Herbal Plant Classification Using Multi-Feature Extraction and Multilayer Perceptron

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ABSTRACT

Herbal plants used for medicine have prompted many researchers in the field of computer science to develop an efficient way to identify these plants through their leaves. This study will propose artificial neural networks, such as Multilayer Perceptron (MLP), to classify herbal plants. This method is used with feature extraction methods like the Gray Level Co-occurrence Matrix (GLCM), Hue Saturation Value (HSV), and Histogram of Oriented Gradients (HOG) to find out about the leaves' texture, color, and histogram. The dataset used was taken directly with a digital camera from various types of herbal plants that people usually see in everyday life. The dataset, which consisted of 450 images, was classified into nine classes. The entire dataset will be processed using a combined feature extraction method before the MLP method is used for clustering. This method is used to better understand the diversity of herbal plants and improve classification accuracy. The experimental results show that the combination of the feature extraction method and the MLP algorithm can achieve the highest accuracy of 95.56% in identifying various types of plants. This research provides significant benefits and contributes to the development of an herbal plant recognition system capable of accurate classification.

Keyword : Herbal Plants; MLP; GLCM; HSV; HOG

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1. INTRODUCTION

Almost all scientific fields have been influenced by technological advances, such as the identification and classification of herbal plants. Herbal plants are essential for medicine, beauty, and the food industry due to their beneficial natural compound content (Yulianto, 2017). Morphological characteristics, such as unique leaf structures, are often used to identify herbal plants (Djufri et al., 2022). The leaf identification process often takes a long time and requires special skills. Therefore, the use of the latest technology, such as image processing and artificial neural networks, is a good and reliable solution.

For years, herbal plants have been widely used and have become an important part of traditional medicine in various regions of Indonesia. These plants are considered to have more value and usefulness in traditional medicine for various diseases (Sapitri et al., 2022). However, the process of identifying these plants usually involves plant experts or botanists, which requires a lot of time and expertise. It is critical to use technology to expedite and simplify this process. The purpose of the research is to use artificial neural network technology and image processing to classify various types of herbal plants. By utilizing the ability of artificial neural networks to recognize complex patterns, this system is expected to provide accurate and effective grouping or recognition results (Pujiati & Rochmawati, 2022).

The application of artificial neural networks to herbal plant classification opens up new possibilities for rapid and accurate plant recognition. This study provides a reliable and efficient solution, especially for addressing the challenges of herbal plant recognition that require a high level of accuracy. It is hoped that the results of the study can simplify and accelerate the identification process, allowing more people, including those who are not botanists, to identify herbal plant types with a high level of accuracy.

Previous studies have evaluated the advantages of artificial neural networks in herbal plant classification. One study showed that the deep learning EfficientNetV2B0 model can achieve excellent accuracy, above 90%, in plant classification (Putra et al., 2024). In a different study, five machine learning classifiers were used on an optimized medicinal plant leaf dataset. They were multi-layer perceptron, logit-boost, bagging, random forest, and simple logistic. The multi-layer perceptron classifier had the best accuracy, at 99.01%, compared to the others (Naeem et al., 2021). Based on previous studies, the use of artificial neural network methods has enormous potential for improving the accuracy of herbal plant classification and paving the way for the development of practical applications in herbal plant recognition through technology.

In addition, the recognition process requires a feature extraction stage to obtain unique characteristics based on the shape, color, and texture of an image. One of these feature extractions is the Gray Level Co-occurrence Matrix (GLCM), which can be used with the Convolutional Neural Network (CNN) and Support Vector Machine (SVM) methods. In this study, the results of herbal leaf recognition obtained a very satisfactory accuracy of 96% with the CNN method (Zahirah et al., 2024). Other studies use a combination of HOG and LBP feature extraction with the SVM method, which has much better performance in detecting plants than using only one extraction method (Aminul Islam et al., 2019). According to this study, the use of good feature extraction and machine learning methods will increase plant recognition accuracy.

In this study, we propose a combination method of feature extraction and artificial neural networks, such as Multilayer Perceptron (MLP), for herbal plant classification. The process of herbal plant classification begins with data collection from leaf images that have label information according to the type of plant (Hassan et al., 2021). After that, the format will be adjusted, and the image will go through a preprocessing and normalization stage, which is carried out to overcome variations in brightness and contrast levels. Feature extraction will be performed using the Hue Saturation Value (HSV) technique for producing color features and the Gray Level Co-occurrence Matrix (GLCM) for texture features (Lesiangi et al., 2021).

In addition, the Histogram of Oriented Gradients (HOG) feature extraction method will be added to improve the system's ability to capture texture patterns that may be characteristic of herbal plant images. It is expected that by integrating HOG features, the system can obtain a more complete image representation of herbal plants, which in turn can improve the accuracy of herbal plant classification. After the feature extraction stage, an MLP model is built specifically for the task of herbal plant classification. This model uses a fully connected hidden layer to process the extracted features and finally connect them to the class output. The hidden layer in the MLP serves to capture non-linear patterns from the data, while the output layer provides the final classification results.

After passing the training stage with the prepared dataset, the model is tested with the validation dataset to assess the accuracy, precision, recall, and F1-score produced. Furthermore, the model obtained during testing can be used to classify images of unknown herbal plants. This process will produce types or classes of plants that are successfully identified. This method allows the herbal plant classification process to be automated through plant image analysis using a combination of feature extraction and artificial intelligence.

2. RESEARCH METHODS

This research methodology will explain the implementation of a herbal plant classification model using the Multilayer Perceptron (MLP) method and feature extraction combination. The procedure used in Figure 1 is described in the block diagram below.

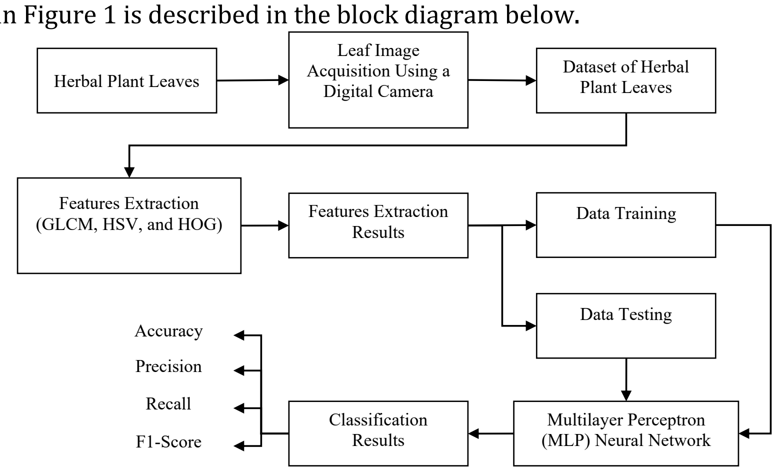

Fig 1. The block diagram illustrates the proposed method for classifying herbal leaves

A. Data Collection

The dataset used is in the form of herbal plant leaf images from nine types of herbal plants, with 50 images taken for each type of plant that is easily found in the surrounding environment. Overall, there are 450 images used for the research object. Figure 2 presents an example of an image of a herbal plant leaf used in this study.

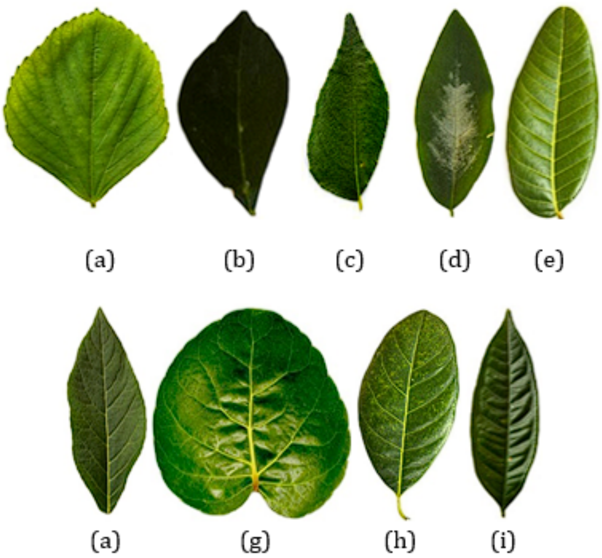

Fig 2. Herbal plants leaf image

(a) Acalypha australis L, (b) Murraya paniculata, (c) Murraya koenigii, (d) Sauropus androgynus, (e) Dimocarpus longan L, (f) Vernonia amygdalina, (g) Polyscias scutellaria, (h) Artocarpus heterophyllus, and (i) Syzygium polyanthum

B. Features Extraction

Before the image classification stage, the feature extraction procedure will be carried out first. This procedure generates parameters that distinguish the leaves of herbal plants. These characteristics function as unique markers that distinguish one leaf image from another. Texture and color features are some of the image characteristics that can be recognized by numeric values. Feature extraction is an important process in image processing because it allows the collection of characteristic data from the image.

One method that can be used to identify an image based on its texture characteristics is the statistical method based on the Gray Level Co-occurrence Matrix (GLCM), which was introduced by Haralick et al. (1973). GLCM is one of the most widely used statistical methods for texture feature extraction. A co-occurrence can be defined as a joint occurrence, i.e., when the gray value of one pixel is adjacent to the gray value of another pixel. Various texture characteristics can be obtained from the Co-occurrence Matrix (GLCM), which will be analyzed using equations 1, 2, 3, and 4 (Listya & Rokhman, 2019):

$$Contrast = \sum_i \sum_j (i-j)^2 P(i,j) \quad (1)$$

$$Correlation = \frac{\sum_i \sum_j i,j \;\; P[i,j] - \mu_i \mu_j}{\sigma_i \sigma_j} \quad (2)$$

$$Energy = \sum_i \sum_j P[i,j]^2 \quad (3)$$

$$Homogeneity = \sum_i \sum_j \frac{P[i,j]}{1+[i-j]} \quad (4)$$

Another feature that can be applied to image grouping is the color feature, which can be analyzed using the Hue Saturation Value (HSV) model. The HSV model is implemented to define RGB colors by converting them into hue, saturation, and value values. The color feature values of the image using the HSV method can be obtained by applying the following equations: 5, 6, and 7 (Lesiangi et al., 2021b; Listya & Rokhman, 2019):

$$V = max(RGB) \tag{5}$$

$$S = \begin{cases} \frac{v-min\ (R,G,B)}{V}, if\ V \neq 0 \\ 0, if\ V = 0 \end{cases} \tag{6}$$

$$H = \begin{cases} \frac{60(G-B)}{(V-min(R,G,B))}, if\ V = R \\ 120 + \frac{60(B-R)}{(V-min(R,G,B))}, if\ V = G \\ 120 + \frac{60(R-G)}{(V-min(R,G,B))}, if\ V = B \end{cases} \tag{7}$$

In addition to using the two features explained previously, this study also utilizes the Histogram of Oriented Gradients (HOG) characteristics. HOG is a feature extraction method used in image processing for object recognition, where this method is suitable for use to assist in performing identification tasks (Rabbani et al., 2024). As for obtaining feature values with the HOG method, equations 8 and 9 can be used as follows (Anggraeny et al., 2020).

$$M(i,j) = \sqrt{(I_x(i,j))^2 + (I_y(i,j))^2} \tag{8}$$

$$\theta(i,j) = arctan\left(\frac{I_y(i,j)}{I_x(i,j)}\right) \tag{9}$$

For each pixel in the image, the magnitude gradient (M) and orientation gradient (θ) can be calculated using the Sobel operator or other operators. After that, the image is divided into small cells (cells), and then the histogram of the orientation gradients is calculated (Cheon et al., 2011). The histogram is then normalized to reduce the influence of light or contrast, as shown in equation 10 below.

$$v_{i,j,k} = \frac{\sum_p \sum_q M(p,q).bin(p,q,i,j,k)}{\sqrt{\sum_p \sum_q M(p,q)^2}} \tag{10}$$

Where $v_{i,j,k}$ are the normalized voxel values, $bin(p,q,i,j,k)$ is the histogram of gradient orientations in cell k at position (i,j), and $\sum p \sum q M(p,q)^2$ is the sum of the squares of the gradient magnitudes.

C. Data Splitting

In the next step, the dataset will be divided between the training process and the testing process. This is done to ensure that the proposed model has excellent results, is reliable, and can be generalized well on data that has never been used before. This step is crucial during the development process of the artificial neural network model. The data collected in this study was divided into two parts, namely, training data and testing data, with a division ratio of 70:30.

D. Multilayer Perceptron (MLP) Neural Network

Multilayer Perceptron (MLP) is an artificial neural network that falls under the category of feedforward neural networks and is used to model non-linear relationships in data (Ariansyah et al., 2023). MLP can be used to solve various cases, such as pattern recognition, classification, and prediction (Rashedi et al., 2024). This network has a structure consisting of several layers of neurons, including an input layer, one or more hidden layers, and an output layer (Al-Saif et al., 2021). The input layer receives raw data from the input features; the number of neurons in this layer corresponds to the number of features in the data. Hidden layers function to process data received from the input layer and can have one or more hidden layers. The neurons in the hidden layer are fully connected to the neurons in the previous layer. The output layer produces the model's final prediction, with the number of neurons typically adjusted to the number of classes for classification problems or one neuron for regression problems The forward propagation process in MLP starts with finding the pre-activation z_l for each neuron in the hidden layer. This is done by multiplying the weight matrix W_l by the output of the previous layer a_{l-1} and adding the bias b_l (Leoni Sharmila et al., 2019). Mathematically, this is expressed in equation 11 below.

$$z_l = W_l a_{l-1} + b_l \tag{11}$$

The hidden layer output is obtained by applying the activation function *f(.)* to the pre-activation using the following equation 12.

$$a_l = f(z_l) \tag{12}$$

For the output layer, the pre-activation is calculated as the result of multiplying the output weight matrix W_{out} with the output of the last hidden layer a_{L-1} and adding the output bias b_{out}, which is expressed using equation 13 below.

$$z_{out} = W_{out} a_{L-1} + b_{out} \tag{13}$$

The final output is obtained by applying the softmax activation function to the pre-activation of the output layer, producing probabilities for each class using equation 14 below.

$$p(y = k \mid x) = \frac{e^{z_{out,k}}}{\sum_{j=1}^{K} e^{z_{out,j}}} \tag{14}$$

In the learning process, MLP uses backpropagation to update the weights and biases based on the gradient of the loss function. A commonly used loss function for classification problems is cross-entropy, which measures the difference between the actual label and the probability predicted by the model (Isabona et al., 2022). The cross-entropy loss function for multinomial classification can be calculated using equation 15 below.

$$L = -\sum_{i=1}^{N} \sum_{k=1}^{K} y_{i,k} \log\left(p(y_i = k \mid x_i)\right) \tag{15}$$

Where $y_{i,k}$ is the actual label for the *i-th* sample and the *k-th* class, $p(y_i=k|x_i)$ is the predicted probability for the *k-th* class, and N is the number of samples.

The loss function's gradient with respect to the weights and biases is calculated using the chain rule, which is then used to update the model parameters. With this structure, MLP can identify patterns in data and make predictions that can be applied in a variety of artificial intelligence and machine learning application

E. Model Evaluation

After the herbal plant classification stage is carried out, the next step is to assess the performance of the method by utilizing the confusion matrix, such as accuracy, precision, recall, and F1-score (Azmi et al., 2023). The proposed method's performance assessment can be done using equations 16, 17, 18, and 19, as follows. (Ramli et al., 2022; Tasnim et al., 2022)

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{16}$$

$$Precision = \frac{TP}{TP+FP} \tag{17}$$

$$Recall = \frac{TP}{TP+FN} \tag{18}$$

$$F1 - Score = 2 \times \frac{Precision \times Recall}{Precision \times Recall} \tag{19}$$

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3. RESULTS AND DISCUSSION

After the feature extraction process using GLCM, HSV, and HOG methods, the next step is to use the Multilayer Perceptron (MLP) technique to identify herbal plants. The HSV color model separates color, clarity, and gray value information. GLCM is applied to the texture pattern, helping to identify the characteristics of the texture pattern of herbal leaf images. In addition, the Histogram of Oriented Gradients (HOG) method is used to extract edge and shape information from herbal leaf images. The HOG method divides the image into small cells, calculates the gradient orientation histogram for each cell, and then combines these histograms into a feature vector. This approach is effective in capturing edge structures and shape patterns that may be important characteristics in herbal plant recognition.

With the combination of these three methods, the color, texture, and shape features of herbal plant leaf images can be extracted comprehensively. Furthermore, the MLP method can process these features to accurately identify and classify herbal plant types. The MLP method will learn patterns in image features to identify herbal plant types with high accuracy, using color and pattern features from HSV, GLCM, and HOG. The results of herbal plant clustering using MLP and a combination of feature extractions are shown in Table 1 below.

Table 1. Results of herbal plant classification using feature extraction and Multilayer Perceptron (MLP) methods

Methods	Accuracy	Precision	Recall	F1-Score
MLP + HSV	74.07%	0.7290	0.7375	0.7294
MLP + GLCM	91.85%	0.9138	0.9171	0.9106
MLP + HOG	94.07%	0.9512	0.9418	0.9397
The Proposed Methods	95.56%	0.9605	0.9669	0.9627

According to the test results presented in Table 1, several conclusions can be drawn about the performance of various methods in herbal plant classification. First, the method that combines MLP with HSV shows quite good performance, with an accuracy of 74.07% and balanced precision, recall, and F1-score. However, this method still has room for further improvement. Second, the use of MLP with GLCM feature extraction produces better performance, with an accuracy of only 91.85% and high precision, recall, and F1-score values. Meanwhile, the method that uses MLP with HOG feature extraction shows very good performance, with an accuracy of 94.07% and higher precision, recall, and F1-score values. The proposed method, which combines MLP with all three feature extractions (GLCM, HSV, and HOG), however, works the best. It has the highest accuracy (95.56%) and very good precision, recall, and F1-score values. This shows that the combined approach is able to extract the most relevant features and provide the highest classification results in herbal plant identification. Thus, the proposed method offers an effective and reliable solution for the task of herbal plant classification.

The combination of MLP and comprehensive feature extraction has the potential to significantly improve classification performance by providing a deeper understanding of herbal leaf characteristics. The combined use of MLP with comprehensive feature extraction has great potential to improve classification performance in a variety of applications, including herbal leaf identification. With this approach, complex and diverse information from leaf images can be better revealed because each feature extraction technique, such as GLCM, HSV, and HOG, has its own advantages and disadvantages in capturing different visual characteristics of the object. For example, GLCM (Gray-Level Co-occurrence Matrix) is able to extract information about leaf texture; HSV (Hue, Saturation, Value) can capture important color information; and HOG (Histogram of Oriented Gradients) can identify texture patterns and contour directions in the image.

By combining various image feature extractions, the identification process using the MLP architecture can produce high accuracy. The MLP method has the ability to model non-linear relationships between various features extracted from leaf images, especially in a spatial context. With deeper processing, the information extracted from these various features can be enhanced. The MLP method can consider the relationship between various features extracted from leaf images, allowing for a more comprehensive understanding of leaf characteristics. Thus, the combined use of MLP with comprehensive feature extraction not only improves classification accuracy but also provides deeper insight into the unique visual properties of herbal leaves. This can aid in the better identification and classification of plant species, as well as a deeper understanding of the genetic and environmental variations present in them. As a result, the use of this combination has enormous potential to support various applications in agriculture, environmental conservation, and biology.

4. CONCLUSION

After looking at the test results, we can say that using the Multilayer Perceptron (MLP) method along with a mix of image feature extraction (GLCM, HSV, and HOG) to classify herbal plants worked very well. The proposed method's accuracy level is 95.56%; precision is 0.9605, recall is 0.9669; and F1-score is 0.9627. These results state that the proposed method, namely the combination of MLP with all image feature extraction, shows the highest performance in the classification of herbal plants compared to using only one type of image feature extraction, with the highest accuracy, very good and balanced precision, recall, and F1-score values.

REFERENCES

Al-Saif, A. M., Abdel-Sattar, M., Aboukarima, A. M., & Eshra, D. H. (2021). Application of a multilayer perceptron artificial neural network for identification of peach cultivars based on physical characteristics. PeerJ, 9, 1–22. https://doi.org/10.7717/peerj.11529

Aminul Islam, M., Billah, M., Sayeed Iftekhar Yousuf, M., & Billah, M. M. (2019). Automatic Plant Detection Using HOG and LBP Features With SVM. Article in International Journal of Computer. http://ijcjournal.org/

Anggraeny, F. T., Rahmat, B., & Pratama, S. P. (2020). Deteksi Ikan Dengan Menggunakan Algoritma Histogram of Oriented Gradients. Informatika Mulawarman : Jurnal Ilmiah Ilmu Komputer, 15(2), 114. https://doi.org/10.30872/jim.v15i2.4648

Ariansyah, M. H., Winarno, S., Nur Fitri, E., & Arga Retha, H. M. (2023). Multi-Layer Perceptron For Diagnosing Stroke With The SMOTE Method In Overcoming Data Imbalances. Innovation in Research of Informatics (INNOVATICS), 5(1), 1–8. https://doi.org/10.37058/innovatics.v5i1.6565

Azmi, F., Gibran, M. K., Ridwan, A., & Saleh, A. (2023). Enhancing Water Potability Assessment Using Hybrid Fuzzy-Naïve Bayes. Indonesian Journal of Computer Science, 12(1), 1032–1043. https://doi.org/https://doi.org/10.33022/ijcs.v12i3

Cheon, M.-K., Lee, W.-J., Hyun, C.-H., & Park, M. (2011). Rotation Invariant Histogram of Oriented Gradients. International Journal of Fuzzy Logic and Intelligent Systems, 11(4), 293–298. https://doi.org/10.5391/ijfis.2011.11.4.293

Djufri, K., Luang, L., & Araie, F. H. (2022). Identifikasi Pemanfaatan Morfologi Tumbuhan Sebagai Obat Tradisional Oleh Mahasiswa Biologi STKIP Kie Raha Ternate. Journal of Biology Education And Sciencee, 2(2), 86–94.

Hassan, S. M., Maji, A. K., Jasiński, M., Leonowicz, Z., & Jasińska, E. (2021). Identification of plant-leaf diseases using cnn and transfer-learning approach. Electronics (Switzerland), 10(12). https://doi.org/10.3390/electronics10121388

Isabona, J., Imoize, A. L., Ojo, S., Karunwi, O., Kim, Y., Lee, C. C., & Li, C. T. (2022). Development of a Multilayer Perception Neural Network for Optimal Predictive Modeling in Urban Microcellular Radio Environments. Applied Sciences (Switzerland), 12(11). https://doi.org/10.3390/app12115713

Leoni Sharmila, S., Dharuman, C., & Venkatesan, P. (2019). A Comparison of Radial Basis Function and Multilayer Perceptron Network as tool for classification of Medical Data. Journal of Physics: Conference Series, 1377(1). https://doi.org/10.1088/1742-6596/1377/1/012028

Lesiangi, F. S., Mauko, A. Y., & Djahi, B. S. (2021a). Feature extraction Hue, Saturation, Value (HSV) and Gray Level Cooccurrence Matrix (GLCM) for identification of woven fabric motifs in South Central Timor Regency. Journal of Physics: Conference Series, 2017(1). https://doi.org/10.1088/1742-6596/2017/1/012010

Lesiangi, F. S., Mauko, A. Y., & Djahi, B. S. (2021b). Feature extraction Hue, Saturation, Value (HSV) and Gray Level Cooccurrence Matrix (GLCM) for identification of woven fabric motifs in South Central Timor Regency. Journal of Physics: Conference Series, 2017(1). https://doi.org/10.1088/1742-6596/2017/1/012010

Listya, F. A., & Rokhman, N. (2019). Classification of Tangerine (Citrus Reticulata Blanco) Quality Using Combination of GLCM, HSV, and K-NN. IJCCS (Indonesian Journal of Computing and Cybernetics Systems), 13(4), 357. https://doi.org/10.22146/ijccs.47906

Naeem, S., Ali, A., Chesneau, C., Tahir, M. H., Jamal, F., Sherwani, R. A. K., & Hassan, M. U. (2021). The classification of medicinal plant leaves based on multispectral and texture feature using machine learning approach. Agronomy, 11(2). https://doi.org/10.3390/agronomy11020263

Pujiati, R., & Rochmawati, N. (2022). Identifikasi Citra Daun Tanaman Herbal Menggunakan Metode Convolutional Neural Network (CNN). Journal of Informatics and Computer Science (JINACS), 3(03), 351–357. https://doi.org/10.26740/jinacs.v3n03.p351-357

Putra, R. P. S., Aditya, C. S. K., & Wicaksono, G. W. (2024). Herbal Leaf Classification Using Deep Learning Model Efficientnetv2B0. JITK (Jurnal Ilmu Pengetahuan Dan Teknologi Komputer), 9(2), 301–307. https://doi.org/10.33480/jitk.v9i2.5119

Rabbani, F. M. R., Bima Sena Bayu Dewantara, & Endra Pitowarno. (2024). Lip Movement Recognition using Histogram of Oriented Gradient (HOG) and Support Machine Vector (SVM) for Arabic Word. Indonesian

Journal of Computer Science, 12(6). https://doi.org/10.33022/ijcs.v12i6.3596
Ramli, N. E., Yahya, Z. R., & Said, N. A. (2022). Confusion Matrix as Performance Measure for Corner Detectors. Journal of Advanced Research in Applied Sciences and Engineering Technology, 29(1), 256–265. https://doi.org/10.37934/araset.29.1.256265
Rashedi, K. A., Ismail, M. T., Al Wadi, S., Serroukh, A., Alshammari, T. S., & Jaber, J. J. (2024). Multi-Layer Perceptron-Based Classification with Application to Outlier Detection in Saudi Arabia Stock Returns. Journal of Risk and Financial Management, 17(2). https://doi.org/10.3390/jrfm17020069
Sapitri, A., Asfianti, V., & Marbun, E. D. (2022). Pengelolahan Tanaman Herbal Menjadi Simplisia sebagai Obat Tradisional. Jurnal Abdimas Mutiara, 3(1), 94–102.
Tasnim, A., Saiduzzaman, Md., Rahman, M. A., Akhter, J., & Rahaman, A. S. Md. M. (2022). Performance Evaluation of Multiple Classifiers for Predicting Fake News. Journal of Computer and Communications, 10(09), 1–21. https://doi.org/10.4236/jcc.2022.109001
Yulianto, S. (2017). Penggunaan Tanaman Herbal Untuk Kesehatan. Jurnal Kebidanan Dan Kesehatan Tradisional, 2(1), 1–7. https://doi.org/10.37341/jkkt.v2i1.37
Zahirah, D., Kurniati, N., & Darwis, H. (2024). DIGITAL IMAGE CLASSIFICATION OF HERBAL LEAVES USING KNN AND CNN WITH GLCM FEATURES. Jurnal Teknik Informatika (JUTIF), 5(1), 61–67. https://doi.org/10.52436/1.jutif.2024.5.1.1162