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Food Detection Using Histogram of Oriented Gradient (HOG) as Feature Extraction and K-Nearest Neighbors (K-NN) as Classifier

Diah Rahmadani[1], Ir. Agus Virgono[2], Casi Setianingsih[3]
[1]Telkom University (Tel-U), Bandung, diahrahmadani@student.telkomuniversity.ac.id
[2]Telkom University (Tel-U), Bandung, avirgono@telkomuniversity.ac.id
[3]Telkom University (Tel-U), Bandung, setiacasie@telkomuniversity.ac.id

ABSTRACT

Food Recognition was an interesting thing to do in computer visualization research. Food had different shapes and colors to be recognized by the senses from human's eye. The computer recognized the image with analog values were converted it to digital value in matrix form. The research conducted aims to create non-manual payment machines. Thus creating an automatic cash register that calculated the price and name of food from an image of food ordered on a tray. The method was used a Histogram of Oriented Gradient (HOG) could be used to find valued feature extraction from an image. HOG method combined with K-Nearest Neighbors (K-NN) classificationed for designing food detection systems. That the dataset used for testing was an image taken from a webcam. An image containing food in one tray was there three types of food placed on a plate. If food was taken, the system issued the name of food on the picture. The best HOG parameter obtained was bin = 8, Pixel peer Cell = 2x2, Cell per Block = 2x2. The optimal one the k value used was 3. The simulation result has accuracy 82%.

Key words : Detection of food types and prices, computer vision, HOG, K-NN, machine learning.

1. INTRODUCTION

The introduction of food is known for its shape and varying colors in each food. The main step taken is to represent how to serve food, how to take food photos, take pictures image dataset values as needed, steps taken [1]. Food detection is a challenging task because every food has different shapes and colors because of how it is cooked. The focus of this paper is on food sold in food stalls.

Problems, detect and recognize the types of local Malaysian food as many as 11 food categories for food / non-food classification. With 5800 food images to be classified [2]. Monitor the freshness of food to find out the quality of food served. Results from a potentially technical tool for traceability of food in the real world [3]. Record or take pictures of food intake served using a mini camera [4]. Detection of food with a food texture detector from food ingredients that appear in the image. Detection results of food ingredients that appear in the picture are histograms of food ingredients [5].

Food placed in trays in campus and restaurant environments. The image is removed from the background and custom non-maximum suppression procedure to avoid duplication of food recognition [6]. Food recognition developed by recording the event of chewing food with the level of violence of each type of food with smart glasses [7]. Recognizing liquid food cannot be recognized by its color and texture because it is the same. Therefore, hybrid sensor techniques are used to carry out simultaneous measurements [8]. Food recognition by associating food methods and ingredients is very necessary in food imagery. The effectiveness of the joint model shows that VNP is more effective in describing food images [9].

Get to know Thai food with 13 types of food images to count calories and advice [10]. Statistical information on color texture recognition that is quantized by incorporating the strategy of patch-based bag to build the model [11]. The accuracy value of food recognition depends on the ratio between the background and foreground of the image. The image is segmented into rectangular areas (inner region), using FOOD-101 as a dataset [12]. Food is placed on a plate filled with one type of food. Because all food combined into one dish will be difficult to detect [13]. Another problem that exists in the recognition of objects in the field of computer vision is recognition of tomato damage based on color and light intensity effects, maturity of tomatoes is identified by taking characteristics [14]. Detection of The Level of Maturity's Blueberries that are affected by Light Outside of

Room [15]. Multi-scales are needed for intelligence application (IoT) the extraction process used is Wavelet Haar IoT [16] [17]. The texture feature used is the Gray Level Co-occurrence Matrix (GLCM) [18].
Food color is an important value for detecting food. There are 6 types of food selected to detect food and in the picture frame there are 3 types of food. Histogram of Oriented Gradient (HOG) method is used to obtain the characteristics of an image and the value of these features is used as input data for the classification of the K-Nearest Neighbors (K-NN) method. K-NN is an unsupervised [19] method that works by finding the value of its closest neighbors [20]. The distance matrix used for K-Nearest Neighbors is the euclidean distance, to practice classification [21] [22].

2. RESEARCH METHOD

2.1 Industri 4.0

The occurence of industry 4.0 was caused by a strategic project in technology in the German Government. With this revolution, it has many benefits to help all human needs in various fields. So that, it will give a very big impact on industry, economy, individual, social. Industry 4.0 is a combination of technology found from industry 3.0. in the 3.0 industry marked by the presence of computer technology, mobile phones, the internet with all of these technologies combined into a digital revolution [23].

2.2 Restaurant

The restaurant is a place that serves dishes to the public and provides a place to enjoy these dishes and set certain rates for food and service [24]. For some workers with a lot of work activities will choose food stalls that are not much in line, so that the efficiency of time at work can be used for other activities.

2.3 Food Classification

Many types of food, colors and various forms. The challenge to detect food is food that has a similar shape. In the food dataset, pictures are taken with the same distance and brightness. In order to obtain a good image used for analysis because it has variability in good image processing. The type of food used in this research are rice (id=1), fried chicken (id=2), spinach stir fried (id=3), fried sambal (id=4), fried tofu (id=5), and opor chicken (id=6). Taking pictures is done by placing 3 types of food on a plate with the same color [25] and different from the type of food. The following is a food label table:

Table 1: Food Label

Grade	Name of The Food	ID	Price (Rupiah)
I	Rice, Fried Chicken, Spinach Stir fried	1-2-3	Rp. 7000
II	Rice, Fried Chicken, Fried Sambal	1-2-4	Rp. 11000
III	Rice, Fried Chicken, Fried Tofu	1-2-5	Rp. 14000
IV	Rice, Fried Chicken, Opor Chicken	1-2-6	Rp. 25000
V	Rice, Opor Chicken, Spinach Stir fried	1-6-3	Rp. 16000
VI	Rice, Opor Chicken, Fried Sambal	1-6-4	Rp. 12500
VII	Rice, Opor Chicken, Fried Tofu	1-6-5	Rp. 18500

2.4 Histogram of Oriented Gradient (HOG)

HOG is a method used to extract features in image objects. The initial process in the HOG method is converting an RGB image into grayscale, which is then followed by calculating the gradient value in each pixel. After getting the gradient value in each pixel. The next process is determining the number of orientation binning. That will be use in making histogram[26]. However, before the gradient compute the training darwing was divided into cells and grouped into larger sizes called blocks. Whereas the block normalization process uses R-HOG geometry calculations. This process is carried out because there are overlapping blocks [27].

a) Image Conversion

Each component in the true color image has 256 possible values. This value starts from zero for black and 255 for white. Converting a true color image to grayscale changes the pixel value which has 3 values namely Red, Green, Blue into one value that is gray.

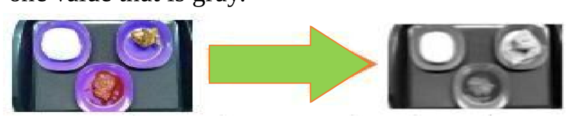

Figure 1: Image Conversion RGB to Grayscale

b) Gradient Compute

After that, calculate the gradient value of each pixel contained in the image.

54	56	36
34	55	46
40	52	30

Figure 2: Sample Pixels for Calculations

Dx = [-1 0 1]

$$Dy = \begin{bmatrix} 1 \\ 0 \\ -1 \end{bmatrix} \quad \textbf{(2.1)}$$

If the object image as I, can get the x and y derivatives using a convolution operation:

$$I_x = Ix * Dx \text{ and } I_y = Iy * Dy \quad \textbf{(2.2)}$$

$I_x = Ix * Dx$

$I_x = [46\ 55\ 34] * [-1\ 0\ 1] = 12$

Ix is the gradient of the x-axis or horizontal then continues to find the value of the gradient on the y-axis or vertical.

$I_y = Iy * Dy$

$$I_y = \begin{bmatrix} 56 \\ 55 \\ 52 \end{bmatrix} * \begin{bmatrix} 1 \\ 0 \\ -1 \end{bmatrix} = 4$$

To calculate the magnitude of gradient, use the formula:

$$|G| = \sqrt{I_x^2 + I_y^2} \quad \textbf{(2.3)}$$

$$|G| = \sqrt{12^2 + 4^2} = 12.649 \approx 13$$

c) Spatial Orientation Binning

Creating a histogram requires a gradient value and the value is obtained from the value of each pixel in the image. Each cell in the image will be made a histogram to find out the value in each cell because it has different values. In making a histogram, a bin is needed to find out the gradient value.

$$\theta = arctan \frac{Ix}{Iy} \quad \textbf{(2.4)}$$

$$\theta = arctan \frac{4}{12} = 0.33^o \approx 0^o$$

The obtained gradient value is 13 and the spatial binning value obtained is 0 degrees. Gradient and spatial binning results are entered in the histogram of gradient column below:

0^o	45^o	90^o	135^0	180^o	225^o	270^o	315^o
13							

0^o 45^o 90^o 135^0 180^o 225^o 270^o 315^o 360^o

Figure 3: Histogram of Gradient

d) Normalization Block

Gradients have different values, therefore it is necessary to group cells into larger blocks or called blocks. Blocks usually overlap because each cell contributes a value more than once. In this block normalization there are two main block geometries, namely the R-HOG (rectangular block). The block normalization used is L2 norm with the following formula:

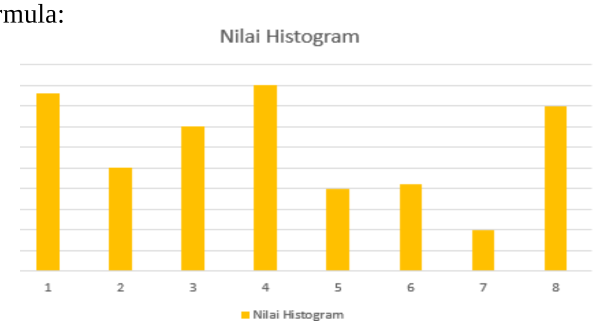

Figure 4: Normalization Block Bin = 8

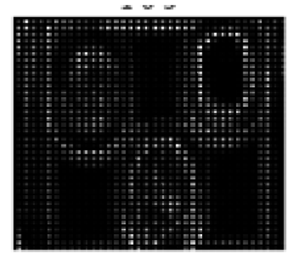

Figure 5: HOG's Feature Extraction

2.5 K-Nearest Neighbors (K-NN)

Algorithm to classify data based on learning data (train data sets), taken from k nearest neighbors. With k's value is the number of nearest neighbors. New classified data is then projected on many dimensional spaces which have included c points of learning data. The classification process is done by finding the nearest c-point of c-new (nearest neighbor). Generally used in K-NN is Euclidean distance is a formula that looks for a distance between 2 points in 2D space.

$$d = \sqrt{(X_2 - X_1)^2 + (Y_2 - Y_1)^2} \quad \textbf{(2.5)}$$

The use of K-NN is to use the value k which indicates to find the 3 closest variables as neighbors. Research generally uses the value k = 3. If the k used is two, then always anticipate odd data. In the use of complex datasets that have many elements. If use K-NN, must find the distance from each element and K-NN always provides good calculation results in machine learning.

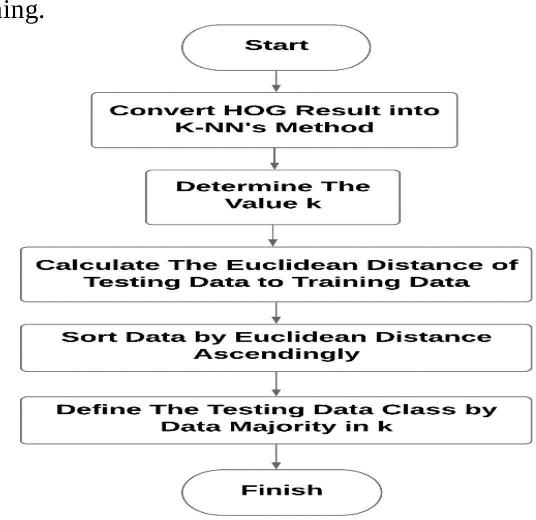

Figure 6: Process of K-NN

a) Converting HOG Result into K-NN's Method

Table 2: Sample Training Data After Conversion

Label (ID)	Feature Extraction HOG	Grade
1	0.45	I
1	0.47	I
2	0.39	II
3	0.32	III
3	0.31	III
4	0.51	IV
5	0.53	V
6	0.44	VI
6	0.49	VI

Table 3: Testing data After Conversion

Label (ID)	Feature Extraction HOG	Grade
1	0.45	I

b) Determine The Value of k (Euclidean Distance) and Calculate Distance of Testing data. Then Sort Data

Table 4: Euclidean Distance Calculation

Label (ID)	Feature Extraction HOG	Grade	Euclidean Distance
1	0.45	I	2.0042
1	0.47	I	2.0056
2	0.39	II	1.0024
3	0.32	III	0
3	0.31	III	0.01
4	0.51	IV	1.0179
5	0.53	V	2.0109
6	0.44	VI	3.0024
6	0.49	VI	3.0048

Table 5: Sort Data from Result Euclidean Distance

Label (ID)	Feature Extraction HOG	Grade	Euclidean Distance
3	0.32	III	0
3	0.31	III	0.01
2	0.39	II	1.0024
4	0.51	IV	1.0179
1	0.45	I	2.0042
1	0.47	I	2.0056
5	0.53	V	2.0109
6	0.44	VI	3.0024
6	0.49	VI	3.0048

c) Choose k = 3

Table 6: Choose and Define Testing Data Class

Label (ID)	Feature Extraction HOG	Grade	Euclidean Distance
3	0.32	III	0
3	0.31	III	0.01
2	0.39	II	1.0024

Table 6 above is the result of K-Nearest Neighbors by selecting the value k = 3. Form the smallest distance, the value of the euclidean distance = 0.01, 1.0024. The results of the food names obtained are Grade III (there are many as 2 data) and grade II (there are as much as 1 data).

d) Classification Result

The conclusion from the simulation results in the Table 6 is grade III, because it has a lot of data in K (that is 2 data). The test was proven because it took the most K values for the K-NN classification results.

2.6 Performance Evaluation

K-NN classification is unsupervised classification. To find out the value of the performance evaluation, it requires a confusion matrix.

Figure 7: Confusion Matrix

		Actual	
		Positive	Negative
Prediction	Positive	True Positive	False Negative
	Negative	False Positive	True Negative

In Figure7 explain about the results of the classification confusion matrix have 4 classes, True Positive (TP), False Positive (FP), True Negative (TN), and False Negative (FN). TP is data that is correctly filled by the system. FP is data that should be wrong but classified correctly by the system. FN is data classified by the system. TN is data that should be correct but is classified incorrectly by the system[28]. Accuracy is the level of closeness between predicted value and actual value (training and testing data). The way to calculate accuracy:

$$Accuracy = \frac{(TP+TN)}{TP+TN+FP+FN} \quad \textbf{(2.6)}$$

Precision is the level of accuracy between the data requested by the user with the data generated by the system.

The way to calculate precision:

$$Precision = \frac{TP}{TP+FP} \quad \textbf{(2.7)}$$

Recall is the level of success of the system in carrying out of the classification or the ability to find all relevant examples in the data set. The way calculate recall:

$$Recall = \frac{TP}{TP+FN} \quad \textbf{(2.8)}$$

3. RESULTS AND ANALYSIS

Food detection is an unsolved problem and researches are still working on it today. This section discusses the literature related to the progress of detection carried out in various objects. The method used is the Histogram of Oriented Gradient (HOG) which is used for feature extraction on various objects. Image search system for interactive search of photo collections that illustrate shapes using hand sketches. The one type of gradient use is Gradient Field HOG, an adaptation form of HOG descriptors suitable for Sketch-Based Image Capturing (SBIR) [29].

3.1 Data Collecting

Data collection taken from photos of the types of food available at Engineering Canteen's Telkom University. Shooting at 1 pm to 3 pm and a distance of 35 cm from food.

Table 7: Data Collecting

Value of k	The Amount of Data				
	Train / Test (50% / 50%)	Train / Test (60% / 40%)	Train / Test (70% / 30%)	Train / Test (80% / 20%)	Train / Test (90% / 10%)
K = 1	100	100	100	100	100
K = 2	95.714	100	100	100	100
K = 3	97.142	100	100	100	100
K = 4	96.190	100	100	100	100
K = 5	96.67	100	100	100	100
K = 6	94.286	100	100	100	100
K= 7	93.33	100	100	100	100
K= 8	92.857	98.809	100	100	100
K = 9	95.238	99.405	100	100	100
Average	95.71	99.8	100	100	100

Distance / Time / Place	Grade / ID	Displacement Place to-
	VI / 1-6-5	1-6-5
		1-5-6
		6-5-1
		6-1-5
		5-1-6
		5-6-1

3.2 Data Partition Testing

This data partition testing is done to determine the performance of the K-NN classification system that has been designed. The best data partition results will be a reference for the next test. The testing process is done by dividing the data into training data and testing data by comparing data as in the table below. In testing the bin data partition used are 8, Pixel per Cell = 2x2 and Cell per Block = 2x2. Because the image results used with these parameters have a clear shape after being extracted.

Table 8: List of Data Partition Testing

Testing to-	Testing Data (%)	Training Data (%)	Bin	Pixel / Cell	Cell / Block	Resize
1	10	90	8	2x2	2x2	60x60
2	20	80				72x72
3	30	70				80x80
4	40	60				

3.3 Train Data

Testing the accuracy of the image data system from the webcam is done to determine the performance of the K-NN as classification. The test uses 420 food images, distance parameters of 35 cm, and outdoor light intensity. Results will be seen from the accuracy of the confusion matrix in the appendix. The testing is done on a training system with 84 test data. The resulting accuracy will be the best input for automation systems on interface design. Here is a table for the results of training system:

Table 9: List of Training System Image Accuracy Testing Parameters

Distance / Time / Place	Grade / ID	Displacement Place to-
35 cm / 13.00 – 17.00 / Canteen of Telkom University Engineering Lux Details: 1 pm – 3 pm (600 – 100) 3 pm – 5 pm (10 – 200)	I / 1-2-3	1-3-2
		3-1-2
		2-1-3
		1-2-3
		3-2-1
		2-3-1
	II / 1-2-4	1-4-2
		4-1-2
		2-1-4
		4-2-1
		2-4-1
		1-2-4
	III / 1-2-5	1-5-2
		1-2-5
		5-2-1
		5-1-2
		2-1-5
		2-5-1
	IV / 1-6-3	1-3-6
		1-6-3
		3-6-1
		3-1-6
		6-1-3
		6-3-1
	V / 1-6-4	1-4-6
		1-6-4
		4-6-1
		4-1-6
		6-1-4
		6-4-1

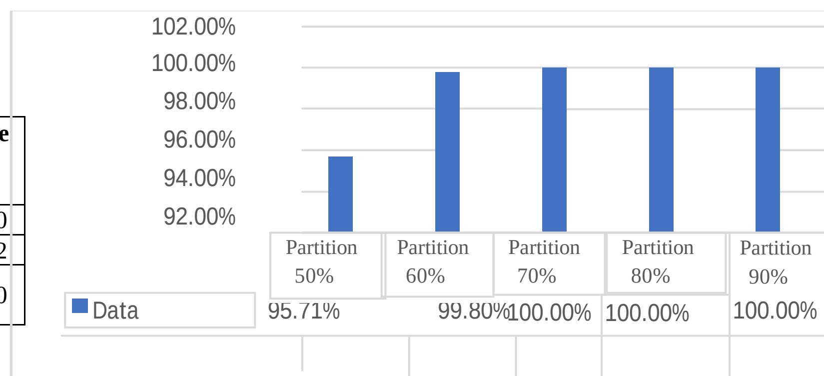

Figure 8: Graph Average Distribution Data

3.5 Experiment Result

This study uses 84 images to be tested. There are 15 pictures in grade I, 12 pictures in grade II, 12 pictures in grade III, 14 pictures in grade IV, 11 pictures in grade V, 9 pictures in grade VI, and 11 pictures in grade VII of food. Tests are also carried out with different k values. This is the result of the study using k = 1, 3, 5, 7, and 9. Here is result of resize image 60x60, resize image 72x72, resize image 80x80:

Table 10: Test Result Bin = 8, Pixel / Cell = 2x2, Cell / Block = 2x2

Value of k	**Resize 60x60**		
	Data Detected Successfully	**Data not Detected Successfully**	**Accuracy (Detected Successfully)**
1	34	50	41%
3	37	47	44%
5	31	53	37%
7	37	47	44%
9	34	50	41%
Value of k	**Resize 72x72**		
	Data Detected Successfully	**Data not Detected Successfully**	**Accuracy (Detected Successfully)**
1	34	50	41%
3	40	48	48%
5	34	50	41%
7	37	47	44%
9	37	47	44%
Value of k	**Resize 80x80**		
	Data Detected Successfully	**Data not Detected Successfully**	**Accuracy (Detected Successfully)**
1	37	47	44%
3	**69**	**15**	**82%**
5	56	28	67%
7	66	18	78%
9	66	18	78%

3.6 Confusion Matrix Result
The calculation of the confusion matrix below uses k = 3.

Confussion Matrix* Prediksi Gambar Makanan Resize 80x80, k=3, *Pixel/Cell=2x2, Cell/Block = 2x2								
		Predicted Class						
Actual Class		I	II	III	IV	V	VI	VII
	I	15	0	0	0	0	0	0
	II	0	9	0	3	0	0	0
	III	0	0	12	0	0	0	0
	IV	0	0	4	6	4	0	0
	V	0	0	1	0	10	0	0
	VI	0	3	0	0	0	6	0
	VII	0	0	0	0	0	0	11
Accuracy	$\frac{15+9+12+6+10+6+11}{15+9+3+12+4+6+4+1+10+3+6+11} = 82\%$							

Figure 9: Calculate Confusion Matrix

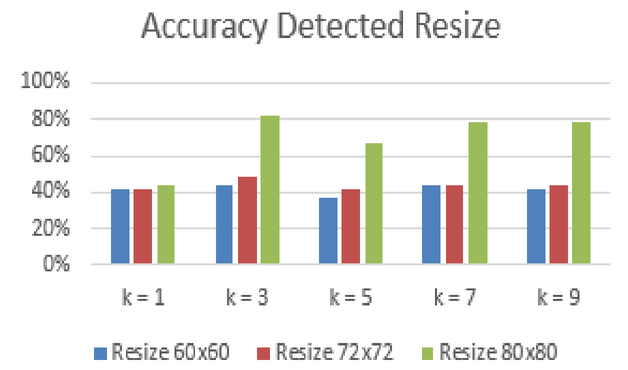

Figure 10: Graphic of Accuracy of Pixel

4. CONCLUSION

Figure 9 namely the highest accuracy obtained with a value of 82%. Accuracy is still small because the way is taken must be determined by various food positions and images converted to grayscale. Testing with different resize produces resize with a good texture if using 80x80. That if we change resize it will affect the accuracy results for the classification of k. The best value of k is 3, bin = 8, Cell / Block = 2x2, and Pixel / Cell = 2x2.

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