

HANDWRITTEN SIGNATURE RECOGNITION USING HISTOGRAM OF ORIENTED GRADIENTS AND SMOOTH SUPPORT VECTOR MACHINE

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ABSTRACT

Signatures are the hallmark of each person as proof of authorizing documents or transactions. This means forgery of signatures, if there is a transaction that is problematic or fails because there is a signature forgery, of course the issue of transfer starts from a difficult transaction or fails to ratify legal documents. Can help overcome this can be done by using signatures by utilizing image processing techniques. To request this signature, some preprocessing methods are needed, such as cropping and grayscale. after the cropping process is carried out for the next process grayscale is performed for feature extraction input with the Gradient Oriented Histogram method to find the value of vector features where this vector feature will be used to classify label labels from owner signatures with the Smooth Support Vector Machine method. In this study 300 data were used. For testing using the k-fold cross validation method while the k used is 10-fold. Based on the results of evaluating the tests on the signatures that have been carried out with the k-fold method, a 10-fold cross validation for all scenarios for the signature owner has obtained an average test value of 88%.

Keywords : Signature Recognition, Image processing, handwriting, Histogram of Oriented Gradients, Smooth Support Vector Machine

1. PRELIMINARY

A signature is a unique handwriting that is unique as a symbolic substance. In signatures commonly used in everyday life and used as identification of someone whose function as proof of the owner of the signature, in a document states that the party who signed, knew and agreed to the contents of a document. In the previous study about offline signature recognations that used the extraction of the Grid Feature Segmentation Image and its classification using Back Propagation obtained an accuracy of 63%, because the results of the accuracy obtained had a small value because preprocessing image rotation was not done, so the signature oblique image with a certain degree would

produce output with very different values and produce errors in the classification results. [1]. Subsequent research has been conducted on Offline Handwritten Signature Verification using the C-program and Associative Memory Net (AMN) features by providing accuracy of 92.3%, because the data used is 12 signatures [2]. Referring to research on handwritten characters using HOG features and classifications using Support Vector Machine (SVM) can get an accuracy of 96.56% [3]. Research on Classification of Diabetes Mellitus Patients Using the Smooth support vector machine method obtained an accuracy of 95.12% [4]. Based on the explanation described above, the authors are interested in taking the topic of the final assignment research entitled "Introduction to Signatures Using Histogram of Oriented Gradients and Smooth Support Vector Machine".

2. RESEARCH CONTENT

This section discusses research methods, theoretical foundations, system analysis, and test results.

2.1 Research methods

The method of research carried out using research methods based on case studies. Case studies, or case studies (Case studies), are researches on the status of a subject based on research relating to the characteristics of the whole personality [5]. The research steps as shown in Figure 1

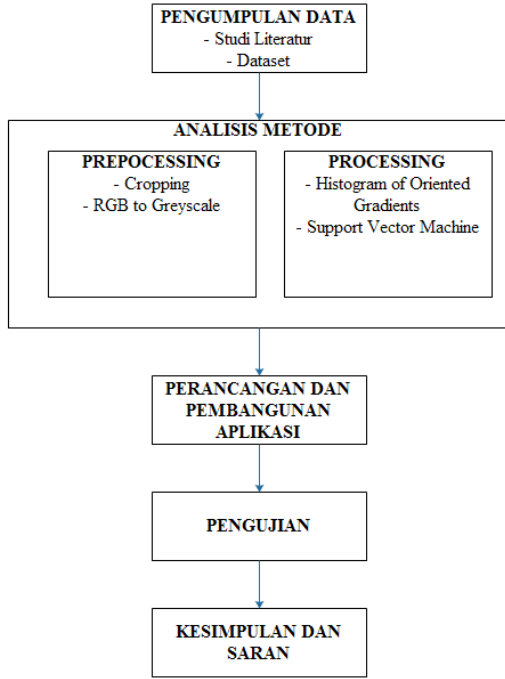


Figure 1 research steps

2.2 Citra Digital

In general, the term digital image processing states "two-dimensional image processing through a digital computer. Photos are examples of two-dimensional images that can be processed easily. Every photo in the form of a digital image (for example from a digital camera) can be processed through certain devices. For example, if the camera shot looks rather dark, the image can be processed to be brighter, it is also possible to separate photos of people from the background. The description shows simple things that can be done through digital image processing. Of course many other difficult things can be done through digital image processing [6].

2.3 Grayscale

Grayscale images handle black and white gradations that produce a gray effect. The color gradation in each image is expressed with intensity. In this case, the intensity ranges from 0 to 255. The value 0 is black and the value 255 is white. In grayscale the intensity value can be uniformed with a function. Following is the formula for color image conversion (RGB) to be the value of grayscale intensity [7].

$$G = wR.Red + wG.Green + wB.Blue \quad (1)$$

Information :

$G(x, y)$ = Grayscale matrix of pixel coordinates.

Red = Red value from a pixel point

Green = Green value from a pixel point

Blue = Blue value from a pixel point

wR, wG, wB = Weights each color element value.

Equation 1 is one of the formulas used to convert color images to grayscale. In grayscale images, each pixel is a representation of the degree of intensity or

grayness. There are 256 types of gray degrees in grayscale images. Starting from white, then getting darker to black. Because there is a possibility of 256 degrees gray, each pixel in grayscale is stored 1 byte in memory (8 bits).

2.4 Histogram of oriented Gradients

Histogram of oriented Gradients are a common way to obtain descriptors for the detection of certain objects. For example, to detect human presence (Human detection) like research that was done by Dalal and Trigs [8]. The process of this algorithm can be explained as follows:

1. *Preprocessing*, doing the intensity of normalization or in other words changing the image of the image to greyscale (Image of gray scale)..
2. Counting the edge map. Estimating the direction of x and y in the image then calculating the gradient magnitudes and gradient angles for each pixel of the image. Following is the calculation formula for gradient magnitudes and gradient angles:

$$|G| = \sqrt{I_x^2 + I_y^2} \quad (2)$$

Where $|G|$ is the absolute number of the magnitude and I gradients is the image of the image that has been greyscale from the results of the previous stage. I_x is a matrix of x-axis and I_y is a matrix of y-axis. I_x and I_y can be calculated by the calculation formula as follows:

$$I_x = I * D_x \text{ and } I_y = I * D_y \quad (3)$$

$$D_x \text{ is a mask } [-1 \ 0 \ 1], \text{ while } D_y \text{ is a mask } \begin{bmatrix} -1 \\ 0 \\ 1 \end{bmatrix}$$

each is calculated by convolution (*). Then the angle gradient into the axis coordinates with angles between 0 and 180 can be calculated by the calculation formula as follows:

$$\theta = \arctan\left(\frac{I_x}{I_y}\right) \quad (4)$$

3. Spatial binning. The next step is to calculate the histogram from the angle gradient to each cell. Each pixel in a cell has its own histogram value based on the value generated in the gradient calculation which is then normalized on each block. Cell has an 8x8 pixel size in an image. While the block has a size of 2x2 cells.
4. Normalize voting values for generating a descriptor. The normalization value of the block feature is then obtained by the calculation formula as follows [8]:

$$norm = \frac{v(n)}{\sqrt{(\sum_{k=1}^{block*l} v(k)^2)+1}} \quad (5)$$

v value is the magnitude gradient value while n is the number of bins and block (2x2 cell) is the number of cells while l is the number of blocks that do not overlap. The block feature is normalized to reduce the effect of changing the brightness of an object on one block.

5. Augment all block vectors consecutively. After the block feature is normalized, the normalization value of each block will be combined into one vector (1 dimensional vector) resulting from this one vector can be referred to as a vector feature of Histogram of oriented Gradients.

The following is an illustration of how the Histogram of oriented Gradients work in Figure 2

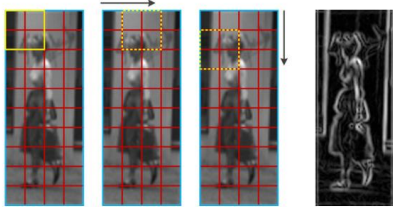


Figure 2 Histogram of oriented Gradients

2.5 Support Vector Machine

There are two ways to implement multiclass SVM by combining several binary SVMs and merging all data consisting of several classes into optimization problems. SVM concept can be explained simply as an effort to find the best hyperplane that functions as a separator of two classes in input space. The following methods are commonly used to implement SVM with the following approach [9]:

1. Method one-against-all

Using this method, a binary SVM model will be built (k is the number of classes). For example, there are classification problems with 4 classes. For training used 4 pieces of binary SVM as in Table 1 and users in classifying classes in new data can be seen in the following equation [10]:

$$\text{Kelas } x = \arg \max_{i=1..k} ((w^{(i)})^T \cdot \varphi(x) + b^{(i)}) \quad (6)$$

By determining the largest hyperplane at the value of x it will classify the class.

Table 1 4 SVM biner method One-against-all

$y_i = 1$	$y_i = -1$	Hipotesis
Kelas 1	Bukan kelas 1	$f^1(x)$ $= (w^1)x + b^1$
Kelas 2	Bukan kelas 2	$f^2(x)$ $= (w^2)x + b^2$
Kelas 3	Bukan kelas 3	$f^3(x)$ $= (w^3)x + b^3$
Kelas 4	Bukan kelas 4	$f^4(x)$ $= (w^4)x + b^4$

2.6 Smooth Support Vector Machine

SSVM is the development of SVM using smoothing techniques. This method was first introduced by Lee in 2001. SVM utilizes optimization with quadratic programming, so for high-dimensional data and large amounts of SVM data to be less efficient. Therefore a smoothing technique was developed which replaced the SVM plus function with the integral of the sigmoid neural network function, which was subsequently known as Smooth Support Vector Machine (SSVM) [11].

2.7 Analysis Sistem

In this section to explain the process of research flow to be more easily understood. This can be seen in the picture of the system flow in Figure 3

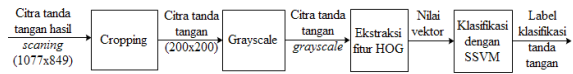


Figure 3 Overview of System Flow

Explanation of the stages above are as follows:

1. Signature image data
Is the initial stage of the image that comes from the signature scanning results in the form of a .jpg file.
2. Cropping
Is the process of cutting the signature image with a size of 200x200 pixels and the cropping used is the resize technique. changes before cropping and after cropping as in Figure 4

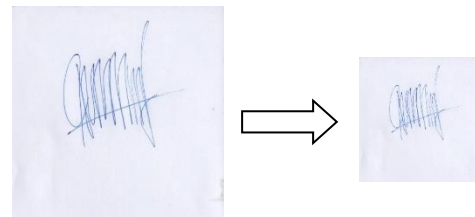


Figure 4 Examples of Cropping Images

3. Grayscale

Grayscale is used to simplify the advanced process by simplifying the values on the matrix to white and gray values for the feature extraction process. Following is the process of changing the image to grayscale as shown in Figure 5

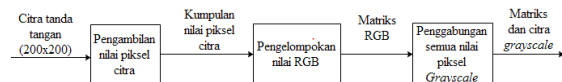


Figure 5 Grayscale Process

For example, an image at pixels 80,120 has a color value Red = 83, Green = 73 and a value of Blue = 73 then based on equation 1 are as follows:

$$\begin{aligned} G(x, y) &= wR.Red + wG.Green + wB.Blue \\ G(0,0) &= (0,299 Red) + (0,587 \times Green) \\ &\quad + (0,114 \times Blue) \\ &= (0,299 \times 84) + (0,587 \times 73) \\ &\quad + (0,114 \times 75) \\ &= 25,12 + 42,85 + 8,55 \\ &= 76,52 \end{aligned}$$

From the calculation above, the pixel value of 76.52 is rounded up to 77.

Examples of results from images before grayscale and after grayscale can be seen in Figure 6 as follows:

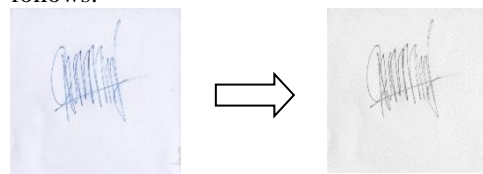


Figure 6 Example of grayscale results

4. Extraction of HOG features

It is a process to get feature extraction for each image that will be used as training data. For example for this stage a sample sample of 200 x 200 RGB matrix image training will be taken which can be seen in Figure 7 as follows:



Figure 7 The training data sample size is 200 x 200

The following is the HOG method process:

a. Count the edge map

In this process a calculation will be made to find the magnitude and angle gradient values for each image pixel that has been grayscale before it will be convoluted with *mask* D_x that is $[-1 \ 0 \ 1]$ and D_y that

is $\begin{bmatrix} -1 \\ 0 \\ 1 \end{bmatrix}$ to find the values of I_x and I_y with a

Grayscale matrix measuring 3 x 3 as a sample to find the value of the magnitudes and angles gradient like equation 3 as follows:

$$I_x = I * D_x \text{ and } I_y = I * D_y$$

$$I_x = \begin{bmatrix} 77 & 84 & 74 \\ 131 & 121 & 88 \\ 239 & 98 & 176 \end{bmatrix} * [-1 \ 0 \ 1]$$

$$I_y = \begin{bmatrix} 77 & 84 & 74 \\ 131 & 121 & 88 \\ 239 & 98 & 176 \end{bmatrix} * \begin{bmatrix} -1 \\ 0 \\ 1 \end{bmatrix}$$

For example the convolution calculation is only at coordinates (1,2) for I_x and I_y , the result is:

$$I_x = |(77 * -1) + (84 * 0) + (74 * 1)|$$

$$I_x = 3$$

$$I_y = |(84 * -1) + (121 * 0) + (98 * 1)|$$

$$I_y = 14$$

Next we will calculate the magnitudes and angles gradients such as equations 2 and 4 as follows:

$$|G| = \sqrt{I_x^2 + I_y^2}$$

$$\theta = \arctan\left(\frac{I_x}{I_y}\right)$$

$$|G| = \sqrt{3^2 + 14^2}$$

$$|G| = \sqrt{9 + 196}$$

$$|G| = 14 \text{ (Dibulatkan)}$$

$$\theta = \arctan\frac{3}{14}$$

$$\theta = \arctan(0,21) \sim 2.3^\circ$$

Then the values of magnitudes and angles are obtained at 14 and 2.3 ° for coordinates (1,2).

b. Spatial binning

In this process a histogram calculation of the gradient angle that has been obtained is processed before each cell. Each pixel in a cell will have its own histogram value based on the value generated in

the gradient calculation which is then normalized on each block. The cell for this study has a size of 7 x 7 which will continue to move to the right and down until the cell is at the end of the image as shown in Figure 8 as follows:

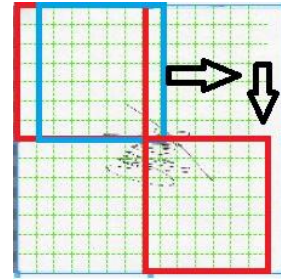


Figure 8 Cell moves to the end of the image

The following is an example of 9 bins with an orientation of 0 - 180 ° as seen in Figure 9 below:

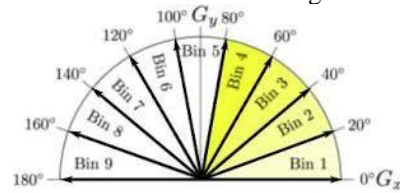


Figure 9 Figure 9 orientation bins 0-180 °

The results of giving all voting in the form of a histogram from the training data image are shown in Figure 10 as follows:

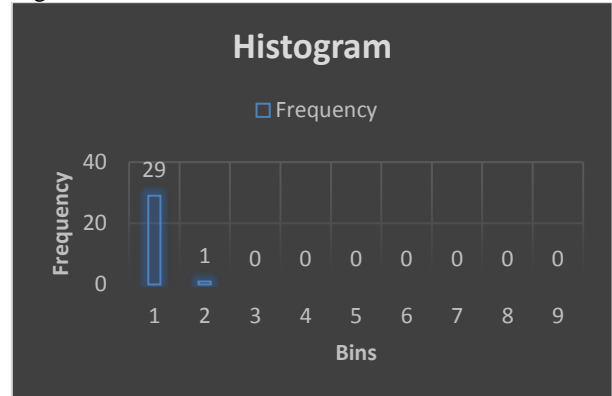


Figure 10 Histogram of training data images

c. Normalize voting values for generating a descriptor

The next step will be to calculate the normalization of block feature values for each gradient magnitude value in the previous process in spatial binning, the calculation formula is like equation 11 as follows:

$$norm = \frac{v(n)}{\sqrt{(\sum_{k=1}^{block*l} v(k)^2) + 1}}$$

$$= \frac{88(9)}{\sqrt{(\sum_{k=1}^{7*7*16} 88(k)^2) + 1}}$$

$$= \frac{88(9)}{\sqrt{(\sum_{k=1}^{784} 88(k)^2) + 1}}$$

$$= \frac{88(9)}{\sqrt{14162505281}}$$

$$= 0,006655$$

The next step will be to calculate the normalization of block feature values for each gradient magnitude value in the previous process in spatial binning, the calculation formula is like equation 11 as follows:

5. Classification with SSVM

The classification process is to choose the decisions to be made regarding the owner of the signature that has been trained [12].

It is the process of training training data from the extraction of HOG features using SSVM. The following is the result of the HOG vector feature of the combined training data image can be seen in Table 2 as follows :

Table 2 The results of the vector HOG feature are training data images

0: 0.09737 1	1: 0.03230 8	2: 0.10675 2	3: 0.02060 4	4: 0.29416 8
5: 0.00413 4	6: 0.03642 7	7: 0.07081 4	8: 0.10966 2	9: 0.04396 3
10: 0.00568 6	11: 0.01713 1	12: 0.02017 1	...	7055: 0.02394 3

a. SSVM training data

It is the process of storing the results of SSVM training data which will later be loaded when the testing phase begins and stored training data in the form of XML.

b. Testing process

It is a process of testing the signature image and matching will be done with SSVM training data stored in XML

c. Make label predictions

It is a SSVM prediction process to predict the numbers that come out from entering the signature image during testing. for example test data that has found its support vector value (0.10067.4.5) will be included in equation 6 as follows :

Kelas x

$$= \arg \max_{k=1..3} \left(\begin{bmatrix} 31,33318391 \\ -61,05419883 \end{bmatrix} \right)^T \cdot \begin{bmatrix} 0,10067 \\ 4,5 \end{bmatrix} \\ + (-7,43025373), \left(\begin{bmatrix} 17,36439644 \\ -27,50146985 \end{bmatrix} \right)^T \cdot \begin{bmatrix} 0,10067 \\ 4,5 \end{bmatrix} \\ + (-2,534268352), \left(\begin{bmatrix} 20,09117293 \\ -31,78081239 \end{bmatrix} \right)^T \cdot \begin{bmatrix} 0,10067 \\ 4,5 \end{bmatrix} \\ + (-2,922409864)$$

Kelas x

$$= \arg \max_{k=1..3} (-278.8184968, -124.5428089, -143.9134872)$$

$$Kelas x = -124.5428089$$

As can be seen in the equation above the highest hyperplane value is -124.5428089 which is where the index value of the hyperplane belongs to class / label 2.

2.8 Accuracy Testing

Accuracy testing in this study was conducted to determine the value of accuracy, in the implementation of performance testing using the k-fold cross validation method. Cross validation is a statistical method for evaluating and distinguishing data by dividing it into two segments, the first segment of training data and the second segment of testing data. Usually cross validation requires training and testing data that must cross-over each iteration. Basically cross validation uses the k-fold method. In k-fold the data validation is divided into how many k, where k is an iteration. [13].

This test aims to test the stability of accuracy if tested with different training data and test data. This test used data as much as 300 data which were divided into 10 subsets, each of which amounted to 30 data. Test scenarios for accuracy performance using the k-fold cross validation method where 10 k-fold is used.

Based on the results of testing the accuracy of the test scenarios that have been carried out the results can be seen in Table 3 as follows :

Table 3 The accuracy of the test scenario

Fold	Data Training	Data Testing	Akurasi
1	270	30	93.33 %
2	270	30	90.00 %
3	270	30	86.67 %
4	270	30	83.33 %
5	270	30	80.00 %
6	270	30	93.33 %
7	270	30	83.33 %
8	270	30	86.67 %
9	270	30	93.33 %
10	270	30	90.00 %
Average accuracy			88.00 %

From these data it can be concluded that the test results using k-fold cross validation with an average accuracy of 88%. Because at the preprocessing stage the process of segmentation is not done on the signature so there is a decrease in the accuracy of the signature recognition.

3. CLOSING

3.1 Conclusion

The conclusion of this study entitled: "The introduction of signatures using the Histogram of Oriented Gradients and Smooth Support Vector Machine" are as follows :

1. The results of the accuracy of the Histogram of Oriented Gradients feature and classification using Smooth Support Vector Machine on the introduction of signatures with the k-fold cross validation testing method obtained data accuracy of 88%. Because at the preprocessing stage the process of segmentation is not done on the signature so there is a decrease in the accuracy of the signature recognition.
2. The more varied the signature data used in the training, the more likely it is to be able to recognize it correctly during the testing process

3.2 Suggestion

The research carried out still has disadvantages, for that development can be done, namely :

1. The need to do segmentation on the image portion of the signature so that better results on the introduction of signatures
2. Using the RCNN method for the classification process on signature recognition to achieve high accuracy

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