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Learning Rate and Epoch Analysis for Medicinal Plant Identification Using GLCM and BPNN

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ABSTRAC

Accurate identification of medicinal plants is essential for pharmacology and biodiversity conservation. However, traditional methods rely heavily on subjective visual inspection, which is prone to misclassification due to subtle differences in leaf textures. A primary challenge that remains unaddressed is the understanding of hyperparameter sensitivity within limited datasets, particularly when the subjects exhibit extremely high visual similarity. This study proposes an automated identification approach using Gray-Level Co-occurrence Matrix (GLCM) and Backpropagation Neural Network (BPNN) to classify three Indonesian medicinal species: white ginger, mango ginger, and yellow turmeric. The distinctive focus of this research lies in its attempt to differentiate these specific plants, which possess leaf texture characteristics so similar that they are often indistinguishable to the human eye**.** This approach involves a systematic analysis of learning rate and epoch parameters to optimize convergence for these nearly identical texture features. A dataset of 63 images was transformed into five GLCM statistical features to serve as the primary inputs for the BPNN. Experimental results demonstrate that classification performance is highly sensitive to parameter tuning. The system achieved its peak accuracy of 65.03% using a learning rate of 0.1 and 100 epochs. The findings reveal that smaller learning rates and limited training iterations facilitate more stable convergence when processing data with high feature similarity. While the accuracy indicates potential for further development, this study provides a significant contribution to creating objective identification methods for visually similar plants and offers empirical insights into optimal parameter selection for texture-based neural network architectures.

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1. INTRODUCTION

The need for fast, accurate, and standardized identification of medicinal plants has become increasingly urgent in the pharmaceutical, cosmetic, and herbal industries, particularly considering Indonesia's extraordinary biodiversity. Indonesia is recognized as one of the world's megabiodiversity countries, hosting thousands of medicinal plant species that play an essential role in traditional and modern medicine [1]. However, in practical applications, medicinal plant identification still largely relies on manual visual observation of leaf morphology, including texture, shape, and color [2]. This condition represents the core research problem, as manual identification is subjective, time-consuming, highly dependent on expert knowledge, and prone to misclassification when different species exhibit similar morphological characteristics [3]. Furthermore, the limited availability of trained botanists, especially in rural and community-based herbal industries, further intensifies this challenge [4].

To overcome these limitations, digital image processing (DIP) has emerged as an objective and scalable solution for medicinal plant identification. DIP enables the extraction of quantitative visual features from leaf images, allowing subtle texture patterns that are difficult to detect by the human eye to be systematically analyzed [5]. Among various visual features, leaf texture is considered one of the most stable descriptors, particularly when shape and color variations are minimal across species [6]. One of the most widely used statistical texture analysis methods is the Gray-Level Co-occurrence Matrix (GLCM), which effectively represents spatial relationships between pixel intensities and quantifies texture properties such as contrast, homogeneity, entropy, and correlation [7], [8]. Several recent studies have confirmed that GLCM-based texture features are effective for distinguishing plant species under controlled and natural imaging conditions [9], [10]. However, most existing approaches using complex architectures like Convolutional Neural Networks (CNN) often suffer from high computational costs and require massive datasets to avoid overfitting [11]. A critical research gap exists regarding the sensitivity of simpler Artificial Neural Network (ANN) parameters—specifically the interaction between learning rates and epochs—when processing limited datasets with high visual similarity [12]. This study addresses these limitations by evaluating a Backpropagation Neural Network (BPNN) specifically for three medicinal plants: white ginger, mango ginger, and yellow turmeric. The specific contribution of this research lies in its systematic parameter analysis to achieve objective identification for species that are nearly indistinguishable to the human eye [13].

The extracted texture features are commonly integrated with artificial intelligence (AI) techniques to perform classification tasks. Artificial Neural Networks (ANNs), particularly those trained using the Backpropagation algorithm, have been widely adopted due to their capability to model non-linear relationships and learn complex patterns from texture data [14], [15]. Leaf-based identification systems offer a practical advantage compared to flower- or fruit-based approaches, as leaves are available throughout the year and are less affected by seasonal variations, enabling sustainable data acquisition [16]. In recent years, deep learning approaches, such as Convolutional Neural Networks (CNNs), have demonstrated superior accuracy in plant image classification; however, these methods generally require large datasets and high computational resources, which are not always feasible for small-scale or local research implementations [17], [18].

Despite the promising performance of ANN-based classification for medicinal plant identification, its successful implementation is highly dependent on the configuration of internal training parameters. In Backpropagation Neural Networks, hyperparameters such as learning rate and number of epochs play a critical role in determining convergence speed, training stability, and model generalization performance [19]. An excessively large learning rate may cause the optimization process to diverge or overshoot the optimal solution, whereas a learning rate that is too small can significantly slow down convergence and hinder effective training [20]. Similarly, an excessive number of epochs may lead to overfitting and increased computational cost without a proportional improvement in classification accuracy [21].

Several previous studies have applied ANN-based classifiers for plant or leaf image classification using various feature extraction techniques, reporting competitive accuracy levels [22], [23]. However, most of these studies primarily emphasize final accuracy values while treating hyperparameter selection as a secondary or fixed experimental setting. As a result, limited attention has been given to systematically analyzing how variations in learning rate and training epochs influence classification stability and performance, particularly when working with texture-based features and limited datasets. This lack of critical evaluation makes it difficult to assess the robustness and reproducibility of ANN models in real-world medicinal plant identification scenarios.

Furthermore, existing studies often rely on relatively large or well-balanced datasets, which may not reflect practical conditions in medicinal plant research, where data acquisition is constrained by species availability, seasonal variation, and environmental factors. Consequently, the sensitivity of ANN performance to hyperparameter settings under small dataset conditions remains insufficiently explored. This unresolved issue highlights a gap in the literature concerning the empirical evaluation of parameter robustness in texture-based ANN frameworks.

In summary, although ANN-based approaches have shown promising performance, limited attention has been given to systematically examining the interaction between learning rate and epoch parameters, particularly under small dataset conditions with texture-based features. Addressing this issue is critical to improving model robustness and ensuring reliable deployment in real-world applications.

Therefore, this study aims to systematically evaluate the effects of learning rate and epoch variations on the classification accuracy of a Backpropagation Neural Network for medicinal plant identification using GLCM-based leaf texture features. This research provides an empirical analysis of hyperparameter sensitivity using real-field medicinal plant leaf image data under limited dataset conditions.

2. RESEARCH METHOD

This study adopts an experimental quantitative design that aims to develop an automatic identification system for medicinal plant leaves based on texture analysis[24]. This method involves the application of digital image processing techniques for feature extraction and Artificial Neural Networks for classification. The stages of this study can be seen in Figure 1.

Methodological Rationale The decision to utilize a Backpropagation Neural Network (BPNN) rather than deep learning architectures like Convolutional Neural Networks (CNN) is driven by the specific dataset constraints and research objectives. While CNNs excel in automatic feature engineering, they typically require massive datasets to achieve convergence and prevent overfitting. In contrast, for a limited dataset of 63 images, a BPNN combined with expert-defined GLCM features offers greater stability and computational efficiency. Furthermore, this architecture allows for a rigorous parameter sensitivity analysis, specifically investigating how varying learning rates and epochs influence the model's ability to distinguish visually similar medicinal species.

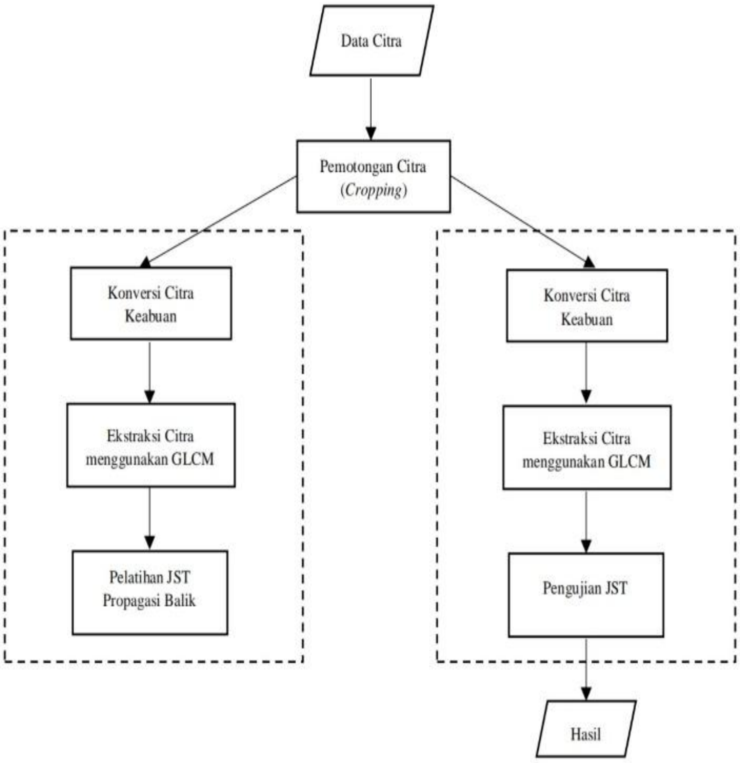

Figure 1. Research Stages

The research procedure begins with the Image Data stage, where leaf images of three medicinal plant species—white ginger, mango ginger, and yellow turmeric are collected to form the initial dataset. Subsequently, these images undergo Image Cropping to focus on the leaf texture and remove irrelevant backgrounds to ensure data consistency. Preprocessing continues with Grayscale Conversion, which transforms RGB images into grayscale to simplify pixel intensity while preserving essential textural details required for analysis. Once the images are prepared, GLCM Feature Extraction is performed to calculate spatial relationships between pixels and extract texture descriptors such as contrast, correlation, energy, and homogeneity, which serve as input features for the neural network. The entire process is divided into two primary tracks; in the Training track, the extracted features are used to train the Backpropagation Neural Network (BPNN) to recognize patterns by adjusting weights based on variations in learning rates and epochs. Finally, in the Testing track, the trained model is evaluated using new data to produce the Classification Accuracy, which serves as the indicator of the system's success in identifying medicinal plant species automatically and objectively.

2.1 Image Data

This study utilizes primary data obtained directly from the Family Medicinal Plant Garden at SMA Negeri 1 Lalan, so that all visual information used comes from actual field conditions and corresponds to the natural growing environment of these plants. The main objects in this study consist of three types of medicinal plant leaves, namely white ginger leaves, mango ginger leaves, and yellow turmeric leaves, each of which has different morphological characteristics and surface textures. The research population included all leaves found on the three species at the cultivation site, so that the data obtained represented the natural variation of each plant type. This approach allowed researchers to obtain more authentic and relevant data for the texture-based image classification process.

A total of 63 digital images were selected as research samples and divided into two groups for the purposes of training and testing machine learning-based classification models. The training data consisted of 45 images, each consisting of 15 images for each type of leaf, with the aim of building a model capable of recognizing the patterns and texture characteristics of each class. Meanwhile, the test data consisted of 18 images, namely 6 images per leaf type, which were used to evaluate the performance, accuracy, and generalization ability of the model against data that had never been seen before. This division followed the basic principles in model classification development, namely providing an adequate portion of data for the learning process without reducing the quality of model performance evaluation.

Data collection was carried out through the process of direct digital image acquisition using a Canon EOS M100 camera, which was chosen for its ability to produce images with high sharpness and a sufficient level of detail for leaf texture analysis. To ensure consistent image quality, images were taken during the day to take advantage of natural light, which was then enhanced with additional lighting using a 12-watt ring light. This effort was made to minimize shadows, improve lighting homogeneity, and produce more accurate color display. From all the images taken, only those with sharp focus, no blurring, and clear leaf objects were selected for further processing. This selection procedure was applied to ensure that the input data used in the image-based classification system was of optimal quality and free from visual disturbances that could reduce model performance.

2.2 Image Scaling

After the data selection stage is complete, the next process is image standardization or scaling, which aims to ensure that each image has a consistent size before being used in the next stage of analysis. This standardization is an important step because differences in resolution or dimensions in images can affect feature extraction results and the performance of the image processing algorithms used. By applying this procedure, each image can be treated uniformly by the system, thereby reducing the potential for bias that may arise due to variations in the original size of the data source.

In this study, all images were then resized to 500×500 pixels as the standard size used throughout the processing and analysis process. The selection of these dimensions was not done arbitrarily, but based on technical considerations that this size is large enough to retain the necessary texture details, while still being efficient for processing by computational algorithms. In addition, the 500×500 pixel size was considered capable of providing a balance between computational complexity and the quality of visual information required in the texture-based feature extraction stage.

This standard size was also chosen to facilitate comparison with previous studies, particularly those focusing on texture analysis such as wood type identification, meat image classification, and other studies using similar approaches. By using a resolution that is in line with previous studies, the results obtained can be evaluated more objectively and comprehensively, in terms of accuracy, algorithm performance, and its contribution to the development of texture-based classification methods. This approach opens up opportunities for researchers to assess the extent to which the methods used are able to compete or provide improvements compared to existing findings.

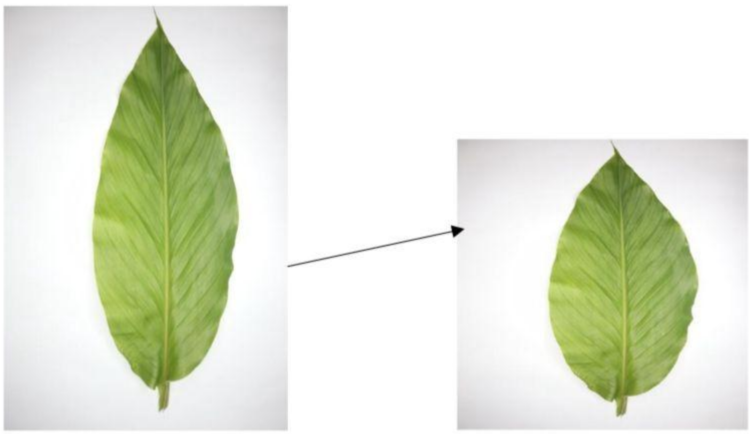

Figure 2. Image scaling 500x500 pixels

2.3 Grayscale Image Conversion

The next pre-processing step after scaling is converting RGB images into grayscale images, which is a fundamental step in various image analysis processes. This conversion is performed because RGB images have three color channels (red, green, and blue), each of which stores intensity information, thereby increasing the complexity of the data that must be processed by the system. By converting it into a single channel, the image becomes simpler but still retains important visual information relevant to texture analysis.

This image conversion process uses an 8-bit intensity value representation, which is a range of values between 0 and 255, where 0 represents pure black and 255 represents pure white. The 8-bit format was chosen because it not only meets common standards in the field of digital image processing, but also offers a balance between detail quality and computational efficiency. This intensity representation ensures that the texture structure and contrast patterns in the image remain clearly visible even though the color information has been reduced.

The transformation of RGB images into grayscale images is also done to standardize the input format before entering the texture feature extraction stage, which is usually more effective when run on images with a single intensity channel. With a uniform format, feature extraction algorithms such as GLCM, LBP, or other statistics-based methods can work more optimally and consistently across the entire dataset. In addition, this simplification helps to significantly reduce the computational load, so that the analysis process can be carried out more quickly without sacrificing the accuracy of the information needed for the subsequent classification or pattern recognition stages.

2.4 Feature Extraction Using GLCM

The core phase of this study focuses on texture feature extraction through the implementation of the Gray Level Co-Occurrence Matrix (GLCM) method. GLCM aims to measure the frequency of paired occurrences between specific pixel gray values [25], considering the distance parameter d=1 and spatial orientation. In this study, the distance was set at d=1 and tested at four orientation angles, namely 0°, 45°, 90°, and 135°. The resulting co-occurrence matrix then underwent a process of symmetrization and normalization. Based on the normalized matrix, five key statistical properties were calculated to serve as input variables for the system, including: Angular Second Moment (ASM), Contrast, Inverse Difference Moment (IDM), Entropy, and Correlation. Collectively, these five quantitative features describe the unique texture patterns of each leaf species. The steps to be taken in feature extraction using GLCM are as follows : Determine the gray level value in the image, Form a framework matrix based on the gray level value that has been determined, Determine the distance and direction used to form the co-occurrence matrix. In this study, the distance used is 1 and the directions used are 0°, 45°, 90°, and 135°, Form a co-occurrence matrix based on the selected distance and direction. Form a symmetric matrix by adding the co-occurrence matrix

to the transpose of the co-occurrence matrix. Normalizing the symmetric matrix by dividing each element of the symmetric matrix by the sum of all elements in the symmetric matrix, Calculating the statistical features of the normalized matrix. The features used are angular second moment, contrast, inverse difference moment, entropy, and correlation.

2.4 Backpropagation Neural Network Training

In the next stage, the Backpropagation Neural Network (BNN) was selected as the main instrument for data analysis and identification. Before the texture data was entered into the JST, it was important to normalize the data against the five GLCM feature values [26]. This normalization stage was essential to ensure that all data was on a uniform scale, thereby optimizing model training efficiency. The BNPN architecture was specifically configured with five input nodes (corresponding to the number of GLCM features), followed by two hidden layers, each consisting of five nodes, and ending with three output nodes representing the leaf classification categories (turmeric, white ginger, and mango ginger).

Data analysis is carried out through two fundamental stages that are crucial. The first stage is the Training Phase, which involves the use of 45 training data. The main objective of this phase is to calibrate the internal weights of the network—done through the backpropagation algorithm—to achieve a condition where the error value is minimized, or the system output is closer to the specified target value. Once the JST successfully internalized and recognized all patterns in the training data, the model was considered ready to enter the evaluation stage, namely the Testing Phase. This testing was conducted exclusively using 18 testing data (which the model had never seen before) by only running the feed forward process. The weights used for this process are those that have been finalized and optimized during training, and the final output is the model's accuracy rate in classifying the tested leaf species.

The backpropagation network testing process is carried out by only implementing the feed forward phase. At this stage, the data tested is the normalized feature extraction data, which is not included in the training data. In the backpropagation testing process, the test data will become input for the backpropagation network and the weights used are the weights resulting from training. In the backpropagation architecture, there are 5 features that will be used as input. The network architecture uses 2 hidden layers, hidden layer 1 (5 nodes) and hidden layer 2 (5 nodes). Then it will produce 3 outputs as shown in the figure.

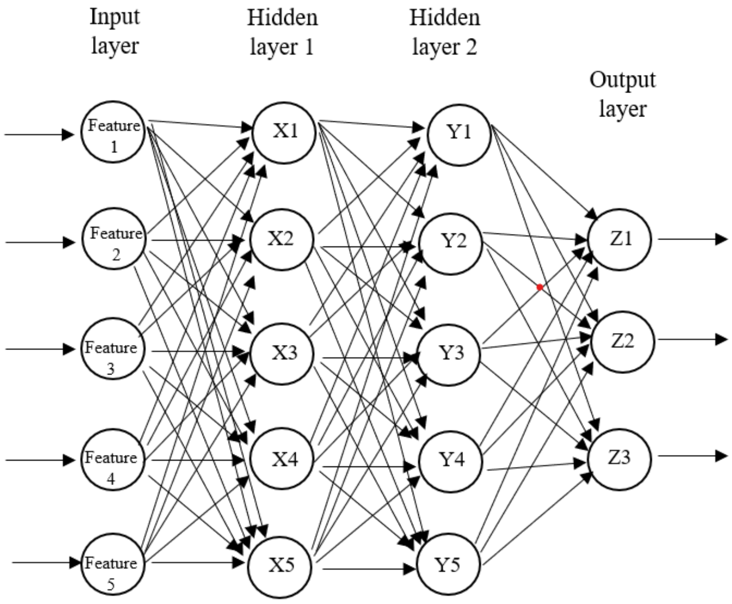

Figure 3. Software architecture

3. RESULTS AND DISCUSSION

The testing in this study was conducted using a total of 63 images of medicinal plant leaves consisting of three types, namely white ginger, mango ginger, and yellow turmeric leaves. These species were selected due to their distinct texture characteristics, allowing for a comprehensive evaluation of the feature extraction method and classification algorithm. The initial stage involved preprocessing, where each image underwent cropping and standardization to a size of 500 × 500 pixels. This standardization is crucial to ensure that the extracted texture information maintains a consistent scale across all samples. Additionally, RGB images were converted to grayscale to simplify computation and align with the requirements of the Gray Level Co-occurrence Matrix (GLCM) algorithm, as grayscale-based analysis is more relevant for intensity-based texture calculations. Theoretically, this 500 × 500 pixel resolution provides an optimal balance between preserving fine texture details and maintaining computational efficiency, ultimately yielding a peak classification accuracy of 65.03%.

Following preprocessing, feature extraction was performed using the GLCM method, which effectively represents texture information through pixel neighborhood relationships to accurately describe surface patterns. These features served as input for the Backpropagation Neural Network (BPNN) algorithm, chosen for its capability to learn non-linear patterns when configured with appropriate training parameters. The experiments involved varying two primary parameters: the learning rate (α) from 0.1 to 1.0 and the number of epochs ranging from 100 to 1,500 iterations. This extensive range allowed for the observation of how α and epoch variations influence the network's ability to achieve convergence.

When compared to previous studies, this accuracy of 65.03% provides a significant benchmark for small-scale medicinal plant identification. Unlike the research by which utilized Convolutional Neural Networks (CNN) on very large datasets to achieve high accuracy, this study demonstrates that the GLCM-BPNN framework is more resilient against the severe overfitting that typically occurs when deep learning models are applied to limited samples. Furthermore, while studies using fixed parameters reported stable results, our systematic variation reveals that the interaction between optimization parameters significantly dictates classification stability. Systematic variations in the learning rate revealed that excessively high values (e.g., α > 0.7$) tend to cause "overshooting" of the optimal solution, whereas smaller values provide more stable convergence but require a higher number of epochs to reach peak performance. This confirms learning theory, which posits that the step size must be precisely adjusted to navigate the complex loss surface of texture-based inputs. Ultimately, the results reflect the inherent challenge of distinguishing species with high morphological similarity, where feature overlap necessitates precise hyperparameter tuning to achieve deeper generalization in resource-constrained environments.

3.1. Experimental Results

The classification performance of the proposed system was evaluated using accuracy as the primary metric. The experiments examined the influence of different learning rate values and numbers of training epochs on the classification accuracy of medicinal plant leaf images.

Table 1 Accuracy of Experimental Results with Epochs 100–500

Learning Rate	Epoch with method accuracy results				
	100	200	300	400	500
0,1	65,03%	63,10%	60,51%	59,92%	58,33%
0,2	62,44%	62,10%	59,92%	59,92%	57,33%
0,3	60,51%	59,51%	58,92%	55,33%	54,22%
0,4	59,38%	58,92%	58,33%	53,75%	53,27%
0,5	57,03%	57,27%	57,33%	51,27%	51,68%
0,6	56,51%	54,44%	56,33%	50,16%	50,68%
0,7	55,92%	51,92%	53,75%	48,57%	49,33%
0,8	52,27%	51,75%	54,75%	48,10%	48,92%
0,9	50,92%	48,33%	45,75%	45,92%	46,92%
1,0	50,92%	46,51%	42,27%	43,33%	44,33%
Average	**57,09%**	**55,39%**	**54,79%**	**51,63%**	**51,50%**

Table 1 presents the classification accuracy results obtained using learning rates ranging from 0.1 to 1.0 with epoch values between 100 and 500. The purpose of Table 1 is to show the model's initial learning behavior at relatively low training iterations. Each row represents a specific learning rate, while each column corresponds to a particular number of epochs. The values in the table indicate the percentage of correctly classified test samples. As shown in Table 1, the highest accuracy of **65.03%** was achieved using a learning rate of 0,1 with 100 epochs, while accuracy gradually decreased as the number of epochs increased for most learning rate configurations.

Tabel 2 Accuracy of Experimental Results with Epochs 600 – 1000

Learning Rate	Epoch with method accuracy results				
	600	700	800	900	1000
0,1	54,16%	54,96%	50,16%	47,92%	48,10%
0,2	50,10%	52,85%	48,92%	46,92%	48,10%
0,3	48,10%	50,33%	47,92%	45,92%	46,51%
0,4	46,92%	47,33%	45,75%	44,75%	45,51%
0,5	45,92%	45,92%	43,75%	44,75%	42,63%
0,6	44,92%	45,33%	43,75%	41,75%	34,81%
0,7	43,33%	42,33%	40,16%	41,75%	33,93%
0,8	43,33%	41,75%	40,16%	40,27%	33,33%
0,9	42,33%	41,75%	38,16%	40,16%	33,33%
1,0	47,59%	47,77%	45,10%	44,43%	41,59%
Average	**56,75%**	**55,10%**	**52,22%**	**50,10%**	**49,68%**

Table 2 summarizes the accuracy results for epoch values between 600 and 1000. This table aims to evaluate the stability of the model when the training process is extended. Similar to Table 1, the rows indicate learning rate values and the columns represent epoch variations. The results in Table 2 show a consistent decline in accuracy across most learning rates as the number of epochs increases. This trend indicates that prolonged training does not necessarily improve classification performance and may instead reduce model generalization.

Tabel 3 Accuracy of Experimental Results with Epochs 1100 – 1500

Learning Rate	Epoch with method accuracy results				
	1100	1200	1300	1400	1500
0,1	46,51%	50,33%	50,03%	51,10%	51,75%
0,2	46,51%	46,51%	43,33%	36,51%	40,16%
0,3	46,51%	45,33%	41,75%	34,92%	38,10%
0,4	44,44%	44,60%	39,68%	34,92%	35,40%
0,5	41,75%	43,35%	38,10%	33,33%	34,92%
0,6	41,75%	40,75%	36,51%	33,33%	34,92%

0,7	40,16%	40,59%	36,51%	32,57%	34,92%
0,8	40,16%	40,16%	36,51%	31,75%	33,33%
0,9	34,44%	36,51%	34,92%	31,75%	31,75%
1,0	30,57%	33,33%	27,53%	28,57%	29,40%
Average	**41,28%**	**42,15%**	**38,49%**	**34,88%**	**36,47%**

Table 3 presents the accuracy results for higher epoch values ranging from 1100 to 1500. The objective of Table 3 is to observe the effect of excessive training iterations on model performance. The results clearly demonstrate a significant decrease in accuracy for almost all learning rate configurations. The lowest accuracy value of **27.53%** was observed at a learning rate of 1,0 with 1300 epochs, indicating severe performance degradation under high learning rate and excessive epoch conditions.

3.2. Analysis of Research Results

Based on the research results presented in Tables 1 to 3, it can be seen that the best parameter combination in the Backpropagation Artificial Neural Network method is obtained when the system uses a learning rate of 0.1 and a number of epochs of 100. This configuration produces the highest accuracy value of 65.03%, which indicates that under certain conditions, the network is able to carry out the learning process stably and quite effectively. Conversely, the lowest accuracy value was shown by the learning rate configuration of 1.0 with 1300 epochs, which only produced an accuracy of 27.53%. This result indicates that the use of a learning rate that is too large causes the learning process to be suboptimal because the network tends to experience instability in updating weights, especially when combined with a very high number of epochs.

Furthermore, referring to Table 4, which displays the average accuracy values from various tests with variations in epochs ranging from 100 to 1500 and different learning rates, it can be seen that the accuracy range is between 27% and 65%. This significant variation in accuracy values shows that parameter configuration greatly affects model performance, where inappropriate learning rates and number of epochs can make it difficult for the network to find patterns optimally. In other words, parameter changes can actually increase the risk of the network experiencing underfitting or overfitting, resulting in less consistent predictions.

Based on the overall observations from the experimental results, this relatively low average accuracy value may be due to the lack of variety in the training data used. The limited variation in the dataset causes the threshold value in the GLCM method to be too broad, so that the resulting texture features are not detailed enough to accurately distinguish between classes. In addition, the relatively small amount of data makes the model more prone to overfitting, which is a condition where the model adapts too much to the training data but fails to recognize new patterns in the test data. The intensity of the image also has a major influence on the feature extraction process, so that inconsistencies in intensity can further reduce the performance of the system. However, the configuration with a learning rate of 0.1 and 100 epochs is still able to produce an accuracy of above 60%, so it can be considered the most optimal parameter compared to other combinations in this study.

Tabel 4**.** Table of Average Accuracy Values per Epoch

Epoch	Accuracy
100	57,09%
200	55,39%
300	54,79%
400	51,63%
500	51,50%
600	47,59%
700	47,77%
800	45,10%
900	44,43%
1000	41,59%
1100	41,28%
1200	42,15%
1300	38,49%
1400	34,88%
1500	36,47%
1500	36,47%

To provide a clearer overview of performance trends, the average accuracy values for each epoch configuration are summarized in Table 4. This table is designed to show the overall classification trend by averaging the accuracy values across all learning rates for each epoch. As shown in Table 4, the highest average accuracy occurs at 100 epochs, and a general downward trend is observed as the number of epochs increases.

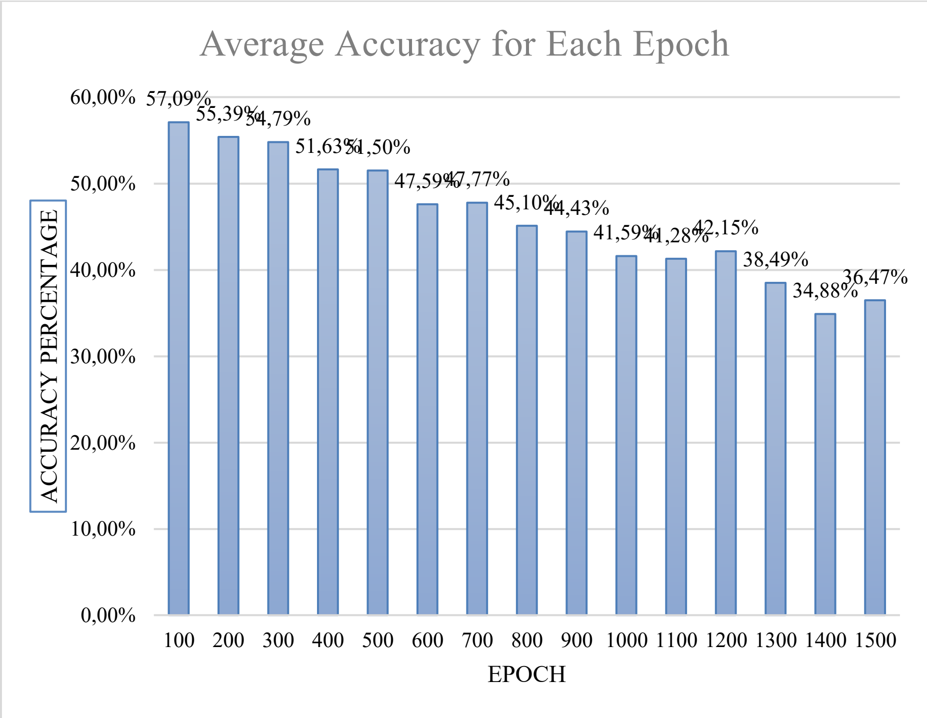

Figure 4. Graph of Average Research Results per Epoch

Figure 4 shows the average accuracy values of classification results obtained from a series of experiments using learning rate variations between 0.1 and 1.0 in each epoch configuration. From this visualization, there is a noticeable trend of decreasing accuracy as the learning rate value used increases. When the learning rate increases, the weight improvement steps in the training process become more aggressive, causing the model to tend to pass the minimum point of the error function and produce an unstable learning process. In these conditions, instead of moving closer to the optimal point, the weight update process can oscillate or even move away from the best solution. This causes the accuracy at each epoch—especially at higher epochs—to experience a significant decline. This fact shows that the selection of the learning rate has a direct impact on the system's ability to converge to an optimal model.

According to [27], a learning rate that is too large can cause the Mean Squared Error (MSE) value to change drastically and uncontrollably, resulting in unstable and unpredictable accuracy values. If the learning rate value is too high, the weight updates become so large that the model does not have time to gradually adapt to the data patterns. Conversely, when the learning rate is small, the model moves more slowly in adjusting the weights so that the process of searching for the optimal value is more stable and the system can achieve higher accuracy. This pattern is in line with what is seen in Figure 4, where accuracy decreases along with an increase in the learning rate value, and on the other hand, a larger epoch configuration does not always result in improved performance. This is because the training process is repeated even though the model has reached a point close to optimal, so that excessive weight updates cause the model to lose its stability.

In addition, Figure 5 shows a condition where the accuracy produced in some configurations can be higher than other configurations that use a lower number of epochs. This phenomenon occurs because, in the training process, the system uses initial weights that are randomly generated before computation begins. Different initial weight values can cause the optimization path followed by the model to differ, so that the model has the opportunity to reach different local or global minimum points in each experiment. This variation causes some experiments with higher epochs to produce better performance even though, in general, increasing the number of epochs tends to decrease accuracy. Thus, this phenomenon confirms that the training process is stochastic and influenced by random values in the initial weights, so that parameters such as learning rate, number of epochs, and weight initialization must be considered together in order for the model to achieve the most optimal results.

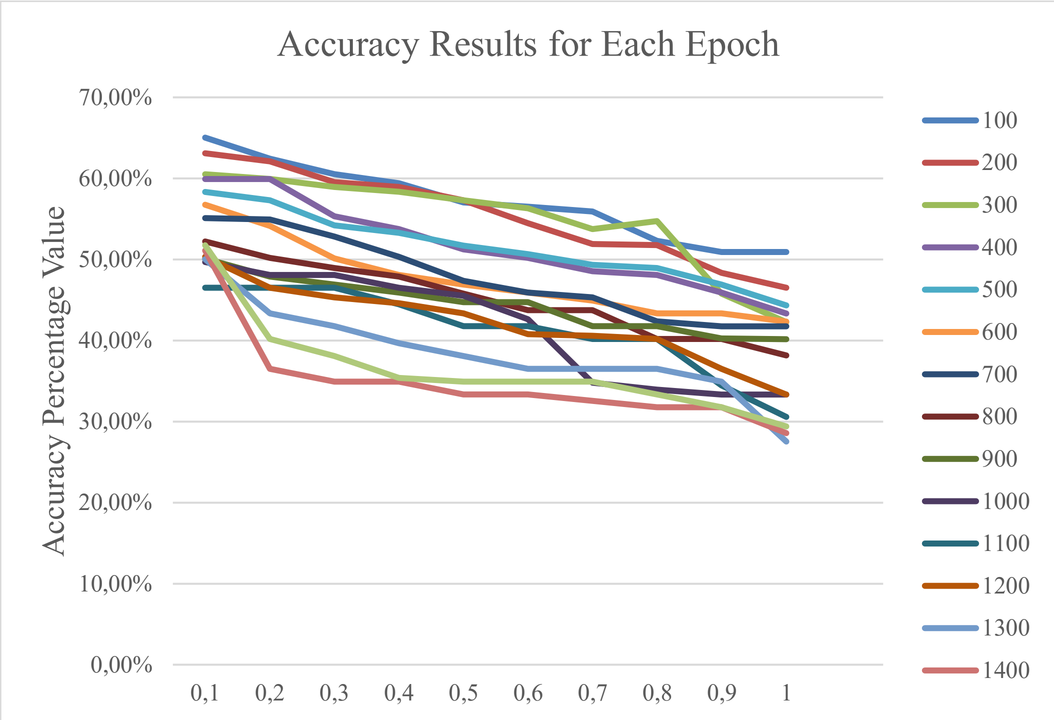

Figure 5. Graph of Research Accuracy Values

Figure 5 presents the distribution of accuracy values across different learning rate and epoch configurations. This figure aims to highlight the variability of accuracy results under different training conditions. The visualization helps illustrate that certain configurations with higher epoch values may still yield relatively better results compared to others due to differences in initial weight initialization.

Based on the experimental results presented in Tables 1 to 3, the best parameter configuration for the Backpropagation Neural Network was obtained using a learning rate of 0.1 and 100 epochs, which resulted in the highest classification accuracy of 65.03%. This finding indicates that smaller learning rates combined with limited training iterations enable the network to converge more stably and effectively.

In contrast, configurations using larger learning rates and higher numbers of epochs consistently produced lower accuracy values. As shown in Table 3, the use of a learning rate of 1.0 combined with excessive epochs led to unstable weight updates and poor generalization performance. These results suggest that an overly aggressive learning process causes the model to overshoot the optimal solution, reducing classification accuracy.

The average accuracy trends shown in Table 4 and visualized in Figure 4 further confirm that increasing the number of epochs does not guarantee improved performance. Instead, excessive training tends to reduce accuracy due to overfitting, where the model becomes overly adapted to the training data and performs poorly on unseen test data. This observation aligns with previous findings that emphasize the importance of careful hyperparameter tuning to maintain model stability.

Additionally, the variability observed in Figure 5 indicates that the training process is influenced by random initial weight values. Different initializations can lead the network to converge to different local optima, causing fluctuations in accuracy across experiments. This finding highlights that learning rate, number of epochs, and weight initialization must be considered simultaneously to achieve optimal classification performance.

Overall, the experimental results demonstrate that appropriate selection of training parameters is critical for maximizing the performance of texture-based medicinal plant classification systems. The findings confirm that simpler configurations with lower learning rates and fewer epochs are more suitable for small datasets, as they provide better generalization and more stable classification results.

The study by [27] utilized CNN and transfer learning (EfficientNet) on a larger and more diverse dataset, yielding substantially higher accuracy. This result highlights that dataset size and model complexity (such as CNN/EfficientNet) are key factors in boosting performance.

Conversely, the lower accuracy observed in this study (65.03%) is attributed to the smaller dataset and the simpler BPNN architecture, rather than an inherent limitation of texture-based features. Furthermore, the study by [28] shows that the choice of texture feature extraction method (GLCM and LBP) significantly influences feature quality (contrast and correlation), which subsequently determines classification accuracy.

Therefore, it can be concluded that improvements to our system should involve, first increasing dataset size and diversity—or using transfer learning on larger pre-trained CNNs—to substantially increase accuracy, as seen in [27], and refining texture extraction (perhaps fusing GLCM with other descriptors like LBP) and standardizing image contrast to enhance feature separability, as demonstrated in [28].

These recommendations align with the empirical trends observed in Tables 1–4 and Figures 4–5, where performance suffered under aggressive training regimes or when feature distinctions were insufficien

4. CONCLUSION

This study successfully addressed the challenge of identifying medicinal plant species with high morphological similarity—specifically white ginger, mango ginger, and yellow turmeric—by integrating GLCM-based texture extraction with a Backpropagation Neural Network. Based on the experimental results of 63 digital images, the system achieved a peak accuracy of 65.03% at α specific configuration of α 0.1 learning rate and 100 epochs. A critical scientific insight gained from this research is that for small-scale texture datasets, smaller hyperparameter values are more effective in maintaining computational stability and preventing weight divergence. The study observed a trend where excessive increases in learning rate and epoch count triggered a decrease in accuracy, indicating that "over-training" on limited texture samples significantly degrades model generalization.

The methodological contribution of this research lies in providing an empirical framework for hyperparameter sensitivity analysis in resource-constrained environments. While previous studies often utilize large-scale datasets or fixed parameters, this research demonstrates that a precise, low-parameter GLCM-BPNN approach remains a viable and computationally efficient tool for distinguishing visually identical leaf textures. These findings inform future small-scale image classification research by highlighting that model depth or high iteration counts do not inherently guarantee better performance when the dataset size is restricted; instead, the focus should be on the synergy between feature resolution (standardized at 500 × 500 pixels in this study) and parameter stability.

As a recommendation for future development, the reliability of artificial intelligence in medicinal plant digitization should be strengthened through the expansion of local plant image datasets. It is advised that relevant research institutions facilitate the creation of a national digital botanical database to optimize model training. Furthermore, subsequent research should explore stricter data normalization methods and hybrid network architectures to minimize classification errors caused by variations in light intensity and image focus in field-captured data.

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