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Glass Packaged Mineral Water Recognition System Based On Logo Using The Histogram Of Oriented Gradients Method

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ABSTRACT

Application of Glass Packaged Mineral Water Recognition System Based on Logo Using Method Histogram of Oriented Gradients is an application program used to introduce brands or logos of glass bottled mineral water. This application was designed on the Windows operating system and uses Python and Open CV software. The methods used in this design are Histogram of Oriented Gradients as a method for feature extraction, Method Euclidean Distance as a method for measuring similarity distance, and k-Nearest Neighbor as a method of recognizing a logo or brand. The average accuracy of the test is 13.575%.

Keywords: Euclidean Distance, Histogram Of Oriented Gradients, K- Nearest Neighbor, Opencv, Logo Recognition, Python.

INTRODUCTION

The rapid evolution of information technology in the era of globalization has led to an array of groundbreaking research and advancements in various IT domains. Among these, image processing stands as a significant field that offers multifaceted applications. Images serve as a rich source of information, enabling innovative tools for detection and recognition, such as in the realm of identifying logos on glass-packaged mineral water.

Research by (Randa et al., 2016), (Marthatiyanda, Maliki, 2019), and (Bahtiar et al., 2020) demonstrates the growing relevance of image recognition systems, specifically emphasizing the potential for logo recognition utilizing techniques like the Histogram of Oriented Gradients (HOG). Despite the strides made in this area, a distinct research gap emerges concerning the application of HOG-based methods in precisely identifying and sorting glass-packaged mineral water products within expansive warehouse settings.

The identified research gap leads to the core problem formulation: the absence of a robust and efficient system tailored for recognizing glass-packaged mineral water logos using HOG methodology, specifically designed for implementation in large-scale warehouse environments. This formulation highlights the need for an optimized recognition system capable of effectively identifying these logos amidst varying environmental conditions, diverse orientations, and potential occlusions.

To bridge this gap and address the formulated problem, we propose a comprehensive method grounded in the fusion of HOG-based logo recognition techniques and enhanced algorithms for efficient detection and categorization of glass-packaged mineral water products. Our proposed method aims to refine the logo recognition process by augmenting the existing HOG methodology with (specific enhancements or novel approaches derived from the aforementioned sources) to achieve higher accuracy and reliability in identifying these logos within warehouse contexts.

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LITERATURE REVIEW

Bottled mineral water is growing rapidly and the market for bottled mineral water industry is getting bigger with the emergence of various local and international brands (Fortuna, 2018). There are hundreds of brands of bottled mineral water circulating throughout Indonesia (Aditya, 2019). Warehouse is a storage place for goods both raw materials and finished goods that are ready to be marketed (Purnomo, H., 2004). Activities in warehousing are not only storage of goods, but include product sorting activities as well (Rahmadhika et al., 2017). To meet consumer needs on time, ways are needed to overcome unnecessary worker activities so as not to cause waste in the sorting process (Afrianto et al., 2022).

Histogram of Oriented Gradients (HOG)

The method to be used primarily is the Histogram of Oriented Gradients or HOG. HOG is used in performing image processing and logo recognition to extract features from images. The initial stage in using HOG will change the image size to 64x128 pixels, followed by the calculation of the gradient value, which is the process of calculating the gradient value of each pixel in the image. HOG works by measuring the directional distribution of gradient in an image (changes in light intensity).

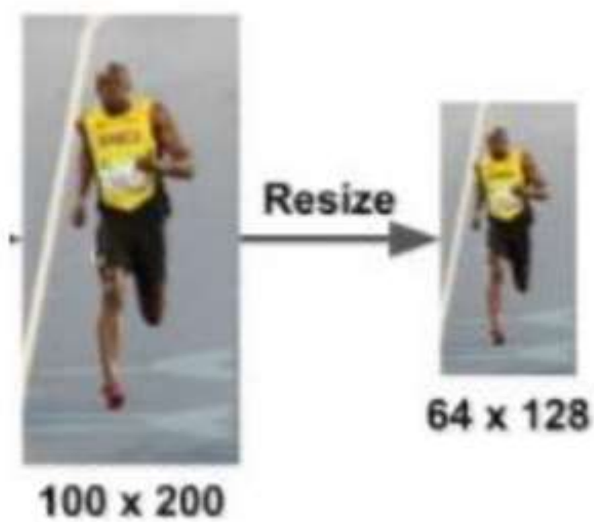

Figure 1. Image Resize Process to 64x128 pixels

In recognizing an object, the HOG method is used to identify important patterns or features in the image, especially in images that correlate with the texture or contour of the object.

After resizing the image to 64x128 pixels as in Figure 1., it is necessary to perform the edge detection stage by calculating the gradient value and orientation in the image. A gradient is the result of measuring changes in an intensity function, and an image can be viewed as a collection of several continuous intensity functions of the image. This process is used to obtain outlines on objects in the image. The gradient of an image can be obtained by filtering with 2-dimensional filters, namely vertical and horizontal filters. The first is to convert the image in grayscale form to avoid considering the contribution of different intensities to each color plane (RGB). The method of calculating gradient or edge detection used is the Prewitt method. The Prewitt method is a development of Robert's method by using an HPF filter that is given a single zero buffer.

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Kernel filters used in the Robert method:

$$G_x = \begin{bmatrix} -1 & 1 \end{bmatrix} \quad (1)$$

$$G_y = \begin{bmatrix} -1 \\ 1 \end{bmatrix} \quad (2)$$

Kernel filters used in the Prewitt method:

$$G_x = \begin{bmatrix} -1 & 0 & 1 \\ -1 & 0 & 1 \\ -1 & 0 & 1 \end{bmatrix} \quad (3)$$

$$G_y = \begin{bmatrix} -1 & -1 & -1 \\ 0 & 0 & 0 \\ 1 & 0 & 1 \end{bmatrix} \quad (4)$$

This method takes its principle from the laplacian function known as the function to generate HPF. The formula for obtaining the magnitude value is as follows:

$$G = \sqrt{G_x + G_y} \quad (5)$$

The formula to get the orientation value is as follows:

$$\theta = \arctan\left(\frac{G_Y}{G_x}\right) \quad (6)$$

The calculation of gradient and orientation will be done in the image that has been divided into 8x8 cells.

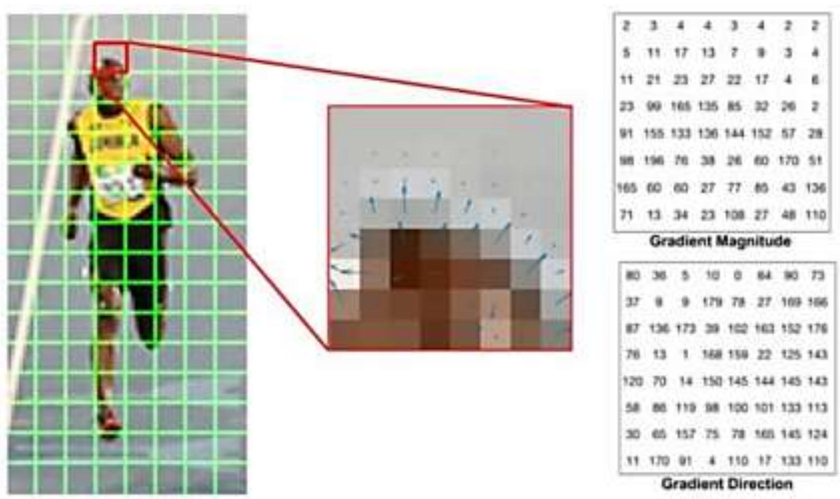

Figure 2. Gradient and Orientation Calculation

To make each cell in the 8x8 pixel image into a Histogram consisting of 9 bins, it is necessary to do Spatial Orientation Binning. Spatial Orientation Binning. This Spatial Orientation Binning process requires the gradient value as the value to be added to the bin and the orientation value as the value that determines the bin to be inserted the gradient value. In the Orientation Binning stage, each orientation value will be entered into the Histogram. The orientation histogram divides various angles into numbers in predetermined bins. The amount of gradient from pixels in a cell is used to vote into the orientation histogram. Vote is the process of selecting and adding input to 1 label or location. For example, a histogram will be constructed distributed through 0°-180° with a number of channels equal to 9. The use of 9 bins will facilitate the distribution or distribution of magnitude values and the maximum degree value is made to 180 degrees because values above 180 degrees can produce negative values.

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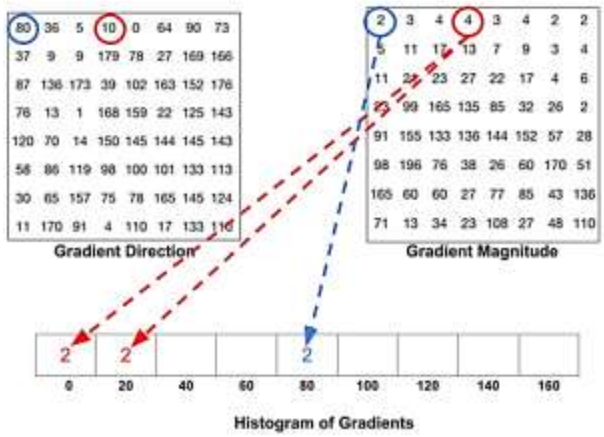

Figure 3. Orientation Binning

The votes in the histogram are as follows:

1. All gradients with large angles [0°-20°] vote for channel 1.
2. All gradients with large angles [20°-40°] vote for channel 2.
3. And so on until the gradient with the angle size [160°-180°] votes for channel 9.

Block Normalization is the process of normalizing the value of a histogram per block consisting of 2x2 cells or 16x16 pixels. In the Block Normalization process, overlap usually occurs because each cell contributes more than once value (50% overlap) and the result is a feature of the detected object in the form of a 3780x1 vector. Normalization blocks have two main block geometries: rectangular (R-HOG) and circular (C-HOG) blocks. R-HOG is represented by three parameters: the number of cells per block, the number of pixels per cell, and the number of bins per histogram. While C-HOG has four parameters, namely the number of angles and radial bin radius of the center bin, and the expansion factor for the addition of the radial bin.

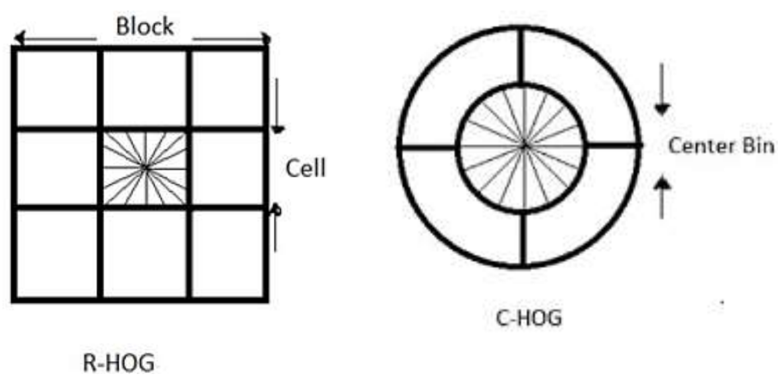

Figure 4. R-HOG and C-HOG

Block normalization is usually overlapping because each cell contributes more than once (50% overlap) and the result is a feature of the detected object that is vectorized 3780x1 and will be compared with the sample image using euclidean distance and classified using k-Nearest Neighbor.

$$L2 - norm : v \to v/\sqrt{||v||_2^2 + \varepsilon^2} \quad (7)$$

Where:

$||v||_2^2 + \varepsilon^2$ = The result of the sum of squares of all elements of the matrix v.

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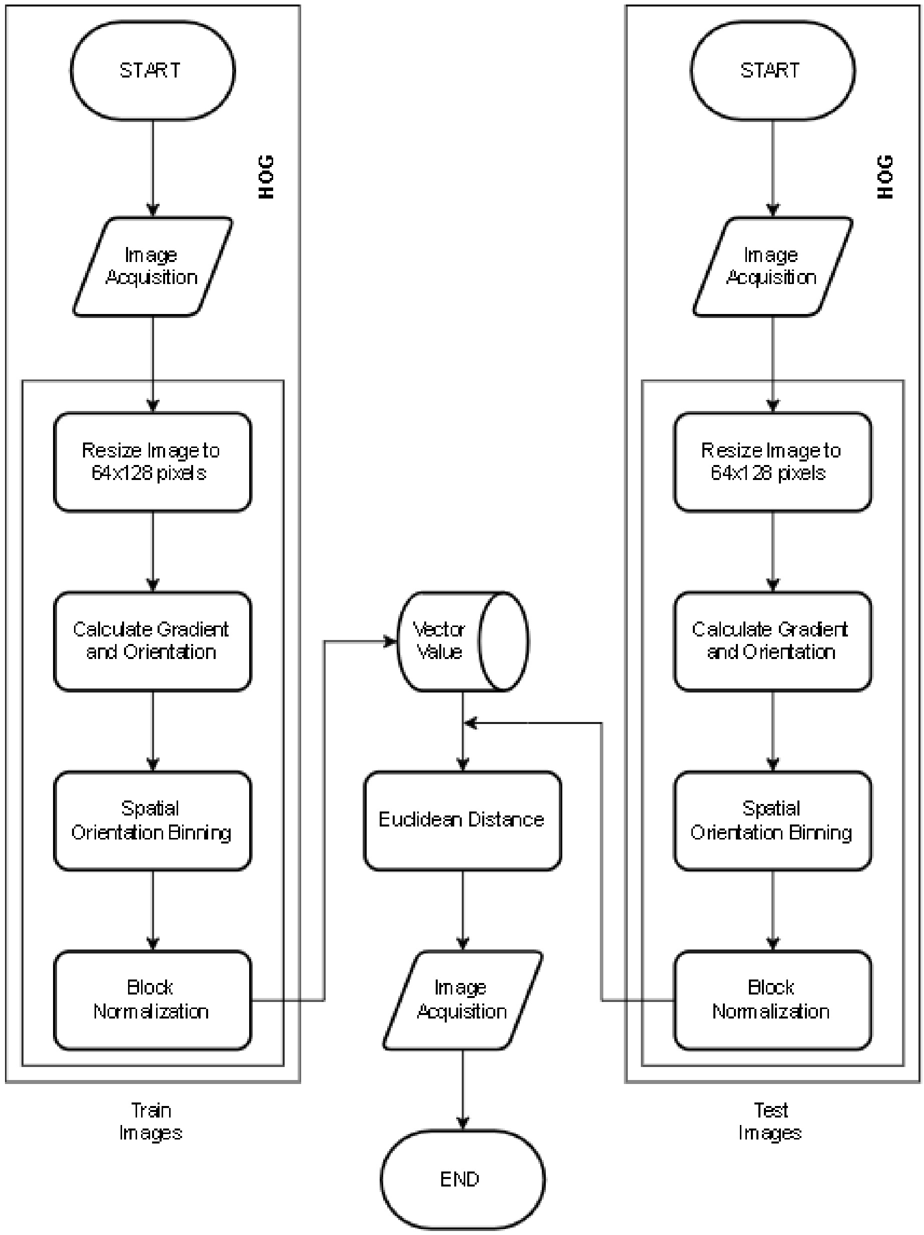

Figure 5. Describes the flow of system development, starting from image capture, resizing process, to implementing the Block Normalization process.

Euclidean Distance

Euclidean distance is one of the mathematical methods used to calculate and compare the similarity of 2 vectors. Here is the formula for the euclidean distance equation:

$$d_{ij} = \sqrt{\sum_{k=1}^{n}(x_{ik} - x_{jk})^2} \quad (8)$$

The result of the euclidean distance value is the distance between the test image vector and the training image vector. The degree of similarity between images can be determined by the Euclidean Distance value.

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K-Nearest Neighbor (k-NN)

k-Nearest Neighbor or KNN is a method for classifying objects based on learning data or training images that are closest to the object or test images. Learning data is projected into multi-dimensional space, where each dimension represents a feature of the data. This space is divided into sections based on the classification of learning data. A point in this space is marked class c if class c is the classification most found in k of the nearest neighbor of that point. The near or far of neighbors is usually calculated based on Euclidean Distance. An example of k-Nearest Neighbor can be seen in Figure 6.

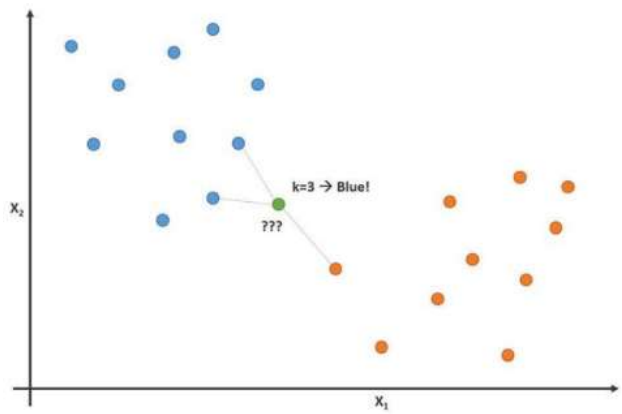

Figure 6. Example of k-Nearest Neighbor

The best k value for this algorithm depends on the data and the amount of data. k-Nearest Neighbor will give good and accurate results if it has a lot of training imagery.

METHOD

The Histogram of Oriented Gradients (HOG) technique has proven to be a pivotal method in the field of image processing and object detection. HOG operates by computing gradients of image intensities, focusing on localized regions to capture shape and edge information. This technique has gained significance due to its robustness in representing object features invariant to changes in lighting, orientation, and scale. In our research, we harnessed the power of HOG as a feature descriptor to recognize glass-packaged mineral water logos. Leveraging its ability to highlight gradient orientation distributions, we aimed to achieve efficient logo recognition amidst varying environmental conditions and orientations.

Before applying the HOG method, preprocessing steps were undertaken to optimize the images for recognition. These steps involved standardizing image dimensions, removing irrelevant background elements, and ensuring consistent brightness levels. Resizing the images to a standard format, typically 64x128 pixels, was carried out to maintain uniformity in the dataset and enhance computational efficiency. Furthermore, contrast enhancement techniques were applied to improve the visibility and clarity of logo features within the images.

Feature extraction through the HOG method involved the computation of gradient histograms in localized cells across the images. Each pixel's gradient magnitude and orientation were calculated, and histograms were formed by accumulating gradients within predetermined cells. This process captured texture and edge information by quantifying the gradient orientations present in various image regions. Parameters such as cell size and block size were carefully selected to balance feature granularity and computational complexity, ensuring the extraction of discriminative logo features. After extracting features using HOG, similarity between images was measured using the Euclidean Distance metric.

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This method calculated the distance between the feature vectors obtained from the test image and those in the training dataset. Lower Euclidean distances signified higher similarity between the images, aiding in the identification of the most similar or nearest neighbors for recognition purposes.

The effectiveness of our recognition system was evaluated through rigorous testing and validation procedures. We employed standard metrics such as accuracy, precision, and recall to assess the performance of the system. A dataset comprising labeled images of glass-packaged mineral water logos was used for training and validation. The experimental setup involved cross-validation techniques to ensure robustness and reliability in the recognition process.

While the HOG-based recognition system displayed robustness, certain limitations were observed. The system's performance might be affected by complex backgrounds, occlusions, or variations in logo designs. To enhance the system, future research could explore advanced feature extraction methods or incorporate deep learning techniques to address these limitations and further improve accuracy and robustness.

RESULT

The creation of the Glass Bottled Water Recognition System program based on the Logo with the HOG Method will be carried out with the System Development Life Cycle (SDLC) process which consists of several stages, namely planning, analysis, design, coding, and testing.

The testing phase is carried out to find out that the application program runs well. The test method used is the *Black Box Testing method. Black Box Testing* is a testing method carried out by observing the results of execution through test data, without knowing the processes that occur in the application program.

Testing this application program using Logitech Webcam with 480p image quality and Asus N43SL Laptop, with specifications Intel Core i7 Processor, 8GB DDR3 RAM Memory, Nvidia 540M 2GB VGA, and 1TB Hard Drive. There is also software used, namely the Windows 10 operating system, Python programming language and OpenCV as a platform to be used for coding.

The testing process of the Glass Packaged Mineral Water Brand Recognition Application based on the Histogram of Oriented Gradients method involves inserting an image of the mineral water brand, which is taken with predefined height, background, and brightness levels. The subsequent stage includes extracting features from the image to be tested using the Histogram of Oriented Gradients method. Next, the similarity distance is computed by comparing the values obtained from the feature extraction of the test image with the training image using the Euclidean Distance method. Following this step is the recognition phase using the k-Nearest Neighbor method. The k-Nearest Neighbor method searches for the k nearest distance values between the test image and all the samples to perform recognition.

Figure 7. Sample rotation of the training image

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The Sample Training Images are used to compare values between the training and test images to achieve recognition results. Examples of samples used for comparison and recognition can be observed in Figures 7. The test and training images will undergo computation using the Histogram of Oriented Gradients method, and the results will be utilized to calculate distances using the Euclidean Distance method. The outcome of the Histogram of Oriented Gradients method computation is a matrix sized 3780x1. The feature extraction results using the Histogram of Oriented Gradients method can be observed in Figure 8.

```
[[ 0.17729802]
[ 0.12772425],
[ 0.22379151],
...,
[ 0.04119349],
[ 0.03541259],
[ 0.03174125]]
```

Figure 8. Histogram of Oriented Gradients Calculation Results

The distance calculation is performed using the Euclidean Distance method between the training image and the test image. The distance is obtained by computing the feature extraction values between the training and test images using the Euclidean Distance formula. A smaller distance indicates a higher similarity between the images. After obtaining the distances between the test image and all training images, the subsequent step involves recognition using the k-Nearest Neighbor method. The k-Nearest Neighbor method will retrieve the nearest k distances and perform voting for each label of the brands included in the closest sequence. The brand label with the highest vote value represents the recognition result. An example of the calculation and recognition results using the k-Nearest Neighbor method with a value of k equal to 20 can be observed in Figure 9.

```
Pengenalan dengan k =  20

Hasil Vote Label Terdekat:
{'fluito': 1, 'prima': 4, 'vides': 2, 'batavia': 2, 'clif': 6, 'amidis': 5}

Jarak rata-rata: 9.98897776604

Brand yang di uji: vides

Hasil pengenalan: clif
```

Figure 9. k-Nearest Neighbor Calculation Results

The test results with sample training images rotated at 3, 5, and 0 degrees will be calculated using multiple scenarios. The test image to be used will be taken from the training image samples without including the same training image. The testing will be conducted by performing recognition using prepared scenarios, and the result will be a confusion matrix. The confusion matrix is a matrix used for statistical classification or multiple recognitions. The second test will be carried out by capturing mineral water label images using a smartphone and performing recognition by comparing the captured image with all training data

The first test was conducted by comparing the rotated training images of 3 degrees, 5 degrees, 10 degrees, and 15 degrees with the test images rotated by 5 degrees, 10 degrees, and 90 degrees, and using k values of 5, 10, 20, 30. The results of the first test with 10 scenarios resulted in an average accuracy of 21.10%.

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Figure 10. Sample rotation of the training image

The second test used test image samples from 12 brand labels taken using smartphone cameras. This test was performed by comparing all samples from a 3-degree dataset, and a 5-degree dataset with a test image and using k values of 5, 10, 20, 30. The second test yielded an average accuracy of 8.3%

DISCUSSIONS

The distance calculation is carried out by the Euclidean Distance method between the training image and the test image. The distance is obtained by calculating the trait extraction value between the training image and the test image with the Euclidean Distance formula. The smaller the resulting distance, the higher the similarity number. After the distance between the test image and all training images is obtained, the next step is to carry out recognition using the k-Nearest Neighbor method. The k-Nearest Neighbor method will take the closest number of k's and will vote for each brand label included in the closest order. Brand labels with the 32 highest vote scores are the result of recognition. Black Box Testing is a test carried out only observing the results of execution through test data (Febriyantia et al., 2021). Black Box Testing evaluates an application only from its external appearance, without knowing the processes that occur in the application program. Test results with 3, 5, and 0 degree rotation sample training images will be calculated with several scenarios. The number of test images to be used is 12 brands or 12 labels. The test image to be used will be taken from a sample of the training image without including the same training image. Testing will be carried out by conducting an introduction using a prepared scenario and the result is a confusion matrix. Confusion matrix is a matrix used to perform multiple recognition or statistical classification. The second test will be conducted by taking a picture of the mineral water label using a smartphone and conducting recognition by comparing the captured image with all the training data. This test was carried out by comparing all samples from the 3-degree dataset and the 5-degree dataset with test images taken using smartphones and the k values used were 5, 10, 20, and 30.

CONCLUSION

Testing of this system resulted in an average accuracy of 13.575% for all scenarios tested. In addition, identification using k values of 5, 10, 20, and 30 from imagery taken with smartphone cameras showed that only 1 of the 12 brands tested were correctly identified. These results show that this recognition system has limitations in recognizing glass bottled mineral water by logo, especially if it uses different k values.

Several suggestions have been put forward for the development of a glass bottled mineral water recognition system based on logos with the Histogram Method of Oriented Gradients. First, the selection of the most suitable trait extraction method for recognizing logos should be seriously considered. By adding *thresholding* features and changing images to grayscale, it can also improve the stability of recognition results. Meanwhile, research on better recognition techniques is also needed to improve the accuracy of the system. Lastly, it is highly recommended to use a high-quality webcam as the captured images must have adequate resolution to make the mineral water logo recognition process more accurate.

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