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Analysis of Music Brand Similarity Levels Using a Visual Computing Approach

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ABSTRACT

Currently, many trademarks have emerged, especially for music equipment products circulating in the community. Especially in Indonesia, musical instrument brands with various models have emerged. The problem occurs when the brand is considered to resemble the original brand, which makes it uncomfortable for musicians. Even though the quality of the tone produced is not assessed from a brand perspective, it is felt by brand owners to be quite a violation of the code of ethics. This has an impact on marketing products that are considered genuine. In this paper, a concept will be proposed in determining whether a trademark is considered authentic in terms of the logo. Use of Visual Computing with SIFT and SURF algorithms. SIFT (Scale-Invariant Feature Transform) and SURF (Speeded-Up Robust Features) are two popular algorithms for feature extraction and matching in image processing. Both are frequently used in computer vision applications such as object detection, image matching, and object recognition. The results of this analysis will be used for musicians who want to buy musical equipment to be able to detect the logo to compare the success of a musical instrument product. The appropriateness of the quality itself will be discussed in a different discussion. The benefits that can be generated will make musicians, especially in Indonesia, more conscientious. The possibility of sorting so that you can like your own product will be very possible.

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INTRODUCTION

SIFT (Scale-Invariant Feature Transform) is an algorithm for detecting and describing different features in images, which are resistant to changes in size, rotation and shift [1]. The SIFT algorithm works by looking for unique and stable key-points in an image, using a method to identify extremes in scale and orientation in an image [2]. Once key-points are found, SIFT uses local descriptors to describe the environment around each key-point. These descriptors are resistant to geometric transformations and are used to compare features between images. The advantage of SIFT is its ability to produce features that are highly descriptive and robust to variations in images, making it suitable for image matching and object detection [3].

SURF (Speeded-Up Robust Features) is a development of SIFT which aims to increase computing speed and efficiency of feature extraction algorithms [4]. The SURF algorithm uses a similar approach to SIFT in detecting key points and generating descriptors, but with some modifications to improve computational efficiency [5]. SURF uses a Gaussian filter and integral image approach to speed up key point detection and descriptor calculations. Although SURF is faster than SIFT, it is sometimes not as strong as SIFT in terms of invariance and robustness to complex image transformations [6].

The main advantage of SURF is its higher computing speed, making it more suitable for real-time or large-scale applications [7]. However, SIFT is often still more accurate and reliable in detecting features, especially in cases where complex geometric transformations of the image occur [8]. These two algorithms are still frequently used in a variety of image processing applications, and the choice between them depends on the specific needs of each project [9].

Facing many counterfeit or counterfeit brands that can confuse consumers is a serious challenge for businesses and consumers themselves [10]. The following are several ways to deal with this problem, (1) Providing education to consumers about how to identify genuine products and recognize the characteristics of legitimate brands. Inform consumers about the risks and consequences of purchasing counterfeit products, such as poor quality and even compromised health and safety. (2) The government and competent authorities must enforce laws and regulations that prohibit the manufacture and sale of counterfeit products. Imposing harsh sanctions for perpetrators of making and selling counterfeit products to prevent the spread of counterfeit products on the market. (3) Building a strong brand image and good reputation for the original brand to differentiate itself from imitation brands. Provide good customer service and provide quality products to maintain consumer loyalty. (4) Industries can work together to protect their brands and products from piracy and counterfeiting. Share information and resources to detect and stop the production and sale of counterfeit products [11].

Using advanced technology such as QR codes, RFID chips, or blockchain to track and authenticate genuine products [12]. Providing a digital platform to verify product authenticity online. Encourage transparency in the supply chain to ensure product authenticity from producers to consumers [13]. Ensure that all parties in the supply chain are responsible for product authenticity and are not involved in trading counterfeit products. Increase public awareness about the dangers and negative impacts of purchasing counterfeit products. Inviting people to support original brands and choose products wisely[14]. By taking these steps seriously, it is hoped that we can reduce the prevalence of counterfeit products on the market and protect consumers from the risks associated with counterfeit products[15].

The analysis's findings will help musicians who wish to purchase musical instruments by enabling them to recognize a logo and assess how successful a certain product is. We shall talk about the appropriateness of the quality itself in a separate conversation. The potential rewards will increase the conscientiousness of artists, particularly those in Indonesia. Sorting will definitely be an option if you want to enjoy your own product.

METHOD

Creating a data set of intellectual property rights (IPR) pertaining to trademark disputes was the first step in the study process. The images in the database and the images for searches are found using this data. The winning brand image will be kept in the database, along with its "Registered" status on the DJKI website. In the interim, brands with a "Rejected" or "Cancelled" status after losing will be utilized as query images.

The brand or brand registration number is derived from the choice. Next, retrieve the company logo from the website of the Intellectual Property Database. Brand logos that are downloaded are divided. While those who cancel or are refused are utilized as queries, those who register are added to the database. Figure 1 shows the process of retrieving a brand image.

Figure 1, Brand Image Rediscovery Process.

SIFT and SURF algorithms are used to extract points of interest and descriptors for each image. The query image features are matched with existing image features in the database. Matching image features will produce the number of image features in the database, the number of query image features and the number of image features that match between the image features in the database and the query image features. For example, image $CCqq$ is the query image and $CCdd$. The SIFT or SURF algorithm will produce the sets Dq and Dd which are expressed in Equation 1.

$D_q = \{(M_i(x,y), d_i)\}$ dan $D_d = \{(M_j(x,y), d_j)\}$
$M_i(x,y)$ adalah *key point* dan d_i adalah vector descriptor untuk citra *query* D_q.
$M_j(x,y)$ adalah *key point* dan d_j adalah vector descriptor untuk citra *query* D_d. (1)

$$T = \left\{ \left(M_i(x,y), M_j(p,q) \right), \left(|T| \le \min(|D_q|, |D_d|) \right) \right\} \quad (2)$$

Then, to determine the match between key points, the query image descriptor vector is compared with the image descriptor vector in the database. Matching will produce the set of matching pairs T stated in Equation 2 previously.

Next, the K-Nearest Neighbors algorithm, with k=2, is used to find correspondence pairs. Figure 2 visualizes key point pairs of query images with images in the database. Figure 2 (a) uses the SIFT algorithm, while Figure 2 (b) uses the SURF algorithm.

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(a) (b)

Figure 2, Visualization of keypoint correspondence pairs using SIFT and SURF algorithms.

The Director General of Intellectual Property Rights uses the DJKI website to create five sets of pertinent test data that have the status "Registered" in order to conduct testing. The query image, meanwhile, makes use of a logo that reads "Cancelled" or "Rejected". There are 136 brand photos that are kept in the database. For every query image, there are 32 relevant brand images. For example, SIFT features 1815 and SURF features 1886 are included in the Marshall query image with registration number IDM000374439. The features in the database will be compared with these features. The query image feature descriptors with the closest distance to the image features in the database are the relevant SIFT and SURF features. Table 1 presents the findings.

Table 1. Example of “Marshall” brand image query results.

Brand Image	SIFT Features	SIFT Compatibility	SURF Features	SURF Compatibility
	571	71	1023	137
	600	102	934	57
	869	23	1866	183
	673	73	899	57
	855	176	1089	176

Every picture in the database is subjected to the SIFT and SURF feature detectors. The quantity of features gleaned from the two detectors and the quantity of feature similarities between the image features in the database and the query image features are displayed in Table 1. A brand's image can take many different forms, including letters alone, letters and images, or photos just. In general, the SIFT method will yield more features for images that just contain letters. Nevertheless, there is a nonlinear relationship between the quantity of feature extractions and the query image feature match. The suitability column, which does not exactly correlate with the degree of feature extraction, illustrates this.

After that, an experiment was conducted using Table 1's data. Euclidean measurements were used to compute the parameters in Table 1 in order to arrange the query results. A similarity distance measure is used to provide a similarity value between the brand image in the database and the brand image retrieved from the query. Euclidean distance is used to quantify similarity [6]. Formula (3) is used to determine the Euclidean distance between the brand image in database D and the feature vector descriptor of the query image q.

$$Dist_{Euclid}(D,q) = \left(\sum_{i=1}^{n} (D_i - q_i)^2 \right)^{1/2} \quad (3)$$

RESULT & DISCUSSION

Kinerja sistem temu kembali citra digambarkan dengan mengukur tingkat presisi dan recall. Precision (P), Recall (R), F-measure biasa digunakan untuk evaluasi kinerja penelitian CBIR. Precision adalah rasio jumlah gambar yang relevan dalam hasil k pertama dengan jumlah total gambar yang diambil N_{TR}.

The measure of accuracy is seen using precision, while the measure of accuracy is recall. Precision (P) and Recall (R) are calculated using Formulas (4) and (5).

$$P = \frac{tp}{N_{TR}} = \frac{tp}{tp + fp} \quad (4)$$

tp represents the relevant image that was taken and *fp* represents the image that was taken but is not relevant. Recall (R) is expressed as the ratio of relevant images taken to the number of relevant images in the database.

$$R = \frac{tp}{N_{RI}} = \frac{tp}{tp + fn} \quad (5)$$

tp represents the relevant image retrieved and NTR represents the relevant image in the database. NTR is obtained from the tp value fn+, fn represents the number of images that are actually included in the relevant group but were not taken. F-Measure is used to measure the harmonic average of P and R, expressed by formula (6). The F-measure value indicates better prediction. P and R are the values of precision and recall.

$$F = 2\frac{P.R}{P + R} \quad (6)$$

High precision, recall and F-measure values (close to 1.0) indicate that the information retrieval system is working effectively. This can be interpreted as meaning that the system is able to present relevant information. Examples of query images and image results found in the database are shown in Figure 3. The image with index (a) is the query image, while the others are images obtained from the database. Image relevance is based on image similarity. For example, the Marshall brand. Examples of brand-relevant images are in Figure 3 (b), (c), (d), (e).

Figure 3, Examples of Brand Image and Query

The experiment was carried out by carrying out two experimental stages. The image with the shortest distance of 20 images will be displayed as the query result. The first stage sorts the query results based on the number of matching pairs using the SIFT algorithm, SURF algorithm and the sum of the number of matching pairs in the SIFT and SURF algorithms. The second stage sorts the query results based on adapting the Euclidean distance formula. The precision and recall results are shown in Figure 4. In this experiment the highest average precision (0.78) and highest F-measure (0.54) were obtained when using the SIFT and SURF algorithms simultaneously. This shows that the system is able to detect the similarity of images that have been "Registered" and stored in the DJKI database compared to the brand image that will be registered (query image). This can be used to consider whether the mark to be registered is acceptable or not.

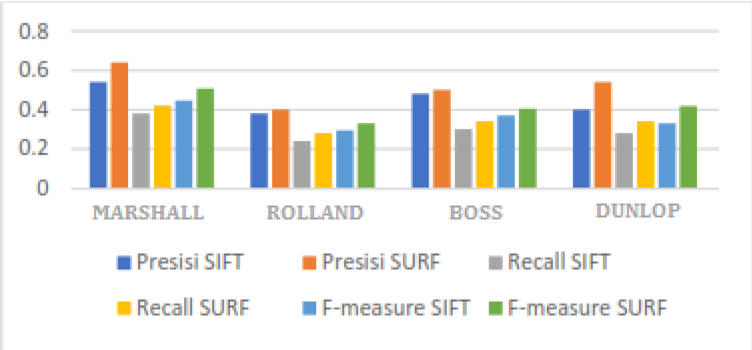

Figure 4, Euclidean Distance Precision and Recall Graph

The computation of precision, recall, and F-measure with sorting based on Euclidean distance is shown in Figure 4. It is evident from the image that this experiment's precision, recall, and F-measure values are lower than those of the first experiment. Consequently, it can be said that despite the poor precision and F-measure values, the system is still able to locate photos that are pertinent to or comparable to the query image.

CONCLUTIONS

In order to retrieve comparable brand pictures from a database, this study evaluates a content-based brand image retrieval (CBIR) system. It is anticipated that this content-based brand image retrieval system would be able to identify early similarities between the brand image that will be registered and the brand image that has already been registered with the Director General of Intellectual Property Rights. This can be applied to evaluate if a brand satisfies the prerequisites for obtaining a brand certificate. In this study, the basis for determining visual relevance is derived from court rulings. The highest average precision value of 0.67 and F-measure of 0.51 were obtained by the system developed utilizing a combination of SIFT and SURF key-point descriptor values.

The quantity of pertinent photos varies with the number of points. Nevertheless, there is a nonlinear relationship between the number of points and the number of matching points between the database image and the query image. The relevancy of search results is impacted by this. The combined match value based on SIFT and SURF feature extraction determines the ordering of the relevance of query results with the highest value. The only foundation for the research that has been done is brand image matching. The brand name, category of products or services, and brand image are all included in brand registration. A database with brand names, class codes, and brand photos will be used in the upcoming study. The research was carried out by testing the similarity of brand names, similarity of pronunciation and similarity of brand image. The algorithm used is a machine learning algorithm to build a brand retrieval system based on both letters and images.

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