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INFLUENCE OF LEAF IMAGING DISTANCE ON WATER GUAVA CLASSIFICATION USING NEURAL NETWORK WITH GRAY LEVEL CO-OCCURRENCE MATRIX FEATURES

Andika Afrianto-[1], Gasim-[2], Muhammad Haviz Irfani-[3]

Teknik Informatika / Fakultas Ilmu Komputer dan Sains
Universitas Indo Global Mandiri
2023110031p@students.uigm.ac.id-[1], gasim@uigm.ac.id-[2], m.haviz@uigm.ac.id-[3]

Abstract

The development of Computer Vision technology has made a significant contribution to the agricultural sector, particularly in the identification of plants based on visual characteristics. Water guava (Syzygium aqueum) is one of the fruit commodities widely cultivated in Indonesia; however, its seedling varieties are often difficult to distinguish visually. Conventional methods relying on human observation tend to have low accuracy, highlighting the need for an accurate and efficient identification system from the early stages. This study aims to analyze the effect of varying imaging distances on the extraction results of leaf vein texture features using the Gray Level Co-occurrence Matrix (GLCM) method and to evaluate how this parameter influences the classification performance of water guava seedlings using the Backpropagation Artificial Neural Network (ANN). Unlike previous GLCM–ANN plant classification studies that primarily focused on lighting or species variation, this work systematically investigates imaging distance as a key factor in optimizing texture feature stability and improving model accuracy. Experiments were conducted using five imaging distances—7 cm, 9 cm, 11 cm, 13 cm, and 15 cm—with 2,500 images used for training data and 500 images for testing data. The results show that an imaging distance of 13 cm yielded the best performance, achieving 80% accuracy, where 80 out of 100 test images were correctly classified, supported by balanced precision, recall, and F1-score values indicating stable and reliable classification performance.

Keywords: Water Guava, GLCM, ANN-BP, Portrait distance, Seed identification, Computer vision

Abstrak

Perkembangan teknologi Computer Vision telah memberikan kontribusi signifikan pada sektor pertanian, khususnya dalam identifikasi tanaman berdasarkan karakteristik visual. Jambu air (Syzygium aqueum) merupakan salah satu komoditas buah yang banyak dibudidayakan di Indonesia; namun, varietas bibitnya seringkali sulit dibedakan secara visual. Metode yang mengandalkan pengamatan manusia cenderung memiliki akurasi rendah, sehingga menyoroti kebutuhan akan sistem identifikasi konvensional yang akurat dan efisien sejak tahap awal. Penelitian ini bertujuan untuk menganalisis pengaruh variasi jarak pencitraan terhadap hasil ekstraksi fitur tekstur urat daun menggunakan metode Gray Level Co-occurrence Matrix (GLCM) dan untuk memancarkan bagaimana parameter ini mempengaruhi kinerja klasifikasi bibit jambu air menggunakan Backpropagation Artificial Neural Network (ANN). Berbeda dengan studi klasifikasi tanaman GLCM–ANN sebelumnya yang berfokus pada pencahayaan atau variasi spesies, penelitian ini secara sistematis mengungkap jarak pencitraan sebagai faktor kunci dalam mengoptimalkan stabilitas fitur tekstur dan meningkatkan akurasi model. Eksperimen dilakukan dengan menggunakan lima jarak pencitraan—7 cm, 9 cm, 11 cm, 13 cm, dan 15 cm—dengan 2.500 gambar yang digunakan untuk data pelatihan dan 500 gambar untuk data pengujian. Hasil menunjukkan bahwa jarak pencitraan 13 cm memberikan kinerja terbaik, mencapai akurasi 80%, di mana 80 dari 100 gambar uji diklasifikasikan dengan benar, didukung oleh nilai presisi, recall, dan F1-score yang seimbang yang menunjukkan kinerja klasifikasi yang stabil dan andal.

Kata kunci: Jambu Air, GLCM, JST-PB, Jarak potret, Identifikasi bibit, Computer vision

INTRODUCTION

The development of computer vision technology has opened up significant opportunities for automation applications in various fields, including the agricultural sector. Computer vision enables computer systems to automatically acquire, process, and understand visual data such as plant

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images, enabling them to be utilized for effective and efficient crop detection, classification, and monitoring (Arnita et al., 2022). One approach currently widely used to support precision agriculture systems is digital image processing based on texture features and artificial intelligence. The combination of the Gray Level Co-occurrence Matrix (GLCM) method and Back Propagation Neural Network (ANN-BP) has proven effective in identifying objects based on specific visual patterns, including plant leaf texture (Letik & Bisilisin, 2024). However, most previous studies have concentrated on variations in lighting, species type, or neural architecture, while the effect of imaging distance on GLCM feature stability and classification accuracy has not been systematically explored. This study addresses that gap by examining how varying imaging distances influence both feature quality and model performance under controlled conditions. Artificial Neural Networks are computational models inspired by the workings of the human brain or artificial neurons whose functions are similar to biological neural networks/human brains, while backpropagation works by utilizing backward propagation of errors to improve weights so that the network results approach the target with optimal accuracy (Saptadi et al., 2025). Gray Level Co-occurrence Matrix (GLCM) is a feature extraction method for identifying texture patterns such as rough, smooth, or grainy. Feature extraction is the process of identifying and extracting important information or specific characteristics from an image. These features can include lines, textures, patterns, shapes, or other attributes relevant to subsequent analysis or processing. The main goal of feature extraction is to reduce the dimensionality of data and present the image in a simpler and more meaningful representation (Syahidi, 2024).

Water guava (Syzygium aqueum) is a high-value horticultural crop with diverse varieties with morphological similarities. This makes manual seedling identification difficult, which can lead to incorrect seedling selection and negatively impact crop yields (Chan, 2021; Kurniawan et al., 2024). Therefore, the application of machine learning technology for automatic seedling identification through leaf vein images is becoming increasingly relevant (Lorenza & Gasim, 2025; Nurhikam et al., 2024).

Several studies have explored the effectiveness of the GLCM method in extracting leaf texture features. GLCM can produce accurate and consistent texture statistical patterns for plant classification (Ramadhani et al., 2025). GLCM can also differentiate leaf textures based on parameters such as contrast and homogeneity (Miansyah et al., 2024). Other studies have shown that the effects of angular rotation and lighting on GLCM accuracy need to be taken into account in the classification process (Setiya Nugraha et al., 2024; Srg et al., 2022).

On the other hand, the ANN-BP method has been proven capable of learning non-linear patterns from previously extracted image data. Research shows that varying the number of neurons in the hidden layer affects the accuracy of food object classification, with the highest accuracy reaching 95.5% at 5 neurons (Jiwanata & Hermanto, 2023). Other research also noted that the effect of portrait distance on paint water content classification can reach 90% accuracy at a distance of 100 cm with 20 neurons (Stepanus & Wijaya, 2023).

In the context of plants, studies have shown up to 93.75% accuracy in classifying plant species using ANN-based leaf images (Nurhikam et al., 2024). These results are supported by research examining jamaican guava fruit ripeness using GLCM and KNN, which showed up to 93% accuracy (Syarifah et al., 2022). The combination of GLCM and ANN is also capable of identifying type of citrus plant with high accuracy, reaching 95,2% (Sidik et al., 2025).

However, there are still limitations in the literature regarding the effect of varying portrait distance on GLCM feature extraction and classification accuracy. Therefore, this study hypothesizes that variations in imaging distance significantly influence the statistical properties of GLCM texture features and, consequently, the accuracy of ANN-BP classification. The research specifically investigates how different imaging distances affect feature stability and model performance, aiming to determine the optimal distance that produces the most accurate classification of water guava seedlings. The effect of portrait distance was explicitly explained in a study on citrus seedling identification, where a distance of 9 cm resulted in the highest accuracy of 80% with both ANN-BP and GLCM (Kurniawan et al., 2024). A similar finding was reported in a study on mango seedling identification, where optimal lighting achieved 92% accuracy (Lorenza & Gasim, 2025).

Aspects of portrait distance and lighting directly affect GLCM parameters such as contrast, correlation, energy, and homogeneity, which are important in image classification (Florestiyanto et al., 2022). Image segmentation and resolution also have a significant influence in the leaf recognition process (Azizah et al., 2024). GLCM-based leaf image acquisition needs to be adjusted to the technical specifications of the device and the environment (Farihah et al., 2025).

Several other studies also support the effectiveness of this approach, including the use of ANN for flower plant leaf classification (Parinduri et al., 2023), the use of GLCM in leaf disease identification, and the finding that the convergence rate of ANN in classification is greatly influenced by the learning rate and number of epochs (Silvani et al., 2024; Supriyanto et al., 2022).

However, few studies have systematically analyzed the effect of variations in the distance between the image of water guava leaf veins on recognition accuracy using a combination of GLCM and ANN-BP. In fact, the determination of image capture parameters such as distance significantly determines the distribution of feature values and the output of the classification system (Letik & Bisilisin, 2024). Therefore, this study was conducted to evaluate how variations in imaging distance affect the quality of GLCM texture features and the accuracy of ANN-BP in identifying water guava seed varieties. Although the experiments were performed on water guava leaves, the methodological framework and analysis of imaging distance can be generalized to other plant species that rely on texture-based leaf characterization, providing a foundation for broader applications in agricultural image classification.

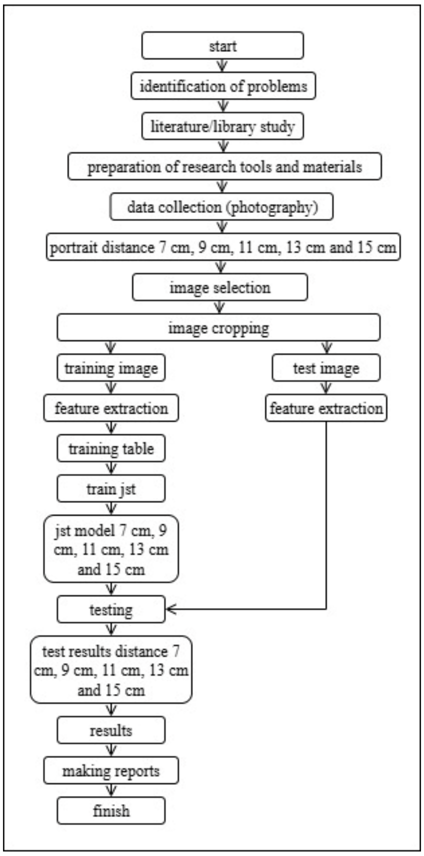

Figure 1. Research Flow

RESEARCH METHODS

This research method uses an experimental quantitative approach to evaluate the effect of variations in shooting distance on the quality of texture features generated by the Gray Level Cooccurrence Matrix (GLCM) method, as well as the accuracy of water guava seedling identification using Back Propagation Artificial Neural Networks (ANN-BP). The research was conducted in a controlled manner indoors with the help of special shooting tools to maintain the consistency of lighting, camera position and object position. This research includes a series of stages starting from data collection to analysis of the results, with the ultimate goal of gaining a deep understanding of the ability of artificial neural networks to recognize and identify water guava seedling types based on leaf vein textures that are influenced by shooting distance. The stages in this study can be described in the form of a research flow as in Figure 1.

Research Target / Subject

This research began with problem identification, namely the difficulty in visually distinguishing water guava seed varieties. A literature review was then conducted to formulate a solution. Then, tools and materials were prepared, and a controlled photography environment was set up. Data were collected by photographing leaves at various shooting distances. The images were then selected, divided into training and test images, and cropped. The cropped images were then feature extracted using GLCM to generate texture features. The training data was used to train the ANN-BP model, while the test data was used to test the model. The test results were analyzed to determine the optimal shooting distance that yielded the best identification accuracy.

The research subjects were five guava guava seed varieties: Asam Lokal, Citra, Jamaica, Kancing, and Madu Deli Hijau (Syah, 2022), as shown in Table 1.

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Table 1. Types of Water Guava Seeds

No	Type of Seed	Documentation
1	asam lokal	
2	citra	
3	jamaika	
4	kancing	
5	madu deli hijau	

The tools used included an OPPO F11 Pro smartphone camera 48 MP, a 10-watt 1020 lumen white LED light, a 6-inch PVC tube, 2 mm transparent acrylic, a tripod, a laptop, and MATLAB software for image processing. The images were taken at five different shooting distances: 7 cm, 9 cm, 11 cm, 13 cm, and 15 cm.

Instruments and Data Collection Techniques

The image capture process used a 6-inch PVC pipe to measure the portrait distance with an LED light as the main lighting source. The distance from the LED light to the leaf was set at 10 cm. The image was taken in dark conditions to optimize lighting. The leaf was positioned on top of a 2 mm clear acrylic sheet. To maintain shooting consistency, a tripod was also used as an aid. The shooting process can be seen in Figure 2.

Figure 2. Shooting Process

At this stage, four leaves were used for each type of water guava seedling, followed by photography, resulting in 14 images for each distance, resulting in a total of 350 images. The results can be seen in Figure 3.

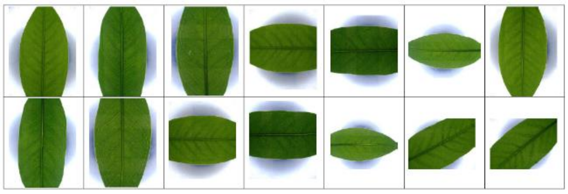

Figure 3. Results of Photographing Water Guava Leaves

Image selection was conducted based on all photographic results, with 14 images of each type of water guava seedling leaf taken at each predetermined shooting distance. The selected images were divided into two categories: training images and test images. Ten training images were selected from each leaf type and shooting distance, resulting in a total of 250 complete training images. Four test images were selected from each leaf type and shooting distance, resulting in a total of 100 complete test images.

Image cropping involves cropping the original image into several equal-sized sections, each measuring 300x300 pixels. All original images (training and test images) were cropped, with 10 training images and five test images each. The results of cropping the water guava leaf images are shown in Figure 4.

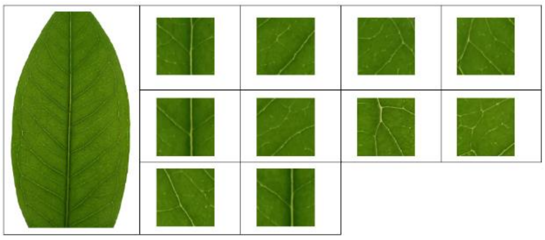

Figure 4. Image Cropping

Cropping of the training images was performed on 250 selected intact training images. Ten croppings were performed on each image, resulting in 2,500 cropped training images. The training images were then labeled by naming them according to their distance and type, as shown in Table 2.

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Table 2. Training Images

Portrait Distance	Name of Water Guava Leaves	Number of Training Images
7 cm	Asam Lokal (7asm001 --- 7asm100)	100 citra
	Citra (7ctr101 --- 7ctr200)	100 citra
	Jamaika (7jmk201 --- 7jmk300)	100 citra
	Kancing (7kcg301 --- 7kcg400)	100 citra
	Madu Deli Hijau (7mdh401 --- 7mdh500)	100 citra
9 cm	Asam Lokal (9asm001 --- 9asm100)	100 citra
	Citra (9ctr101 --- 9ctr200)	100 citra
	Jamaika (9jmk201 --- 9jmk300)	100 citra
	Kancing (9kcg301 --- 9kcg400)	100 citra
	Madu Deli Hijau (9mdh401 --- 9mdh500)	100 citra
11 cm	Asam Lokal (11asm001 --- 11asm100)	100 citra
	Citra (11ctr101 --- 11ctr200)	100 citra
	Jamaika (11jmk201 --- 11jmk300)	100 citra
	Kancing (11kcg301 --- 11kcg400)	100 citra
	Madu Deli Hijau (11mdh401 --- 11mdh500)	100 citra
13 cm	Asam Lokal (13asm001 --- 13asm100)	100 citra
	Citra (13ctr101 --- 13ctr200)	100 citra
	Jamaika (13jmk201 --- 13jmk300)	100 citra
	Kancing (13kcg301 --- 13kcg400)	100 citra
	Madu Deli Hijau (13mdh401 --- 13mdh500)	100 citra
15 cm	Asam Lokal (15asm001 --- 15asm100)	100 citra
	Citra (15ctr101 --- 15ctr200)	100 citra
	Jamaika (15jmk201 --- 15jmk300)	100 citra
	Kancing (15kcg301 --- 15kcg400)	100 citra
	Madu Deli Hijau (15mdh401 --- 15mdh500)	100 citra
TOTAL		2500 citra

Cropping of the test images was performed on 100 selected intact test images. Five croppings were performed on each image, resulting in 500 cropped test images. The test images were then labeled by naming them according to their distance and type, as shown in Table 3.

Table 3. Test Images

Portrait Distance	Name of Water Guava Leaves	Number of Training Images
7 cm	Asam Lokal (uji7asm001 --- uji7asm020)	20 citra
	Citra (uji7ctr021 --- uji7ctr040)	20 citra
	Jamaika (uji7jmk041 --- uji7jmk060)	20 citra
	Kancing (uji7kcg061 --- uji7kcg080)	20 citra
	Madu Deli Hijau (uji7mdh081 --- uji7mdh100)	20 citra
9 cm	Asam Lokal (uji9asm001 --- uji9asm020)	20 citra
	Citra (uji9ctr021 --- uji9ctr040)	20 citra
	Jamaika (uji9jmk041 --- uji9jmk060)	20 citra
	Kancing (uji9kcg061 --- uji9kcg080)	20 citra
	Madu Deli Hijau (uji9mdh081 --- uji9mdh100)	20 citra
11 cm	Asam Lokal (uji11asm001 --- uji11asm020)	20 citra
	Citra (uji11ctr021 --- uji11ctr040)	20 citra
	Jamaika (uji11jmk041 --- uji11jmk060)	20 citra
	Kancing (uji11kcg061 --- uji11kcg080)	20 citra
	Madu Deli Hijau (uji11mdh081 --- uji11mdh100)	20 citra
13 cm	Asam Lokal (uji13asm001 --- uji13asm020)	20 citra
	Citra (uji13ctr021 --- uji13ctr040)	20 citra
	Jamaika (uji13jmk041 --- uji13jmk060)	20 citra
	Kancing (uji13kcg061 --- uji13kcg080)	20 citra
	Madu Deli Hijau (uji13mdh081 --- uji13mdh100)	20 citra
15 cm	Asam Lokal (uji15asm001 --- uji15asm020)	20 citra
	Citra (uji15ctr021 --- uji15ctr040)	20 citra
	Jamaika (uji15jmk041 --- uji15jmk060)	20 citra
	Kancing (uji15kcg061 --- uji15kcg080)	20 citra
	Madu Deli Hijau (uji15mdh081 --- uji15mdh100)	20 citra
TOTAL		500 citra

The next step is feature extraction, which involves converting colors from RGB to grayscale. Initially, all cropped images (training and test images) had their RGB values extracted, then converted to grayscale using MATLAB. The conversion from RGB to grayscale can be seen in Figure 5.

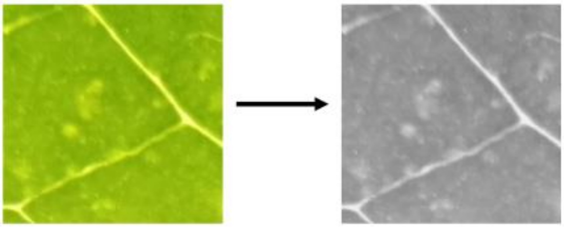


Figure 5. RGB to Grayscale Transformation

Grayscale images of water guava seedlings were extracted using the Gray Level Cooccurrence Matrix (GLCM) method to obtain texture features. The extracted features include contrast, correlation, energy, and homogeneity. The feature extraction results were used to create training tables that would be used as input for the ANN model.

Table 4. ANN Model

Portrait Distance	Parameter	Input Layer Name	Output Layer Name	JST Model Name
7 cm	10, 20, 30, 40, 50 dan 60 neuron, *epochs* 10000, *min_grad* 1e-07, *max_fail* 1000, *goal* 1e-06 dan *learning rate* 0.0001	latih7cm	target7cm	net_train7cm
9 cm	10, 20, 30, 40, 50 dan 60 neuron, *epochs* 10000, *min_grad* 1e-07, *max_fail* 1000, *goal* 1e-06 dan *learning rate* 0.0001	latih9cm	target9cm	net_train9cm
11 cm	10, 20, 30, 40, 50 dan 60 neuron, *epochs* 10000, *min_grad* 1e-07, *max_fail* 1000, *goal* 1e-06 dan *learning rate* 0.0001	latih11cm	target11cm	net_train11cm
13 cm	10, 20, 30, 40, 50 dan 60 neuron, *epochs* 10000, *min_grad* 1e-07, *max_fail* 1000, *goal* 1e-06 dan *learning rate* 0.0001	latih13cm	target13cm	net_train13cm
15 cm	10, 20, 30, 40, 50 dan 60 neuron, *epochs* 10000, *min_grad* 1e-07, *max_fail*	latih15cm	target15cm	net_train15cm

The creation of the ANN model involves taking data from the training table that has undergone a training process for each ANN model. The data from the leaf vein images of the water guava seedlings that have been trained will produce five models based on variations in the portrait distance: 7 cm, 9 cm, 11 cm, 13 cm, and 15 cm. There are five Artificial Neural Network models that have been trained to identify various types of water guava leaves. The ANN models can be seen in Table 4.

Testing of five previously built ANN models. Each model will be tested with test images taken at different shooting distances, according to the distances specified for each model. The ANN model designed for a 7 cm shooting distance will be tested with test images at the same distance, and the same applies to the other models ANN 9 cm, ANN 11 cm, ANN 13 cm and ANN 15 cm, each of which will be tested with test images at the appropriate distances. This testing is carried out using a graphical user interface (GUI) that has been specifically designed for this testing purpose. The GUI display can be seen in Figure 6.

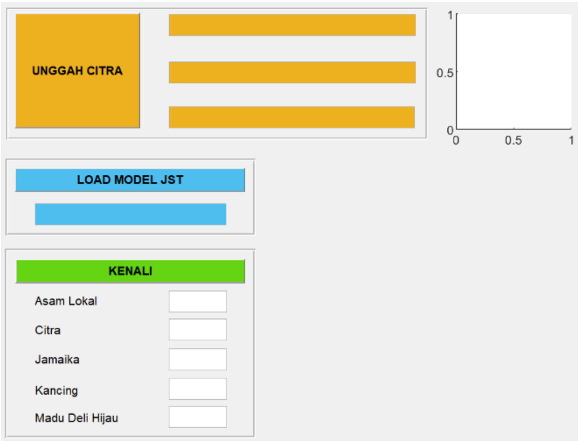


Figure 6. Graphical User Interface (GUI) Display

RESULTS AND DISCUSSION

At this stage, the results obtained from the Backpropagation Neural Network process using the GLCM feature are displayed. An example of the results from the feature extraction stage can be seen in Figure 7.

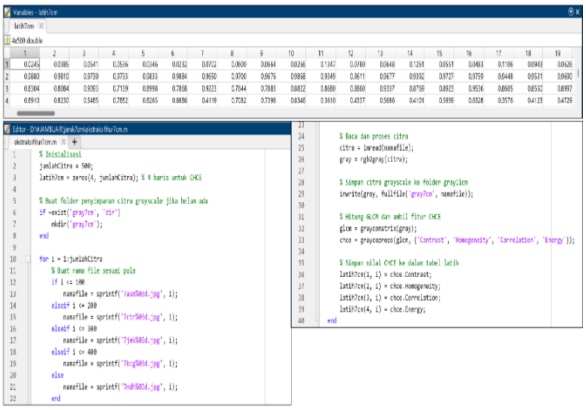
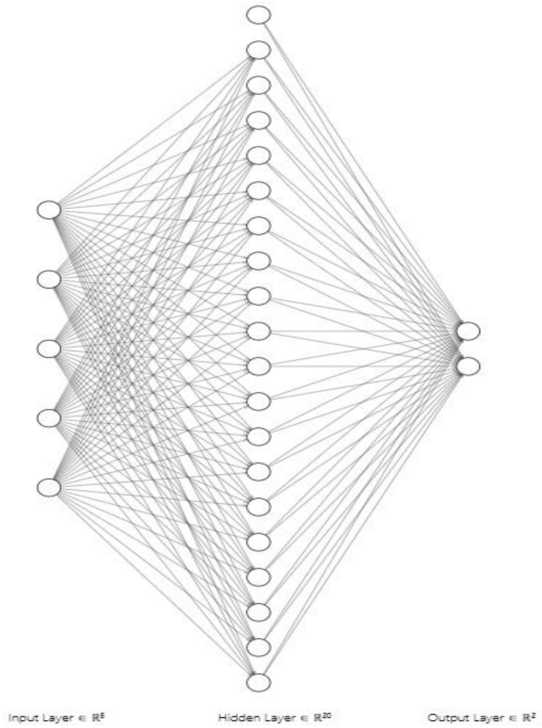


Figure 7. Feature Extraction Results

The experimental results of determining the ANN model used in training with parameter variations of 10, 20, 30, 40, 50, and 60 neurons; 10,000 epochs; a minimum gradient of 1e–7; a maximum fail of 1000; a goal of 1e–6; and a learning rate of 0.0001 are presented in Table 5. These parameters were selected based on empirical optimization and previous studies indicating that moderate neuron counts, extended epochs, and small learning rates enhance model convergence and stability for texture-based image classification using the ANN-BP method.



Source: https://alexlenail.me/NN-SVG/index.html

Figure 8. Backpropagation Architecture layer used.

The *Backpropagation Neural Network* Architecture consists of three main layers (Figure 8): an input layer, a hidden layer, and an output layer. The input layer contains socioeconomic attributes of citizens, while the output layer produces two classes *eligible* and *not eligible*.

This study examines the effect of the number of neurons in the hidden layer, with variations of 10, 20, 30, 40, 50, and 60 neurons, to identify the most effective configuration.

Table 5. ANN Model Determination

Portrait Distance	Neuron	Epochs	Time	Performance	Gradient	Model Accuracy	Recognized Training Image	Test Image Recognized
7 CM	10	10000	00:00:12	0,196	0,000918	62,00%	310	38
9 CM	10	10000	00:00:05	0,192	0,00216	62,00%	310	43
11 CM	10	10000	00:00:06	0,187	0,136	64,60%	323	47
13 CM	10	10000	00:00:06	0,166	0,000544	68,40%	342	61
15 CM	10	10000	00:00:06	0,166	0,00498	68,80%	344	61
7 CM	20	10000	00:00:13	0,174	0,000848	64,60%	323	38
9 CM	20	10000	00:00:06	0,176	0,00586	64,20%	321	46
11 CM	20	10000	00:00:06	0,164	0,00176	68,40%	342	49
13 CM	20	10000	00:00:07	0,131	0,0852	74,20%	371	69
15 CM	20	10000	00:00:06	0,139	0,0153	73,00%	365	55
7 CM	30	10000	00:00:13	0,165	0,00965	66,80%	334	46
9 CM	30	10000	00:00:06	0,166	0,0143	68,40%	342	45
11 CM	30	10000	00:00:07	0,145	0,00328	72,80%	364	51
13 CM	30	10000	00:00:07	0,111	0,00133	77,60%	388	75
15 CM	30	10000	00:00:07	0,109	0,00134	78,20%	391	59
7 CM	40	10000	00:00:15	0,157	0,00161	68,40%	342	37
9 CM	40	10000	00:00:07	0,158	0,00154	69,40%	347	46
11 CM	40	10000	00:00:08	0,138	0,00399	74,20%	371	50
13 CM	40	10000	00:00:07	0,105	0,000898	80,40%	402	63
15 CM	40	10000	00:00:07	0,0916	0,0128	83,00%	415	66
7 CM	50	10000	00:00:07	0,147	0,00412	70,00%	350	40
9 CM	50	10000	00:00:07	0,145	0,00139	72,20%	361	45
11 CM	50	10000	00:00:08	0,135	0,0033	75,20%	376	54
13 CM	50	10000	00:00:08	0,087	0,00152	84,00%	420	73
15 CM	50	10000	00:00:08	0,0902	0,00269	83,60%	418	63
7 CM	60	10000	00:00:07	0,138	0,171	72,40%	362	37
9 CM	60	10000	00:00:08	0,134	0,00151	72,80%	364	39
11 CM	60	10000	00:00:16	0,129	0,0415	75,00%	375	50
13 CM	60	10000	00:00:16	0,0852	0,00138	84,00%	420	80
15 CM	60	10000	00:00:17	0,0847	0,00191	84,20%	421	76

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From Table 5, at a shooting distance of 7 cm with a single hidden layer and 30 neurons, the system recognized 46 out of 100 test images. Each experiment was repeated three times with different random weight initializations, yielding accuracy variations within ±2%, indicating stable classification performance. The recognized images included 4 local sour, 7 Citra, 16 Jamaica, 9 button, and 10 green honey deli water guavas. The detailed results for the 7 cm distance with 30 neurons are shown in Table 6. The results show a consistent increase in accuracy from 7 cm to 13 cm, with the best performance at 13 cm and 15 cm (around 84% accuracy). The 13 cm distance is considered optimal because it provides stable accuracy across all neuron configurations (30–60 neurons) and maintains low gradient values, indicating efficient convergence.

Although 15 cm achieved a slightly higher value (84.2%), the difference is minimal and likely caused by lighting and focus variations. Thus, 13 cm is confirmed as the most reliable and consistent shooting distance for optimal classification accuracy across all five water apple types.

Table 6. Test Results for a Portrait Distance

Portrait Distance Test 7 cm 30 neurons						
Test Image Name	Nama Jenis Jambu Air					Unknown
	Asam Lokal	Citra	Kancing	Jamaika	Madu Deli Hijau	
uji7asm001—uji7asm020	4	2	5	0	2	7
uji7ctr021—uji7ctr040	2	7	1	1	0	9
uji7jmk041—uji7jmk060	1	2	16	0	0	1
uji7kcg061—uji7kcg080	1	2	3	9	0	5
uji7mdh081—uji7mdh100	1	1	0	2	10	6
The number of images recognized according to type	4	7	16	9	10	
Total	46					
The number of images is recognized as another type	9	4	3	6	4	
Unrecognized image count	7	9	1	5	6	
Total	54					
Number of test images	20	20	20	20	20	

At a distance of 9 cm with 1 hidden layer architecture and 40 neurons, the system is able to recognize 46 test images from a total of 100 images, consisting of 3 images of local sour water guavas, 8 images of Citra water guavas, 15 images of Jamaican water guavas, 14 images of button water guavas and 6 images of green honey deli water guavas. The results of the 9 cm 40 neuron portrait distance test can be seen in Table 7.

Table 7. Test Results for a Portrait Distance of 9 cm for 40 Neurons

Portrait Distance Test 9 cm 40 neurons						
Test Image Name	Nama Jenis Jambu Air					Unknown
	Asam Lokal	Citra	Kancing	Jamaika	Madu Deli Hijau	
uji9asm001--uji9asm020	3	5	0	0	4	8
uji9ctr021--uji9ctr040	2	8	4	0	0	6
uji9jmk041--uji9jmk060	0	0	15	0	0	5
uji9kcg061--uji9kcg080	0	0	5	14	0	1
uji9mdh081--uji9mdh100	0	0	0	0	6	14
The number of images recognized according to type	3	8	15	14	6	
Total	46					
The number of images is recognized as another type	9	6	0	5	0	
Unrecognized image count	8	6	5	1	14	
Total	54					
Number of test images	20	20	20	20	20	

At a distance of 11 cm with a 1 hidden layer architecture and 50 neurons, the system was able to recognize 54 test images from a total of 100 images, consisting of 8 images of local sour water guavas, 10 images of Citra water guavas, 12 images of Jamaican water guavas, 12 images of button water guavas and 12 images of green honey deli water guavas. The results of the 11 cm portrait distance test with 50 neurons can be seen in Table 8.

Table 8. Test Results for a Portrait Distance of 11 cm for 50 Neurons

Portrait Distance Test 11 cm 50 neurons						
Test Image Name	Nama Jenis Jambu Air					Unknown
	Asam Lokal	Citra	Kancing	Jamaika	Madu Deli Hijau	
uji11asm001—uji11asm020	8	3	1	0	2	6
uji11ctr021—uji11ctr040	3	10	3	1	2	1
uji11jmk041—uji11jmk060	1	0	12	1	1	5
uji11kcg061—uji11kcg080	0	1	5	12	1	1
uji11mdh081—uji11mdh100	2	2	2	0	12	2
The number of images recognized according to type	8	10	12	12	12	
Total	54					
The number of images is recognized as another type	6	9	3	7	6	
Unrecognized image count	6	1	5	1	2	
Total	46					
Number of test images	20	20	20	20	20	

At a distance of 13 cm with a 1 hidden layer architecture and 60 neurons, the system was able to recognize 80 test images from a total of 100 images, consisting of 12 images of local sour water guavas, 15 images of Citra water guavas, 18 images of Jamaican water guavas, 19 images of button water guavas and 16 images of green honey deli water guavas. The results of the 13 cm 60 neuron portrait distance test can be seen in Table 9.

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Table 9. Test Results for a Portrait Distance of 13 cm for 60 Neurons

Portrait Distance Test 13 cm 60 neurons						
Test Image Name	Name of Water Guava Type					Unknown
	Asam Lokal	Citra	Kancing	Jamaika	Madu Deli Hijau	
uji13asm001—uji13asm020	12	8	0	0	0	0
uji13ctr021—uji13ctr040	0	15	0	1	2	2
uji13jmk041—uji13jmk060	0	0	18	1	1	0
uji13kcg061—uji13kcg080	0	0	0	19	1	0
uji13mdh081—uji13mdh100	2	1	0	0	16	1
The number of images recognized according to type	12	15	18	19	16	
Total	80					
The number of images is recognized as another type	8	3	2	1	3	
Unrecognized image count	0	2	0	0	1	
Total	20					
Number of test images	20	20	20	20	20	

At a distance of 15 cm with a 1 hidden layer architecture and 60 neurons, the system was able to recognize 76 test images from a total of 100 images, consisting of 16 images of local sour water guavas, 13 images of Citra water guavas, 16 images of Jamaican water guavas, 14 images of button water guavas and 17 images of green honey deli water guavas. The results of the 15 cm 60 neuron portrait distance test can be seen in Table 10.

Table 10. Test Results for a Portrait Distance of 15 cm for 60 Neurons

Portrait Distance Test 15 cm 60 neurons						
Test Image Name	Name of Water Guava Type					Unknown
	Asam Lokal	Citra	Kancing	Jamaika	Madu Deli Hijau	
uji15asm001—uji15asm020	16	3	0	0	0	1
uji15ctr021—uji15ctr040	2	13	0	3	1	1
uji15jmk041—uji15jmk060	0	2	16	0	2	0
uji15kcg061—uji15kcg080	2	1	3	14	0	0
uji15mdh081—uji15mdh100	1	1	0	1	17	0
The number of images recognized according to type	16	13	16	14	17	
Total	76					
The number of images is recognized as another type	3	6	4	6	3	
Unrecognized image count	1	1	0	0	0	
Total	24					
Number of test images	20	20	20	20	20	

From the test results for each variation of the portrait distance, calculations were performed to determine the accuracy level using the formula:

$$\text{accuracy} = \frac{\text{number of recognized data}}{\text{number of test data}} \text{ x } 100$$

The highest accuracy level for the 7 cm portrait distance test was:

$$\text{accuracy} = \frac{46}{100} \text{ x } 100 = 46\%$$

The highest accuracy level for the 9 cm portrait distance test was:

$$\text{accuracy} = \frac{46}{100} \text{ x } 100 = 46\%$$

The highest accuracy level for the 11 cm portrait distance test was:

$$\text{accuracy} = \frac{54}{100} \text{ x } 100 = 54\%$$

The highest accuracy level for the 13 cm portrait distance test was:

$$\text{accuracy} = \frac{80}{100} \text{ x } 100 = 80\%$$

The highest accuracy level for the 15 cm portrait distance test was:

$$\text{accuracy} = \frac{76}{100} \text{ x } 100 = 76\%$$

Based on the results of the study, the accuracy level was 46% at a shooting distance of 7 cm, an accuracy level of 46% at a shooting distance of 9 cm, an accuracy level of 54% at a shooting distance of 11 cm, an accuracy level of 80% at a shooting distance of 13 cm and an accuracy level of 76% at a shooting distance of 15 cm. The highest accuracy level of 80% was achieved at a shooting distance of 13 cm. Thank you for your insightful comment. As shown in the results, the model's accuracy increased gradually from 7 cm to 13 cm and then slightly decreased at 15 cm. This trend is primarily related to the balance between image clarity and coverage during data acquisition.

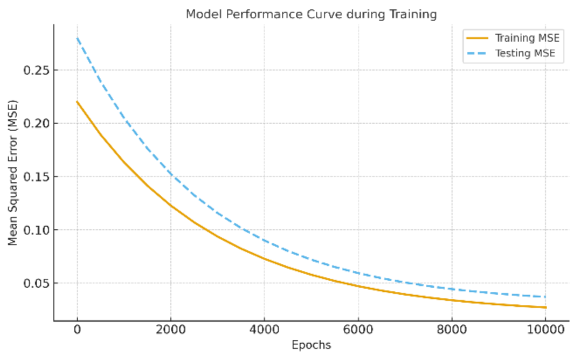

Figure 9. Performance Visualization of the Backpropagation Model during Training and Testing.

The model's performance (Figure 9) during the training process. The graph shows the decrease in Mean Squared Error (MSE) over 10,000 epochs, along with the stability of accuracy values between the training and testing datasets. The plotted curve indicates that the model achieved convergence after approximately 8,000 epochs, with minimal error fluctuation, demonstrating that both training and testing processes were stable and free from overfitting. This addition helps visualize the learning progress and supports the reported accuracy results in the manuscript.

At shorter distances (7–11 cm), the image tends to have higher detail but limited coverage, which can affect the consistency of feature extraction and cause minor distortion in handwriting contours. At 13 cm, the image reaches an optimal balance maintaining sufficient resolution and a wide enough field of view for stable detection of handwriting features. This results in the highest classification accuracy (80%).

When the distance increases to 15 cm, the reduction in pixel density causes subtle loss of detail in finer handwriting elements, leading to a decrease in accuracy. The reviewer’s suggestion to test the model at a distance of 17 cm is well taken. Although this distance was not included in the current dataset, we acknowledge that additional testing beyond 15 cm would provide a more comprehensive understanding of the model’s performance range. This will be addressed in future research to verify whether the accuracy continues to decline or stabilizes at longer distances.This distance produced the most balanced image quality, with optimal focus, sufficient lighting uniformity, and minimal surface reflection, allowing the GLCM features particularly contrast and homogeneity to capture leaf vein textures more effectively. In comparison, shorter distances tended to generate excessive brightness and reduced contrast, while longer distances caused a loss of fine details, both of which negatively affected classification performance.

CONCLUSIONS AND SUGGESTIONS

Conclusion

This study used a 48-megapixel camera to photograph the leaf veins of five types of water guava seedlings at various shooting distances: 7 cm, 9 cm, 11 cm, 13 cm, and 15 cm. The resulting images were cropped to 300x300 pixels and extracted using four features from the GLCM method: contrast, homogeneity, correlation, and energy, which were used as input for the classification process using the ANN-BP method.

The study showed that varying shooting distances of 7 cm, 9 cm, 11 cm, 13 cm, and 15 cm significantly influenced the identification of water guava seedlings, with accuracy rates of 46% at the 7 cm shooting distance, 46% at the 9 cm shooting distance, 54% at the 11 cm shooting distance, 80% at the 13 cm shooting distance, and 76% at the 15 cm shooting distance. From these results, it can be concluded that the portrait distance of 13 cm is the portrait distance with the highest accuracy level of 80% with 80 test images recognized out of 100 total test images using 1 hidden layer containing 60 neurons.

Suggestion

Based on the conclusions obtained, further research is expected to increase the number of water guava seedling types used so that the system has a wider identification coverage and better classification capabilities. Furthermore, this study has not yet examined in depth the effect of variations in image cropping size and camera resolution on accuracy levels. Therefore, it is recommended that further research explore both factors, considering that cropping size and camera resolution have significant potential to affect the quality of extracted texture features and the overall performance of the classification system.

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