Logo Detection Using AI ML

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Abstract - *With increasing in brands, companies and organizations as startups, existing ones as market rulers; There is also increment in the scams of fake/cloned variants of products and services from the existing companies. Users are unable to distinguish between the original and a duplicate variant of the services and products provided from one company or brand. So there comes "Logo Detection Using Machine Learning", With our detection mechanism, we compare the user provided logo from the original ones and clear the ambiguity of the customers. We also implement service marks such as TM (Trademark), © (Copyright) symbols and slogan/quote verification with the original brands or companies in order to provide the best accuracy as possible to the users depending on our detection mechanism.*

Key Words: Index Terms Feature Extraction, kNN Search Tree, Logo Recognition, Nearest Neighbor, SURF, SURF Features

1. INTRODUCTION

Logos are a critical aspect of business marketing. The Marketing of business must include logos. A company's logo, which serves as its primary visual expression, serves to anchor its brand and elevates it above all others in the eyes of its target audience. This makes a quality logo an important component of any business's entire marketing plan. There are millions of businesses and millions of logos in the globe. To differentiate their brands from those of competitors, businesses often invest a lot of effort and money into creating distinctive logos. In order to satisfy their customers' requests and maintain the logo's quality, it becomes fairly difficult for logo designers. Features of a logo are a huge concern when defining the requirements for developing a logo, and for this reason, logo recognition plays a large role.

Corporate logos are used to represent the "face" of an organisation. They are visual representations of a company's distinctive identity that use colours, fonts, and pictures to convey vital details about the business and help clients' core brands be recognised by their target audiences. Additionally, logos serve as a convenient abbreviation for the company name in marketing and advertising materials. They also serve as a unifying element for the numerous fonts, colours, and design options used in all other corporate marketing materials. The goal of the thesis is to visualise the associated, comparable elements that previously belonged in the current logos, which will aid the designer in creating a matching, distinctive logo for a firm. It will also be useful for the customers of the logo to acquire accurate information about whether the logo was created as a master work or whether it was copied by any other party. designed as a ma—s—te—r —pi—ec—e—o—r—it—i—s —co—p—ie—d—by any other logos.

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A consumer's ability to accurately identify a certain item or service based only on its logo, tagline, packaging, or marketing campaign is known as logo recognition.

Researchers have used string-matching techniques [4-6], template matching [7], combined measure [8], algebraic and differential invariants [1], positive and negative form features [2], Zernike moments [3], and interactive feedback [9] to work on detecting logos. We may build and develop a system for detecting logos of various corporations and organisations by using methods previously utilised for face detection, identification, and fingerprint detection.

Previously, a car logo could be recognised using SIFT characteristics [13] [14].

In this study, SURF characteristics are used to offer a technique of logo recognition. SURF: "Speeded Up Robust Features" is a functioning interest point detector and descriptor that is scale- and rotation-invariant.

A mix of innovative description, matching, and detection stages are produced by SURF. It is shown in experimental findings [16] on images taken in the context of a real-world object recognition application and on a standard evaluation set. Both exhibit SURF's outstanding performance. Because of this, SURF characteristics are used to identify logos.

This study uses a kNN search tree to find the closest neighbours of the matched characteristics in order to identify a logo. It was utilised in facial recognition previously [17]. A straightforward algorithm called kNN categorises new instances based on a similarity metric after storing all of the existing data (e.g., distance functions). Statistical estimation and pattern recognition both require kNN [18].

2. SURF FEATURES AND KNN SEARCH TREE

SURF properties are taken into account in our suggested approach for recognising logos. Understanding what a feature is, how features are categorised, and which characteristics are deemed SURF features are all necessary for understanding SURF features. Understanding how SURF characteristics may be recognised after understanding the principles behind them is crucial to comprehending this logo recognition method.

The distance between two closest neighbours of the features is determined using a kNN search tree in this manner.

2.1 SURF (Speeded Up Robust Features)

SURF is a performing scale and rotation-invariant interest point detector and descriptor which outperforms repeatability, distinctiveness and robustness, yet can be computed and compared much faster.

It is accomplished by

- using integral images in image convolutions

- enhancing the effectiveness of the best existing detectors and descriptors (using a distribution-based detector and a Hessian matrix-based measure for the detector)

- Reducing this approach to its bare minimum

2.2 Procedure of SURF Features Detection

The detectSURFFeatures function, which employs the Speeded-Up Robust Features (SURF) technique to locate blob features, is used to find SURF features.

2.3 kNN (k-nearest neighbor) search using a kd-tree

A KDTreeSearcher object depicts a kNN (k-closest neighbour) search using a kd-tree. KDTreeSearcher model objects hold results of a nearest neighbours search using the Kd-tree algorithm. The data utilised, the distance metric and parameters, and the maximum number of data points in each leaf node are all saved by search objects. Sparse input data cannot be used to build this object. When compared to the ExhaustiveSearcher object, this object often performs better for lower dimensions (10 or less) and worse for bigger dimensions.

2.4 Limitation of kNN search function

Two closest neighbours in the dataset are discovered for each feature in the picture, and the distance to each neighbour is calculated using the kNNSearch function. Even if none of the characteristics are a close match, the kNNSearch method nonetheless returns the closest neighbours [11].

3. PROPOSED METHOD

In this work of ours, a dataset of logo images is used, and from the images of the logos, feature points are discovered and shown. By initialising a KDTreeSearcherObject, all of the image's features from the dataset are integrated into a feature dataset. A query picture is one that has the item to be identified loaded into it, and the object is chosen by defining a bounding box that encloses the object. The query image's feature points are identified and shown. Two closest neighbours are located in the dataset for each feature in the query picture, and the distance to each neighbour is calculated. Even if none of the characteristics are a close match, the kNNSearch function is utilised to yield the closest neighbours. To exclude the poor matches, a ratio of the distances between the two nearest neighbours is calculated. As a result, the whole procedure is broken down into two portions that are each detailed in depth, step by step, in the Proposed Algorithm section, and then visually represented by a flow chart.

Step1: Assembling the database of photographs for the search The collection of reference photographs is seen, each of which has a unique logo. To capture obscured or concealed regions, this collection might comprise many perspectives of the same item.

Step 2: Finding the feature points in a series of images The first image's feature points are identified and shown. Utilizing local characteristics serves two objectives. The quantity of data that has to be kept and evaluated is decreased as a result of making the search process more resistant to changes in size and orientation.

Step 3: Setting up a feature dataset

A ma-trix is created by adding all of the attributes from each picture together. The Statistics ToolboxTM's KDTreeSearcher object is initialised using this matrix. This object enables quick closest neighbour searches for high-dimensional data. In this situation, an SURF descriptor's closest neighbour might be another viewpoint of the same location.

Step 4: Picking the query image

The logo is chosen by defining a bounding box that encloses the item after loading a picture that includes the logo.

Step 5: Finding feature points in the requested picture Feature points in the requested picture are found and shown.

Step 6: Searching the image's closest neighbours

Two closest neighbours are located in the dataset for each feature in the query picture, and the distance between each neighbour is calculated. Even if none of the characteristics are a close match, the kNNSearch method returns the closest neighbours. A ratio of the two nearest neighbour distances is utilised to discard such poor matches. More information on this method is provided in [11]. The number of features from each picture that matched are tallied using histc. Each pair of indices that corresponds to a picture in the index intervals below makes up an index interval. Every picture in the collection is compared to the query image to determine how closely it matches. Each picture below is scaled according to the quantity of matching characteristics. It is shown that the desk-containing picture is still regarded as a good match. The next step eliminates it as an anomaly.

Step 7: Distance tests are used to get rid of outliers.

The dataset does not have any features that match several of the SURF features found in the query picture. It is crucial to exclude closest neighbour matches that are distant from their query characteristic in order to avoid false matches. When comparing the distances between the first and second closest neighbours, it is possible to identify the poorly matched characteristics. The match is disqualified if the distances are comparable as determined by their ratio [1]. ignore matches that are far apart are also prohibited [12].

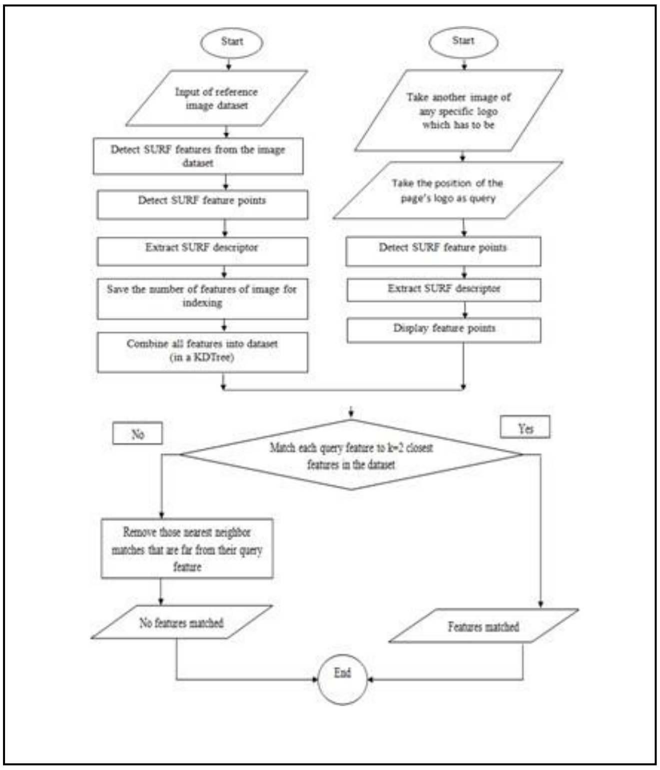


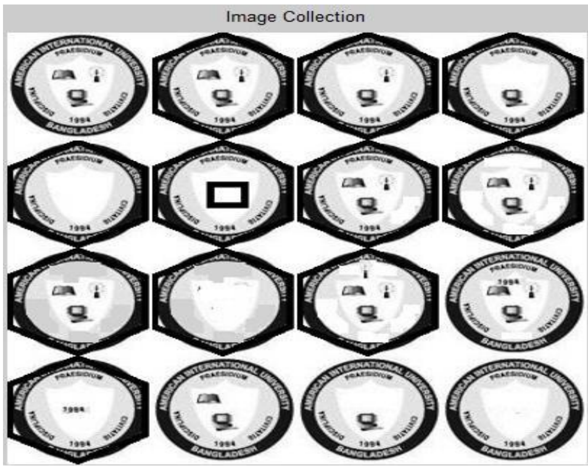
Fig -1: shows the flow chart of our proposed method description

4. EXPERIMENTAL RESULTS AND EVALUATION

Matlab is used to carry out this task. Here are some of the findings. This experiment makes use of many datasets. To demonstrate how this experiment was genuinely conducted, just one dataset from these sources is provided.

This implementation starts with a selection of AIUB institution logo pictures, all of which include both the original institute logo and an altered version of the original copy to the left of them. At the conclusion of this trial, the original AIUB logo is effectively identified. Some elements from the original edition are missing or have been replaced in the altered versions. In Table 1, it is shown. The original logo from Table 1 is positioned in the first row, furthest to the left. It is apparent that the other photos on the left are altered versions of the original logo that include other elements that are missing from the original image. One or more elements are missing from the altered copies of the original picture, or there may be more than one element that was absent from the original copy.

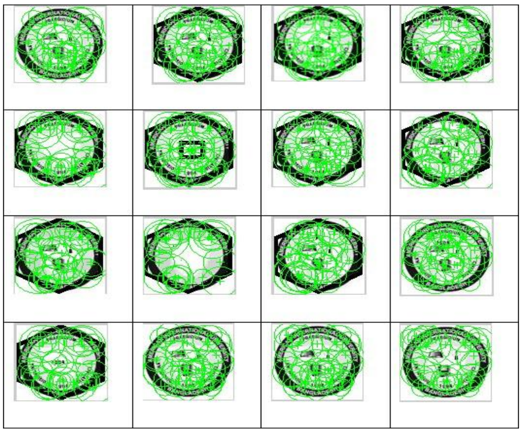
Table -1: REFERENCE IMAGE DATASET I



Same logo modified in Table 1 by:

- ✓ Removal of one, two, or more elements from the original copy of the reference picture.
- ✓ The addition of a square shape within the logo, a hexagon outside the logo's rounded border, and the copying and insertion of a logo component.
- ✓ The identical logo has its components removed and a hexagonal form added outside of its circular border.
- ✓ Strongest SURF feature points of each picture collection are found using the suggested approach after collecting the reference image dataset, as shown in Table 2.

Table -2: SURF OF THE REFERENCE IMAGES



A matrix is created by combining all of the attributes for each picture in Table 2. In order to create an SURF feature dataset, this matrix is utilised to establish a KDTreeSearcher object from the Statistics ToolboxTM. This object enables quick searches for high-dimensional data's closest neighbours.

The location of the logo's original picture is then captured in an image. A rectangular box, as illustrated in Fig. 2, is used to specify the location where the picture contains the logo.

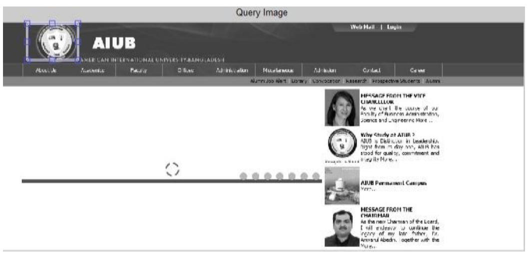


Fig -2: AIUB webpage containing AIUB logo at the left corner of the image defined by a square

Fig. 3 is regarded as a search picture. Strongest SURF feature points from the question picture are found using the same method as for the reference image, as illustrated in Fig 3.

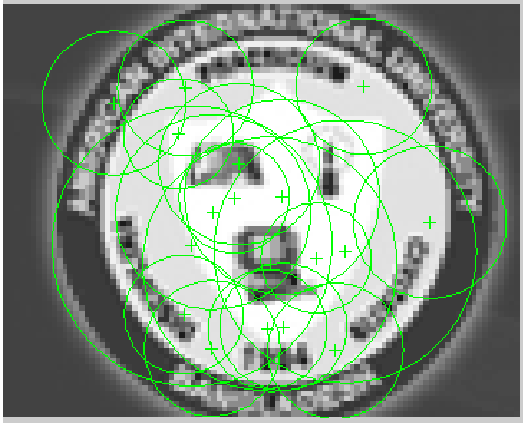


Fig -3: AIUB webpage containing AIUB logo at the left corner of the image defined by a square

The query image's strongest SURF feature points are found. For every of the characteristics in the query picture, the kNN search algorithm is used to locate the two closest neighbours in the dataset. Each neighbor's distance is calculated. The number of characteristics that matched from each image in Table 2 is tallied using the Matlab function histc (which stands for Histogram Count). Each pair of indices in the index intervals below makes up an index interval that is shown in Fig. 4 and corresponds to a picture.

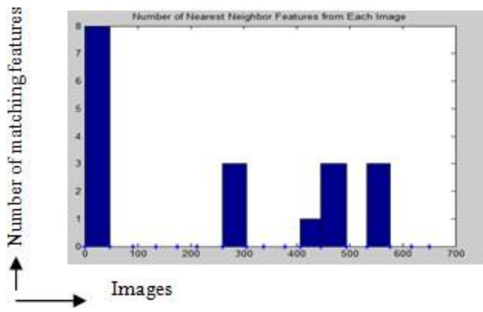
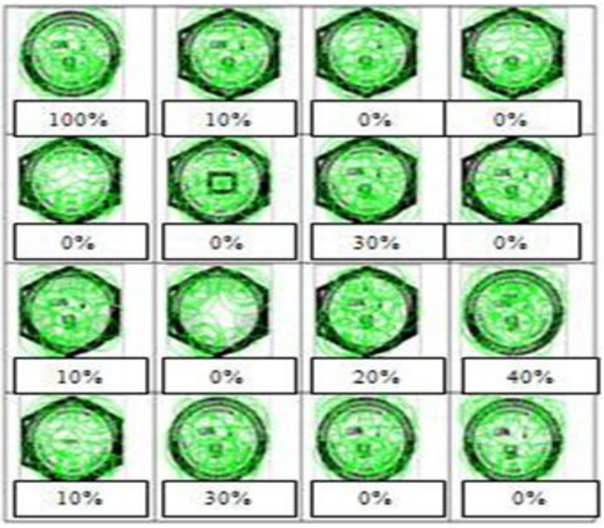


Fig -4: The number of features is counted that matched from

The proportion of each picture in the collection that matches the search image in Table 3 helps to illustrate the strength. From Fig. 4 and Table 3, it is clear if the query picture has the features or how much of it resembles the stored feature dataset from Table 2.The proportion of each picture in the collection that matches the search image in Table 3 helps to illustrate the strength. From Fig. 4 and Table 3, it is clear if the query picture has the features or how much of it resembles the stored feature dataset from Table 2.

Table -3: PERCENTAGE OF MATCHING FEATURES OF THE QUERY IMAGE TO THE REFERENCE IMAGE DATASET



Even if none of the characteristics are a close match, the kNNSearch function is used to get the closest neighbours with k=2.

Nearest neighbor distance ratio means:

1) Distances between the descriptor in one picture and its first and second-closest neighbours in the second image

are calculated.

d1 = d (desc1_img1, descA_img2); d2 = d (desc1_img1, descB_img2).

2) Distance ratio calculation R = d1/d2. Match is probably excellent if R 0.6. It is done because, regardless of how awful the second picture is, the "nearest" descriptor will be obtained from it due to ratio checking. To avoid the fractional section, ratios are shown by multiplying by 100.

A ratio of the two nearest neighbour distances is utilised to discard such poor matches. By comparing the distances between the first and second closest neighbours, the poorly matched characteristics are discovered. The match is disqualified if the distances, as determined by their ratio, are comparable. Furthermore, far-off matching features are not taken into account. The final result is shown in Fig. 5 by displaying the biggest icon for the matching characteristics and demonstrating how the logo is recognised if the query picture is already in the image collection in Table 1.

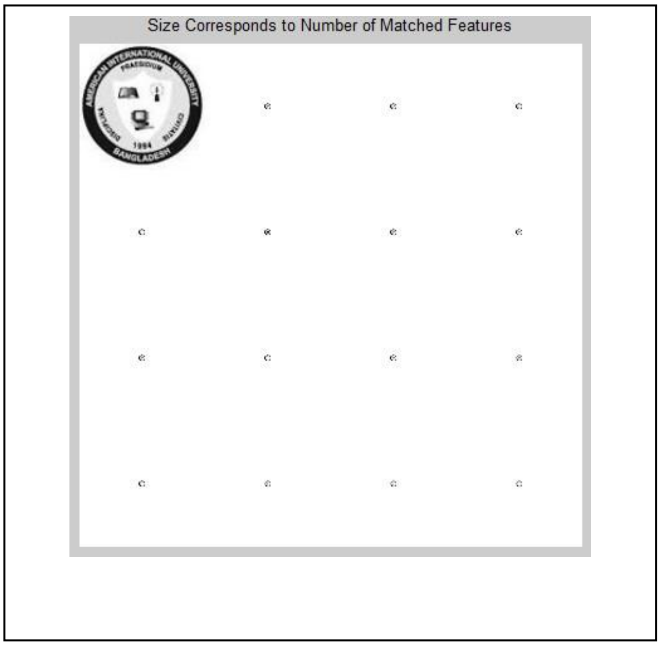


Fig -5: The matched nearest neighbors that are far from their query feature are removed

This result demonstrates that the reference image dataset's first logo picture from Table 1 can be identified as the AIUB logo.

For the purpose of evaluating our performances, the implemented suggested approach is used on a new example using the identical processes as before.

Fig -6: Collection of reference images dataset II

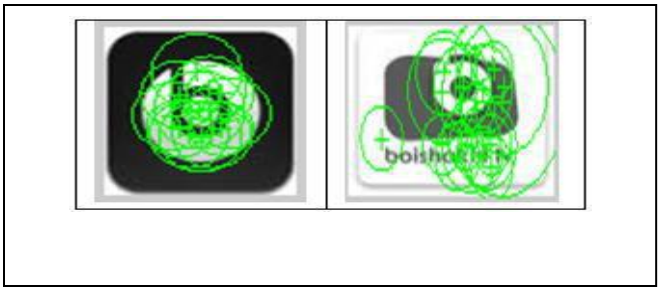


Fig -7: Detection of feature points from Fig 6

The results of this suggested approach are tested using the logos of the Beats music company and Baisakhi TV because of how similar they both seem to be. To compare, find the aspects that are comparable. Any logo that is compared to other logos may have certain design elements changed to improve the brand's quality and value and give the logo a grade. Two logos (Beats , Baisakhi TV) are used as a reference image collection in Fig. 6. The reference photos' characteristics are identified. Fig. 7 displays the reference picture collection's feature points.

Fig -8: Choose query image from Beats's website

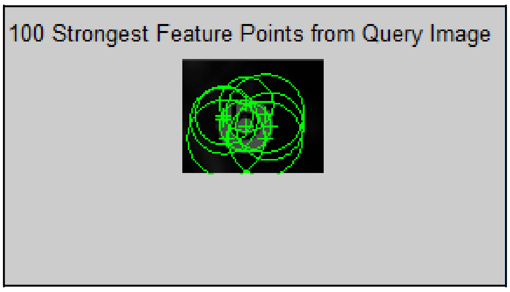


Fig -9: Detection of feature points from query image

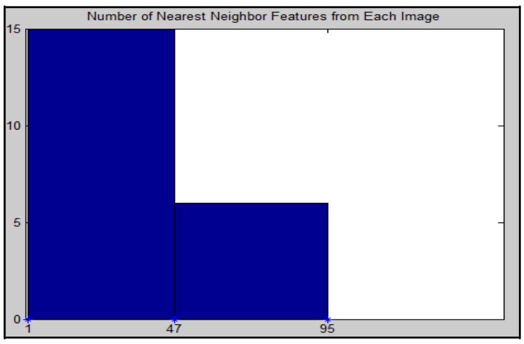


Fig -10: Matched numbers of features

The Beats logo is derived from the Beats website, which is used to contrast the picture collection. The Beats logo is chosen from the website by defining a bounding box around the logo in Fig. 8 and treating it as the query image. The query image's feature points are identified and shown in Fig 9 as features. Using histc, Fig. 10 counts the number of characteristics from each picture that matched. Each pair of indices in the index intervals in Fig. 11 together form an index interval that corresponds to one picture.

Fig -11: Logo completely matched to the stored features after eliminating false matches

5. DISCUSSION

IOnly grayscale photographs are taken into account in this study. Few logo pictures are included in the reference image collection used in our investigation. In a big reference picture, the proportion of matching features may be improved.

In order to assess the degree of uniformity in the use of this logo recognition technology, logos are compared. It is determined by the degree of similarity between the collection of logos, or roughly the proportion of correctly matching a certain logo with another group of logos. Furthermore, if we have a huge reference picture collection, each organization's logo may be identified without a doubt. Better recognition results would arise from more training examples. Only SURF characteristics are taken into consideration for the proposed technique at this time; hereafter, more features may be included. In this paper, the distance is determined using the kNN searching algorithm; other algorithms may be employed, and a comparison of such algorithms may be conducted in future work.

5. CONCLUSIONS

In this work a new technique of logo recognition is provid-ed. Our technique can understand the similarities among the set of logos clearly. Only the SURF features are considered in this work which gives a clear concept that how can a logo be recognized. It measures the matching percentage of a specific logo based on these SURF features with other set of logos suc-cessfully. It will be able to assist the designers to create a new concept for logo designing by this technique. It also can be helpful for logo evaluation and maintaining the standard level of logo designing.

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