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Recognition of Medicinal Plant Leaf Patterns Using Morphology-Based and GLCM Feature Extraction

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Abstract

This research aims to develop a medicinal plant leaf pattern recognition system using morphological feature extraction and GLCM (Gray-Level Co-occurrence Matrix). This approach utilizes a combination of morphological features that describe the shape and structure of the leaves, as well as texture features that capture the surface patterns of the leaves. A diverse dataset was collected, and features such as area, perimeter, aspect ratio, circularity, and Hu Moments were extracted for morphological description. Meanwhile, texture features such as contrast, dissimilarity, homogeneity, and energy were extracted using GLCM. An Artificial Neural Network model was then trained and evaluated using precision, recall, and F1-score metrics. The research results indicate that the combination of morphological and texture features enhances the accuracy of leaf pattern recognition, with the model achieving an accuracy of 87% on the test dataset. This system has the potential for applications in the health sector, pharmaceuticals, biodiversity conservation, and education.

Keywords: *Gray-Level Co-occurrence Matrix, Morphological Features, Medicinal Plant Leaves, Pattern Recognition*

1. Introduction

Medicinal plants have been used for centuries in traditional medicine around the world [1]. In Indonesia, the utilization of such plants has become deeply ingrained within the cultural fabric and routine practices of the people [2], [3]. Accurate and rapid identification of medicinal plants is crucial to ensure their safe and effective use [4]. As such, the development of systems capable of automatically recognizing medicinal plant leaves has become an urgent necessity [5].

Leaf morphology, including shape, size, and margin patterns, is one of the primary criteria used in plant classification by botanists [6]. However, manual observation and analysis of these features is time-consuming and requires significant expertise [7]. This challenge has been addressed by the advancements in digital image processing, which have enabled the automated extraction of leaf morphological features [8].

In addition to morphology, leaf texture also provides important information that can be leveraged for plant identification [9]. Texture analysis methods, such as the Gray-Level Co-occurrence Matrix (GLCM), quantify the spatial relationships between pixels in an image, measuring the frequency with which pairs of pixels with specific intensity values occur at defined distances and orient themselves in particular angular orientations [10]. The resulting textural features like contrast, homogeneity, and correlation can then be used to distinguish between different leaf types [11]. The combination of morphology and texture analysis is expected to improve the accuracy of medicinal plant leaf pattern recognition.

Previous studies have indicated that using morphological and texture features independently presents limitations regarding accuracy and robustness [12]. Consequently, this research suggests an integrated approach that merges both feature types to improve the effectiveness of leaf pattern recognition systems. By leveraging the strengths of morphological analysis, which details the shape and structure of leaves, alongside texture analysis, which captures leaf surface patterns, a more comprehensive and precise model is anticipated.

The deployment of a medicinal plant leaf pattern recognition system utilizing morphological and GLCM feature extraction holds significant potential applications. Beyond aiding the healthcare and pharmaceutical sectors, this system can also contribute to biodiversity conservation and education. Over time, this system can be expanded to support a more extensive and diverse medicinal plant database and be integrated with additional technologies such as neural networks and machine learning for more sophisticated and adaptive pattern recognition.

2. Research Methods

This research aims to develop a medicinal plant leaf pattern recognition system using morphological and texture feature extraction with GLCM, and train an artificial neural network model for classification. The following are the steps involved in the research methodology:

A. Data Collection
The first step is to gather a relevant and representative dataset. The data used must encompass various conditions and variations to ensure that the developed model can handle real-world cases.
   1. Dataset Collection: Collect images of medicinal plant leaves from various trusted sources, ensuring a diverse variety of species. Each image should be labeled according to its species for classification purposes.
   2. Preprocessing: Resize the images to 300x300 pixels to ensure uniformity. Convert the images to grayscale for consistency in further analysis.

B. Feature Extraction
After the data is collected, the next step is to extract features from the raw data. These features are numerical representations of the data that will be used by the model to make predictions.
   1. Morphological Feature Extraction: One type of feature extracted is morphological features, which include information about the shape, size, and structure of objects in the data. These features are important for understanding the physical characteristics of the classified objects.
      a. Thresholding: Convert each grayscale image to a binary image using thresholding techniques.
      b. Contour Detection: Identify the contours of the leaves to analyze their shapes.
      c. Feature Calculation: Extract morphological features such as Area, Perimeter, Aspect Ratio, Circularity, and Hu Moments (Hu1 to Hu7) from the detected contours.

   2. Texture Feature Extraction: In addition to morphological features, we also extract texture features that provide information about the patterns and surface variations of objects. Texture features are very useful in distinguishing objects with similar visual characteristics but different texture patterns.
      a. Gray-Level Co-occurrence Matrix (GLCM): Calculate the GLCM for each leaf image.
      b. Texture Feature Calculation: Extract texture features such as Contrast, Dissimilarity, Homogeneity, and Energy from the GLCM.

C. Data Augmentation
To increase the amount and diversity of data, data augmentation techniques are used. Data augmentation involves applying transformations such as rotation, scaling, and flipping to the original data to generate new variations that help the model become more robust to variations in real data.

D. Dataset Splitting
After the data is augmented and optimized, it is divided into two sets: a training set and a testing set. The training set is used to train the model, while the testing set is used to evaluate the model's performance on unseen data.

E. Artificial Neural Network Model Development
At this stage, the classification model is developed using an appropriate algorithm. The model is trained using the training set to learn patterns in the data.
   1. Model Architecture: Develop the artificial neural network model using TensorFlow and Keras.
   2. Model Compilation: Compile the model with the Adam optimizer, categorical cross-entropy loss function, and accuracy metric.
   3. Model Training: Train the model using the split dataset with 200 epochs and a batch size of 32.

F. Model Evaluation
After the model is trained, the next step is to evaluate its performance. Evaluation is done using key evaluation metrics such as precision, recall, f1-score, and support. This evaluation is crucial to ensure that the model is not only accurate but also effective in recognizing patterns and making reliable predictions.
   1. Performance Evaluation: Evaluate the model's performance using precision, recall, F1-score, and support metrics on the validation set.
   2. Results Visualization: Visualize the training results by plotting accuracy and loss for both training and validation data.

3. Result dan Discussion

3.1. Effectiveness of Morphological and Texture Feature Extraction

The research results indicate that the combination of morphological and texture features provides a more comprehensive description of the characteristics of medicinal leaves. Morphological features are effective in describing the general shape and structure of the leaves, while texture features are effective in capturing fine surface patterns. Morphological feature extraction provides information about the contour and dimensions of the leaves, such as area, perimeter, and aspect ratio, which are very useful for distinguishing leaves of different shapes. On the other hand, texture features extracted using GLCM (Gray Level Co-occurrence Matrix) can detect variations in pixel intensity that reflect surface texture patterns, such as roughness or smoothness. The combination of these two types of features results in a more complete representation of the visual characteristics of the leaves, ultimately enhancing the system's ability to identify and differentiate various types of medicinal leaves.

Area	**18259,5**
Perimeter	840,6976093
Aspect Ratio	0,025835047
Circularity	0,324652776
Hu1	0,418429564
Hu2	0,148863136
Hu3	0,002434116
Hu4	0,00188153
Hu5	4,0265E-06
Hu6	0,000724588
Hu7	-2,75995E-08
Contrast	164,9392642

Dissimilarity	2,212804145
Homogeneity	0,826924185
Energy	0,789082097
Correlation	0,936913361
ASM	0,622653758

Fig. 1: Dataset Features

In this research, we performed morphological feature extraction from medicinal plant leaf images to obtain a more detailed description of the shape and structure of the leaves. The extracted morphological features include:

a. Area: The area of the leaf is calculated as the total number of pixels that constitute the leaf in the binary image. This area provides information about the size of the leaf, which can vary significantly between species.
b. Perimeter: The perimeter of the leaf is calculated as the total length of the leaf's contour. This feature helps in determining the complexity of the leaf shape and can provide additional information besides the area.
c. Aspect Ratio: The aspect ratio is calculated as the ratio of the length to the width of the bounding box of the leaf. This feature is useful for identifying leaves with longer and narrower shapes versus those that are shorter and wider.
d. Circularity: This feature gives a value close to 1 for more circular shapes and lower values for elongated or irregular shapes.
e. Hu Moments (Hu1 to Hu7): Hu moments are a set of seven values that are invariant to translation, scale, and rotation. These features are used to capture finer and more complex shape information of the leaves.

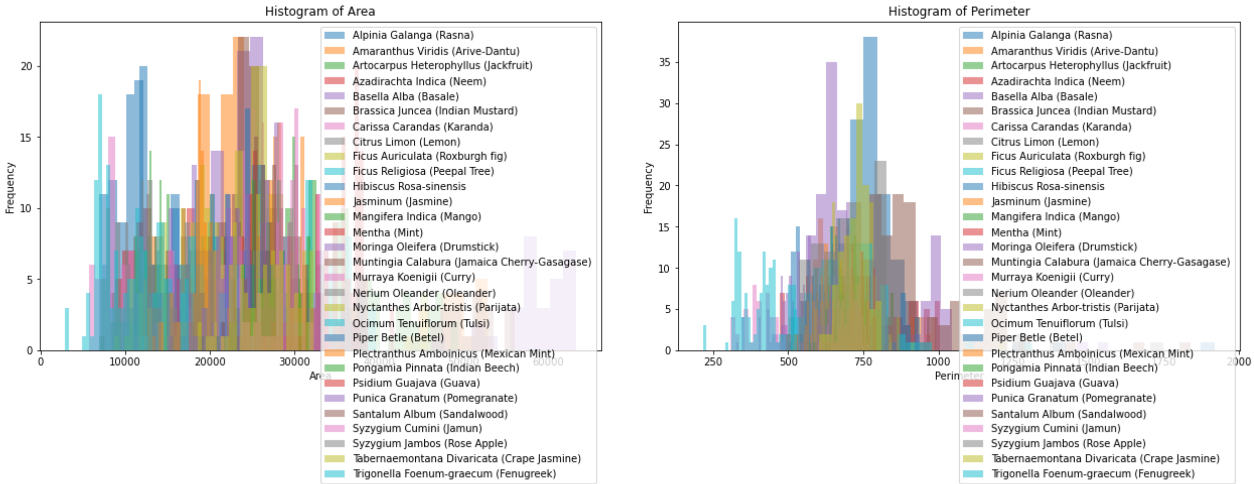

Fig. 2: Histogram Area and Perimeter

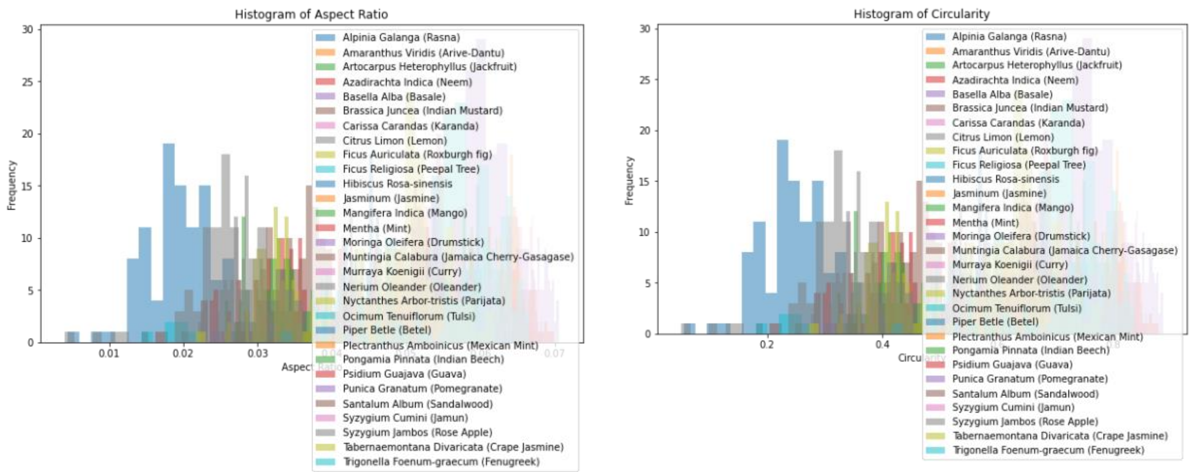

Fig. 3: Histogram Aspect Ratio and Circularity

In this research, we also performed texture feature extraction using the Gray-Level Co-occurrence Matrix (GLCM) to analyze the surface patterns of medicinal plant leaves. The extracted texture features include:

a. Contrast: Contrast measures the local intensity contrast in the image. It is calculated by measuring the intensity difference between a pixel and its neighbor over the entire image. High contrast values indicate large intensity variations, which often signify rough or textured leaf surfaces.
b. Dissimilarity: Dissimilarity measures the local intensity differences in the image. It is similar to contrast but places more emphasis on the absolute difference between the intensity of a pixel and its neighbor. High dissimilarity values indicate significant intensity differences between adjacent pixels, reflecting irregular textures.

c. Homogeneity: Homogeneity measures the closeness of the distribution of elements in the GLCM to the GLCM diagonal. This feature gives high values for images with uniform textures and little intensity variation. High homogeneity values indicate that the pixel intensities and their neighbors are similar, reflecting smooth leaf surfaces.

d. Energy: Energy measures the uniformity in the image. It is calculated as the sum of squared elements in the GLCM. High energy values indicate the presence of repeated and regular patterns in the image, reflecting smooth and homogeneous textures. Energy is also known as Angular Second Moment (ASM).

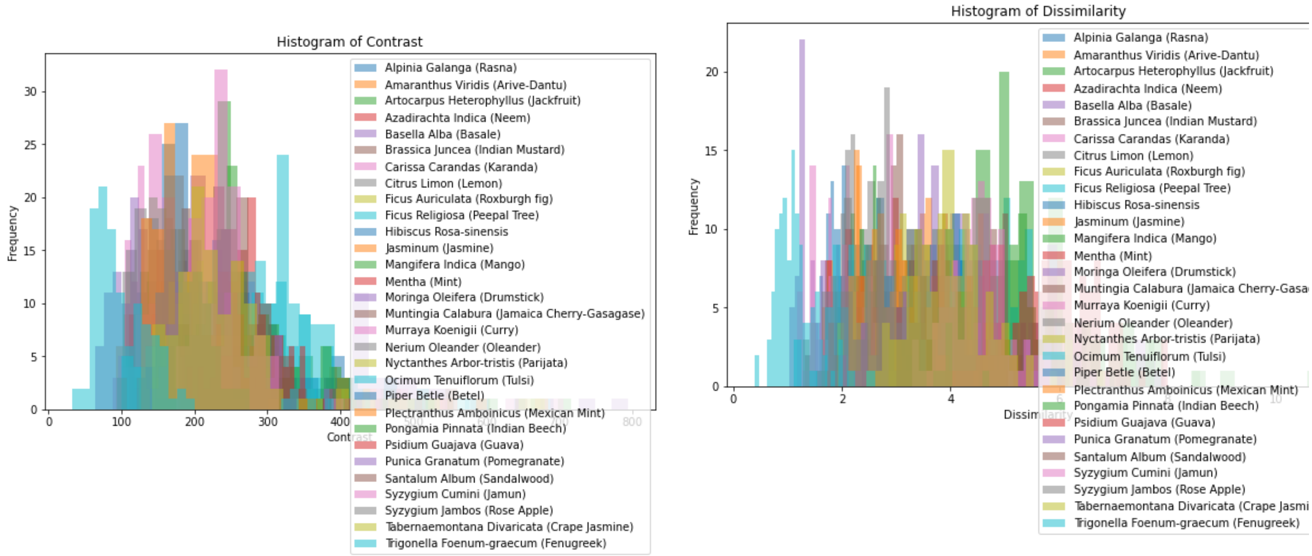

Fig. 4: Histogram Contrast and Dissimilarity

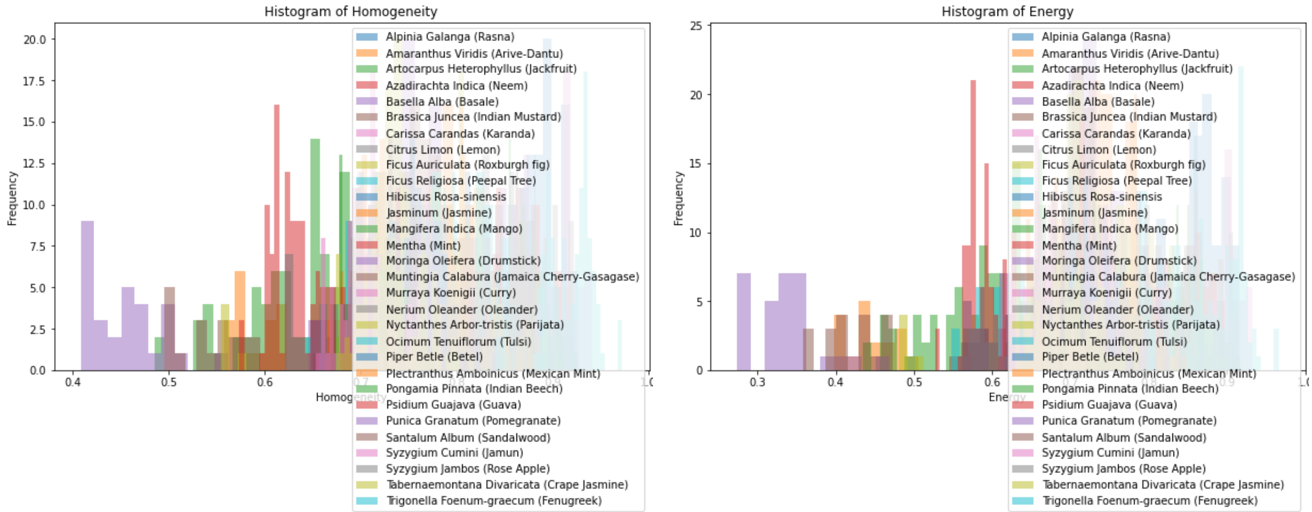

Fig. 5: Histogram Homogeinity and Energy

3.2. Model

For this research, we developed and trained a neural network model using TensorFlow and Keras. The model architecture was designed with multiple layers to capture complex features from the extracted data. Here is a description of the model architecture used:

Table 1: Model Layers and Hyperparameters

No	Layer Type	Units/Parameters	Activation	Additional Information
1	InputLayer	Input Shape = (X_train.shape[1],)	N/A	-
2	Dense	100	ReLU	-
3	BatchNormalization	N/A	N/A	Normalizes the activations of the previous layer
4	Dropout	00.05	N/A	50% dropout rate to prevent overfitting
5	Dense	500	ReLU	-
6	BatchNormalization	N/A	N/A	Normalizes the activations of the previous layer
7	Dropout	00.05	N/A	50% dropout rate to prevent overfitting
8	Dense	900	ReLU	-
9	BatchNormalization	N/A	N/A	Normalizes the activations of the previous layer
10	Dropout	00.05	N/A	50% dropout rate to prevent overfitting
11	Dense	500	ReLU	-
12	BatchNormalization	N/A	N/A	Normalizes the activations of the previous layer
13	Dropout	00.05	N/A	50% dropout rate to prevent overfitting

14	Dense	100	ReLU	-
15	BatchNormalization	N/A	N/A	Normalizes the activations of the previous layer
16	Dense	len(label_encoder.classes_)	Softmax	Output layer with number of units equal to the number of classes

For this research, the neural network model was trained using the TensorFlow and Keras frameworks. The training process involved optimizing the model's weights to accurately classify medicinal plant leaves based on the extracted features. The following hyperparameters were used for training: 200 Epochs and 32 Batch Size. The dataset was split into training and validation sets to ensure the model's performance could be evaluated on unseen data during training. The training set was used to update the model weights, while the validation set provided a measure of the model's accuracy and loss after each epoch.

In this research, the data preparation phase was crucial to ensure the neural network model received high-quality and diverse training samples. The dataset consisted of images of medicinal plant leaves, with each class containing between 114 to 130 images. All images in the dataset were resized to a standard size of 300x300 pixels. This step was essential to ensure uniformity in the input data, allowing the model to process each image consistently. Resizing helps in reducing the computational complexity and memory requirements while maintaining sufficient detail for feature extraction. To enhance the diversity of the training data and prevent overfitting, several data augmentation techniques were applied: Horizontal Flip, Rotation, Translation and Shear.

The dataset was divided into training and validation sets. The training set was used to update the model weights, while the validation set was used to evaluate the model's performance on unseen data. A typical split ratio of 80% for training and 20% for validation was used to ensure enough data for both purposes.

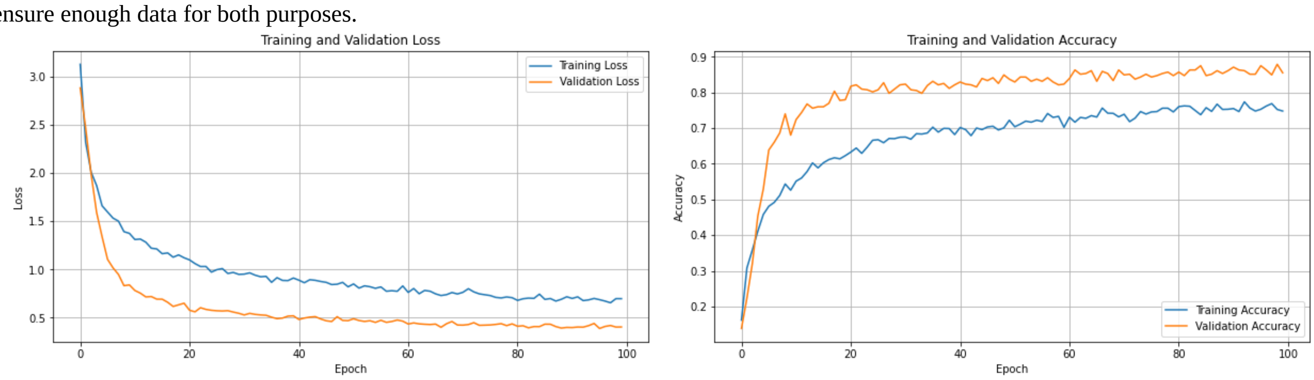

Fig. 6: Training Result

3.3. Result

To evaluate the performance of the classification model that has been built, the author uses several key evaluation metrics, namely precision, recall, f1-score, and support. Model evaluation is crucial to ensure that the created model is not only accurate but also effective in recognizing patterns and making reliable predictions. By using these metrics, the author can identify the strengths and weaknesses of the model in various performance aspects. The following table displays the results of precision, recall, f1-score, and support for each class in the test data:

Table 2: Test result

Class	Precision	Recall	F1-Score	Support
0	1,00	1,00	1,00	39
1	0,88	0,67	0,76	42
2	0,83	0,93	0,88	43
3	0,95	1,00	0,98	40
4	0,83	0,70	0,76	43
5	1,00	0,91	0,95	34
6	0,82	0,95	0,88	39
7	0,80	0,61	0,69	33
8	0,67	0,79	0,73	39
9	1,00	1,00	1,00	40
10	0,75	0,94	0,83	32
11	0,96	0,79	0,87	34
12	0,94	0,94	0,94	31
13	0,77	0,79	0,78	43
14	1,00	0,97	0,99	35
15	0,95	0,97	0,99	35
16	0,93	0,93	0,93	28
17	0,93	0,75	0,83	36
18	0,97	1,00	0,99	34
19	0,88	0,73	0,80	30
20	0,88	0,94	0,91	32
21	0,77	0,83	0,80	36
22	0,68	0,83	0,75	36
23	0,88	0,94	0,91	31
24	0,78	0,92	0,84	38
25	0,75	0,72	0,74	29

26	0,67	0,74	0,70	35
27	0,83	0,98	0,90	41
28	0,96	0,56	0,71	41
29	0,97	1,00	0,98	29

The following table provides a summary of the model evaluation measured based on accuracy metrics as well as macro average and weighted average.

Table 3: Accuracy of the models

	Precision	Recall	F1-score	Sample
accuracy			0,87	1080
macro avg	0,88	0,87	0,87	1080
weighted avg	0,88	0,87	0,86	1080

The model has an accuracy of 0.87 or 87%, which means the model correctly classified 87% of the 1080 samples.

The macro average of precision is 0.88, indicating that the average precision across all classes is 88%. The macro average of recall is 0.87, indicating that the average recall across all classes is 87%. The macro average of the F1-score is 0.87, which is the harmonic mean of precision and recall for all classes.

The weighted average of precision is 0.88, indicating that the overall precision, which considers the distribution of samples from each class, is 88%. The weighted average of recall is 0.87, indicating that the overall recall, which considers the distribution of samples from each class, is 87%. The weighted average of the F1-score is 0.86, which is the harmonic mean of precision and recall for all classes, considering the distribution of samples from each class.

Overall, this model shows good performance with an accuracy of 87% and consistent scores between the macro average and weighted average. The total number of samples used in this evaluation is 1080.

4. Conclusion

This research successfully demonstrates that the combination of morphological and texture features provides a more comprehensive description of the characteristics of medicinal plant leaves. Morphological feature extraction is effective in describing the general shape and structure of the leaves, while texture features are effective in capturing fine surface patterns. The simultaneous use of both types of features results in a more complete visual representation of the leaves, enhancing the system's ability to identify and distinguish various types of medicinal plant leaves. The developed artificial neural network model shows good performance with an accuracy of 87%, a macro average precision of 88%, and a macro average recall of 87%. These results indicate a significant potential for the system's application in various fields such as healthcare, pharmaceuticals, and biodiversity conservation.

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