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APPLICATION OF ORIENTED FAST AND ROTATED BRIEF (ORB) AND BRUTEFORCE HAMMING IN LIBRARY OPENCV FOR CLASSIFICATION OF PLANTS

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Abstract

The identification of plants is a process of recognition of plants to discover the types to disseminate knowledge, but the names of the plants can be different from each person (community, profession, language) in different geographical locations. Artificial vision is very useful for mobile devices, together with the appearance of cell phone cameras equipped with phones, new opportunities and challenges have been generated in the field of artificial intelligence (AI). The combination of ORB and BruteForce_Hamming has better computational efficiency based on the highest accuracy and identification efficiency in the implemented software and can perform accurate real-time identification. The design and implementation of the plant classification identification identification program is based on the Android operating system with a minimum level of system 21 (Lollipop) to show the key match point of the live camera to obtain type information. This application can classify plants with a correct accuracy rate of 88% and an identification error rate of 12% on pandanus leaves.

Keywords: plants, species, Android, Keypoint, ORB, BruteForce Hamming

I. INTRODUCTION

Biodiversity continues to decline throughout the world [1], the current rate of extinction is the result of direct and indirect human activity [2], due to the environmental consequences of human population growth and urbanization which has caused habitat loss and fragmentation, exploitation, alien species invasion, pollution and climate change [3]. Plant identification is a process of identifying plants to find out the types of plants in detail and in full and can be justified scientifically. The purpose of plant identification is to facilitate students, students, researchers or the public who need plant clarity (identification) in the context of the dissemination of knowledge [4]. Unknown plant names, following everyday language for alternative interpretations, common names may differ from person (community, profession, language) in different geographical locations and their use may change over time [5].

This creates obstacles for beginners who are interested in gaining knowledge about species [6], more than 10 years ago, K. J. Gaston dan M. A. O'Neill stated that the development of artificial intelligence and digital image processing will make the automatic identification of species based on digital images become real in the near future [7]. Object recognition is a lot of topics in Machine Vision and can be useful for mobile devices [8], along with the emergence of a cellphone camera equipped with a telephone, new opportunities and challenges have been generated in the field Artificial Intelligence (AI).

One of these challenges is that resources, available memory, bandwidth and processing accuracy are the limiting factors in image classification [9]. This provides basic tools in a more sophisticated way of guiding and assisting people in identifying plant species, in addition, trend approaches and technologies such as Augmented reality (AR), Big data, and 3D features give this research topic a long-term perspective [10].

In image processing, the first thing to do is to determine the detection and description that creates a local descriptor, based on local gradients and with real valued parameters [11]. As a result of the emergence of mobile applications has shifted the focus to the decline in computing and storage requirements and led to the development of binary descriptors, such as Oriented Fast and Rotated Brief (ORB), the descriptors presented are thoroughly evaluated on several benchmarks in combination with various keypoint detectors and compared to baselines and various descriptors are studied, ORB is proven to achieve good performance [12].

ORB forms a binary descriptor that is designed to be compact and fast in calculating binary strings by

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comparing pairs of intensity values of patterns in the keypoint, the similarity between the two descriptors is calculated as a matching Hamming that can be implemented efficiently [13]. Keypoint matching is an important task that is widely applied in areas such as make image [14], the purpose of keypoint matching is to find the pixel correspondence representing the same real keypoint in two images, many local 2D descriptors have been proposed in recent years for this task, each of which has advantages and disadvantages and the most popular is ORB [15]. The combination of ORB and BruteForce Hamming has better computational efficiency based on the highest accuracy and identification efficiency in the implemented software and can realize accurate identification of dairy cows in real-time [16].

II. Related Research

2.1 Zhao et al (2019) Model

The identification of individual Holstein dairy cattle based on the detection and matching of keypoint features in body pattern images is a study of vision machine based animal identification systems using Radio frequency identification (RFID). Video of 66 Holstein cows was recorded using a Nikon D5200 camera three times a day at 16:00: 18:00, when they walked back to the warehouse after milking milk at a research dairy farm at the University of Kentucky, USA in early August 2016 and the video resolution was 720x1280 pixels.

The cows taken have no contaminated mud on their bodies and are captured under natural lighting conditions. Image of each cow captured once a day for 8 consecutive days. Thus, each cow gives a total of 8 videos during the experiment. Among the 8 videos from each cow, 3 were randomly selected for the reference dataset and the remaining 5 videos were used as test data. Therefore for all 66 cows, the reference data set and test data set each contain 198 and 330 videos, with a total of 528 videos when the cow runs in each video, frame images are processed to identify the cows inside.

Figure 2.1 Interface of cow identification software

Figure 2.1 shows the image processing flow to extract the body image from a frame. The first step is to detect the target cow from the background. BGS Library is an integrated Cþþ (C ++) open library that implements different methods for foreground-background separation.

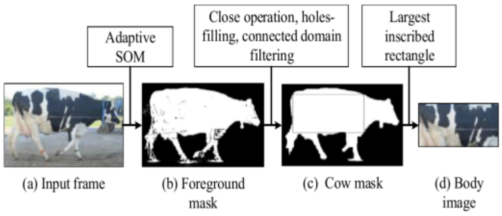

Figure 2.2 Steps for extracting patterns from the input frame

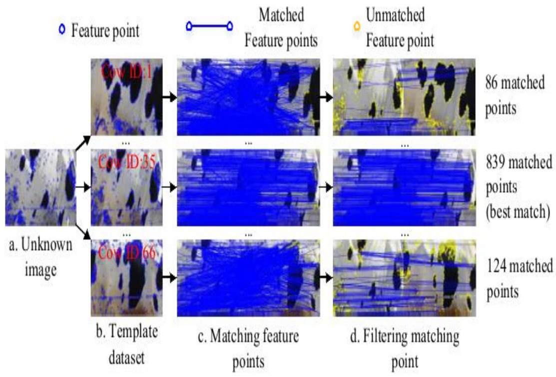

Figure 2.3 Extracting, matching and filtering feature points

Figure 2.3 shows the results of testing using three algorithms will be individual patterns to convert and match feature points. The accuracy of the Scale-Invariant Feature Transform (SIFT) algorithm when applied is 91.39% and the Speed Up Robust Feature (SURF) is 91.46%. The detection

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efficiency of the SURF method is clearly higher than SIFT, compared to SIFT, the reference load time dataset is reduced by about 50% and the average grading time for each image is reduced from 16.19 seconds to 10.6 seconds.

Between high algorithms, ORB has high accuracy and efficiency. The overall detection accuracy is 95.41% and the loading time is less than 5 seconds. The determining time for one frame is only 0.77 seconds, which is much lower than other algorithms and accepts real time. The ORB algorithm has a high detection because it detects 366 keypoints that can be obtained for each image.

2.2 Yang et al (2018) Model

A study of emotional recognition models based on face recognition in a virtual learning environment. The goal is to recognize emotions in a virtual learning environment in real time. The classification and accuracy of detection uses the Cascades HAAR method to detect eyes and mouth and identify all types of emotions through the Artificial Neural Network (ANN) method. Subject analysis was collected for face classification data as subject feeling analysis data. The data can be obtained from different physical features such as facial expressions, body movements and other biological physical signals. However, students' emotions are expressed first through facial expressions which can be divided into six types of categories: sadness, happiness, surprise, fear, anger and disgust.

The face recognition process consists of three main stages: acquisition, feature extraction and emotion classification. Face acquisition is the process of determining which faces are included in an image, as well as their shape and size. Face localization can be used to complete face localization. In addition, facial texture information is often used for face localization proving face localization using face grayscale. Skin color has special features, it is in a relatively independent position in the color space, so skin color information is often used to do localization of the face. The method of facial feature extraction mainly depends on the classification method, the classification method and other methods that can be applied differently in different environments.

The classification method using temporary information can be called the spatial domain method. All images are used as input from ANN or image processing. This learning process is repeated repeatedly to minimize the value of output errors, for all patterns in the training set. This application imports the openCV Library to complete the Computer Vision process. The openCV Library method is used to detect combined object data and object tracking. To test the images, this study adopted the JAFFE (Japanese Female Facial Expression) database.

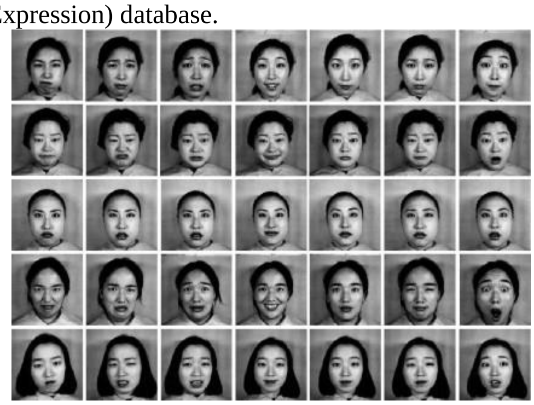

Figure 2.4 JAFFE database

The database contains 213 images (each image: 256 * 256 pixels) of the face of a Japanese woman in which each image is determined in its original expression. The results of this test use three data groups, with each data group used in six expressions (happiness, sadness, surprise, anger, disgust and fear), the last data group only shows happy and sad expressions. There are a total of 20 images; accuracy is expressed as a percentage; efficiency is expressed in seconds.

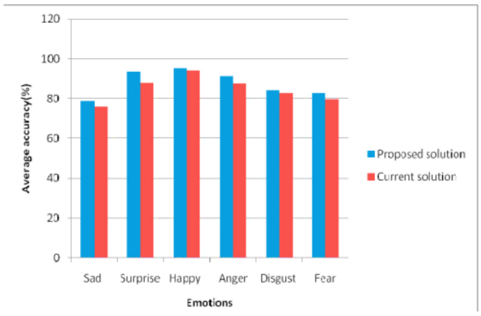

Figure 2.5 Rate of classification results (%)

In Figure 2.5 shows that the level of happiness classification is significantly higher than the others, followed by surprise emotions, while the lowest is sadness. The value of happiness characteristics is clear and the value of other facial expression characteristics are prominent, but the value of sadness characteristics is not too prominent than the value of other facial expression characteristics, which leads to a low level of recognition.

Table 2.2 Accuracy of emotional detection
TIME (s)

	Sad	Surprise	Happy	Anger	Digust	Fear
Propsed Solution	130.25	163.66	114.5	112.16	114.16	154.16
Current Solution	143.62	170.52	121	116	117	159

2.3 Fajri et al (2018) Model

A study on the identification of Indonesian mango types, namely Manalagi mango and Gadung mango. Based on the introduction based on the shape and texture of the leaves using back propagation methods of Artificial Neural Networks.

The texture features used in this study were the average intensity, smoothness, entropy, 5-moment variants, energy, and contrast in the dataset totaling 300 images of mango leaves consisting of 150 images of mango leaves of Manalagi varieties and 150 images of Gadung leaves. To get internal contours arranged according to pixel position is to use the Moore contour detection algorithm which can be seen in the following image

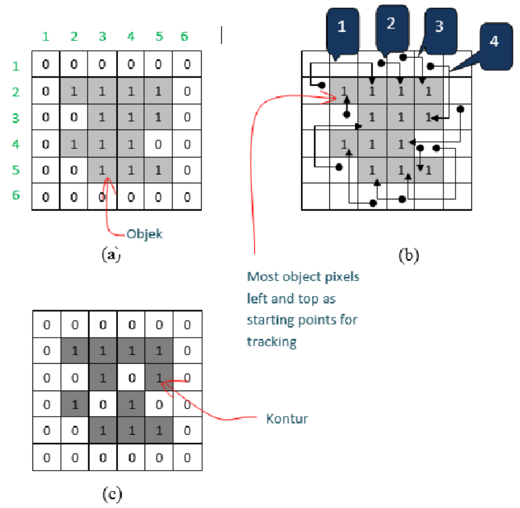

Figure 2.6 Moore contour detection

The dataset is made in several stages, namely preprocessing, then extraction of shape and texture features, classification models of back propagation neural networks for the introduction of training and testing data. The preprocessing phase aims to eliminate noise and cropping so that the mango leaf object can be distinguished from the background color. The steps taken in the preprocessing stage are the selection of the mango leaf image object then change the background color to white or in an RGB color combination.

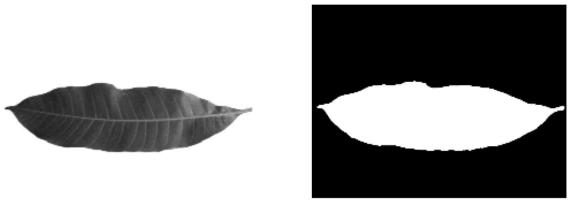

Figure 2.7 Extraction of image features

Based on tests conducted on the classification of mango leaf varieties by combining the extraction of shapes and textures on mango leaves, the process of testing the test of mango leaf images using 100 image datasets and the results of 96 pictures of mango leaves have the same or the same. yields as their varieties, and the four pictures of mango leaves do not match the introduction of mango varieties. So that the accuracy of the mango leaf image testing process is 96%.

2.4 Zhuo et al (2016) Model

A porn web identification research based on ORB function which aims to identify porn web based on image recognition. The introduction method uses Scale Invariant Feature Transform (SIFT) but the computational complexity of feature extraction is very high. Therefore, various fast extraction algorithms from local characteristics have been proposed, such as the combined strong acceleration characteristics of SURF Oriented FAST and ROTED BRIEF. ORB Compared to SIFT, the extraction speed of ORB characteristics is much greater. faster than SIFT and can be used in image classification, training, and other applications.

In a good detection process, ORB features are first extracted and represented compactly using a Bag-of-Words (visual) histogram based on the Bag-of-Words (BOW) model, which is then combined with the Color histogram of all images forming characteristics. Vector to represent image content, Support Vector Machine (SVM) is used to train these feature vectors to get a classification model, which will be used for the introduction of pornographic images.

Skin color detection is done in the YCbCr color space [17], the reason being that the distribution of all skin color races is more concentrated in the YCbCr space than in other color spaces. On applying the skin color model to detect skin color areas from the image and the face detection algorithm is described as: (Cb ≥ 97.5 and Cb ≤ 142.5) and (Cr ≥ 134 and Cr ≤ 176).

At the training stage, the ORB descriptor will be extracted from the specified skin color area. And then, bag-of-words (visual) histogram words about ORB are made using the Bag of Words (BOW) model. The global feature color histogram is extracted from the entire image to create a feature vector with ORB, which will be trained to obtain a classification model by SVM.

In the BOW model to compactly represent the ORB descriptor. First, the ORB feature is extracted from the specified skin color area to form the feature library. And then, this descriptor will be grouped using the K-means method and the center of each cluster is treated as a visual word. All visual words can form visual vocabulary. Next, a bag-of-words (visual) word histogram is created by using ORB's visual vocabulary by calculating the frequency of each visual word image and representing the image content as a concise feature vector.

Test data were selected from 5000 pornographic images and 6000 non-pornographic images from the dataset to train classifiers and the rest of the images were considered as test sets. More than 4.6 million (ORB), 6.8 million (SIFT) keypoints were extracted and grouped to build visual vocabulary using the respective K-means method.

Table 2.3 Table of results of detection methods

The dimension of features	ORB (ms)	SIFT (ms)	SIFT/ORB (multiple)
100+72	769	3143	4.1
250+72	818	3161	3.8
400+72	832	3203	3.8
550+72	891	3280	3.7
700+72	902	3316	3.7

The accuracy of the proposed method can reach 93.03%. Compared to the SIFT-based method, the proposed ORB method has the advantage of increasing the recognition speed up to about 4 times.

III. PROPOSE METHOD

In this study the proposed method is the classification of plant images using Oriented FAST and Rotated BRIEF (ORB) and BruteForce Hamming applied to Android devices, so that the classification process in this study begins with the feature extraction process to produce invariant rotation features using ORB and then from the feature. classification process will be carried out.

The initial stage of this method is leaf image input from the dataset provided. Leaf data is processed by invariant, meaning that the leaf data to be recognized does not depend on the size or color of the image. Input images will also be tested on images that have a background, so this study does not require a pre-processing stage to separate objects from the background.

The image from the input will go through the feature extraction process using the ORB method, this stage is the core stage of this study. At this stage, interest points will be detected based on the gray level of each pixel that will form a collection of keypoints that indicate the characteristics of the object. From the set of keypoints, the strongest keypoint feature will be chosen based on pixel intensity.

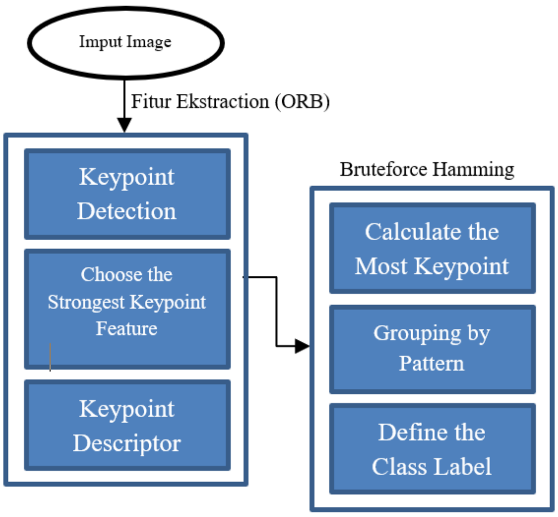

Figure 3.1 Stages of the Proposed Method

This method will produce an image with a keypoint (local feature) that is invariant to various changes, such as rotation, lighting, and noise. Then, the descriptor of both the input image and the image produced by the ORB will be matched by each keypoint to classify the plant type from the input image. The proposed method will be able to distinguish plant types from leaf shapes that vary invariantly.

3.1 Dataset

In this study, the dataset used is the leaf dataset. Data in the form of image files with JPEG extension with RGB color space, this leaf dataset consists of 25 images collected from 5 types of plants.

The stages in this study do not require pre-processing steps to segment images because the data used in this study will also be tested with different backgrounds to recognize the features produced.

Preparation of the image dataset is done by improving image quality using the Photoshop application to eliminate image noise and increase the detail of the leaf shape structure.

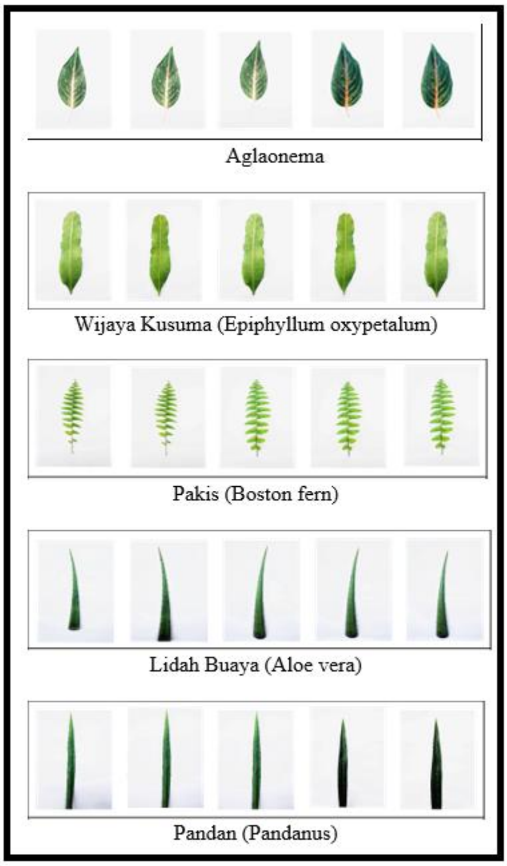

Figure 3.2 Dataset

3.2 Fitur Ekstraction

ORB [15] is used to detect local key points in an image. To extract keypoint quickly and accurately, first ORB will detect the feature of the Accelerated Segment Test (FAST) keypoint on the image [18] and Orientation is needed to build a descriptor, in its application calculating the angle orientation, called centroid intensity. This method assumes that the angle intensity is offset from its center, and this vector can be used to determine orientation [19] [20] defines patch moment (1).

$$m_{pq} = \Sigma_{x,y} x^p y^q I(x, y) \quad (1)$$

Where m is denoted as the moment patch p and q are the moment sequences which are analogous to mechanical moments and x, y is the pixel coordinate keypoint of the image. Then by considering the moment in equation (1), the centroid can be found with the following equation (2).

$$C = \left(\frac{m_{10}}{m_{00}}, \frac{m_{01}}{m_{00}} \right) \quad (2)$$

Where the centroid will be found through the matrix in pixels of the image that is defined as m00, m01 and so on. The vector is constructed from the center of the angle θ to the centroid C. Simply put, the orientation of the patch becomes equation (3).

$$\theta = \operatorname{atan2}(m_{01}, m_{10}) \quad (3)$$

The pixel intensity is calculated with x and y remaining in the area of the circle with radius r. The optimal choice for patch size is r in a way that ensures that the path from x, y is from [-r, r]. With the Hessian size, because the C value is close to zero, it tends to be unstable but this does not happen with the FAST angle, which is beneficial for system efficiency.

Then ORB involves the addition of a rotational conscious component called r-BRIEF which is an evolutionary version of the steered BRIEF descriptor which is then added with related learning steps to find binary features that are less correlated. The bit description string of the image patch is built from a set of binary intensity tests. Considering the refined image patch p, the binary test r is defined on patch p. The binary test is represented as (4).

$$r(p;x,y)=\begin{cases}1: p(x)<p(y)\\0: P(x)\geq P(y)\end{cases} \tag{4}$$

Where p (x) shows the intensity of the patch covering the given keypoint x and p (y) shows the intensity of the patch covering the given keypoint y. Furthermore, the features which are functions of the patch obtained will be represented as vectors of the binary n test in equation (5).

$$f_n(p)=\sum_{1\leq i\leq n} 2^{i-1}\tau(P;x_i,y_i) \tag{5}$$

Furthermore, this method will obtain a keypoint descriptor that is invariant to changes in light intensity or changes in three-dimensional perspective. So the resulting output is a feature description of the leaf image that has been detected and a feature keypoint on the leaf that will be matched with the leaf that is most similar to the leaf type in the dataset.

3.3 Classification

Matching Algorithms (Matchers) are methods that determine which characteristics are represented in the descriptors of the same two images according to their criteria. The chance of finding patterns in an image increases with the number of similar or matching features found. Brute-Force Hamming matches every feature of the first descriptor compared to all features of the second descriptor based on the distance metric with the closest matched pair [21]. The minimum distance value determines whether the pair will be considered relevant or not, a brief description of the matching algorithm used next is presented according to the following BruteForce-L1 equation (6).

$$d(V_1,V_2)=\sum_{i=1}^{M}|v_1[i]-v_2[i]| \tag{6}$$

In the above equation, V1 and V2 are the feature vectors of the two images created in the feature extraction, M vector size and v1 [i] and v2 [i] are the i-elements of each vector. The BruteForce-L1 algorithm uses the L1 metric distance known as Manhattan or City Block [15] to determine the distance between floating point descriptors. BruteForce is used by floating point descriptors and the distance considered is L2, also known as Euclidean Distance. This method requires more processing power than BruteForce-L1 because it is a quadratic function as shown in Equation (7).

$$d(V_1,V_2)=\sqrt{\sum_{i=0}^{M}(v_1[i]-v_2[i])^2} \tag{7}$$

The BruteForce-Hamming implementation is used by binary descriptors. The equation is the sum of the results of a bitwise bit XOR operation between the two vector description images, according to Equation (8).

$$d(V_1,V_2)=\sum_{i=1}^{M} v_1[i]\otimes v_2[i] \tag{8}$$

BruteForce-Hamming (7) is also used by binary descriptors and uses two bits rather than one bit in XOR operations compared to the previous algorithm [22]. This method was proposed by [23], the FlannBased algorithm is used with a floatingpoint descriptor. It uses a framework for the preprocessing stage, usually faster than the brute force algorithm with greater memory utilization costs. The final result of this method is a leaf image with a class label in the form of a leaf type that has been detected and an accuracy value obtained from the correct amount of test data divided by the amount of data that is presented [24] in equation (9).

$$\text{Accuracy}=\frac{\sum data\ is\ correct}{\sum test\ data}x100\% \tag{9}$$

Then the calculation equation to assess the accuracy of the results of the entire test against the entire dataset.

IV. CONCLUSIONS

Testing the proposed method in classifying the entire dataset directly. The data tested is a dataset with a total of 5 types of plants in the training data. The results of this test will display the classification of all types of all datasets. Calculation of accuracy using the following simple equation:

Table 4.2 Overall Testing Results Data

Calculation

Types of Plants	Testing	Classification Results		Level of Accuracy
		True	False	
Aglaonema	10	10	0	100%
Lidah Buaya	10	10	0	100%
Pakis	10	10	0	100%
Pandan	10	4	6	70%
Wijaya Kusuma	10	10	0	100%
Total	**50**	**44**	**6**	**88%**

Plants are properly classified	**88%**
Plants classified incorrectly	**12%**

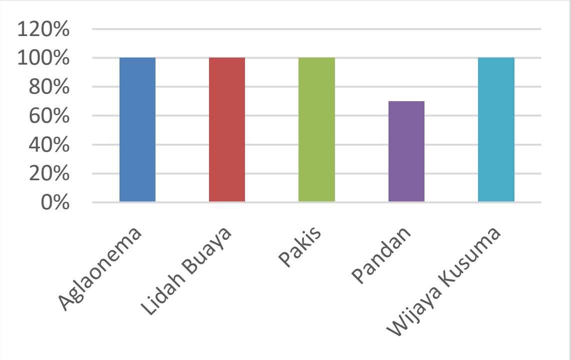

Figure 4.1 Comparison of Accuracy of Each Type

From the test results, the ORB and BruteForce_Hamming methods can classify plants with 88% correct accuracy rate and 12% misidentification rate on pandan leaves. Can be interpreted ORB and BruteForce_Hamming have good specifications in the classification system. ORB is a data learning technique for machine vision that is used to find keypoint features on target images that match the pattern extraction image and BruteForce_Hamming matches how much the pattern matches the target image, the higher the accuracy of the results of the identification process.

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