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Reverse Image-Based Search Engine for IP Trademarks**

Abeer S. Al-Humaimeedy [1,*], Abeer S. Al-Hammad [1], and Ghada Al-Hudhud [1]
[1] *College of Computer and Information Sciences, King Saud University, Riyadh, Saudi Arabia.*

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ABSTRACT

In a world full of many ideas turning to various kinds of products which need to be protected and here comes the importance of intellectual property rights. The intellectual property has many types however, our interest is in trademarks. The Madrid system is a system which used by a group of countries that were in the Madrid level of agreement so they authorize it and they that has the agreement with them to use but the problem with it that it is a text-based system because of that we proposed a reverse image engine and that is because the reverse search image is better than the text-based system.

1 Introduction

These days there are a lot of ideas that turn to various kinds of products. Therefore, these products need to be protected and here comes the importance of the intellectual property (IP) [1] which led to intellectual property rights (IPRs). Based on the intellectual property statistics that have been reported by World Intellectual Property Organization (WIPO) [2] which is an international forum for services, policy information, and collaboration on intellectual property (IP) [2]. Their IP statistics in 2018 [3] shows that the applications for patents and trademarks have been growing for nine years. Worldwide, innovators filed 3.3 million applications for patents in 2018. A total of 14.3 million worldwide filing activity of trademark. Worldwide industrial design filing activity reached 1.3 million, while utility model applications amounted to 2.1 million [4].

* Corresponding author.
**The ICCMIT'20 program committee effort is highly acknowledged for reviewing this paper.
Email addresses: abeer@ksu.edu.sa, 438203016@student.ksu.edu.sa, galhudhud@ksu.edu.sa
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The Madrid system [5] is a system which used by a group of countries that were in the Madrid level of agreement so they authorize it and they that has the agreement with them to use but the problem with it that it is a text-based system because of that we proposed a reverse image engine and that is because the reverse search image is better than the text-based system.

1.1 Content-Based Image Retrieval (CBIR) System

CBIR is considered as a computer vision application of the image retrieval problem. The "Content" term might be referring to the feature, as has been mentioned before, for example, the shape, color, texture, etc. [6]. The meaning of the Content-based is searching among the images and that is done by using the similarities between the images, as opposed to the usage of the tags, associated keywords, or descriptions [7]. CBIR system's basic block diagram is as shown in Figure 1 [6].

The success of the CBIR system depending on the usage of the image features. The visual features used in CBIR systems are such as texture, shape, color and the objects spatial location in the images. There are

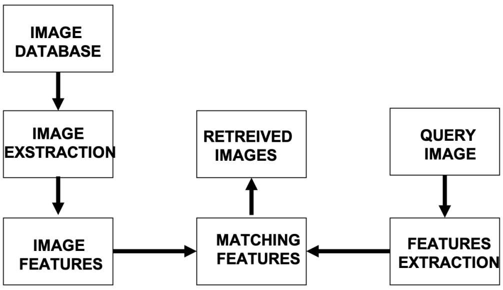

Figure 1. CBIR system's basic block diagram [6]

some of the things that the CBIR system performance depends on which are the methods that have been adopted for the extraction of the feature, the features types, also the features nature [8]. In the image retrieval field, several techniques have been developed such as Gray Level Co-Occurrence Matrix, Relevance Feedback, Gabor Filter Technique, Support Vector Machine, etc. [6]. In the following part, we will discuss some of the CBIR techniques in color, texture, and shape.

1.1.1 Color-based CBIR Techniques

Color is considered one of the visual features that are most descriptive and is commonly used in CBIR [6]. The conventional color retrieval methods contain color histograms [9], Weighted average [6, 10].

1.1.2 Texture-based CBIR Techniques

Like the color, the texture is as well considered to be an important low-level feature that for an object surface property and their connection to the surrounding environment, the texture describes it. Texture is commonly used for applications in image search and retrieval [6]. The popular descriptors of the texture are Gabor-filters [6, 11], Wavelet Transform [12], co-occurrence matrices [13] and Gabor wavelets [14], Tamura features [6, 15].

1.1.3 Shape-based CBIR Techniques

One of the basic features is the shape which is used to describe the content of the image. Description of the shape or representation in object recognition and classification is an important issue [6]. Shape characteristics are defined and represented by two classes namely Region-based methods and boundary-based [16] which also named as Methods of Contour based [6]. Several techniques, including chain code, polygonal approximations [17], also curvature, moment descriptors and Fourier descriptors [17], etc. For the shape feature, various applications have been proposed and used [6].

1.2 The Most Famous Reverse-image Search Engine

CBIR has been used to search for general images and in Table 1 we can see an analysis of the most famous reverse-image search engine [18]. Also, it has been used to search in other fields, for example, medical images such as [19]. However in the rest of this chapter we will talk about the endeavors in searching the IP images.

After discussing the most famous reverse - image search engine. [18] In the rest of this chapter we will concentrate in research engine in IP. We will discuss some of them.

Table 1. Analysis of the most famous reverse-image search engine [18]

	Google	Tin Eye	Yandex
Developer	Google Inc.	Idee Inc.	Yandex
URL	https://image.google.com	https://www.tineye.com	https://www.yandex.com
Accessibility	Free	Paid, Limited free for non commercial use	Free
Input options	Paste URL, Upload image	Paste URL, Upload Image, Drag & Drop	Paste URL, Upload image
Retrieval Speed (Seconds)	0.93	0.615	0.912
Relevant Results	285	10	11
No. of Results	304	12	12
Index Size	11.94 Billion	9.14 Billion	5.6 Billion
Additional Features	Best Guess term, Visually similar images	Best Match, Most Changed, Biggest Image,	Similar Images

1.3 IP Search Engines

1.3.1 WIPO

We will start with WIPO trademark search engine [20]. It is relay on Madrid system [5] which is text-based system. Figure 2 shows the result of testing the "dunkin donuts logo" and we can see it retrieved the similar once.

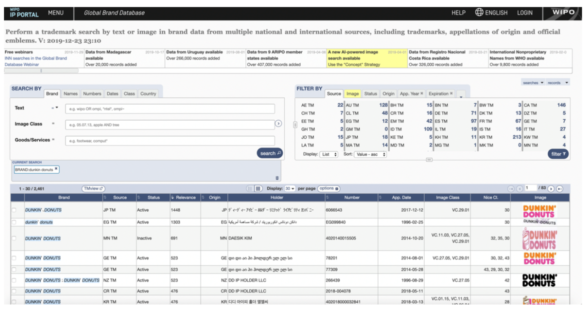

Figure 2. WIPO retired result [20]

1.3.2 Trademark Engine

Trademark Engine [21] focuses on offering a quick, easy and economical approach for small business owners to protect their brand and company around the world [21].

Figure 3 shows the result of testing the "dunkin donuts logo" and we can see it retrieved the similar once [22].

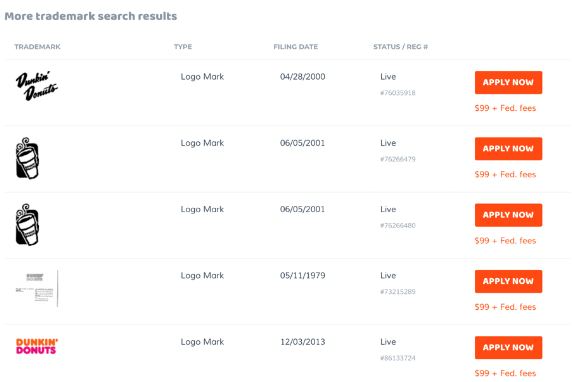

Figure 3. The Trademark Engine retired result [23]

1.3.3 TrademarkVision

For this search engine which is the TrademarkVision they concentrate on brand protection via computer vision and technology for machine learning [24] they work with a government client Working with government clients across the world to make brand protection possible for thousands of users every day, including the European Union, the United Kingdom, France and Australia [24] and based on their web page they mentioned that the intellectual property office of the european union (EUIPO) is actively exploring ways to improve the industry because of that they are now providing visual search to the world with the aid of TrademarkVision for trademarks submitted through eSearch and TMview in the EU, UK and France [25]. Therefore, we tested below the eSearch plus [26] and in Figure 4 the result of uploading an image of dunkin donuts logo and another testing with nike logo in Figure 5.

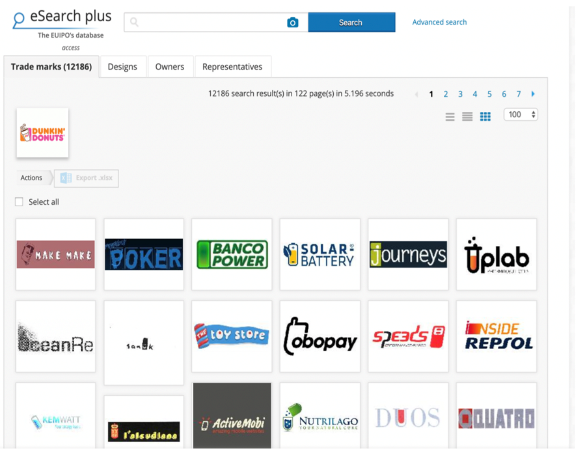

Figure 4. The result of the search engine with dunkin donuts logo [26]

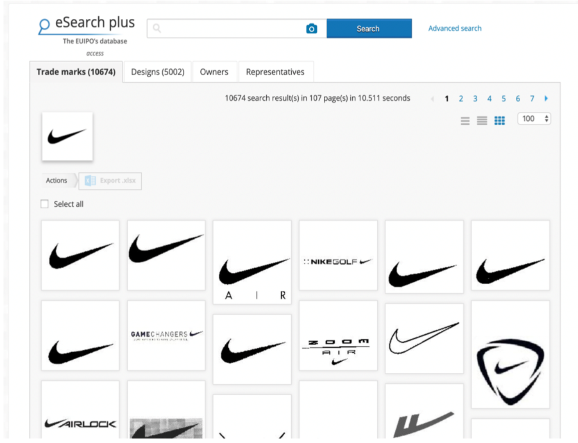

Figure 5. The result of the search engine with nike logo [26]

1.3.4 Australian Trade Mark Search

For this search engine is also one of TrademarkVision project. In collaboration with IP Australia (IPA), they are reconstructing all IP Rights search systems in Australia with the most innovative technology including their new visual search. they launched Australian Trade Mark Search to the world on February 10th 2017 and are continuing to work on exciting projects [27]. Therefore, we tested below the Australian Trade Mark Search [28] and in Figure 6 the result of uploading an imageof dunkin donuts logo and another testing with nike logo in Figure 7 [28]. Table 2 shows a comparison between the above IP search engines.

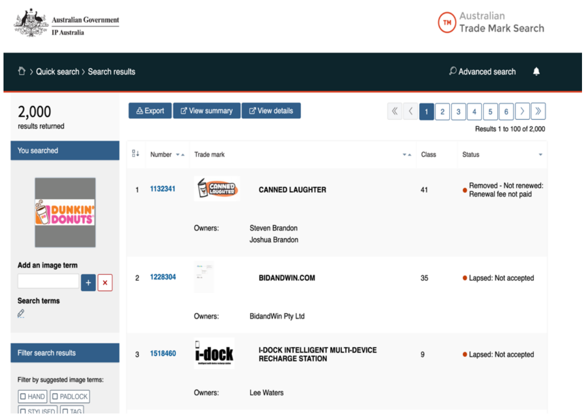

Figure 6. The result of the search engine with dunkin donuts logo [28]

1.3.5 IP Image Retrieval

In the following part [29], we will introduce examples of the first systems of trademark image retrieval (TIR) that are TRADEMARK [30], STAR [31] and ARTISAN [32].

TRADEMARK [30]. The system uses vectors of graphic descriptors derived from features of the

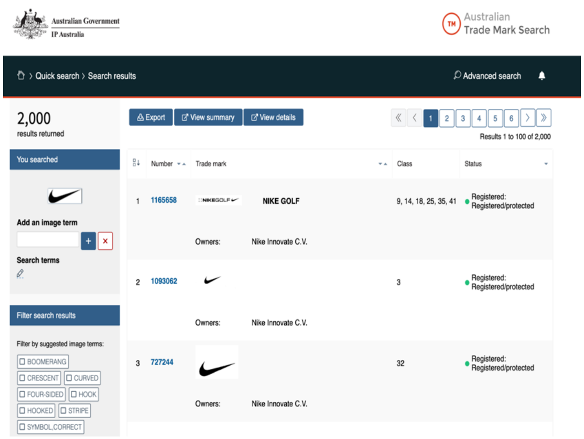

Figure 7. the result of the search engine with nike logo. [28]

Table 2. shows a comparison between the previous IP search engines.

Search engine	Text-based / Image-based	Relay on	Country	Result of retrieved trademarks
WIPO [5]	Text-based	Madrid system	International	dunkin donuts logo/ 2461
Trademark Engine [23]	Text-based	United States Patent and Trademark Office	United States	dunkin donuts logo/10
eSearch plus [26]	Image-based	Trademark Vision	Europe	nike logo / 10674 dunkin donuts logo/12186
Australian Trade Mark Search [28]	Image-based /Text-based	Trademark Vision	Australia	nike logo /2000 dunkin donuts logo/2000

shape [29]. The system has no aim to segment images into component regions-an an image analysis was conducted at the whole image level and similarity matching was achieved [33]. Queries can either be provided as examples of similar images, or as hand-drawn sketches [33]. The system was evaluated utilizing a series of whole-image and sketch queries that were placed in a database of 2000 graphic symbols. Within the first 10 images, the target image was retrieved, which has been shown in 100% of whole-image queries and 95% of sketch queries. whole images limit the ability of the system to identify images of similar structure or components of similar shape [33].

STAR [31]. This system from Singapore University, utilizes a multidimensional process that involves structure, shape, and semantics [29]. Although it focuses heavily on the key stages of manual intervention [33]. In addition to a collection of shape-based descriptors, along with gray-level projection, Fourier descriptors, and moment invariants, the system utilizes a framework of the traditional CBIR [29]. It can handle text, device-and-word or device-only marks although this report only covers its image handling capabilities [33]. The system works on the assumption that it is possible to view trademark images as a whole and as a set of individual components [33]. STAR evaluation on a pilot database of 500 trademarks provided results that were found satisfactory by members of the trademark office [33] some of the system limitations are lack of partial image matching facilities or weight variance given to different aspects of image similarity in the light of user feedback. While inverted files are used to enhance word mark search performance, image matching tends to be performed sequentially [33].

ARTISAN [32]. This system from the University of Northumbria, together with the United Kingdom's patent office, applies shape-based feature descriptors but adds principles of Gestalt-based in order to retrieve Abstract designs of the trademark [29]. The scope of ARTISAN is intentionally more limited than that of STAR: it does not attempt to capture textual references within a trademark, or any form of semantic image similarity, designed solely for use with device-only trademarks consisting of abstract geometric designs [33]. Its methodology for grouping image components into regions or families that are perceptually important [33]. The image extracts two sets of form elements, a boundary shape vector and a family characteristics vector [33]. Analysis of retrieval failure cases: Lack of recognition of suggested shape features, Inappropriate segmentation of queries or stored images, particularly when noise is present, Failure to identify perceived image similarity alone, Miscellaneous issues, including the inability to cope with textured regions, inconsistent handling of borders surrounding query images and ineffective grouping into families of components [33]. Table 3 shows a comparison between the three first systems of trademark image retrieval (TIR).

1.4 Some of The Related Work in IP and Trademark

In the paper [34], they established an approach in the automated extraction of concept information defining the content of patent images to help searchers during patent retrieval tasks. The suggested approach is based on a supervised framework for machine learning, based on techniques for the analysis of image and text. The suggested approach tackles the second challenge and considers a predefined set of concepts to utilize image analysis and machine learning algorithms in the patent domain. Precisely, they drive low-level textual and visual features (developed particularly to handle complex drawings) from images of patents after that they used a framework of a supervised machine learning recognized with Support Vector Machines (SVM). Next, they utilized manually data that have been an-

Table 3. First Systems of Trademark Image Retrieval (TIR) comparison

TIR system	Authors/year	Approach	Image analysis	Submitted Query	Testing data set	Evaluation of the retrieving	Limitation
TRADEMARK [30].	Kato, 1992 [33]	CBIR [33]	Whole image [33]	Similar images, or as hand-drawn sketches. [33]	Database of 2000 graphic symbols [33]	Whole-image queries 100% Sketch queries 95% [33]	Whole images limit the ability of the system to identify images of similar structure or components of similar shape [33]
STAR [31]	[31, 33]	The system uses a traditional CBIR framework along with a collection of shape-based descriptors including descriptors for Fourier, gray-level projection, and invariants of moment [29],	Whole image or as a series of individual components [33]	Text, device-and-word or device-only marks [33]	A pilot database of 500 trademarks [33]	Representatives of the trademark office were found satisfactory [33]	Lack of partial image matching facilities or weight variance given to different aspects of image similarity in the light of user feedback [33]
ARTISAN [32]	Eakins et al., 1998 [33]	CBIR [33]	Whole image, Regions within the image perceptually significant, Individual components among each region [33]	Device-only trademarks consisting of abstract geometric designs. [33]	A sample of the UK Trademarks Register just over 10,000 images [33]	Results of human and machine **matching compared** [33]	Failure cases includes • Lack of recognition of suggested shape features, [33] • **Inappropriate** segmentation [33] • **Failure to** identify perceived image similarity alone [33] • **Inability** to cope with textured regions, • **Inconsistent** handling of borders and ineffective grouping into families of components [33]

notated in order to train a detector for every concept. In the visual feature vectors. They use the algorithm that has been introduced in [33] to extract the Adaptive Hierarchical Density Histograms (AHDH). Finally, in the evaluation phase, they chose a dataset from the footwear domain to test this approach and trained concept detectors with different combinations of features. The experimental results show that the combination of textual and visual patent image information shows the best performance that outperforms the results of both single visual and textual features. The result of this experiment gives with first evidence that concept detection can be used in the patent image retrieval domain and can be incorporated into existing applications in the real world to help to search for patents. In the Figure1. 8 below it shows the result of their system for the "ski-boots" via the hybrid approach [34].

On the other hand, in this paper [29] their concerning was about the process of registering a new

Figure 8. The result of their system for the "ski-boots" via the hybrid approach

trademark image that should be distinguished from all registered trademarks in the application and how it is impossible for humans to make these distinctions visually because of the number of trademark registration applications and the size of the database which holds registered trademarks. Thus, technological tools are crucial to this mission. their goal was to develop a TIR method that is helpful for an IP office, a closed set task in which each image includes a trademark, and it is necessary not only to identify identical trademarks but also similar logos to avoid the registration of new trademarks that are very close to those already in existence.

In the study [29], they used a pre-trained, publicly accessible VGG19 (CNN) trained on the database of ImageNet. Their method based on deep CNNs. They adapted the VGG19 for the task of the trademark image retrieval (TIR) by using two different databases to fine-tune the network. Using these databases, two VGG19 versions have been obtained. For the first version was VGG19v and the training process of it has been done with an organized database with images of trademarks via visual similarities. For the second version was VGG19c and the training process of it has been done by utilizing trademarks organized utilizing the understanding of conceptual similarities. The VGG19v database was developed using trademarks that have been downloaded from the WEB and arranged by the IP office experts on the basis of visual similarity. The VGG19c database was developed using U.S. Patent and Trademark Office trademark images and arranged according to the conceptual protocol of Vienna. The TIR was evaluated using the normalized average rank for a test collection containing 922,926 trademark images from the METU database.

For VGG19v, VGG19c, they calculated the normalized average ranks, and for both networks combination. In conclusion, they claim that in the METU database, their approach obtained significantly better results than those previously published. In Figure 9 is an example of retrieved images in a query. The first one is considered to be the query image and the rest considered to be the first images that have been retrieved via their method with their position in the computed ranking. They mentioned that the images with the green letters are same class images of the query image [29].

Now we will discuss some of studied that used another approach in order to retrieve the trademark. As we see in this paper [35], their contribution was in retrieving the image but instead of using the CBIR they used the sift algorithm and the theory of bag of view words model in order to obtain trademark image matching. An image retrieval system for the trademark image is constructed based on this image matching algorithm. The SIFT algorithm is known to be the most robust feature-based matching algorithm, benefiting from scale-invariance and rotation-invariance advantages. But it also suffers from complex computation,

Figure 9. System output [29]

too many feature points, and unnecessary matching time, although BOVW (Bag-Of-Visual-Words) model can effectively solve these problems. In their study, they collected through the network a large number of trademark images and arranges them into a library of an image. In order to reduce computational complexity, image features are extracted with SIFT and clustered. Next images are quantified utilizing BOVW to get each image's vectors to construct an image matching vector library. And then, it estimates the maximum coefficient of dissimilarity between the vector of the provided image and the vector of the image in the library with the highest method of coefficient of dissimilarity when comparing the image of the trademark and finally achieves the results of matching the image. They used the C++ language to build the image retrieval system. As a conclusion of this paper confirms that, under certain conditions, the program can accurately identify the same trademark as the original image. Figure 10 below shows the searching result of their system and based on them that their system can accurately find all similar images to the target [35].

Figure 10. Searching result of the system [35]

1.4.1 The Previous Related Work Comparison

From the previous study of the papers in this field, in our system, we decided to go with applying our system in CBIR because our interest is in retrieving the trademark images, therefore, CBIR would be an ideal application area for this process for some of the reasons [32]:

- The images searching process that is done by Trademark examiners, they do need to do it by primitive features along with particular shape [32].
- Several national trademark registries have huge images collections in electronic form. The maintaining task of these images with manual indexes has become increasingly onerous [32].
- The retrieval process of trademark images must be accurate and reliable as the images could be commercially significant [32].
- There is little knowledge in many application areas about why users want to retrieve images or how they determine the importance of a retrieved image to their query. In the field of trademarks, on the other hand, successful conditions for retrieval are usually clearly defined. Consequently, the objective measurement of the effectiveness of retrieval is relatively straightforward [32].

2 System Analysis

As a machine learning project, we follow the life cycle of the data analytic life cycle which consists of discovery, data preparation, model planning, model building, communicate results, and operationalize. As shown in Figure 11 and in the following parts we will explain each step briefly as been explained in [38, 39]. We would like to mention that in the rest of this report, we use image as we use trademark.

2.1 Data Analytic Life Cycle

2.1.1 Discovery

For this phase, we can briefly explain it as that the team of data science needs to learn and analyze the problem in this process, build background and understanding, and learn about the data sources required and accessible for the project.

2.1.2 Data Preparation

Data Analytics Lifecycle's second phase includes data preparation, which involves the following steps discover, pre-process, and condition data prior to the analysis and modeling.

2.1.3 Model Planning

In the third phase, the data science team selects candidate models in order to apply it to data for clustering, classifying, or identifying data relationships depending on the project's goal.

2.1.4 Model Building

In this fourth phase, the team of data science will build data sets for the purposes of training, testing, and production.

2.1.5 Communicate Results

During Phase 5, the team discusses how best to communicate the observations and conclusions to the different team members and stakeholders, taking into account assumptions, cautions, and any results limitations.

2.1.6 Operationalize

In the last phase, the team is more generally explaining the project's benefits and setting up a pilot project to deploy the work in a controlled manner before extending the work to a full organization or ecosystem of the client.

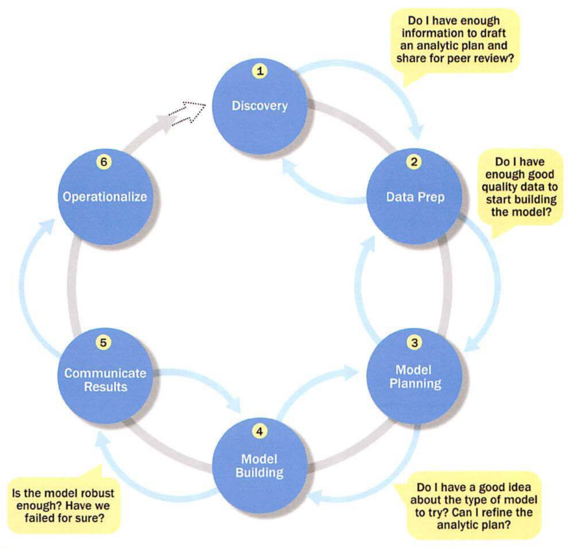

Figure 11. Data Analytics Lifecycle Overview [38]

After discussing the life cycle of the data analytics that we will follow, let's talk about our system. In the following of this report, we will explain how the discovery, data preparation and data modeling steps going to be applied in our system However, model building, communicate results, operationalize will be

Table 4. The previous related work comparison

Refences	**Text-based or image-based**	**Approach/Algorithm**	IP type	**Data set**	**Clustering / classification**
[34]	Combining visual and textual data [34]	Visual features: They use the algorithm that has been introduced in [33] to extract the Adaptive Hierarchical Density Histograms (AHDH) as visual feature vectors. [34] Textual features: Porter stemmer [36] and frequent stop words have been removed [34]	Patent image [34]	domain of Footwear [34]	Support Vector Machines (SVMs) classifier [37]
[29]	Image-based [29]	CNNs which are deep [29]	images of trademark [29]	The database VGG19v (images of trademarks have been downloaded from the WEB) [29] Database VGG19c (images of trademarks that have been used from Trademarks Office and the United States Patent) [29]	Classification [29]
[35]	Image-based [35]	algorithm of Sift, The visual-words-bag model [35]	images of trademark [35]	Trademarks whish have been collected via network [35]	Clustered [35]

covered in graduation project 2 (GP2). For that we will describe first our system description then moving to the steps.

2.2 System Description

Our system will be an image search. It is an intelligent system that will be based on the CBIR as we have been explained on a similar system in the introduction and background sections. Our system will allow the users to search for similar trademarks by uploading a trademark image that the user wants to search for its similarities among the approved trademarks. Also, the user can upload the URL of the trademark image. For that, this is basically the main features that our system will provide for the users. As has been mentioned now we will define how we manage to apply the data analytics lifecycle in our system.

2.2.1 Data Analytics Lifecycle in Our System

2.2.1.1 Discovery

The functional requirements are the user can search for a trademark image by entering the trademark image URL or by uploading it , the system will use the CBIR sub to retrieve similar trademark images and if there are similar trademark images the system will retrieve it and if not the system will display a message to till that there are no similar trademark images. The non-functional requirements are usability, availability, reliability, maintainability, probability.

2.2.1.2 Data Preparation

The data of the system has been provided by SAIP as XML files and it contains all the trademarks which have been approved.

2.2.1.3 Model Planning

As for our system, we will build it as a website for an image-based search engine. To model the convolutional neural networks and as brief definition of convolutional neural networks (CNN) convolutional neural networks are constructed to work with grid-structured inputs with strong spatial dependencies in grid sections. [40]

Neural Networks. The human nervous system consists of cells called neurons. The neurons are connected to one another via axons and dendrites, And the regions connecting the axons to the dendrites are called synapses. These associations are shown in Figure 12. In response to external stimuli, the strengths of synaptic connections often change. This alteration is how learning in living organisms takes place [40] and for artificial neural networks (ANN) were developed in a way that stimulates the nervous system of humans for machine learning tasks and that is done by treating the computational units which are located in a learning model in a way that is similar to the human neurons. This is clearly not a simple task, because today's fastest computer's computational power is a tiny fraction of a human brain's computational power [40] also, we would like to mention that in the rest of this report, we use neural networks as we use artificial neural networks.

In the ANN, the computational units are linked by weights, which play the same job in biological organisms as the strengths of synaptic connections. Per input that enters to a neuron is scaled by a weight that affects this unit's calculated function. The illustration of the architecture is in Figure 13 the ANN estimates an input function by propagating the determined values from the input neurons to the output neurons and using the weights to be the intermediate parameters and the learning happens by altering the weights Linking the neurons [40].

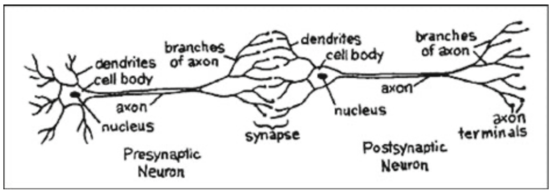

Figure 12. Biological neural network [40]

2.2.2 Convolutional Neural Networks (CNN)

Convolutional neural networks are constructed to work with grid-structured inputs with strong spatial dependencies in grid sections. A 2-dimensional image is the most obvious example of grid-structured data. This type of data also shows spatial dependencies, as there are often similar color values of the individual pixels in adjacent spatial locations in an image. An extra dimension captures the various colors, creating a 3-dimensional volume of input. Thus, the features in a convolutional neural network have spatial distance

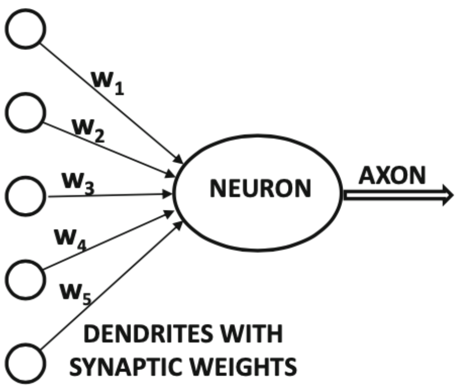

Figure 13. Artificial neural network [40]

based on dependencies among themselves. However, Certain kinds of sequential data such as text, time series, and sequences can also be considered as special grid-structured data cases with different types of adjacent object relationships. Although one can also use such networks for all kinds of temporal, spatial, and spatiotemporal data, the vast majority of applications of convolutional neural networks concentrate on image data [40].

In CNN, one of the significant defining of the CNN characteristic is an operation that reference, to as convolution. A convolution operation is a dot-product operation in the input volume between a grid-structured set of weights and similar grid-structured inputs from various spatial locations. This kind of operation is helpful for data that have a high level of spatial or different locality, like image data. Therefore, convolutional neural networks are classified as networks that use convolutional operation in at least one layer, although this operation is used in multiple layers by most convolutional neural networks [40].

Going back a little bit and of speaking of a historical perspective, we need to mention that convolutional neural networks were one of the deep learning's first success stories. Recent advances in training techniques have resulted in improved performance in other forms of architecture. Indeed, the eye-catching successes of some CNN architectures in post-2011 image classification contests led to a wider focus on the deep learning field [40]. We will suggest the data flow model in Figure 14.

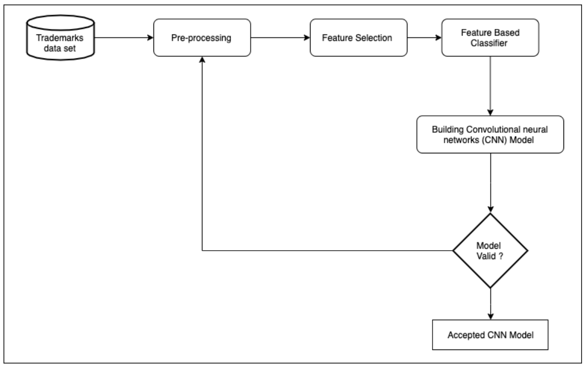

Figure 14. Model planning of CNN

User: Has a minimum technical background with an understanding of the trademark concept. Our user can search for a trademark image by entering the trademark image URL or uploading it to the system.

3 Conclusion

In conclusion for this report, we have discussed all of the terms and terminology that we need in our project. Along with reviewing the famous reverse-image search engines and the first systems of trademark image retrieval (TIR) and some of the related papers. Introducing our project with all the system analysis phases. The project approach is a reverse image search engine, it will be designed using a CBIR system with deep neural networks. This project will be implemented in the second semester of the 2020 year.

References

[1] Rami M Olwan. The history of international intellectual property and development. In *Intellectual Property and Development*, pages 35–98. Springer, 2012.

[2] W.I.P.O.,n.d. *Inside WIPO ,What is WIPO?* Available at: https://www.wipo.int/about-wipo/en/, Accessed 05 02 2020.

[3] W.I.P.O.,n.d. *Intellectual Property Statistics.* Available at: https://www.wipo.int/ipstats/en/#accordion_collapse_01, Accessed 05 02 2020.

[4] W.I.P.O.,n.d. *Facts and Figures.* Available at: https://www.wipo.int/edocs/infogdocs/en/ipfactsandfigures2018/, Accessed 05 02 2020.

[5] W. I. P. O., n.d. wipo | madrid, madrid the international trademark system. Available at: https://www.wipo.int/madrid/en/, Accessed 05 02 2020.

[6] Supreet Sidhu and Jyoti Saxena. Content based image retrieval a review. *International Journal Of Research In Computer Applications And Robotics*, 3(5):84–88, 2015.

[7] Hyun-Ho Han, Seuc-Ho Ryu, Gyoo-Soo Chae, and Sang-Hun Lee. Image retrieval using cbir including light position analysis. *Wireless Personal Communications*, 105(2):525–543, 2019.

[8] Ghanshyam Raghuwanshi and Vipin Tyagi. Impact of feature extraction techniques on a cbir system. In *International Conference on Advances in Computing and Data Sciences*, pages 338–348. Springer, 2019.

[9] Snehal Mahajan and Dharmaraj Patil. Image retrieval using contribution-based clustering algorithm with different feature extraction techniques. In *2014 Conference on IT in Business, Industry and Government (CSIBIG)*, pages 1–7. IEEE, 2014.

[10] Mushtaq Ali, Le Dong, Yan Liang, Zongyi Xu, Ling He, and Ning Feng. A color image retrieval system based on weighted average. In *2014 IEEE International Conference on Signal Processing, Communications and Computing (ICSPCC)*, pages 184–189. IEEE, 2014.

[11] S Mangijao Singh and K Hemachandran. Content-based image retrieval using color moment and gabor texture feature. *International Journal of Computer Science Issues (IJCSI)*, 9 (5):299, 2012.

[12] Manimala Singha and K Hemachandran. Content based image retrieval using color and texture. *Signal & Image Processing*, 3(1):39, 2012.

[13] S Sulochana and R Vidhya. Texture based image retrieval using framelet transform-gray level co-occurrence matrix (glcm). *International Journal of Advanced Research in Artificial Intelligence*, 2 (2):68–73, 2013.

[14] Nitin Jain and Dr SS Salankar. Color & texture feature extraction for content based image retrieval. *IOSR Journal of Electrical and Electronics Engineering (IOSR-JEEE) e-ISSN*, pages 2278–1676, 2014.

[15] Amandeep Khokher and Rajneesh Talwar. Content-based image retrieval: Feature extraction techniques and applications. In *International conference on recent advances and future trends in information technology (iRAFIT2012)*, pages 9–14, 2012.

[16] A Bhagyalakshmi and V Vijayachamundeeswan. A survey on content based image retrieval using various operators. In *Proceedings of IEEE International Conference on Computer Communication and Systems ICCCS14*, pages 018–023. IEEE, 2014.

[17] Chaudhari Reshma and AM Patil. Content based image retrieval using color and shape features. *International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering*, 1(5):386–392, 2012.

[18] AF Adrakatti, RS Wodeyar, and KR Mulla. Search by image: a novel approach to content based image retrieval system. *International Journal of Library Science*, 14(3):41–47, 2016.

[19] B Ramamurthy and KR Chandran. Content based image retrieval for medical images using canny edge detection algorithm. *International Journal of Computer Applications*, 17(6):32–37, 2011.

[20] Wipo ip portal. Available at: https://www3.wipo.int/branddb/en/, Accessed 2019 12 24.

[21] trademarkengine, n.d. *trademarkengine.* Available at: https://www.trademarkengine.com/free-trademark-search/trademark-search, Accessed 05 02 2020.

[22] trademarkengine, n.d. *About Trademark Engine.* Available at: https://www.trademarkengine.com/support/about, Accessed 05 02 2020.

[23] trademarkengine, n.d. *free trademark search.* Available at: https://www.trademarkengine.com/free-trademark-search/trademark-search, Accessed

29 12 2014.

[24] Trademarkvision, n.d. *Welcome*. Available at: https://trademarkvision.compumark.com/about/, Accessed 05 02 2020.

[25] Trademarkvision, n.d. *Home*. Available at: https://trademarkvision.compumark.com/, Accessed 05 02 2020.

[26] EUIPO european union intellectual property office esearch plus, n.d. *eSearch plus The EUIPO'S database access*. Available at: https://euipo.europa.eu/eSearch/, Accessed 2019 12 24.

[27] Trademarkvision, n.d. *Powering governments*. Available at: https://trademarkvision.compumark.com/government, Accessed 05 02 2020.

[28] Australian government ip australia australian trade mark search, n.d. *Quick search*. Available at: https://search.ipaustralia.gov.au/trademarks/search/quick, Accessed 2019 12 24.

[29] Claudio A Perez, Pablo A Estévez, Francisco J Galdames, Daniel A Schulz, Juan P Perez, Diego Bastías, and Daniel R Vilar. Trademark image retrieval using a combination of deep convolutional neural networks. In *2018 International Joint Conference on Neural Networks (IJCNN)*, pages 1–7. IEEE, 2018.

[30] Toshikazu Kato, Koreaki Fujimura, and Hiroyuki Shimogaki Nonmember. Trademark: multimedia image database system with intelligent human interface. *Systems and computers in Japan*, 21(11):33–46, 1990.

[31] Jian-Kang Wu, Chian-Prong Lam, Babu M. Mehtre, Yong Jian Gao, and A Desai Narasimhalu. Content-based retrieval for trademark registration. In *Representation and Retrieval of Visual Media in Multimedia Systems*, pages 69–91. Springer, 1996.

[32] John P Eakins, Jago M Boardman, and Margaret E Graham. Similarity retrieval of trademark images. *IEEE multimedia*, 5(2):53–63, 1998.

[33] Michael S Lew. *Principles of visual information retrieval*. Springer Science & Business Media, 2013.

[34] Stefanos Vrochidis, Anastasia Moumtzidou, and Ioannis Kompatsiaris. Concept-based patent image retrieval. *World Patent Information*, 34(4): 292–303, 2012.

[35] Zhengkang Chen and Xiaohong Wang. Trademark image retrieval system based on sift algorithm. In *2018 IEEE/ACIS 17th International Conference on Computer and Information Science (ICIS)*, pages 740–743. IEEE, 2018.

[36] Martin F Porter. An algorithm for suffix stripping. *Program*, 2006.

[37] Bernhard E Boser, Isabelle M Guyon, and Vladimir N Vapnik. A training algorithm for optimal margin classifiers. In *Proceedings of the fifth annual workshop on Computational learning theory*, pages 144–152, 1992.

[38] D Dietrich, B Heller, and B Yang. Data science & big data analytics discovering, analyzing, visualizing and presenting data (pp. 420), 2015.

[39] KG Srinivasa, GM Siddesh, and H Srinidhi. *Network data analytics: a hands-on approach for application development*. Springer, 2018.

[40] Charu C Aggarwal et al. Neural networks and deep learning. *Springer*, 10:978–3, 2018.

Abeer Sulaiman Al-Humaimeedy is a faculty member of the College of Computer and Information Science at King Saud University. She finished her bachelor and master degrees at the College of Computer and Information Science at King Saud University. At the same time, she was a visiting researcher at the Department of Informatics at King's College London where she obtained her PhD and conducted most of her research in the area of formalizing SOA systems and cloud computing.

Abeer Salman Al-Hammad received her Bachelor's degree from the College of Computer and Information Sciences, King Saud University, Riyadh, Saudi Arabia. Her interests are in the field of reverse image-based search engines.

Ghada Al-Hudhud currently serves as a faculty member at Information Technology Department, King Saud University, Riyadh, KSA. Ghada holds a PhD in Designing software models and developing communication protocols for multiple mobile cooperative robots 2005, De Montfort University, Leicester, UK. Ghada completed her MSc. digital signal and image processing, 2003, De Montfort University, Leicester, UK. Her area of interests includes software design & integration, image processing, biometric identification, compression, brain signal interaction, biometric identification systems and smart office control via brain computer interaction system.