

Optimizing Bit Depth for Longan Seedling Identification Using ANN and GLCM

Rizki Andika^{1*}, Gasim², Zaid Romegar Mair³

^{1,2,3}Universitas Indo Global Mandiri, Indonesia

¹2021110092@students.uigm.ac.id, ²gasim@uigm.ac.id, ³zaidromegar@uigm.ac.id



*Corresponding Author

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ABSTRACT

Accurate identification of longan (*Dimocarpus longan*) seedling varieties is essential for agribusiness to select cultivars meeting market and environmental needs, but manual identification is error-prone due to similar leaf textures. This study optimizes grayscale image bit depth using Artificial Neural Networks (ANN) and Gray Level Co-occurrence Matrix (GLCM) to enhance longan seedling classification accuracy, addressing a gap in texture-based identification efficiency. Leaf images from five longan varieties (Itoh, Pingpong, Merah, Matalada, Diamond River) were captured with a USB digital microscope and converted to grayscale at bit depths of 4 (0–15), 5 (0–31), 6 (0–63), 7 (0–127), and 8 (0–255). Texture features (contrast, correlation, energy, homogeneity, entropy, standard deviation) were extracted using MATLAB. An ANN model, trained with the *trainidx* algorithm on 800 training and 200 test images, classified the varieties. The 6-bit and 4-bit depths yielded the highest accuracy (84.5%), followed by 7-bit (84.0%), 5-bit (83.5%), and 8-bit (82.0%), with Matalada achieving 90.0% accuracy. The 8-bit depth introduced texture noise, reducing performance. A 6-bit depth is optimal for longan leaf texture classification, though distinguishing similar varieties like Itoh and Pingpong remains challenging. Future research should incorporate color or morphological features to improve agricultural image processing.

INTRODUCTION

Longan (*Dimocarpus longan*) is a highly valued tropical fruit in Indonesia due to its sweet flavor and high nutritional content, including vitamin C and antioxidants (Nugraha, 2023). Accurate identification of longan seedling varieties is critical for agribusiness to select cultivars that align with market demands and environmental conditions (Aini et al., 2014). However, manual identification is error-prone due to visual similarities in leaf texture, color, and morphology among varieties such as Itoh and Pingpong, which can lead to financial losses in productivity and marketing (Anggraini, 2024). These challenges highlight the need for automated, reliable identification methods.

Digital image processing provides a promising solution through computer-based texture analysis (Arnita et al., 2022). The Gray Level Co-occurrence Matrix (GLCM) effectively extracts texture features like contrast, correlation, energy, homogeneity, entropy, and standard deviation, which represent complex visual patterns (Srg et al., 2023). Converting RGB images to grayscale is a key preprocessing step that simplifies data while preserving essential visual information and reducing computational load (Arnita et al., 2022). However, selecting the optimal grayscale bit depth is critical: low bit depths (e.g., 4-bit) may lose critical texture details, while high bit depths (e.g., 8-bit) may introduce noise without improving performance (Mahbod et al., 2021).

Previous studies have demonstrated the effectiveness of GLCM and Artificial Neural Networks (ANN) in plant pattern recognition. Anggraini and Sriani (2024) achieved 87.5% accuracy using GLCM and K-Nearest Neighbor (KNN) for longan leaf classification with a small dataset of 80 images. (Al Wajieh, 2023) reported 73.33% training and 95% testing accuracy using GLCM for longan leaf morphology classification. Nugraha (2023) achieved 75% accuracy with GLCM and ANN under varying lighting conditions. Despite these advancements, no study has specifically explored the impact of grayscale bit depth variation on longan seedling identification accuracy, a gap that could enhance texture representation and classification efficiency.

This study addresses this gap by developing an ANN-based system with GLCM features to identify five longan varieties (Itoh, Pingpong, Merah, Matalada, Diamond River) using leaf vein images. The study evaluates the influence of grayscale bit depth (4, 5, 6, 7, 8 bits) on classification accuracy to determine the optimal configuration. Images were captured using a USB digital microscope at a distance of 10 cm with 5-watt LED lighting. The primary objective is to identify the bit depth that maximizes classification accuracy while minimizing computational complexity, contributing to AI-based image processing for agriculture.

LITERATURE REVIEW

Longan (*Dimocarpus longan*) varieties, including Itoh, Pingpong, Merah, Matalada, and Diamond River, exhibit distinct leaf characteristics critical for identification. Pingpong has small, thin leaves (4–6 cm long, 2–3 cm wide), while



Matalada's leaves are similarly sized but thicker with prominent veins (Aini et al., 2014). Merah features reddish leaves due to genetic mutations, Itoh has dark green leaves with clear veins, and Diamond River has wider, smoother leaves (Abdi Wahyu Nugroho, 2024). These morphological and textural differences form the basis for digital image-based identification (Nafiiyah & Prasetyo, 2023).

Computer vision enables image analysis through acquisition, preprocessing, feature extraction, and classification, with applications in agriculture. For instance, GLCM and Support Vector Machines (SVM) achieved 83.12% accuracy for potato leaf disease identification, while GLCM and K-Means classified spinach freshness with 88.33% accuracy (Khaidir et al., 2024). GLCM captures texture patterns by analyzing pixel intensity relationships at angles of 0°, 45°, 90°, and 135°, producing features like contrast, correlation, energy, homogeneity, entropy, and standard deviation (Srg et al., 2023). These features effectively describe complex visual patterns for classification tasks (Syam et al., 2021).

Artificial Neural Networks (ANN) with backpropagation, such as the traingdx algorithm, mimic biological neural systems to recognize complex patterns through adaptive learning (Hasanah & Permatasari, 2020). The process involves initializing random weights, forward propagation, error calculation, backward propagation, and weight updates until optimal results are achieved (Wilsen et al., 2021). MATLAB supports this through robust numerical computation and algorithm development (MathWorks, 2024). The effectiveness of ANN in handling high-dimensional data and complex textures makes it suitable for tasks like longan seedling identification and material classification (Gasim et al., 2025).

Bit depth determines the number of gray levels in a grayscale image, impacting texture detail. Higher bit depths provide finer details but may introduce noise, while lower bit depths risk losing critical information (Mahbod et al., 2021). Similarly, image resolution affects classification accuracy by altering the level of detail captured, as seen in concrete mix recognition where optimal resolutions balance detail and noise (Gasim et al., 2025). Optimizing bit depth is crucial for balancing image quality and processing efficiency in classification tasks (Arnita et al., 2022). This study evaluates bit depths (4–8 bits) to identify the optimal configuration for longan seedling classification, addressing a gap in prior research.

METHOD

This experimental study employs a quantitative approach to evaluate the impact of grayscale bit depth (4, 5, 6, 7, 8 bits) on the accuracy of longan seedling identification using ANN and GLCM features. The methodology, adapted from established image processing techniques, is outlined below and illustrated in Fig. 1.

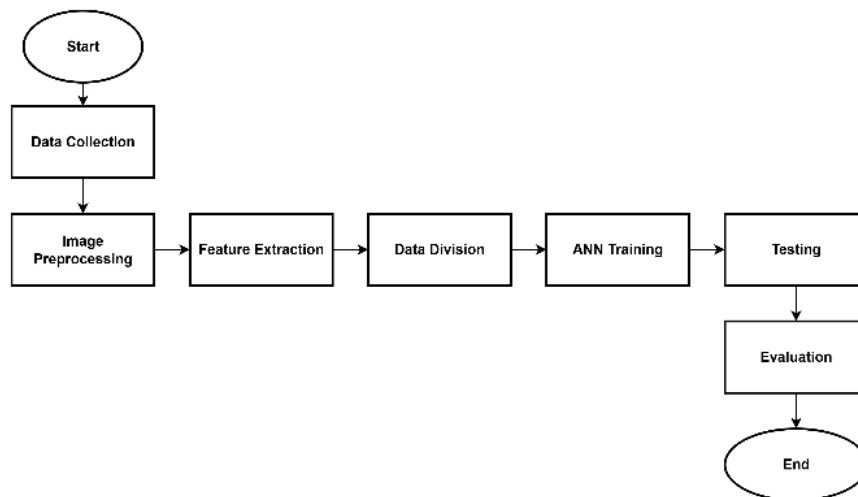


Figure 1. Research Methodology Flowchart

Data Collection

Fresh leaves from five longan varieties (Itoh, Pingpong, Merah, Matalada, Diamond River) were imaged using a USB digital microscope (0.3 MP, CMOS sensor, 3–60 mm focus, 1600x magnification) at a 10 cm distance, with 5-watt LED lighting at 7 cm to highlight texture. A total of 1000 images (640x480 pixels) were collected under uniform conditions.

Image Preprocessing and Feature Extraction

Images were converted from RGB to grayscale with bit depths of 4 (0–15), 5 (0–31), 6 (0–63), 7 (0–127), and 8 (0–255). Six texture features (contrast, correlation, energy, homogeneity, entropy, standard deviation) were extracted using MATLAB's *graycomatrix*, *graycoprops*, *entropy*, and *std2* functions. Features were normalized to a 0–255 range.

Data Division

Images were divided into 800 training (160 per variety) and 200 testing (40 per variety) sets, as shown in Table 1. Selection ensured clear vein texture visibility.

Table 1. Image Division for Training and Testing

Variety	Training Images	Testing Images
Matalada	160	40
Itoh	160	40
Pimpong	160	40
Diamond River	160	40
Merah	160	40
Total	800	200

ANN Training

A Multilayer Perceptron (MLP) with 6 input neurons (features), one hidden layer (20 neurons, determined experimentally), and 5 output neurons (varieties) was trained using the traingdx algorithm with a tansig activation function. Parameters included a 0.01 learning rate, 1000 maximum epochs, 1e-6 minimum gradient, and 6 maximum validation failures (Table 2). Target outputs were binary vectors (Table 3).

Table 2. ANN Training Parameters

No	Parameter	Value	Description
1	Training Algorithm	traingdx	Gradient Descent with Momentum and Adaptive Learning Rate
2	Number of Input Neurons	6	Corresponds to the number of extracted features (6 image statistics features)
3	Number of Hidden Layer Neurons	30	Determined experimentally
4	Number of Output Neurons	5	Representing five lychee seed classes
5	Learning Rate	0.01	Learning rate
6	Maximum Epoch	1000	Maximum number of training iterations
7	Minimum Gradient	1e-6	Stop limit if the gradient is too small
8	Maximum Failures	6	Training stops if validation fails 6 times in a row
9	Hidden Activation Function	tansig	Bipolar sigmoid, output range [-1, 1]
10	Output Activation Function	tansig	Same as in the hidden layer

Table 2 details the configuration parameters for the ANN model, including the training algorithm, neuron counts, learning rate, and activation functions, which guide the training process for classifying longan varieties.

Table 3. ANN Training Target Outputs

Neuron Ouput	K 1	K 2	K 3	K 4	K 5
<i>Neuron 1</i>	1	0	0	0	0
<i>Neuron 2</i>	0	1	0	0	0
<i>Neuron 3</i>	0	0	1	0	0
<i>Neuron 4</i>	0	0	0	1	0
<i>Neuron 5</i>	0	0	0	0	1

Table 3 shows the binary target outputs for the ANN, where each neuron corresponds to one of the five longan varieties (K1–K5), enabling precise classification during training.

Testing and Evaluation

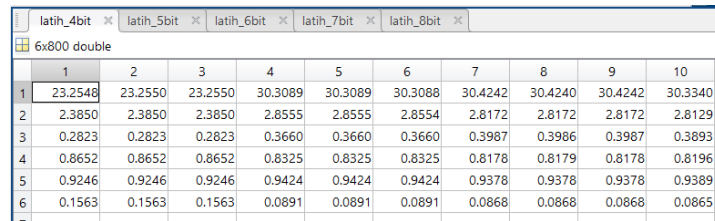
The testing was conducted through a MATLAB-based Graphical User Interface (GUI), which facilitated the selection of test images, bit depth conversion, feature extraction, model loading, and classification processes. Test results are displayed in the form of confidence scores and recognition status, indicating whether the image was successfully recognized as belonging to one of the longan seed classes or not. Evaluation is based on the number of images correctly recognized to determine the bit depth that provides the best accuracy.

RESULT

Feature extraction was performed on grayscale images with bit depths of 4–8, normalized to a 0–255 range. Six features (contrast, correlation, energy, homogeneity, entropy, standard deviation) were extracted using MATLAB



functions and stored in training tables (Fig. 2). The ANN, with a 6–20–5 architecture, achieved the highest training accuracy (76.20%) with 20 hidden neurons (Table 4).



	1	2	3	4	5	6	7	8	9	10
1	23.2548	23.2550	23.2550	30.3089	30.3089	30.3088	30.4242	30.4242	30.4242	30.3340
2	2.3850	2.3850	2.3850	2.8555	2.8555	2.8554	2.8172	2.8172	2.8172	2.8129
3	0.2823	0.2823	0.2823	0.3660	0.3660	0.3660	0.3987	0.3986	0.3987	0.3893
4	0.8652	0.8652	0.8652	0.8325	0.8325	0.8325	0.8178	0.8179	0.8178	0.8196
5	0.9246	0.9246	0.9246	0.9424	0.9424	0.9424	0.9378	0.9378	0.9378	0.9389
6	0.1563	0.1563	0.1563	0.0891	0.0891	0.0891	0.0868	0.0868	0.0868	0.0865

Figure 2. Example of Training Feature Table

Figure 2 displays a sample table of extracted GLCM features (contrast, correlation, energy, homogeneity, entropy, standard deviation) for training images, used as input for the ANN model.

Table 4. ANN Training Results

Hidden Neuron	Average Accuracy(%)	Average Performance (Error)
10	73.95	0.1387
20	76.20	0.1371
30	74.95	0.1366
40	72.71	0.1411
50	74.18	0.1393

Table 4 summarizes the ANN training performance across different hidden neuron counts, showing that 20 neurons yielded the highest accuracy (76.20%) with the lowest error (0.1371).

Testing on 200 images via the graphical user interface (Fig. 3) showed 6-bit and 4-bit depths yielding the highest accuracy (84.5%), followed by 7-bit (84.0%), 5-bit (83.5%), and 8-bit (82.0%) (Table 5). Matalada achieved the highest individual accuracy (90.0%).

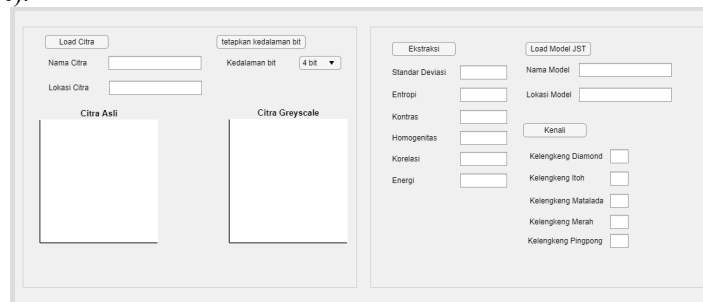


Figure 3. ANN Testing Interface

Table 5. Testing Results Summary

Bit depth	Correct	Incorrect	Accuracy (%)
4 bit	168	32	84.0
5 bit	167	33	83.5
6 bit	169	31	84.5
7 bit	169	31	84.5
8 bit	164	36	82.0

Table 5 presents the classification results for different bit depths, indicating that 6-bit and 7-bit depths achieved the highest accuracy (84.5%) for identifying longan varieties.

DISCUSSION

This study shows that bit depth variation affects the accuracy of longan seedling type recognition. A depth of 6 bits and 7 bits produced the highest accuracy of 84.5%, while 8 bits actually decreased slightly to 82%. This indicates that increasing bit depth does not always improve accuracy, as excessive detail can add noise to the image. The texture features used (GLCM, entropy, and standard deviation) effectively represent leaf characteristics. The 6–20–5 JST architecture used is effective in learning texture patterns for classifying five types of seedlings. Testing via the GUI interface also demonstrates that the system can be practically operated by users. These results reinforce that the selection of the appropriate bit depth is crucial for the accuracy of digital image-based recognition systems.

CONCLUSION

This study successfully developed a system for recognizing longan seed types based on grayscale image texture features with varying bit depths using the Artificial Neural Network (ANN) method. The results showed that bit depth had a significant effect on recognition accuracy, with the highest values achieved at 6 bits and 7 bits, each at 84.5%.

The use of GLCM texture features, entropy, and standard deviation proved effective in distinguishing the leaf vein characteristics of each variety. The ANN architecture with 20 neurons in the hidden layer provided the best training performance. The system has also been implemented in a GUI that facilitates interactive testing processes.

These findings indicate that optimizing bit depth can enhance image recognition performance and may serve as a foundation for developing future digital image-based plant classification systems.

REFERENCES

- Abdi Wahyu Nugroho. (2024). *KERAGAMAN FENETIK BEBERAPA VARIETAS KELENGKENG (Dimocarpus longan L.) BERDASARKAN KARAKTER BATANG DAN DAUN*. UNIVERSITAS ISLAM NEGERI MAULANA MALIK IBRAHIM MALANG.
- Aini, N., Setyati, D., & Umiyah. (2014). *STRUKTUR ANATOMI DAUN LENGKENG (DIMOCARPUS LONGAN LOUR.) KULTIVAR LOKAL, ITOH, PINGPONG DAN DIAMOND RIVER*.
- Al Wajieh, M. W. (2023). Klasifikasi Jenis Kelengkeng Berdasarkan Morfologi Daun Dengan Ekstraksi Ciri RGB, GLCM, dan Bentuk Menggunakan Metode BPNN. *Jurnal Aplikasi Teknologi Informasi Dan Manajemen (JATIM)*, 4(2), 183–193. <https://doi.org/10.31102/jatim.v4i2.2341>
- Anggraini, C. (2024). *KLASIFIKASI DAUN KELENGKENG MENGGUNAKAN METODE GRAY LEVEL CO-OCCURRENCE MATRIX (GLCM) DAN K- NEAREST NEIGHBOR (KNN)*. 11(2), 72–78. <https://doi.org/10.30656/jsii.v11i2.9157>
- Arnita, Marpaung, F., Aulia, F., & Nabila, R. C. (2022). *Computer Vision Dan Pengolahan Citra Digital* (Ahmad Baharuddin Surya (ed.); 1st ed.). PUSTAKA AKSARA. www.pustakaaksara.co.id
- Gasim, G., Heriansyah, R., Puspasari, S., Irfani, M. H., Purnamasari, E., Permatasari, I., & Samsuryadi, S. (2025). Improving the Accuracy of Concrete Mix Type Recognition with ANN and GLCM Features Based on Image Resolution. *Jurnal Infotel*, 17(1), 96–110. <https://doi.org/10.20895/infotel.v17i1.1201>
- Hasanah, S. H., & Permatasari, S. M. (2020). METODE KLASIFIKASI JARINGAN SYARAF TIRUAN BACKPROPAGATION PADA MAHASISWA STATISTIKA UNIVERSITAS TERBUKA. *BAREKENG : Jurnal Ilmu Matematika Dan Terapan*, 14(1), 243–252. <https://doi.org/10.30598/barekengvol14iss2pp243-252>
- Khaidir, Reyna Buryani Al'Safinat, A. Muhammad Fuad Fadhlurrahman, By Tri Agung Nusantara Kr. J. Tompong, & Jessica Crisfin Lapendy. (2024). Klasifikasi Tingkat Kesegaran Sayur Bayam Berdasarkan Tekstur Daunnya Berbasis Citra Digital. *Journal of Deep Learning, Computer Vision and Digital Image Processing*, 2022, 88–99. <https://doi.org/10.61255/decoding.v2i2.549>
- Mahbod, A., Schaefer, G., Löw, C., Dorffner, G., Ecker, R., & Ellinger, I. (2021). Investigating the impact of the bit depth of fluorescence-stained images on the performance of deep learning-based nuclei instance segmentation. *Diagnostics*, 11(6). <https://doi.org/10.3390/diagnostics11060967>
- MathWorks. (2024). *Matlab Documentation*. https://www.mathworks.com/products/matlab.html?s_tid=hp_products_matlab
- Nafiiyah, N., & Prasetyo, P. R. (2023). Klasifikasi Jenis Kelengkeng Berdasarkan Daun Menggunakan Convolutional Neural Network Multilayer Perceptron. *Jurnal Telematika*, 17(2), 75–79. <https://doi.org/10.61769/telematika.v17i2.496>
- Nugraha, D. S. (2023). *PENGARUH PENCAHAYAAN PADA PEMOTRETAN URAT DAUN PADA IDENTIFIKASI JENIS BIBIT KELENGKENG DENGAN METODE PENGENALAN JST-PB DAN FITUR GLCM*.
- Srg, S. A. R., Irhamna, Aldi, M. F., Ramadhan, M., & Siregar, N. L. (2023). Ekstraksi Fitur Citra Berdasarkan Tekstur Dengan Glcm (Gray Level Co-Occurrence). *JUTISAL (Jurnal Teknik Informatika Komputer Universal)*, 3(1), 44–51.
- Syam, A. A., Rifka, S., & Aulia, S. (2021). Implementasi Pengolahan Citra Untuk Identifikasi Daun Tanaman Obat Menggunakan Levenberg-Marquardt Backpropagation. *Elektron : Jurnal Ilmiah*, 13, 1–8. <https://doi.org/10.30630/eji.0.0.176>
- Wilsen, E. B., Gasim, G., & Teguh, R. (2021). Perbandingan Akurasi Pengenalan Kadar Semen Berdasarkan Tingkat Pencahayaan Menggunakan Jaringan Syaraf Tiruan. *Jurnal Algoritme*, 2(1), 55–61.