JURNAL IPTEK
MEDIA KOMUNIKASI TEKNOLOGI
homepage URL : ejurnal.itats.ac.id/index.php/iptek

Implementation of Convolutional Neural Network in Detecting Avocado Ripeness Level

Miclyael Luge, Zulfahmi Indra, Hermawan Syahputra, Said Iskandar Al Idrus, Kana Saputra S.
Department of Mathematics, Universitas Negeri Medan, Indonesia

ARTICLE INFORMATION

Jurnal IPTEK – Volume 29 Number 1, May 2025

Page:
11–18
May 30, 2025

DOI:
10.31284/j.iptek.2025.v29i1.6737

ABSTRACT

Squeezing avocados to determine ripeness can cause physical damage or bruising, reducing the fruit's quality and resulting in losses for sellers and buyers. This research aims to develop an Android-based mobile application to detect avocado ripeness based on skin color, avoiding physical damage to the fruit. The study uses three simple Convolutional Neural Network architectures to evaluate the algorithm's ability to detect avocado ripeness. The dataset includes 385 images across four classes: immature, half-ripe, ripe, and overripe (74 images each), and an additional 89 images for the non-avocado class. The model was trained with learning rates of 0.001, 0.0001, and 0.00001. The architecture with the most convolutional layers achieved the best performance with a 0.001 learning rate, yielding a test accuracy of 94.15%, a test loss of 19.28%, and an F1-score of 94.0%. The best model was then converted to TFLite format and successfully integrated into an Android application that functions effectively.

Keywords: *Android application; Avocado; Convolutional Neural Network; Deep Learning; Machine learning*

E-MAIL

miclyaelluge@mhs.unimed.ac.id
zulfahmi.indra@unimed.ac.id
hsyahputra@unimed.ac.id
kanasaputras@unimed.ac.id
saidiskandar@unimed.ac.id

PUBLISHER

LPPM- Institut Teknologi Adhi Tama Surabaya
Address:
Jl. Arief Rachman Hakim No. 100, Surabaya 60117,
Tel/Fax: 031-5997244

ABSTRAK

Meremas buah alpukat untuk mengetahui tingkat kematangannya dapat menyebabkan kerusakan fisik atau memar pada buah. Memar pada buah mengurangi mutu pada buah Alpukat dan menyebabkan kerugian baik pagi penjual dan pembeli. Penelitian ini bertujuan untuk membangun sebuah aplikasi mobile berbasis Android yang dapat mendeteksi tingkat kematangan buah Alpukat berdasarkan warna kulit buah untuk menghindari kerusakan fisik buah Alpukat. Penelitian ini menggunakan tiga arsitektur Convolutional Neural Network sederhana untuk menguji kemampuan algoritma dalam mendeteksi tingkat kematangan buah Alpukat. Dataset yang digunakan pada penelitian berjumlah 385 data dengan kelas belum matang, setengah matang, matang dan terlalu matang masing-masing berjumlah 74 gambar dan 89 gambar untuk kelas non-Alpukat. Penelitian ini menggunakan *hyperparameter learning rate* 0.001, 0.0001, dan 0.00001. Model dengan peforma terbaik dihasilkan oleh arsitektur dengan lapisan konvolusi paling banyak dengan learning rate sebesar 0,001 dengan nilai akurasi uji sebesar 94,15%, *loss* uji sebesar 19,28%, dan F1-*score* sebesar 94,0%. Model terbaik kemudian disimpan ke dalam format TFLite dan berhasil diimplementasikan ke aplikasi Android dan aplikasi dapat berjalan dengan semestinya.

Keyword: *Alpukat; Aplikasi Android; Convolutional Neural Network; Deep Learning; Machine Learning*

INTRODUCTION

Avocado, or *Persea americana*, is a plant native to Mexico and Central America. It is believed that avocados were introduced to Indonesia in the 18th century. In Indonesia, avocados are known by different names, such as *alpuket* (West Java), *alpokat* (East/Central Java), and *buah pokat/jambu pokat* (North Sumatra). The most commonly used part of the avocado plant is its fruit, which can be eaten directly or processed into various types of food [1]. In Indonesia, there are 20 different varieties of avocado, with *Alpukat Mentega* being one of the most common. Avocado is consumed when it reaches the ripe stage due to its sweet and savory taste. Unripe or semi-ripe avocados are avoided because of their bitter and sour flavor. The softness of the avocado is generally the main factor in determining its ripeness. Avocados that are approaching maturity become softer compared to those that are still unripe or semi-ripe [2]. Some studies suggest that avocados are generally sorted by assessing their softness or by shaking the fruit [3]. This method is effective for determining avocado ripeness, but the fruit is at risk of physical damage if squeezed excessively. Such damage accelerates the rotting process, leading to material losses for both buyers and sellers. An alternative method for determining avocado ripeness is by observing the skin color. Besides being non-destructive, there is a significant correlation between color change and the fruit's ripeness, making color observation a strong alternative for assessing avocado maturity [4].

Research on detecting avocado ripeness through skin color has been conducted in previous studies. A study by Saputra in 2023 implemented the K-Nearest Neighbor method and achieved an accuracy rate of 80%. However, the resulting model was less effective at detecting semi-ripe avocados, where the accuracy obtained was 66% [5]. Furthermore, a study conducted by Nuryani implemented the Naïve Bayes method and achieved an accuracy rate of 83%.[6]. Lastly, a study conducted by Mukhofifah used RGB value weighting as the basis for classifying ripeness levels, achieving an accuracy rate of 73.33% [7]. These three studies yielded less than perfect accuracy rates and did not produce a system that could be easily accessed by the general public for detecting avocado ripeness. Therefore, this research focuses on developing a model that is more accessible to the general public and creating a detection system that is superior to previous studies.

Convolutional Neural Network (CNN) is a deep learning method that works by detecting objects in images, which are then categorized based on patterns derived from the input image with dimensions *m x n* provided by the user [8]. CNN is a popular method used in image classification because it has higher scalability, can handle various types of images effectively, and can identify relevant features without human supervision [9]. CNN has demonstrated strong capabilities in image classification. This is evidenced by several studies, such as the classification of Badami Mangoes to determine ripeness levels, which resulted in a model with an accuracy of 97.2% [10], next, the identification of ripeness levels in papaya fruit resulted in a model with an accuracy of 97% [11], Lastly, the classification of ripeness in fig fruit resulted in a model with an accuracy of 94% [12]. These three studies achieved testing accuracies above 80%, indicating that the models developed are suitable for identifying fruit ripeness. Building on these successes, this research contributes to the field by developing a CNN model specifically tailored for avocado ripeness detection, addressing gaps in previous studies and leveraging CNN's strengths for improved performance.

Given the issues related to avocado ripeness and the effectiveness of CNN in processing relevant features in images, the author assumes that a CNN model capable of classifying avocado ripeness levels could be a solution for automating the detection of avocado ripeness. To facilitate access to the model, the CNN developed will be implemented on smartphones. The choice of smartphones is supported by data from Badan Pusat Statistik, which indicates that approximately 89.45% of households in Indonesia have access to smartphones [13]. Therefore, access to smartphones is not a challenge for farmers, distributors, or buyers.

LITERATURE REVIEW

Avocado

Avocado (*Persea americana Mill.*) is a tropical fruit that belongs to the Lauraceae family and the Laurales order. Avocado is generally consumed when ripe, as unripe avocados tend to have a bitter taste and a hard texture. In addition to assessing the softness of the fruit, the ripeness of avocados can also be determined by the color of their skin. For example, *alpukat mentega* that is not ripe has a bright green color, which becomes darker as it approaches maturity [14].

Convolutional Neural Network

Convolutional Neural Network (CNN) is a neural network architecture commonly used for image classification problems. CNNs are similar to Artificial Neural Networks (ANNs) in that both consist of neurons that optimize themselves through learning, following a similar learning process. Each neuron in a CNN receives input, performs operations such as dot multiplication, and is followed by a non-linear activation function [15]. The structure of a CNN generally consists of an Input Layer, Convolution Layer, Pooling Layer, and Fully Connected Layer/Hidden Layer. The operation of a CNN is divided into several stages, flow of these stages can be seen in Figure 1 [16].

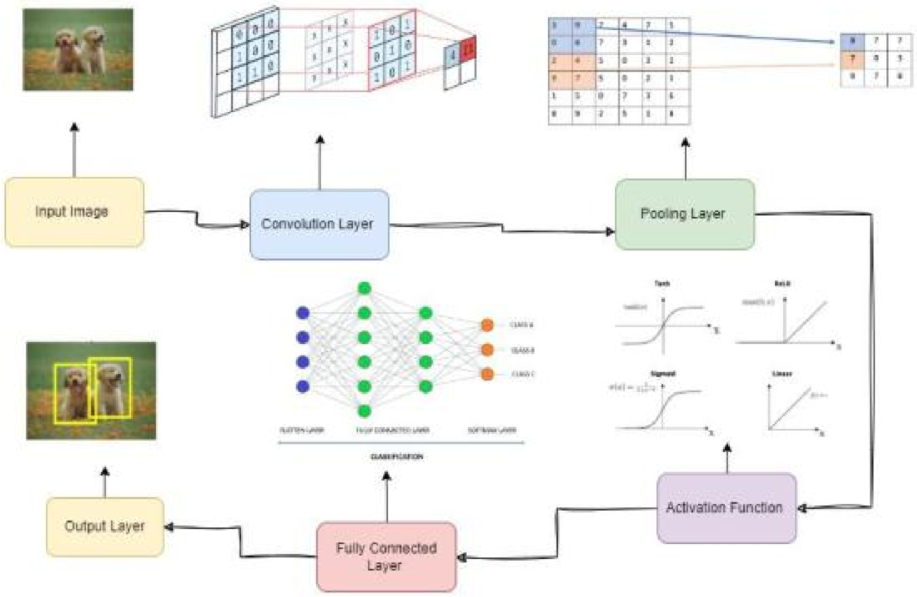

Figure 1. CNN algorithm flow.

Image data enters the input layer as a matrix or tensor of size $m \times n \times d$ where d is the number of channels. The convolution layer extracts features using kernels, producing feature maps. The pooling layer, such as max or average pooling, reduces dimensions while preserving key features to improve efficiency. The fully connected layer then learns complex feature relationships and outputs probabilities via activation functions like softmax or sigmoid. Over multiple epochs, backpropagation updates weights using optimization algorithms like SGD or ADAM to minimize loss.

METHOD

The research method used in this research is quantitative research, using numerical data that is processed with certain formulas to get results based on calculation [17]. This research method centered around testing the capability of Convolutional Neural Network based on the calculation of the model accuracy. Steps of method that used in this research can be seen in Figure 2.

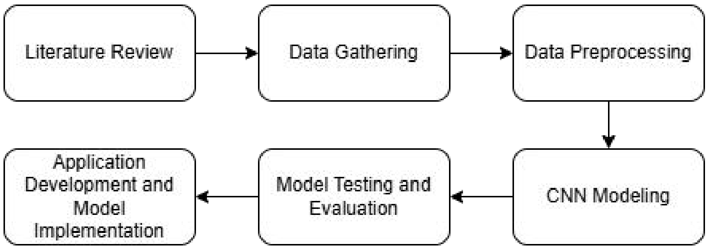

Figure 2. Research flow.

Literature Review

Literature review is a stage of research conducted to understand and strengthen knowledge about the subject and methods to be used in the study. The literature review serves to build foundational references about the subject and methods through academic sources such as books and journals.

Data Gathering

The data used in this research consists of images of alpukat mentega at various stages of ripeness, as well as images of non-avocado items. The avocado images are categorized into four types: unripe, semi-ripe, ripe, and overripe. The avocado images were taken directly using a digital camera at a distance of no more than 40 cm for each shot, while the non-avocado images were obtained through web scraping. A total of 74 images were captured for each ripeness stage and 89 images for the non-avocado data, resulting in a total of 385 data samples.

Data Preprocessing

Before model training, the collected images were processed to improve accuracy. This involved resizing images to 272×272 pixels and applying image augmentation techniques such as rescaling, rotation, flipping, and adding random noise. Rescaling normalized pixel values to ensure stability, while rotation, flipping, and noise introduction created variations to enhance the model's generalization capability. These preprocessing steps aimed to prepare robust training data for the model.

Convolutional Neural Network Modeling

After undergoing the preprocessing stages, the data will be used for model training. This study utilizes three architectures and two hyperparameters. The architecture refers to the arrangement of layers in the model, while hyperparameters are parameters that can be adjusted to control the model’s performance during the training phase. The selection of architecture and hyperparameters is used to evaluate the effectiveness of the Convolutional Neural Network algorithm in classifying the trained data. The architectures used are presented in Table 1, while the hyperparameters can be found in Table 2.

Model Testing and Evaluation

The trained model was tested using allocated test data, with performance evaluated through a Confusion Matrix. Metrics included training and test accuracy and training and test loss. Accuracy measures correct predictions, while loss reflects the distance between predictions and actual classes. While loss is calculated using Categorical Cross Entropy due to the multiclass nature of the model. Greater emphasis was placed on training accuracy and loss, assessed overall model performance. Formula to calculate both accuracy and loss can be seen in Equation 1 and 2 respectively [18].

Table 1. Architecture layers.

Architecture	Name	Layer Size	Filter Size
1	Input (Rescaling)	(272,272,3)	-
	Convolution1	(272,272,72)	(2,2)
	Max Pooling 1	-	(2,2)
	Convolution 2	(272,272,128)	(2,2)
	Max Pooling 2	-	(2,2)
	Flatten	-	-
	Dense 1	(128)	-
	Dropout 1	(0.5/50%)	-
	Dense 2	(128)	-
	Dropout 2	(0.5/50%)	-
	Dense (Output)	(5)	-
2	Input (Rescaling)	(272,272,3)	-
	Convolution1	(272,272,72)	(2,2)
	Max Pooling 1	-	(2,2)
	Convolution 2	(272,272,72)	(2,2)
	Max Pooling 2	-	(2,2)
	Convolution 3	(272,272,128)	(2,2)
	Max Pooling 3	-	(2,2)
	Flatten	-	-
	Dense 1	(128)	-
	Dropout 1	(0.5/50%)	-
	Dense 2	(128)	-
	Dropout 2	(0.5/50%)	-
	Dense (Output)	(5)	-
3	Input (Rescaling)	(272,272,3)	-
	Convolution1	(272,272,72)	(2,2)
	Max Pooling 1	-	(2,2)
	Convolution 2	(272,272,72)	(2,2)
	Max Pooling 2	-	(2,2)
	Convolution 3	(272,272,128)	(2,2)
	Max Pooling 3	-	(2,2)
	Convolution 4	(272,272,128)	(2,2)
	Max Pooling 4	-	(2,2)
	Flatten	-	-
	Dense 1	(128)	-
	Dropout 1	(0.5/50%)	-
	Dense 2	(128)	-
	Dropout 2	(0.5/50%)	-
	Dense (Output)	(5)	-

Table 2. Hyperparameters.

Name	Type/Value
Loss Function	Categorical Cross Entropy (CCE)
Loss Optimization	Adaptive Moment Estimation (ADAM)
Batch Size (Train and Test)	32
Learning Rate	10^{-3},10^{-4},10^{-5}
Epochs	50,100
Ratio (train data:test data)	70:30

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad \text{.....(1)}$$

$$Loss = -\sum_{j=1}^{C} y_j \log(\hat{y}_j) \quad \text{.....(2)}$$

Android Application Development and Model Implementation

The model with the best evaluation metrics is converted to TFLite format for deployment on Android using the TensorFlow Lite library. This enables the app to classify avocados directly via the camera or uploaded images without an internet connection. Once the user selects an image, the app processes it to generate classification results, displaying the avocado's ripeness level, the model's confidence score, and detailed explanations based on the predicted ripeness level.

RESULTS AND DISCUSSION

Convolutional Neural Network Model Training and Evaluation

Model training was conducted according to the predefined architectures and hyperparameters using Google Colab. The results of the model training based on each architecture and hyperparameter, along with the testing results for each model, can be found in Table 3.

Table 3. Training and testing results.

Architecture	Total Epochs	Learning Rate	Accuracy		Loss		Model Size (MB)
			Train	Test	Train	Test	
1	16/50	10^{-3}	0.9369	0.9255	0.1728	0.2493	289.21
	50/50	10^{-4}	0.5953	0.6507	0.9335	0.8453	
	49/50	10^{-5}	0.4944	0.7305	1.1428	0.9897	
	9/100	10^{-3}	0.7970	0.7907	0.7907	0.5645	
	77/100	10^{-4}	0.9455	0.9302	0.1899	0.2597	
	99/100	10^{-5}	0.7970	0.8372	0.6000	0.5826	
2	16/50	10^{-3}	0.8713	0.9291	0.3315	0.1985	72.54
	33/50	10^{-4}	0.9367	0.9397	0.1852	0.2028	
	49/50	10^{-5}	0.6881	0.8635	0.8489	0.5896	
	12/100	10^{-3}	0.8416	0.8023	0.5059	0.6556	
	59/100	10^{-4}	0.8713	0.8837	0.2595	0.3317	
	99/100	10^{-5}	0.7970	0.8488	0.5927	0.4893	
3	25/50	10^{-3}	0.9278	0.9415	0.1808	0.1928	18.60
	29/50	10^{-4}	0.9254	0.9326	0.2412	0.2209	
	50/50	10^{-5}	0.7053	0.8316	0.7736	0.5793	
	22/100	10^{-3}	0.8416	0.7558	0.3601	0.6153	
	44/100	10^{-4}	0.9158	0.8837	0.2613	0.3315	
	95/100	10^{-5}	0.7921	0.8837	0.5624	0.4164	

Based on Table 3, a smaller learning rate tends to yield less optimal results compared to a larger learning rate. Although some models with good performance are produced with smaller learning rates, the time required to train these models is longer than for those with larger learning rates. More complex architectures tend to produce better performance than simpler architectures. Additionally, the more complex architectures also result in smaller model sizes compared to the other architectures, which is an important consideration due to the size limitations imposed by the TFLite library. The smaller the model size, the faster it can be implemented in the Android application for image classification. The best model was produced by Architecture 3 with a learning rate of 10^{-3} and 50 epochs. Figure 3 compares the best result obtained in this research with similar studies that used different algorithms, based on their test accuracy.

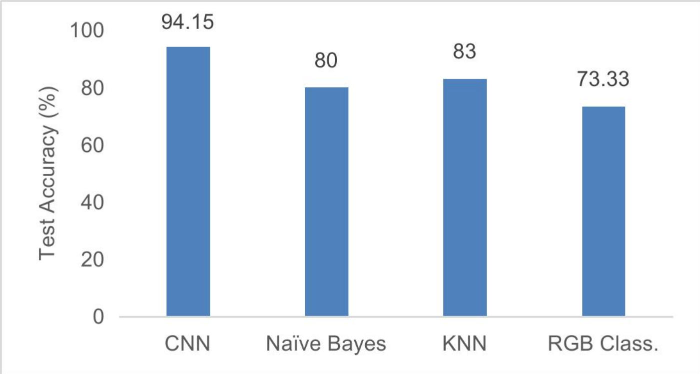

Figure 3. Comparison between similar research.

Android Application Development and Model Implementation

The model is implemented by converting the best-performing model into TFlite format. This file will be directly integrated into the developed Android application. The Android application consists of two pages: the main page for displaying options for capturing avocado images and the detail page for showing classification results and ripeness descriptions. The results of the Android application development and model implementation can be seen in Figure 4.

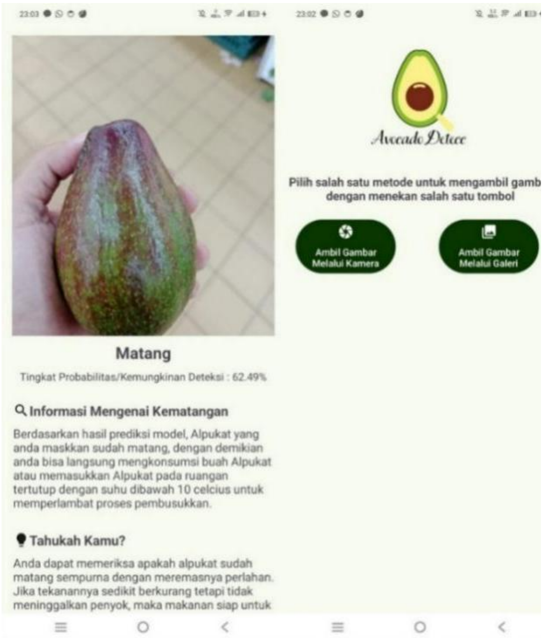

Figure 4. Application and model implementation result.

CONCLUSION

Based on the results of the research conducted on the implementation of Convolutional Neural Networks (CNN) in detecting avocado ripeness levels, the conclusions are as follows: The training and evaluation results indicate that CNN can be used to detect avocado ripeness and achieve a satisfactory performance with a test accuracy of 94.15%, a testing loss of 19.28%, indicating that the model produced is a good fit. Compared to previous research with similar objects, the model obtained in this research has significantly better performance based on their test accuracy values. Furthermore, the model is successfully implemented in a simple Android application, making it easier for people to detect Avocado ripeness based on their skin color.

BIBLIOGRAPHY

[1] K. Prihatman, “Alpukat (Persea americana Mill / Persea gratissima Gaerth),” 2000.
[2] B. Schaffer, N. Wolsentholme, and A. Whiley, *The avocado*, vol. 16, no. 1. 2014. doi: 10.14321/fourthgenre.16.1.0075.
[3] S. S. Harjadi, “AVOCADO PRODUCTION IN INDONESIA,” Bangkok, 2000.
[4] C. A. Jaramillo-acevedo, W. E. Choque-valderrama, G. E. Guerrero-álvarez, and C. A. Meneses-escobar, “Hass avocado ripeness classi fi cation by mobile devices using digital image processing and ANN methods,” vol. 16, no. 12, 2020.
[5] J. Saputra, Y. Sa, V. Yoga, P. Ardhana, and M. Afriansyah, “Klasifikasi Kematangan Buah Alpukat Mentega Menggunakan Metode K- Nearest Neighbor Berdasarkan Warna Kulit Buah,” vol. 3, no. 5, pp. 347–354, 2023.
[6] I. Nuryani, A. M. N. Fadli, N. D. Saputri, A. N. Fadhilah, M. R. A. Yudianto, M. Maimunah, “Classification of Avocado Ripeness Levels using Naïve Bayes Method,” *Prosiding University Research Colloquium*, pp. 468–473, 2022, [Online]. Available: http://repository.urecol.org/index.php/proceeding/article/view/2172
[7] Mukhofifah and E. Nurraharjo, “SISTEM DETEKSI KEMATANGAN BUAH ALPUKAT MENGGUNAKAN METODE PENGOLAHAN CITRA,” vol. 11, no. 1, pp. 12–23, 2019.
[8] M. W. Ilahi1, C. N. Apriyani, A. Desiani, N. Gofar, Y. Andriani, and M. R. Halim, “Classification of Geometric Batik Motif Typical of Indonesian Using Convolutional Neural Network,” vol. 15, no. 1, pp. 91–100, 2022.
[9] L. Alzubaidi *et al.*, *Review of deep learning: concepts, CNN architectures, challenges, applications, future directions*, vol. 8, no. 1. Springer International Publishing, 2021. doi: 10.1186/s40537-021-00444-8.
[10] A. Arkadia, S. Ayu Damayanti, and D. Sandya Prasvita, “Klasifikasi Buah Mangga Badami Untuk Menentukan Tingkat Kematangan dengan Metode CNN,” *Pros. Semin. Nas. Mhs. Bid. Ilmu Komput. dan Apl.*, vol. 2, no. 2, pp. 158–165, 2021, [Online]. Available: https://conference.upnvj.ac.id/index.php/senamika/article/view/1813
[11] A. M. Lesmana, R. P. Fadhillah, and C. Rozikin, “Identifikasi Penyakit pada Citra Daun Kentang Menggunakan Convolutional Neural Network (CNN),” *J. Sains dan Inform.*, vol. 8, no. 1, pp. 21–30, 2022, doi: 10.34128/jsi.v8i1.377.
[12] M. A. Yusman, E. Evanita, and A. A. Riadi, “Klasifikasi Kematangan Buah Tin Menggunakan Convolutional Neural Network Berbasis Android,” *J. Tek. Inform. dan Sist. Inf.*, vol. 9, no. 2, pp. 167–176, 2023, doi: 10.28932/jutisi.v9i2.5701.
[13] B. P. Statistik, “Persentase Penduduk yang Memiliki/Menguasai Telepon Seluler Menurut Provinsi dan Klasifikasi Daerah 2019-2021.” [Online]. Available: https://www.bps.go.id/indicator/2/395/1/persentase-penduduk-yang-memiliki-menguasai-telepon-seluler-menurut-provinsi-dan-klasifikasi-daerah.html
[14] B. H. Cho, K. Koyama, E. Olivares Díaz, and S. Koseki, “Determination of ‘Hass’ Avocado Ripeness During Storage Based on Smartphone Image and Machine Learning Model,” *Food Bioprocess Technol.*, vol. 13, no. 9, pp. 1579–1587, 2020, doi: 10.1007/s11947-020-02494-x.
[15] M. M. Taye, “Theoretical Understanding of Convolutional Neural Network: Concepts, Architectures, Applications, Future Directions,” *Computation*, vol. 11, no. 3, 2023, doi: 10.3390/computation11030052.
[16] E. Seeram and V. Kanade, “Artificial Intelligence in Computed Tomography Image Reconstruction,” in *Artificial Intelligence in Medical Imaging Technology: An Introduction*, Cham: Springer Nature Switzerland, 2024, pp. 125–139. doi: 10.1007/978-3-031-64049-0_7.
[17] J. Rana, P. Lorena, L. Gutierrez, and J. Oldroyd, “Quantitative Methods,” *Glob. Encycl. Public Adm. Public Policy, Gov.*, no. June 2022, 2020, doi: 10.1007/978-3-319-31816-5.
[18] M. Grandini, E. Bagli, and G. Visani, “Metrics for Multi-Class Classification: an Overview,” pp. 1–17, 2020, [Online]. Available: http://arxiv.org/abs/2008.05756