining strawberry ripeness is quite high. Nearly-mature strawberries proved challenging for the model to classify, suggesting that more accurate classification is required. Subsequent investigations may explore the utilization of complex models, such as transformers, and broaden the dataset to encompass diverse crops and environments. Testing the system with bigger datasets and real-world scenarios, like farms with different lighting, would also be beneficial.

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Conflict of Interest

Authors declare that there is no conflict of interests regarding the publication of the paper.

Author Contribution

The authors confirm contribution to the paper as follows: ***design and development:*** *Wan Mohamad Syakir;* ***data collection:*** *Wan Mohamad Syakir;* ***analysis and interpretation of results:*** *Wan Mohamad Syakir;;* ***draft manuscript preparation and revision:*** *Wan Mohamad Syakir, Mohamad Hairol. All authors reviewed the results and approved the final version of the manuscript.*

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