SMATIKA : STIKI Informatika Jurnal
Accredited Sinta 4 Ministry of Higher Education, Science and Technology Republic of Indonesia SK No. 79/E/KPT/2023
E-ISSN: 2580-6939 || P-ISSN: 2087-0256

Avocado Ripeness Classification Based on Digital Imagery Using an Artificial Neural Network

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Keyword

Artificial Neural Network; Avocado; Digital Image; Multi-Class Classification; Ripeness Classification

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Abstract

Traditional methods for determining avocado ripeness rely primarily on subjective visual observation, which is highly prone to error. This study aims to develop an automated classification system for avocado ripeness using a sequential Artificial Neural Network (ANN) based on digital image data. The dataset consisted of 1,500 balanced avocado images distributed across three classes: Ripe (500 images), Rotten (500 images), and Unripe (500 images). A total of 1,200 images were used for training and 300 images for validation. Images were preprocessed through resizing to 128 × 128 pixels and pixel intensity normalization. The proposed ANN architecture consisted of a Flatten layer, two hidden Dense layers with ReLU activation, and an output layer with Softmax activation. Experimental results showed that the model achieved an overall accuracy of 89.00%, with macro-average Precision, Recall, and F1-Score values of 0.92, 0.89, and 0.89, respectively. The best classification performance was achieved for the Rotten class, with a Precision of 1.00 and a Recall of 0.96. Classification errors mainly occurred between the Unripe and Ripe classes, where visual similarities during the ripening transition stage led to cross-class predictions. Overall, the proposed ANN model demonstrated reliable performance for avocado ripeness classification using digital image data and showed its potential as a simple image-based decision-support tool for post-harvest quality assessment.

1. Introduction

The development of image processing and intelligent computing technologies in recent years has significantly transformed the field of precision agriculture, particularly in post-harvest handling of horticultural commodities. The utilization of artificial intelligence based on digital image processing enables fruit quality and ripeness identification to be performed automatically, rapidly, and more consistently compared to conventional manual methods. Conventional fruit ripeness classification generally relies on human visual inspection, making the process subjective, time-consuming, and prone to assessment errors [1]. Previous studies reported that avocado maturity assessment remains challenging because external visual characteristics do not always accurately reflect internal ripeness conditions. Consequently, objective and image-based evaluation methods have become increasingly important for maintaining fruit quality and consumer acceptance [1],[2],[3]. Furthermore, manual sorting processes on a large scale are considered inefficient for supporting the modern food industry, which demands speed, accuracy, and product quality standardization[4]. Several recent studies also emphasized that non-destructive fruit quality evaluation techniques are increasingly important for supporting consistent post-harvest monitoring and reducing product losses in agricultural supply chains [5].

Avocado (*Persea americana*) is one of the high-economic-value horticultural commodities whose ripeness level strongly influences taste quality, shelf life, and market value. Accurate determination of fruit ripeness is essential for maintaining distribution quality and minimizing post-harvest losses [6]. Several studies have investigated machine learning and deep learning approaches for avocado ripeness classification. A YOLOv8-based model has demonstrated high accuracy in classifying avocados into multiple ripeness stages while simultaneously supporting shelf-life prediction [2]. In addition, previous studies have demonstrated that Artificial Neural Network (ANN), digital image processing, and image-based classification techniques are capable of classifying avocado ripeness effectively based on RGB color characteristics, texture, and visual features extracted from fruit images [7],[3]. Furthermore, ANN-based approaches have shown strong predictive capability and high accuracy in processing agricultural classification and forecasting data [7],[8]. Several previous studies also utilized smartphone-based image processing and color transformation techniques such as HSI and RGB extraction to evaluate avocado maturity levels under controlled lighting conditions [9],[10]. Recent studies have also highlighted that machine learning and image-based fruit quality assessment techniques can improve classification consistency and support objective ripeness evaluation in agricultural applications[11]. Similar findings have also been reported in recent image classification studies employing Convolutional Neural Networks (CNNs) and hybrid deep learning models, which achieved high classification performance through automatic extraction of discriminative visual features from image data [12],[13]. Moreover, recent surveys emphasized that deep learning, smart farming technologies, and image-based agricultural monitoring systems play an important role in improving crop monitoring, disease detection, and precision agriculture management [14],[15]. Recent studies also demonstrated that computer vision and deep learning approaches can significantly improve the effectiveness of automated fruit maturity classification and post-harvest quality assessment systems [16].

Although deep learning-based approaches demonstrate excellent performance, complex architectures generally require substantial computational resources, high energy consumption, and high-specification hardware support. These conditions create challenges for implementing automatic classification systems in local farming environments and small-to-medium-scale agricultural operations where computational resources may be limited. Although modern deep learning models have demonstrated high classification accuracy, their substantial computational requirements may limit practical deployment in resource-constrained environments [2]. Furthermore, recent studies in image-based agricultural classification have shown that limited datasets, variations in image acquisition conditions, and insufficient feature diversity may reduce the generalization capability of classification models under real-world environments [5]. In addition, previous studies based on RGB feature extraction and K-Nearest Neighbor classification still reported limitations in classification accuracy and feature discrimination for avocado maturity detection [7],[17]. Recent hyperspectral imaging studies combined with deep learning regression models have also demonstrated high computational complexity and dependency on specialized imaging equipment for avocado ripeness estimation[18]. Moreover, recent studies reported that conventional deep learning architectures are highly dependent on large-scale datasets and tend to suffer from overfitting under limited training conditions, while few-shot learning approaches showed better generalization capability for avocado maturity determination[19]. Several recent multimodal deep learning studies also reported that combining RGB and hyperspectral imaging can improve fruit maturity classification performance, although the approach requires more complex computational processing and larger multimodal datasets[16]. In addition, several recent studies highlighted that advanced multimodal imaging systems and hyperspectral-based deep learning models often require expensive acquisition devices and intensive computational resources, limiting their practical implementation in low-resource agricultural environments [20],[21].

On the other hand, most previous studies have primarily focused on identifying fruit ripeness levels, while the classification of "Rotten" fruit conditions has received relatively limited attention[22]. In fact, rotten fruit is a crucial parameter in quality control processes because it directly affects the product rejection rate in food distribution and retail systems. Therefore, the ability to distinguish rotten fruit from acceptable-quality fruit is essential for improving post-harvest quality control and minimizing economic losses in agricultural supply chains.

Based on these problems, this study proposes the development of an automatic avocado ripeness classification model using an Artificial Neural Network (ANN) architecture based on digital image processing. The proposed system classifies avocados into three main categories: Rotten, Unripe, and Ripe. Unlike complex deep learning architectures, the proposed model is designed to be more compact while maintaining good classification capability for recognizing fruit visual characteristics.

The novelty of this research lies in the development of a compact multi-layer Artificial Neural Network (ANN) architecture specifically designed to classify avocado ripeness and decay conditions using raw pixel color intensity features extracted from digital images. Unlike many previous studies that focus primarily on ripeness-stage identification or employ more complex deep learning architectures, the proposed approach simultaneously distinguishes Rotten, Unripe, and Ripe avocado classes using a relatively simple feed-forward network structure. The proposed model demonstrates that satisfactory classification performance can be achieved using a relatively simple feed-forward ANN architecture for image-based avocado ripeness classification.

2. Research Method

This study employed a quantitative experimental approach based on machine learning to classify avocado ripeness levels using digital image data. The proposed method was designed to identify three primary categories of avocado ripeness, namely Rotten, Unripe, and Ripe, by utilizing an Artificial Neural Network (ANN) architecture. In general, the research methodology consisted of four main stages: dataset collection and preparation, image preprocessing, ANN model architecture design, and model training and evaluation.

2.1 Data Collection

The dataset used in this study consisted of primary data in the form of digital avocado images grouped into three ripeness categories: Rotten, Unripe, and Ripe. Visual representations of each category are presented in Figure 1. The class grouping was determined based on the visual characteristics of the fruit surface, including color changes, texture variations, and indications of fruit decay. This categorization approach was adapted from previous avocado postharvest maturity assessment studies that utilized visual ripening indicators and external fruit characteristics to determine ripeness stages [20],[21].

All image data were stored and organized using Google Drive cloud storage to facilitate data accessibility, management, and integration throughout the experimental process. During the data preparation stage, all image files were extracted from compressed formats, followed by restructuring the dataset directories by grouping images according to their respective classes. The dataset structure was organized hierarchically to ensure compatibility with the data loading and model training processes using deep learning frameworks. Furthermore, all images were manually reviewed by the researchers prior to model training to ensure visual quality and labeling consistency. Images exhibiting severe blur, inadequate illumination, partially visible fruit objects, or substantial background interference were excluded from the dataset. This screening process was conducted to improve dataset consistency and reduce potential noise that could affect classification performance during model training. The final dataset used in this study consisted of 1,500 images, with 500 images allocated to each ripeness category (Rotten, Unripe, and Ripe). The dataset was organized to maintain balanced class representation for training and evaluation purposes. For reproducibility purposes, the image dataset is available from the corresponding author upon reasonable request for research and academic purposes. Google Drive was utilized solely as a temporary cloud storage platform for dataset organization, management, and accessibility during the research process and was not intended as a public data repository.

a) Rotten *b) Unripe* *c) Ripe*

Figure 1. Sample Images of Avocado Ripeness Classes

2.2 Data Preprocessing

The next stage involved loading the image dataset into the programming environment using the TensorFlow Keras library. During this process, image standardization was performed by resizing each image to a resolution of 128 × 128 pixels and organizing the dataset into batches of 32 images. To evaluate model performance, the dataset was randomly divided into two subsets, consisting of 80% training data and 20% validation data. After the data loading stage, image preprocessing was carried out through pixel value normalization by transforming the original intensity range from [0, 255] into a normalized range of [0, 1]. This normalization process was applied to improve numerical stability, accelerate model convergence, and enhance computational efficiency during the training phase. Similar preprocessing techniques involving image resizing, normalization, and color-based image handling have been widely implemented in previous avocado image classification and digital image processing studies [9],[10],[22]. Furthermore, dataset memory management optimization was implemented to improve input/output (I/O) performance and ensure more efficient data streaming during computation. This optimization enabled the training process to run more consistently and reduced computational bottlenecks during model execution.

2.3 ANN Model Architecture Development

The avocado ripeness classification model was developed using a sequential Artificial Neural Network (ANN). The overall structure of the proposed model is presented in Figure 2. Input images with a resolution of 128 × 128 × 3 were first transformed into a one-dimensional representation through a Flatten layer, producing a feature vector consisting of 49,152 elements.

This process allowed the image data to be processed by a fully connected neural network. The extracted feature vector was then forwarded to two hidden layers containing 128 and 64 neurons, respectively. Both layers employed the Rectified Linear Unit (ReLU) activation function to enable the network to learn non-linear relationships from the image features. The final classification stage consisted of an output layer with three neurons corresponding to the three ripeness categories, namely Ripe, Rotten, and Unripe. A Softmax activation function was applied to produce probability values for each class and determine the final prediction.

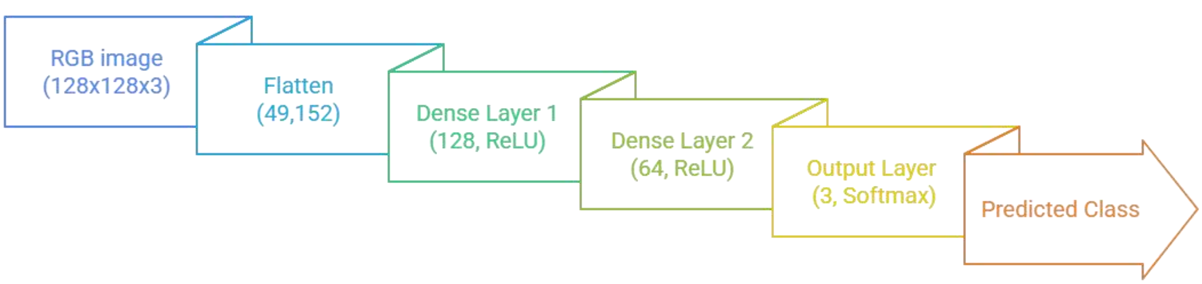

Figure 2. Proposed ANN Architecture for Avocado Ripeness Classification

As shown in Figure 2, the model follows a straightforward feed-forward structure in which image features are progressively transformed through successive fully connected layers before classification. Based on the TensorFlow model summary, the architecture contains 6,300,035 trainable parameters. Most of these parameters are concentrated in the first hidden layer because it directly receives the high-dimensional flattened feature vector. The hidden-layer configuration of 128 and 64 neurons was selected empirically during the preliminary development stage to obtain stable training behaviour while maintaining a relatively simple network structure. Although alternative configurations may influence classification performance, a systematic hyperparameter optimization or ablation analysis was beyond the scope of this study and is therefore recommended for future investigation.

Previous studies have reported that ANN-based approaches can be effectively applied to agricultural prediction and image classification tasks by utilizing visual characteristics such as color and texture information [7],[8]. Therefore, the proposed architecture was considered suitable as a baseline model for evaluating avocado ripeness classification using digital images.

2.4 Model Training

The model compilation process was conducted by defining optimization components appropriate for the multi-class classification task. The Adam optimizer was employed to adaptively update the network weights based on the learning rate during the training process. The loss function used in this study was Sparse Categorical Crossentropy, as the target labels were represented in the form of integer indices. In addition, accuracy was utilized as the primary evaluation metric to monitor model performance throughout the training phase. During each iteration, the model recorded both accuracy and loss values for the training and validation phases. These recorded metrics were subsequently analyzed to evaluate the convergence behavior of the model and to identify potential overfitting during the learning process. Previous deep learning studies emphasized that training stability, dataset size, and convergence behavior are important factors affecting the performance and generalization capability of image-based agricultural classification models [2],[19].

The ANN model was trained for 50 epochs using the Adam optimizer with a learning rate of 0.001 and Sparse Categorical Crossentropy as the loss function. No additional regularization techniques, such as Dropout, Batch Normalization, or Early Stopping, were applied in this study because the primary objective was to evaluate the baseline performance of a simple ANN architecture for avocado ripeness classification. The training process was monitored using both training and validation accuracy metrics to assess convergence behavior and identify potential overfitting during model development.

3. Results and Discussions

3.1 Accuracy and Loss Curve Analysis

The training process of the ANN model for avocado ripeness classification was continuously monitored using the historical graphs of Training and Validation Accuracy as well as Training and Validation Loss over 50 epochs, as illustrated in Figure 3. Based on the visualization results, the model performance demonstrated a significant improvement trend from the early stages of training. In the accuracy curve, the training accuracy (blue line) increased consistently from the initial epochs and gradually converged in the later stages of training. Similarly, the validation accuracy (orange line) also exhibited an increasing trend, although accompanied by relatively sharp fluctuations during the first 10 epochs before becoming more stable. The relatively small gap between the training and validation accuracy curves indicates that the model maintained comparable performance on both datasets. This finding suggests that overfitting was limited and that the learned feature representations remained reasonably generalizable.

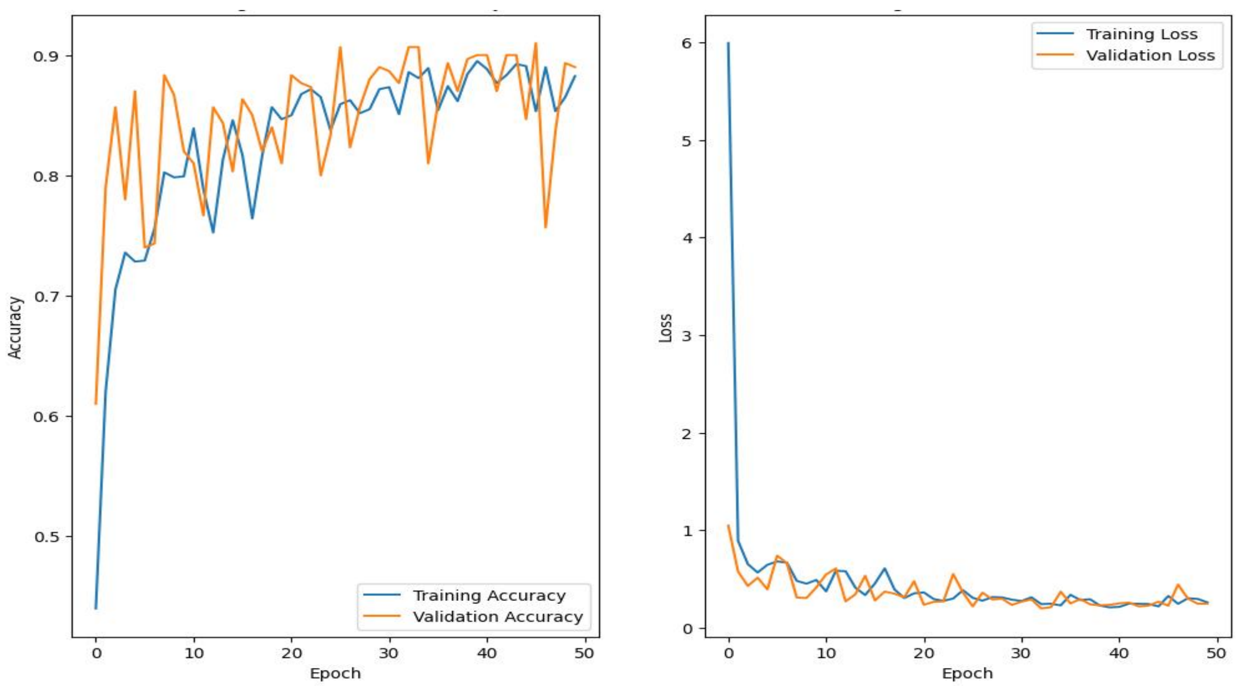

Figure 3. Historical Graph of Accuracy and Loss Values

The fluctuations observed in the early training phase indicate that the model was still adapting to the data distribution and learning the underlying feature patterns from the avocado images. As the training progressed, both the training and validation accuracy curves became more stable, suggesting that the model successfully learned representative features for distinguishing the three avocado ripeness classes. In addition to the accuracy metric, the loss curves also demonstrated a consistent downward trend throughout the training process. The training loss decreased progressively as the number of epochs increased, indicating that the optimization process effectively minimized prediction errors. The validation loss followed a similar pattern and did not exhibit a substantial increase in the final training stages, suggesting that the model did not experience severe overfitting.

Overall, the training results indicate that the proposed ANN architecture achieved stable learning behavior and demonstrated reasonable generalization capability for avocado ripeness classification based on digital image data.

3.2 Confusion Matrix Analysis

A detailed evaluation of the model prediction behavior was conducted using a Confusion Matrix on the final validation dataset after completing 50 training epochs, as presented in Figure 4. A total of 300 validation images were independently evaluated during this stage, with varying classification performance across each class. Based on the classification results shown in Figure 4, the prediction distribution demonstrates that the model achieved very strong recognition performance for the "Rotten" category. The model successfully classified most actual Rotten samples into the True Positive category by correctly identifying 95 images. Only a small number of misclassifications occurred in this class, where 4 Rotten avocado images were incorrectly predicted as "Ripe," while no samples were misclassified as "Unripe." For the "Unripe" category, the 50-epoch training process significantly improved the model's decision boundaries. The model successfully identified the majority of actual Unripe samples, achieving 70 correct predictions, which indicates a substantial improvement in recall performance for this category. However, 29 actual Unripe images were still incorrectly classified as "Ripe."

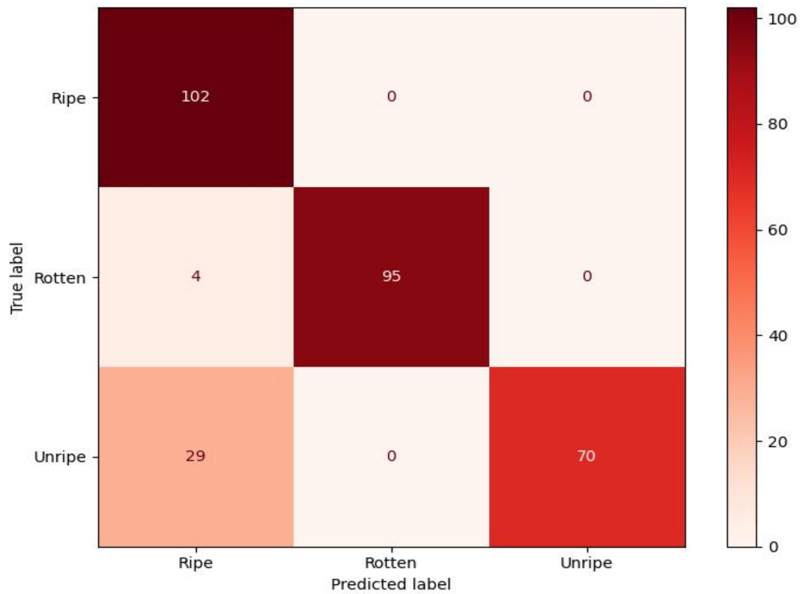

Figure 4. Confusion Matrix of Model Prediction Results

Meanwhile, in the "Ripe" category, the model demonstrated a highly inclusive prediction behavior. The model correctly classified all 102 Ripe avocado images without any misclassification into the Rotten or Unripe classes. However, several actual Unripe images were still incorrectly predicted as "Ripe" due to visual similarities between adjacent ripeness stages.

The occurrence of cross-misclassification between the Unripe and Ripe classes indicates the existence of visual similarities and subtle color gradation transitions during the avocado ripening process. These similarities represent a significant challenge for the ANN architecture in determining optimal classification decision boundaries between adjacent ripeness stages.

3.3 Per-Class Evaluation Metrics Analysis

To comprehensively evaluate the classification performance of the proposed model, an in-depth analysis was conducted using Precision, Recall, and F1-Score metrics for each class after the completion of the training process. A summary of the numerical evaluation results is presented in Table 1, while the comparison of evaluation metrics across classes is illustrated in the bar chart shown in Figure 5.

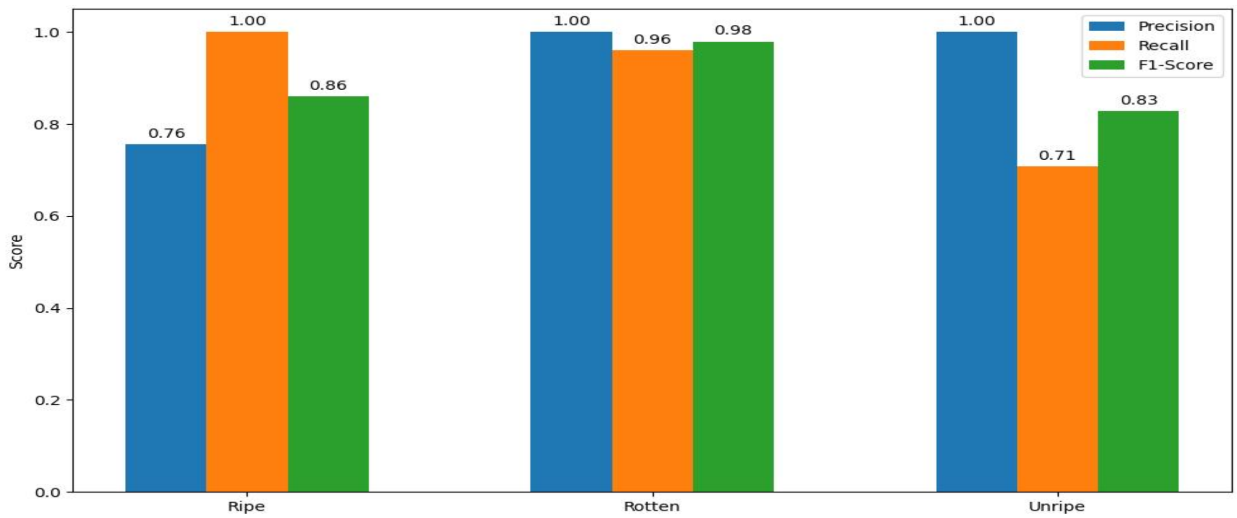

Figure 5. Bar Chart Comparison of Per-Class Evaluation Metrics

Based on the obtained results, the “Rotten” class demonstrated the best classification performance among all categories. The Precision value for the Rotten class achieved a perfect score of 1.00, indicating that all images predicted as Rotten were correctly classified without any false positive predictions from other classes. In addition, the model showed a strong capability in identifying actual Rotten samples, as reflected by the Recall value of 0.96 and the balanced F1-Score of 0.98.

Table 1. Summary of ANN-Based Image Classification Performance

Class	Class Accuracy	Precision	Recall	F1-Score
Rotten	0.99	1.00	0.96	0.98
Unripe	0.90	1.00	0.71	0.83
Ripe	0.89	0.76	1.00	0.86
Macro-average	-	0.92	0.89	0.89

It should be noted that the dataset used in this study was balanced across the three avocado ripeness classes, consisting of 500 images for each category (Rotten, Unripe, and Ripe). Therefore, the reported overall accuracy of 89.00% was not influenced by class imbalance and can be considered representative of the model's actual classification performance.

Meanwhile, the “Unripe” and “Ripe” categories exhibited contrasting classification characteristics due to the visual similarity that occurs during the avocado ripening transition phase. The Unripe class achieved a relatively low Recall value of 0.71, indicating that several actual Unripe samples were still incorrectly classified as Ripe. However, its Precision achieved a perfect value of 1.00, suggesting that all images predicted as Unripe were classified correctly without false positive predictions from other classes.

In contrast, the Ripe category demonstrated a more inclusive prediction behavior, achieving a Recall value of 1.00 but a lower Precision value of 0.76. This result indicates that the model successfully identified all actual Ripe samples correctly; however, several Unripe samples were still incorrectly predicted as Ripe, thereby reducing the Precision performance of this category. Overall, the proposed ANN model achieved macro-average values of 0.92 for Precision, 0.89 for Recall, and 0.89 for F1-Score. These balanced evaluation results indicate that the proposed ANN architecture demonstrates reliable and stable classification performance in classifying avocado ripeness levels based on digital image data.

3.4 ROC Curve and AUC Analysis

The overall capability of the proposed model in distinguishing and separating inter-class characteristics was evaluated using the Receiver Operating Characteristic (ROC) curve with a One-vs-Rest (OvR) approach, as illustrated in Figure 6. The ROC curve evaluation provides an objective representation of the trade-off between the True Positive Rate (sensitivity) and the False Positive Rate (1–specificity) across various classification threshold values. The Area Under the Curve (AUC) values obtained from Figure 6 indicate exceptionally strong discriminative performance across all avocado ripeness categories.

For the "Rotten" class (blue curve), the model achieved a perfect AUC value of 1.00. This result indicates that the proposed ANN model demonstrated a very strong capability to distinguish Rotten samples from the other classes, as reflected by the perfect AUC value obtained for this category. Furthermore, the 50-epoch training process appeared to strengthen the model's decision boundaries for this category, contributing to its excellent discriminative performance.

Meanwhile, the "Unripe" class (orange curve) and the "Ripe" class (green curve) achieved very high AUC values of 0.98 and 0.97, respectively. These values, which are significantly above the 0.90 threshold, demonstrate that the model has a highly reliable probability discrimination capability and performs substantially better than random classification. In addition, the ROC curves for the Unripe and Ripe classes were observed to closely approach the upper-left corner of the graph, indicating that the model maintained high sensitivity and specificity despite the existence of slight visual overlaps between adjacent ripeness stages. Although previous analyses revealed several cross-misclassification cases between the Unripe and Ripe categories, the ROC-AUC evaluation indicates that the proposed ANN architecture achieved stable classification performance in recognizing avocado ripeness transition phases based on digital image data.

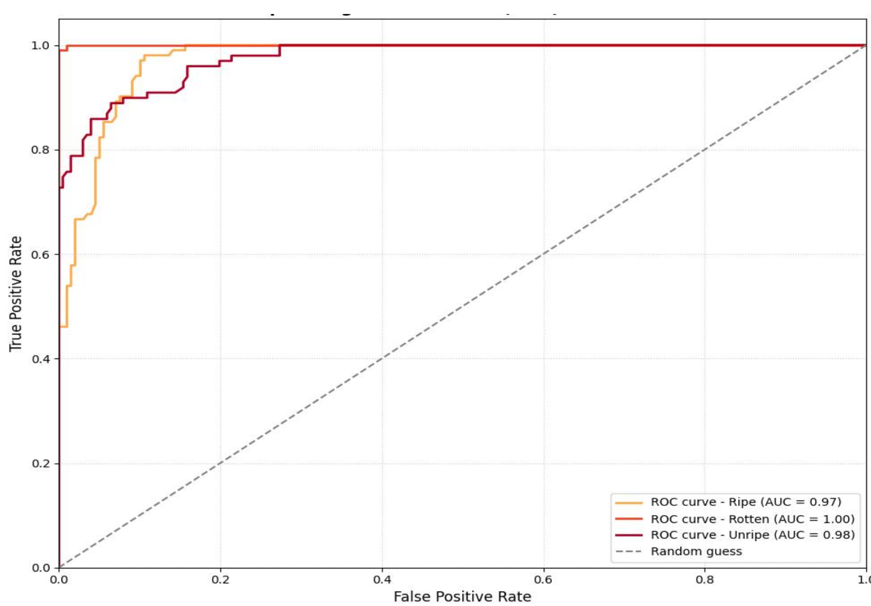

Figure 6. ROC Curve of the Training Results

Overall, the ANN model developed in this study demonstrated varying performance characteristics across different classes. Comprehensive evaluation results indicate that the model performed well in identifying samples belonging to the "Rotten" category. This performance is reflected by the perfect Precision value and the very high Recall score, suggesting that rotten avocados possess highly distinctive visual degradation characteristics, particularly in terms of color and texture changes, which can be effectively recognized by the artificial neural network model. These findings are consistent with previous studies reporting that severe ripening degradation and decay conditions generally produce more distinguishable visual features compared to intermediate ripening phases [19],[20].

However, the primary challenge identified in this study lies in the classification decision boundary between the "Unripe" and "Ripe" categories. Based on the evaluation metrics, the Unripe class achieved perfect Precision performance but relatively lower Recall, whereas the Ripe class demonstrated perfect Recall performance with lower Precision. This phenomenon indicates that several actual Unripe avocado images were incorrectly classified as Ripe due to visual similarities between adjacent ripeness stages.

Several critical factors contributed to these classification challenges. The first factor is the high degree of visual feature similarity between the Unripe and Ripe categories, particularly in the gradual transition of greenish-dark color intensity and external skin texture during the ripening phase. These subtle visual overlaps make it difficult for conventional ANN architectures to establish clear class separation boundaries. Similar findings were also reported in previous avocado maturity classification studies using RGB color extraction and image processing techniques, where overlapping visual characteristics between adjacent maturity stages reduced classification consistency [9],[17],[22].

The second factor is related to the intrinsic limitation of the sequential ANN architecture itself. The flattening process, which transforms the image matrix into a one-dimensional feature vector at the input stage, causes the model to lose important local spatial information and structural hierarchies contained within the image. Traditional ANN models process raw pixel values in a linear manner and are therefore less sensitive to micro-texture variations and subtle color transitions that are essential in image-based object recognition tasks. Previous studies also emphasized that CNN-based architectures generally outperform conventional ANN models in image classification tasks because convolutional layers are more effective in preserving spatial information and extracting hierarchical visual features automatically [5],[16],[18].

In addition, the third factor is likely associated with dataset variability. Variations in lighting conditions, image capture angles, and visual inconsistencies within the ripening transition phase may have introduced anomalies during the feature extraction process, thereby affecting classification consistency. This issue has also been highlighted in previous agricultural image classification studies, which reported that limited dataset diversity and inconsistent image acquisition conditions may significantly affect model generalization performance [15],[19].

To address these limitations, future studies are strongly recommended to adopt a Convolutional Neural Network (CNN) architecture, which is specifically designed with convolutional and pooling layers to automatically extract spatial features while preserving image topology. Furthermore, the implementation of data augmentation techniques, such as image rotation, shifting, and contrast adjustment, is also recommended. These approaches are expected to artificially enrich training data variability, improve model generalization capability, and further enhance model robustness while reducing the possibility of overfitting during the training process.

Another limitation of the present study is the absence of direct benchmarking against alternative classification approaches such as Support Vector Machine (SVM), K-Nearest Neighbors (KNN), or Convolutional Neural Network (CNN)-based models. Although the proposed ANN architecture achieved satisfactory classification performance with an overall accuracy of 89.00%, the relative competitiveness of this performance cannot be fully assessed without comparative evaluation. Therefore, the reported accuracy should not be interpreted as evidence of superiority over other machine learning or deep learning approaches. Future studies should conduct systematic benchmarking using multiple classification models to provide a more comprehensive assessment of classification effectiveness, computational complexity, and practical applicability for avocado ripeness classification.

4. Conclusion and Future Work

This study successfully developed and evaluated a sequential Artificial Neural Network (ANN) model for avocado ripeness classification based on digital image data. The proposed model classified avocados into three categories: Rotten, Unripe, and Ripe. Experimental results demonstrated that the ANN model achieved a satisfactory overall accuracy of 89.00%, with the best performance observed in the Rotten category, which achieved a perfect Precision value of 1.00 and a Recall value of 0.96.

Nevertheless, the model encountered classification challenges during the ripening transition phase, particularly between the Unripe and Ripe categories. Several actual Unripe images were incorrectly classified as Ripe due to visual similarities and subtle color transitions between adjacent ripeness stages. This condition resulted in a lower Recall value of 0.71 for the Unripe category and a lower Precision value of 0.76 for the Ripe category. In addition, minor fluctuations observed in the validation loss curve indicate the presence of mild overfitting caused by the limitations of the traditional ANN architecture, especially the loss of local spatial information during the flattening process of raw image matrices.

Although the proposed ANN model demonstrated reliable classification performance with an overall accuracy of 89.00%, there remains substantial room for improvement. For future research, the implementation of Convolutional Neural Networks (CNNs) is strongly recommended to automatically exploit spatial image features without losing topological information. Furthermore, the integration of broader data augmentation strategies and more extensive hyperparameter tuning is also suggested to enrich dataset variability, reduce overfitting risks, and improve the model's generalization capability under real-world image conditions.

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