Fruit Plant Leaf Identification Feature Extraction Using Zernike Moment Invariant (ZMI) and Methods Backpropagation

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***Abstract--* The concept of pattern recognition is often used to identify a wide range of objects. Due to the ability to recognize objects is needed by humans. One of them is for pattern recognition on the leaves as identification in determining the types of leaves. However, in the acquisition, very frequent disturbances called noise. Noise in the image is a region of pixel image intensity of unwanted or deemed to disturb the segmentation process until the introduction. The impact of noise can degrade the image quality when the segmentation process. Therefore, in this study, the researchers added a preprocessing stage to reduce noise modest invisible when the acquisition using the camera. Gaussian filter used as a technique to tackle the problem at last preprocessing. Aside from the noise, constraints at the time of feature extraction of natural researchers also because the study took shape characteristic based on the area of the image. So if the object changes the coordinates of the start pixel image was unrecognizable. Based on these problems do research to identify the leaves by using Zernike Moment invariant feature extraction (ZMI) and Backpropagation algorithm. Based on the testing that was done on 100 test data success rate Based on these problems do research to identify the leaves by using Zernike Moment invariant feature extraction (ZMI) and Backpropagation algorithm. Based on the testing that was done on 100 test data success rate78%.**

Keywords-Feature Extraction, Gaussian filter, Zernike Moment invariant, Backpropagation, Leaf Recognition

I. INTRODUCTION

The need for acceleration of the screening or sorting items have been and are being developed by the industry. Products that do the screening or sorting was so diverse, one of them is fruits. In fruits, usually, the industry players perform sorting by type. It can be given a solution by performing classification [1], whether it is based on the color of the fruit or leaves, the shape of the fruit or leaves, or the mass (weight) of fruit but the color or mass is less effective if given nearly all types of fruit have leaves that are the same color and the masses is not a barometer of good considering there are some pieces that mass same. Thus, the reason researchers make the leaves as a better approach than the others is that the leaves have a unique image pattern for each type of fruit.

Free digital image processing by [2], Leaf classification techniques can be identified by taking the image of leaves of fruit trees leaf pattern recognition then carried out by identifying structural characteristics such as leaf shape and texture of the leaves. The pattern that is processed in the shape of the leaves and the leaf edge. Differences in the pattern of a leaf can be used as identifiers types of fruit crops based on the shape of the leaves.

The development of the leaf pattern recognition methods includes the classification under the form (shape-based) by [3] using 17 parameters of the feature extraction with Canny Edge Detector method and Support Vector Machine (SVM), which has an accuracy rate of 87%. [1]conduct research in herbal leaf classification based on shape (geometry) or shape-based methods Naive Bayes classifier and K-Nearest Neighbor (KNN) by which has an average accuracy of 70.83%. Then, the identification of fruit plant based on features of shape, color, and texture of the leaves by using Learning Vector Quantization (LVQ) submitted by [4] with a 86% accuracy rate while [5]has a 90% accuracy rate. Then, [6] conducting research with convolution methods Neural Network (CNN) - GoogleNet which has an accuracy rate of 94% with the challenge of damaged leaves by 30%. In fact, until now no method has an accuracy of 100%. However, we can conclude that the results of previous studies had an average level of accuracy above 70% so as to perform a classification based on geometry is better suited to improve the accuracy of detection rather than on the edge.

Shape-based classification also often experience obstacles to dependence on the moment of the object to be in ektrasi its features. In other words. it is of course severely restricts research in the classification due to the moment of the object dependent on a data point and the reconstruction of the form [7][8][9], From the literature review, researchers found the right method to overcome these problems the method invariant Zernike Moment (ZMI). Another advantage is the ease of Zernike moments of image reconstruction because of orthogonality function.

In addition to performing feature extraction, the final stage of recognition or identification of objects is to capture features that have been extracted can be supervised or unsupervised. By conducting a literature review, researchers chose a supervised learning approach that is a Backpropagation Neural Network (BNN). BNN mostly used in multi-layer networks in the hope of minimizing the error with the results of engineering calculations performed by the network [10], BNN excellence in research[11] is resiliently algorithm, where the algorithm is one of the best algorithms on BNN to overcome the slow convergence and can obtain high accuracy. It is also claimed by[12]which they compare Conjugate Gradient algorithm, Levenberg-Marquardt, and Resilient. The results show that the algorithm Resilient provides the highest accuracy of two other algorithms.

II. THEORY

Before performing a stage of the methodology, we must know in advance the theoretical basis that we will use. This is necessary because it can be used as a reference or the cornerstone in understanding what method or approach will be used so that research is directed. Here is the basic theory used in this study.

A. Gaussian Filter

Gaussian blur filter is an example of the Low Pass Filter (LPF) most famous of which is implemented by the kernel is not uniform. The coefficient for the Gaussian blur filter mask is an example of a 2D Gaussian function. 2D Gaussian filter equations can be seen in equation (1).

$$G(x,y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}} \quad (1)$$

Where:
G (x, y): Gaussian element at position (x, y)
σ: distribution standard deviation (sigma)

$\sigma$is the standard deviation of this function is used to maintain the effect of blur in the image. In the case of the gray level image and a normal distribution, an area that has a value brighter became darker as we move from the center to the edge of the bright area. Gaussian kernel array typically is used in convolution, convolution involved in the multiplication of a set of pixels of the image with the corresponding pixel value of the array in the form of a convolution mask, which has the size, and the coefficient decreases with increasing distance from hub kernel. The size of the array of different kernels contain a different number patterns because one of the properties of the Gaussian distribution will be zero everywhere and as such, would require a much larger kernel [13][14],

B. thresholding

thresholding a process of converting a gray image into a binary image with a background in order to separate the actual object or information used on an image. Image thresholding result is used as a reference to look up the values contained in the image of the image used to perform feature extraction from the leaves. Thresholding produces a black and white image that has a pixel scale of 0-255, in this case, the intensity value of 0 indicates black, while 255 or 1 worth of white. Process Grayscale to RGB input image can be seen in Figure 1.

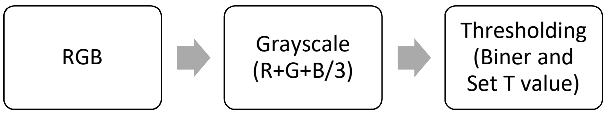


FIGURE 1. The process of image processing from RGB to thresholding

There are 3 ways to determine the threshold value on an image[2], that is:

1. Global threshold value (Global Threshold T)
   Value Threshold (T) on the global threshold value depends on the value of the gray level of the pixel at position x, y is written with the function T = T {f (x, y)}
2. Local threshold value
   The threshold value (T) on the local threshold value depends on the property of the neighboring pixel, can be written with the function T = T {A (x, y), f (x, y)}, where A (x, y) states neighboring pixel values
3. Dynamic threshold value
   The threshold value (T) on a dynamic threshold value depends on the coordinates of the pixel, can be written with the function T = T {xy, A (x, y), f (x, y)}.

C. Zernike Moment Invariants (ZMI)

ZMI included in *descriptor* region-based shape which means that ZMI is an efficient feature extraction for pattern recognition. This is because the ZMI has orthogonality properties on Zernike polynomials in feature extraction results formed and has a property that does not depend on the rotation of the image. To calculate the ZMI of an image, the image of the center will be declared as the center and the pixel coordinates mapped to the distance from the unit circumference. Pixels outside the circumference of the unit will not be used in the computation. ZMI election as feature extraction has a reason because ZMI has a good invariant and results in a system with a good authentication, ZMI is also believed to be more accurate, flexible and more easily reproducible than Hu Moment[15],

ZMI calculation steps are described as follows:

1. Read the input image data from left to right and from top to bottom.
2. Calculate the value of regular moments of the image, with the formula:m_{pq}

$$m_{pq} = \sum_x \sum_y x^p y^q f(x,y) \quad (2)$$

Information:

m_{pq}	: moment;
p and q	: a moment of the order;
x	: coordinates of the image on the x axis;
y	: coordinates of the image on the y axis;
$f(x,y)$	: Image intensity values between 0 or 1.

3. Calculate the intensity of the moment (,) with the formula:$\bar{x}\bar{y}$

$$\bar{x} = \frac{m_{10}}{m_{00}} \text{ and } \bar{y} = \frac{m_{01}}{m_{00}} \quad (3)$$

Information:
$\bar{x}$: Average - Average coordinates x
$\bar{y}$: Average - Average coordinate y

4. Calculate central moment, with the formula:μ_{pq}

$$\mu_{pq} = \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} (x-\bar{x})^p . (y-\bar{y})^q f(x,y) \quad (4)$$

Information:

μ_{pq}	: Central moment;
p and q	: moment of the order;
x	: coordinates of the image on the x axis;
y	: coordinates of the image on the y axis;
$\bar{x}$	: Average - Average coordinates x;
$\bar{y}$	: Average - Average y coordinates;
$f(x,y)$	: Image intensity values between 0 or 1.

5. Normalization moment, with the formula:η_{pq}

$$\eta_{pq} = \frac{\mu_{pq}}{(\mu_{00})^{\frac{p+q+2}{2}}} \quad (5)$$

Information:

η_{pq} : Normalization of the moment;
μ_{pq} : Central moment
p and q : the moment of the order.

6. Calculate Zernike moment, with the formula below: $ZM_1 sampai ZM_6$

$$ZM_1 = \frac{3}{\pi}[2(\eta_{20} + \eta_{02} - 1)],$$
$$ZM_2 = \frac{9}{\pi^2}[(\eta_{20} - \eta_{02})^2 + 4\eta_{11}^2],$$
$$ZM_3 = \frac{16}{\pi^2}[(\eta_{03} - 3\eta_{21})^2 + (\eta_{30} - 3\eta_{12}^2)],$$
$$ZM_4 = \frac{144}{\pi^2}[(\eta_{03} - 3\eta_{21})^2 + (\eta_{30} + \eta_{12})^2],$$
$$ZM_5 = \frac{13824}{\pi^4}\left\{\begin{array}{l}(\eta_{03} - 3\eta_{21})(\eta_{03} + \eta_{21})[(\eta_{03} + \eta_{21})^2 - 3(\eta_{30} + \eta_{12})^2] \\ -(\eta_{30} - 3\eta_{12})(\eta_{30} + \eta_{12})[(\eta_{30} + \eta_{12})^2 - 3(\eta_{03} + \eta_{21})^2]\end{array}\right\},$$
$$ZM_6 = \frac{864}{\pi^3}\left\{\begin{array}{c}(\eta_{02} - \eta_{20})[(\eta_{30} + \eta_{12})^2 - (\eta_{03} + \eta_{21})^2] + \\ 4\eta_{11}(\eta_{03} + \eta_{21})(\eta_{30} + \eta_{12})\end{array}\right\} \quad (6)$$

D. backpropagation

In general, the architecture Backpropagation Neural Network (BNN) (Artificial Neural Network) is the architecture of the ANN consisting of several layers: the input layer (input layer). Each layer has a number of nodes or neurons Different[25],

The neural network architecture can be illustrated in the following figure:

1. The input layer (input layer)
   The input layer is a layer consisting of a few neurons that will receive a signal from the outside and then go on to other neurons in the network layer is inspired by the characteristics and workings of cells in the sensory nerves in biological neural networks.
2. Hidden layer (hidden layer)
   The hidden layer is a clone of nerve cells connector on biological neural networks. A hidden layer serves to increase the network's ability to solve the problem. The consequences of this layer are the training becomes more difficult or longer.

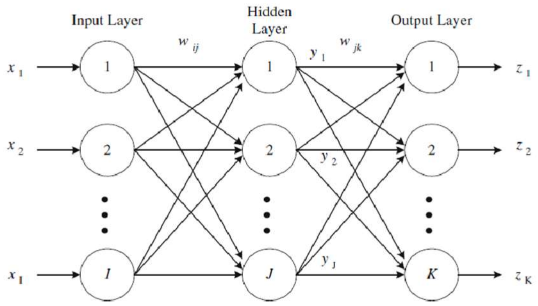


FIGURE 2.B Network Architectureackpropogation Neural Network (BNN)[16]

3. The output layer (output layer)
   Output layer serves to distribute the signals output of the network processing. The layer also contains a number of neurons. The output layer is a clone of motor nerve cells in biological nervous.

III. METHODOLOGY

At this stage, the researchers present a methodology that researchers use in achieving recognition system-based feature extraction type of leaf area of geometry. Broadly speaking, the workflow of the system is represented in figure 3.

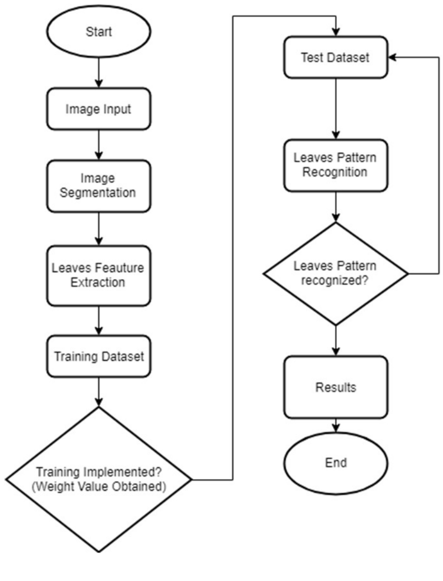


FIGURE 3. FLOWCHART OF SYSTEM INTRODUCTION IN RESEARCH'S LEAF TYPE

A. Data acquisition

Data acquisition is the process of performing image capture to be managed. In this research, image sampling with catches MINI WEBCAM (PK-836F) A4Tech by 16 mp. The leaves will be placed on Acrylicwebcam camera position 40 cm above the leaves. The format of the image of the webcam is the catch-type RGB jpeg model. The test data used in this study as many as 10 types of leaves (leatherback, Ceri, Mirror, Duku, Durian, Longan, Passion, Miss, Rambutan, and Sawo), where each leaf is composed of 10 images, so the total of test data in this study ie 100 pieces of leaf samples.

B. Noise Removal

To smooth the results of engineering grayscale image in order to obtain a better image than the previous image used technique gaussian filter for smoothing the image.

(a) (b) (c)

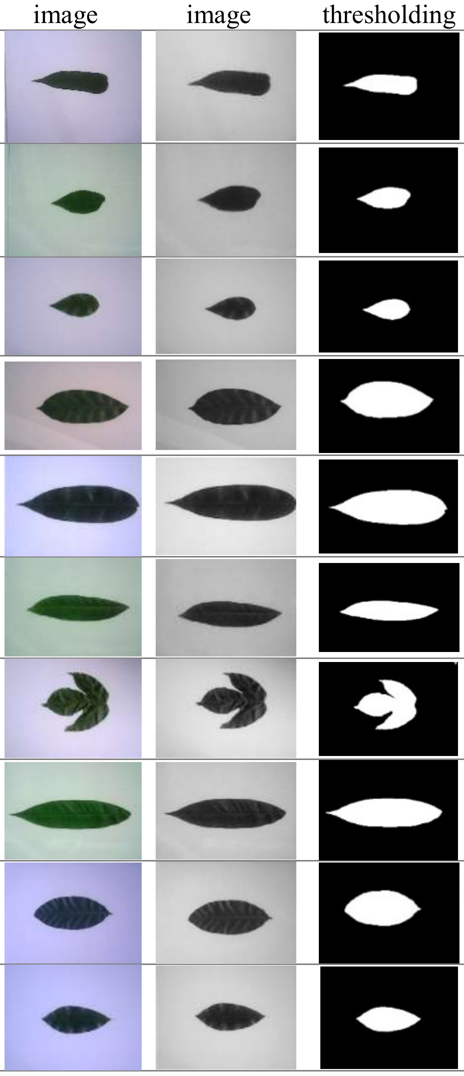
FIGURE 4. (A) INPUT IMAGE (RGB) (B) RESULTS IN GRAYSCALE (C) FILTERING WITH GAUSSIAN

C. Segmentation

Image segmentation using the thresholding technique, which is split between the leaf stage (foreground) and the background. The threshold value taken was 128. The image which is outside of the value will be 1 (black) and who are at the value will be 0 (white).

TABLE 1.
Image Processing Results

No.	input image	Grayscale image	image thresholding
1			
2			
3			
4			
5			
6			
7			
8			
9			
10			



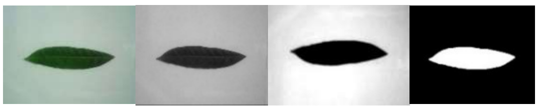


FIGURE 5. (A) INPUT IMAGE (RGB) (B) RESULTS IN GRAYSCALE (C) FILTERING WITH GAUSSIAN (D) RESULTS OF THRESHOLDING

D. Feature extraction

After getting the results of image segmentation is then performed whole then the test data testing stage Zernike Moment invariant feature extraction (ZMI). ZMI can store image information with minimal information redundancy and has properties as rotational invariance. ZMI algorithm can be seen in Figure 6.

E. Imagery training

Once at the Zernike moment can score invariant (ZMI), this value will be the reference for the process of identifying the leaf using backpropagation learning algorithm. This stage is the stage which would create an object neural network that consists of 2 pieces of object layers (two hidden layers and one output layer) but the system up to a maximum of 24 hidden layers.

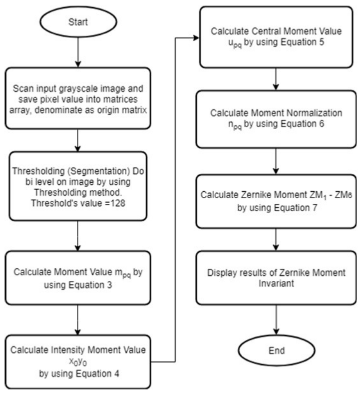


FIGURE 6. FLOWCHART EXTRACTIO FEATURE GEOMETRY WITH ZERNIKE MO

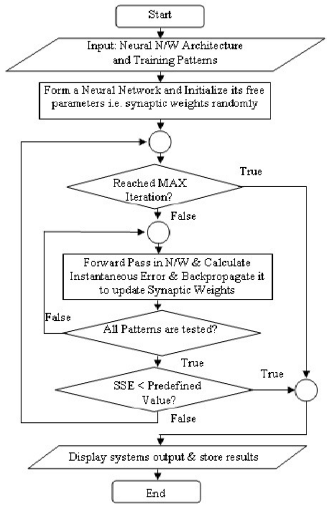


FIGURE 7. FLOWCHART BACKPROPAGATION NEURAL

The total output node is determined based on the area of the object (geometry) that must be recognized that consists of spacious area.

As for the number of nodes in the hidden layer is determined based on the results of experiments in which the number of nodes that too little will cause the training process will not produce a stable weight, but the number of nodes that too much will cause the training process becomes slower.

IV. RESULTS AND DISCUSSION

This stage is the stage where researchers show results and discuss the results. Once at the Zernike moment can score invariant (ZMI), this value will be the reference for the process of identifying the leaf using backpropagation learning algorithm.

Then, the feature extraction using Zernike Moment Invariants (ZMI), the results in Table 2 show that ZMI able to take a moment invariant to the order 6. In Table 1, represented the results of image processing from RGB input to the segmentation process. the results of the standard segmentation thresholding.

Input image has a difference in background and lighting so do the techniques and refine grayscale image with a Gaussian filter is able to optimize

At the training, backpropagation algorithm input data in the form of vector (x) for the training amounting to 6point which is 6th grades Zernike moment invariant (ZMI) that we can be on top, to the hidden layer and is attempted at this training were 24 hidden layer, while the target (y) of 8 targets. This time using a training process error tolerance value = 0.0001, for the learning rate = 0.5 and max epoch iteration = 25000 1000000. Table 3 is a comparison of the epoch.

TABLE 2.
Results Feature Extraction Using the ZMI

ZMI	imagery 1	Citra 2	image 3	Citra 4	Citra 5
Z1	-0.95	-1.5058	-1242	-1.38	1,293
Z2	0.1316	0017	0:05	0047	0072
Z3	0198	0.0003	0314	0.0001	1655-5
Z4	0293	0.0002	2965	0.0001	9573-6
Z5	0482	-1794-6	5262	-6122-7	-1556-8
Z6	-1013	-0.0003	0141	-0.0004	-7071-5

ZMI	image 6	Citra 7	image 8	Citra 9	Citra 10
Z1	-1.55	-1353	-1486	1,524	1.5
Z2	0.0002	0.0544	0.0214	0.0044	0:02
Z3	0.0005	7288-5	9688-5	0.0026	0.0004
Z4	0.0002	0.0001	3982-7	0.0001	0.0006
Z5	3911-8	-2835-7	-2.2053-7	2026-7	-1.64-6
Z6	-3.93-6	0.0003	-0.0001	-9613-6	-0.0003

V. CONCLUSION

Preprocessing segmentation method using a Gaussian filter intended to soften in order to disguise the noise, successfully implemented and have had great results. Based on the results of an experiment that has been done can be deduced, the method invariant Zernike moment (ZMI) and back propagation algorithm can be applied to identify the leaves of the plant with the accuracy of ± success78% of test data as many as 100. The Epoch <100000 produces a low introductory rate, ± 48%.

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