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BANANA SPECIES CLASSIFICATION USING NEURAL NETWORKS

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ABSTRACT

Indonesian bananas represent a strategic horticultural commodity with significant economic potential, yet post-harvest supply chains face persistent challenges due to subjective and labor-intensive manual sorting. To overcome these limitations, this study proposes an automated image-based classification framework evaluating eight Indonesian banana cultivars (Musa spp.). The computational pipeline integrates deep feature extraction via a pre-trained Inception-V3 model with a Multi-Layer Perceptron Artificial Neural Network (ANN) comprising three hidden layers. Evaluated across 1,020 test images using a 10-fold stratified sampling protocol, the model achieved a classification accuracy of 86.7%, a balanced F_1-score of 86.7%, and an Area Under the ROC Curve (AUC) of 0.985. Pisang Cavendish achieved the highest class-wise accuracy at 96.9%, whereas misclassifications occurred predominantly between morphologically similar cultivars, such as Pisang Kepok and Pisang Barangan. Overall, the low cross-entropy log loss (0.419) and high Matthews Correlation Coefficient (0.848) confirm strong prediction stability. These findings demonstrate that combining deep visual embeddings with neural networks offers a reliable, high-throughput tool for automated produce grading, supporting quality standardization and digitalization in agribusiness supply chains.

INTRODUCTION

Indonesian bananas represent a vital tropical fruit commodity with a long history of international trade (Zainuddin et al., 2025). While Indonesia ranks third globally in banana production, its contribution to the global banana export market remains disproportionately low (Evans et al., 2020). Consequently, comprehensive measures are required to enhance both productivity and quality, including market research on competitor nations, analysis of global consumer preferences, agricultural extension services, and product diversification (Hopid et al., 2023). As a strategic horticultural commodity, Indonesian bananas possess distinct competitive advantages, notably high varietal diversity and unique flavor profiles (Fettig et al., 2023). Enhancing banana production and productivity is critical for satisfying both domestic and export demands, ultimately fostering local economic growth, supporting food security, and reinforcing national economic security.

At the macro-economic level, Indonesia's banana sector generates an estimated economic value of IDR 10 trillion annually (Wisnubroto et al., 2024), serving as a vital economic safeguard for smallholder farmers. For instance, in Talaga and Sarampad villages, 76% of surveyed households rely heavily on agriculture, with 53% cultivating bananas as their primary crop and others using it as a supplementary income source (Pratama et al., 2025; SUNARSI et al., 2023).

Despite this immense economic potential, the banana supply chain faces significant operational challenges at the post-harvest and distribution stages (Sulistyowarni et al., 2020). Morphological characteristics - such as fruit shape (Rai et al., 2023) and skin color variation during ripening (Dewi et al., 2022) - differ considerably across cultivars. Manual differentiation of these varieties is particularly challenging for farmers and agribusiness operators who lack specialized botanical knowledge, leading to inconsistent product standardization, suboptimal cultivation management, and improper raw material selection for downstream processing (Pamungkas & Fadlil, 2023). Furthermore, manual sorting is labor-intensive, time-consuming, and prone to human subjectivity, which severely hinders sorting efficiency and quality consistency (Guo et al., 2020).

Recent advancements in computer vision and machine learning offer a promising avenue to overcome these manual inspection bottlenecks (Ergün, 2025). In agricultural processing, automated image-based classification systems have proven significantly more consistent and scalable than visual estimation by human operators (Melesse, 2026). By extracting precise spatial and spectral features - such as texture, geometric proportions, and chromatic variations - computer vision models can identify subtle inter-variety differences that are often imperceptible or easily misclassified by non-expert personnel (Martínez-Mora et al., 2025).

Specifically, Artificial Neural Networks (ANNs) have demonstrated remarkable efficacy in pattern recognition tasks involving complex biological objects

(Huixian, 2020). Unlike traditional rule-based algorithms, ANNs can learn hierarchical feature representations directly from raw image data, rendering them highly resilient to natural variations in lighting, surface blemishes, and orientation (Pardede et al., 2023). Integrating such automated models into post-harvest handling pipelines provides an objective, repeatable, and high-throughput mechanism for quality control and cultivar identification.

To address these limitations, this study proposes an automated visual classification approach using a custom Artificial Neural Network (ANN) architecture integrated with digital image processing. Experimental evaluation demonstrates that the proposed system achieves a classification accuracy of 87%, offering a reliable alternative to traditional manual sorting methods.

RESEARCH METHODS

Data Collection

This study utilizes secondary image data obtained from the public repository Kaggle (tensorflow_jenis_pisang) (Alviansyz, 2020). The dataset comprises a total of 1,195 digital images categorized into 8 distinct Indonesian banana (Musa spp.) cultivars. The distribution of sample images across all categories is detailed in Table 1.

Table 1. Dataset Class Distribution

Cultivar Category	**Image Count (N)**
Ambon (*Pisang Ambon*)	140
Barangan (*Pisang Barangan*)	144
Cavendish (*Pisang Cavendish*)	167
Kepok (*Pisang Kepok*)	165
Nangka (*Pisang Nangka*)	116
Raja (*Pisang Raja*)	145
Susu (*Pisang Susu*)	147
Tanduk (*Pisang Tanduk*)	171

All collected images are stored in .jpg and .png formats. Due to the diverse origin of the raw data, the dataset exhibits spatial dimension variance, encompassing 159 distinct image resolutions. To illustrate the inter-class visual variations across cultivars, representative image samples from each of the eight categories are depicted in Figure 1.

As illustrated in Figure 1, the dataset encompasses substantial morphological and visual diversity across the eight banana cultivars, presenting realistic classification challenges for the model:

1. Morphological Characteristics: Each cultivar exhibits distinct geometric

shapes, aspect ratios, and curvature profiles. For instance, cultivars such as Pisang Tanduk display elongated, significantly curved shapes, whereas Pisang Kepok features flattened, distinctly angular cross-sections.

2. Color and Ripeness Variance: The images capture varying degrees of maturity, ranging from green (unripe) to vibrant yellow (ripe), along with natural brown spotting (senescence). These variations introduce significant intra-class heterogeneity (e.g., Pisang Cavendish and Pisang Ambon sharing similar color spectrums during specific ripening stages).
3. Unstructured Environment: The samples reflect unconstrained acquisition conditions, including diverse background contexts (e.g., wooden surfaces, market stalls, foliage), uncontrolled lighting, and varying camera distances/angles.

These real-world visual complexities underscore the necessity for robust pre-processing and feature extraction steps within the computational pipeline to ensure reliable classification performance.

Figure 1. Sample Images from the Dataset

Data Cleaning and Directory Setup

The raw dataset retrieved from the public repository was initially stored in a compressed archive format (.zip). Prior to model ingestion within the Orange Data Mining framework, the archive was extracted and organized into a structured directory hierarchy compatible with the Import Images module.

A rigorous data cleaning procedure was subsequently performed. Outlier images, low-quality samples, and irrelevant artifacts—collectively identified as noise—were manually filtered out. This preprocessing step ensures data integrity, improves feature interpretability, and mitigates potential biases during subsequent classification phases.

Feature Extraction via Inception-V3 Embedding

Feature extraction was conducted using the Image Embedding widget in Orange, leveraging a pre-trained Deep Convolutional Neural Network (CNN) model, specifically Inception-V3.

Developed as an evolution of GoogleNet (Inception-v1), Inception-V3 is optimized for high-performance visual recognition tasks. Its architecture incorporates advanced deep-learning techniques, including asymmetric factorized convolutions, auxiliary classifiers, and batch normalization, which collective balance computational efficiency and prevent model overfitting.

The underlying computational pipeline of the Inception-V3 feature extractor operates as follows:

1. Input Dimensionality: Input images are standardized and resized to a uniform spatial dimension of 299×299 pixels across three color channels (RGB).
2. Convolutional Processing: The architecture processes input images through stacked multi-scale convolutional blocks, pooling operations, and regularization mechanisms such as dropout and label smoothing (Daniel et al., 2025).
3. Dimension Reduction: Factorized convolutions reduce the total parameter count, while auxiliary classifiers facilitate gradient flow toward earlier layers during backpropagation (Ichsan et al., 2024).
4. Bottleneck Vector Representation: For feature extraction, the final Softmax classification layer is truncated. Consequently, the network transforms each high-dimensional image into a dense, lower-dimensional continuous feature vector (bottleneck representation), which serves as the numerical input for subsequent classifier evaluation.

Model Architecture and Experimental Design

The overall classification pipeline follows a systematic machine learning workflow (Kreuzberger et al., 2023):

1. Raw dataset images are pre-processed and standardized.
2. High-level visual features are extracted using the pre-trained Inception-V3 model.
3. The extracted feature vectors are fed into a Multi-Layer Perceptron (MLP) Artificial Neural Network for training.
4. Model performance and class predictions are evaluated using standard metrics and a multi-class Confusion Matrix.

The proposed Artificial Neural Network consists of an input layer, three fully connected hidden layers, and a multi-class output layer. The detailed structural configuration and hyperparameter settings are summarized in Table 3.

Table 3. Artificial Neural Network Hyperparameter Specifications

Component / Parameter	Configuration / Value	Description / Mathematical Formulation
Input Layer	NNeurons	Dimension matches the extracted Inception-V3 feature vector.
Hidden Layer 1	50 Neurons	Fully connected dense layer.
Hidden Layer 2	50 Neurons	Fully connected dense layer.
Hidden Layer 3	50 Neurons	Fully connected dense layer.
Output Layer	8 Neurons	Corresponds to the 8 target banana cultivars.
Activation Function	Identity / Linear	$f(x) = x$
Optimization Solver	Adam	Adaptive Moment Estimation algorithm for gradient optimization.
L2 Regularization (α)	10^{-4}	Weight decay penalty coefficient to prevent overfitting.
Max Iterations	200	Maximum training epochs allowed for convergence.

The final output layer computes class probability distributions to classify each input image into one of eight distinct Indonesian banana cultivars: Ambon, Barangan, Cavendish, Kepok, Nangka, Raja, Susu, or Tanduk. Model performance, misclassification trends, and class-wise accuracy are evaluated using a multi-class Confusion Matrix.

Model Evaluation Metrics

To rigorously assess the performance of the proposed classification model, several quantitative evaluation metrics were employed. These metrics are derived from the elements of the confusion matrix, including True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN).

1. Area Under the ROC Curve (AUC-ROC)
   The Receiver Operating Characteristic (ROC) curve illustrates the trade-off between the True Positive Rate (TPR) and False Positive Rate (FPR) across various decision thresholds. The Area Under the Curve (AUC) quantifies the model's overall capability to discriminate between distinct classes, with values closer to 1.0 indicating superior classification performance. The AUC is expressed as:
   $$\text{AUC} = \int_0^1 \text{TPR}(\text{FPR})\ d(\text{FPR}) \quad (1)$$
   Where:
   $$\text{TPR} = \frac{\text{TP}}{\text{TP+FN}}, \quad \text{FPR} = \frac{\text{FP}}{\text{FP+TN}} \quad (2)$$
2. Classification Accuracy (CA)
   Classification Accuracy measures the proportion of correctly identified samples (both true positives and true negatives) relative to the total number of evaluated samples:
   $$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+TN+FP+FN}} \quad (3)$$
3. Precision
   Precision evaluates the exactness of the model by determining the proportion of positive predictions that are truly correct:
   $$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \quad (4)$$
4. Recall (Sensitivity)
   Recall, or Sensitivity, measures the model's completeness by calculating the proportion of actual positive samples that were correctly identified:
   $$\text{Recall} = \frac{\text{TP}}{\text{TP+FN}} \quad (5)$$
5. F_1-Score
   The F_1-Score represents the harmonic mean of Precision and Recall. It provides a balanced single-metric evaluation, particularly useful when dealing with class imbalance within the dataset:
   $$F_{1\text{-Score}} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision+Recall}} = \frac{2\text{TP}}{2\text{TP+FP+FN}} \quad (6)$$

Analytical Framework and Expected Outcomes

The primary objective of this evaluation framework is to assess the classification performance and generalization capability of the proposed Artificial Neural Network model across the eight predefined Indonesian banana cultivars (Ambon, Barangan, Cavendish, Kepok, Nangka, Raja, Susu, and Tanduk). The analytical procedure encompasses four key operational steps:

1. Comprehensive Metric Evaluation: Quantifying model performance using AUC-ROC, Classification Accuracy, Precision, Recall, and F_1-Score to obtain an objective measure of classification fidelity.
2. Confusion Matrix Analysis: Examining class-specific predictions to isolate specific misclassification patterns, identify highly ambiguous cultivar pairs, and detect potential model bias toward dominant classes.
3. Performance Interpretation: Evaluating whether the Multi-Layer Perceptron configuration - comprising three hidden layers with 50 neurons each - provides sufficient representation capacity, or whether further enhancements (such as dataset expansion, data augmentation, or hyperparameter optimization) are required.
4. Practical Synthesis: Formulating evidence-based conclusions regarding the model's reliability, aiming to deliver a robust, high-accuracy computational tool suitable for automated produce identification and post-harvest quality control.

RESULTS AND DISCUSSION

Confusion Matrix Analysis

The overall classification performance of the proposed model was evaluated across 1,020 test images spanning eight banana cultivars. The resulting multi-class Confusion Matrix provides a detailed breakdown of correct predictions versus misclassification trends across all target categories.

In the matrix, rows represent the ground-truth target classes (actual labels), whereas columns denote the predicted classes generated by the Artificial Neural Network model. The values along the primary diagonal correspond to correctly classified instances (true positives), reflecting strong overall predictive reliability.

The class-wise classification accuracies derived from the empirical matrix are summarized in Table 4.

Table 4. Class-Wise Classification Accuracy Across Banana Cultivars

Cultivar Category	Actual Samples (N)	Correctly Classified (%)
Pisang Cavendish	130	96.9%
Pisang Ambon	95	91.2%
Pisang Susu	117	89.9%
Pisang Nangka	113	89.3%
Pisang Raja	123	88.0%
Pisang Tanduk	156	86.2%
Pisang Barangan	132	80.3%
Pisang Kepok	154	77.6%

The classification results presented in Table X demonstrate that the proposed model achieved varying levels of accuracy across the eight banana cultivars. Overall, the model exhibited strong classification performance, with the percentage of correctly classified samples ranging from 77.6% to 96.9%.

Among all cultivars, Pisang Cavendish achieved the highest classification accuracy, with 96.9% of its 130 samples correctly identified. This result indicates that the model was highly effective in recognizing the distinctive characteristics of Pisang Cavendish, suggesting that this cultivar possesses features that are more easily distinguishable from those of other cultivars.

The second-highest classification performance was observed for Pisang Ambon, with 91.2% of 95 samples correctly classified. Similarly, Pisang Susu and Pisang Nangka demonstrated high classification accuracies of 89.9% and 89.3%, respectively, indicating that the model was able to reliably differentiate these cultivars with relatively few misclassifications.

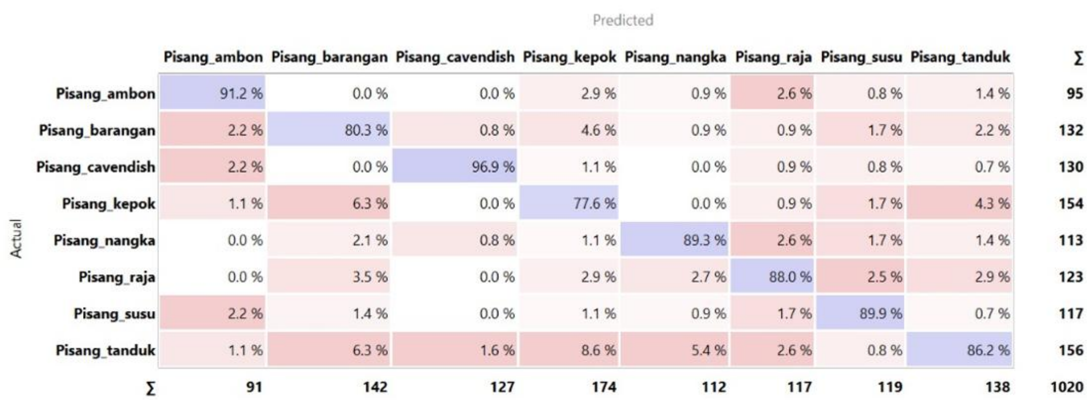
Pisang Raja and Pisang Tanduk exhibited moderate classification performance, achieving accuracies of 88.0% and 86.2%, respectively. Although these values remain relatively high, they suggest that a greater proportion of samples from these cultivars shared similar characteristics with other classes, leading to an increased number of classification errors.

The lowest classification accuracies were obtained for Pisang Barangan and Pisang Kepok, with 80.3% and 77.6% of samples correctly classified, respectively. These results imply that the distinguishing features of these cultivars may overlap considerably with those of other banana varieties, making them more challenging for the classification model to discriminate accurately. The relatively lower performance may also indicate greater intra-class variability or higher inter-class similarity within the dataset.

Overall, the results demonstrate that the classification model achieved satisfactory performance across all eight banana cultivars, with classification accuracies exceeding 75% for every class. The consistently high recognition rates suggest that the extracted features effectively captured the discriminative characteristics of most cultivars, although further improvements may be necessary to enhance the classification performance for cultivars such as Pisang Barangan and Pisang Kepok, where misclassification rates remain comparatively higher.

Figure 2 presents the confusion matrix of the classification model, providing a comprehensive overview of the model's performance in distinguishing the eight banana cultivars. Unlike the summary presented in Table X, which reports the percentage of correctly classified samples for each cultivar, the confusion matrix illustrates both correct classifications and misclassifications across all classes. The diagonal elements represent the number of correctly classified samples, whereas the off-diagonal elements indicate instances in which samples were incorrectly assigned to other cultivars.

Therefore, the confusion matrix offers a more detailed evaluation of the classification performance by revealing the distribution and patterns of classification errors, enabling a better understanding of the similarities among banana cultivars and the strengths and limitations of the proposed model.



Actual \ Predicted	Pisang_ambon	Pisang_barangan	Pisang_cavendish	Pisang_kepok	Pisang_nangka	Pisang_raja	Pisang_susu	Pisang_tanduk	Σ
Pisang_ambon	91.2 %	0.0 %	0.0 %	2.9 %	0.9 %	2.6 %	0.8 %	1.4 %	95
Pisang_barangan	2.2 %	80.3 %	0.8 %	4.6 %	0.9 %	0.9 %	1.7 %	2.2 %	132
Pisang_cavendish	2.2 %	0.0 %	96.9 %	1.1 %	0.0 %	0.9 %	0.8 %	0.7 %	130
Pisang_kepok	1.1 %	6.3 %	0.0 %	77.6 %	0.0 %	0.9 %	1.7 %	4.3 %	154
Pisang_nangka	0.0 %	2.1 %	0.8 %	1.1 %	89.3 %	2.6 %	1.7 %	1.4 %	113
Pisang_raja	0.0 %	3.5 %	0.0 %	2.9 %	2.7 %	88.0 %	2.5 %	2.9 %	123
Pisang_susu	2.2 %	1.4 %	0.0 %	1.1 %	0.9 %	1.7 %	89.9 %	0.7 %	117
Pisang_tanduk	1.1 %	6.3 %	1.6 %	8.6 %	5.4 %	2.6 %	0.8 %	86.2 %	156
Σ	91	142	127	174	112	117	119	138	1020

Figure 2. Confusion Matrix of the 8-class Banana Classification

Analysis of Correct Predictions and Misclassifications

As demonstrated in Table 4 and Figure 2, the model exhibits exceptional discrimination capabilities for distinct cultivars. Notably, Pisang Cavendish achieved the highest true positive rate at 96.9%, followed closely by Pisang Ambon (91.2%) and Pisang Susu (89.9%). These high recognition rates suggest that the feature representations extracted via Inception-V3 successfully captured distinct geometric and chromatic characteristics unique to these varieties.

Conversely, minor misclassifications occurred primarily between cultivars sharing similar morphological features:

1. A portion of Pisang Kepok samples was misclassified as Pisang Tanduk (4.3%), likely due to similarities in fruit thickness and angular skin contours during certain growth stages.
2. Pisang Barangan exhibited a 4.6% misclassification rate as Pisang Kepok.
3. Pisang Tanduk samples were occasionally misclassified as either Pisang Kepok or Pisang Barangan.

4. These confusion patterns underscore the inherent visual ambiguity present in non-standardized agricultural images, where variations in fruit maturity, surface blemishes, and camera perspectives can blur inter-class boundaries.

Experimental Validation Protocol

To evaluate the generalization performance and stability of the proposed Artificial Neural Network model, a stratified random sampling cross-validation approach was conducted with 10 repeated iterations. In each iteration, the dataset was partitioned into 66% training data and 34% testing data, maintaining consistent class proportions across splits.

The quantitative performance metrics obtained across the 10-fold repeated sampling iterations are summarized in Table 5.

Table 5. Overall Quantitative Evaluation Metrics

Metric	Empirical Value	Percentage Equivalent	Performance Interpretation
AUC	0.985	98.5%	Superior class discrimination capability
CA	0.867	86.7%	High overall correct prediction rate
F_1	0.867	86.7%	Strong balance between Precision and Recall
Precision	0.870	87.0%	High exactness in positive class prediction
Recall	0.867	86.7%	High completeness in identifying true instances
MCC	0.848	84.8%	High quality multi-class prediction correlation
Specificity	0.980	98.0%	Exceptional true negative identification rate
Log Loss	0.419	-	Low cross-entropy prediction uncertainty

Quantitative Metric Interpretation

As presented in Table 5, the model demonstrated robust performance across all evaluation dimensions:

1. Discrimination Power
   The near-unity AUC score reflects an exceptional capacity to distinguish between distinct banana cultivars across varying decision thresholds.
2. Accuracy and Balance
   The overall classification accuracy of 86.7% aligns with a identical F_1-score, indicating that performance is balanced and unwarped by class imbalance.

3. Statistical Association
   The high Matthews Correlation Coefficient confirms strong statistical agreement between ground-truth labels and model predictions in a multi-class context.
4. Prediction Confidence
   The low cross-entropy loss confirms that the model assigns high probability confidence to correct class assignments with minimal prediction entropy.

Practical Implications for Industry and Agribusiness

The empirical results confirm that combining pre-trained Inception-V3 visual features with a 3-hidden-layer Artificial Neural Network delivers a highly dependable, high-throughput classification framework. Given its low misclassification rate and high overall accuracy, this approach holds significant promise for deployment in automated agricultural processing, particularly in post-harvest sorting, packaging, distribution tracking, and quality assurance. Furthermore, integrating such automated vision systems can accelerate supply chain digitalization, reduce manual labor requirements, and mitigate human error in commercial produce grading.

CONCLUSION

This study successfully developed and evaluated an automated visual classification framework for eight Indonesian banana cultivars (Musa spp.) by integrating pre-trained Inception-V3 feature extraction with a three-hidden-layer Artificial Neural Network (ANN). Experimental validation using a 10-fold stratified sampling protocol demonstrated robust predictive performance, achieving an overall classification accuracy of 86.7%, a balanced F_1-score of 86.7%, and a high AUC of 0.985. Prominent cultivars such as Pisang Cavendish and Pisang Ambon exhibited superior recognition rates of 96.9% and 91.2%, respectively, confirming the capacity of deep visual embeddings to effectively isolate subtle geometric and chromatic features. The primary practical contribution of this approach lies in its potential to automate post-harvest sorting, thereby enhancing supply chain efficiency, standardizing fruit quality grading, and reducing human subjectivity in commercial agricultural distribution. Despite these promising outcomes, several research limitations should be acknowledged. The lower classification accuracies observed for Pisang Barangan (80.3%) and Pisang Kepok (77.6%) highlight the persistent challenge of distinguishing cultivars with significant morphological overlap and variable ripeness stages. Furthermore, utilizing secondary image data captured under unconstrained environmental conditions introduced noise related to lighting and background variations. To overcome these challenges, future research should prioritize expanding dataset diversity through controlled multi-angle image acquisition, exploring fine-tuned vision transformers to better resolve class ambiguities, and deploying lightweight models on edge devices for real-time, on-field applications.

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