TradeMarker - Artificial Intelligence Based Trademarks Similarity Search Engine

Idan Mosseri[1,2], Matan Rusanovsky[1,3], and Gal Oren[1,2](✉)

[1] Department of Computer Science, Ben-Gurion University of the Negev, P.O.B. 653, Be'er Sheva, Israel
{idanmos,matanru,orenw}@post.bgu.ac.il
[2] Department of Physics, Nuclear Research Center-Negev, P.O.B. 9001, Be'er-Sheva, Israel
[3] Israel Atomic Energy Commission, P.O.B. 7061, Tel Aviv, Israel

Abstract. A trademark is a mark used by a company or a private human for the purpose of marking products or services that they manufacture or trade in. A restriction on the use of the trademark is necessary to enable sellers and manufacturers to build a reputation for themselves, to differentiate themselves from their competitors and thereby promote their businesses. In addition, the restriction also serves consumers and prevents their misuse by a name similar to another product. This restriction is done through the formal examination and approval of the trademarks. This process entails trademark examination against other approved trademarks which is currently a long manual process performed by experienced examiners. Current state-of-the-art trademark similarity search systems attempt to provide a single metric to quantify trademark similarities to a given mark [6–11]. In this work we introduce a new way to carry out this process, by simultaneously conducting several independent searches on different similarity aspects - *Automated content similarity*, *Image/pixel similarity*, *Text similarity*, and *Manual content similarity*. This separation enables us to benefit from the advantages of each aspect, as opposed to combining them into one similarity aspect and diminishing the significance of each one of them.

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1 Introduction

The main function of patent offices is to provide legal protection of industrial intellectual properties through the registration of patents, designs and trade-

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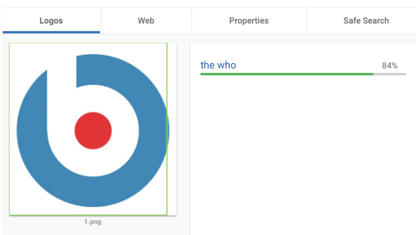
marks [1]. Granting a right to intellectual properties depends on the examination of the specific application. An examination is essential to ensure the exclusivity for said property [2].

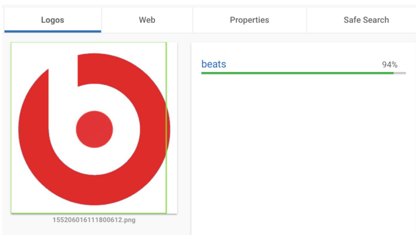
The current examination process [3] is done manually and slowly, using human trademark examiners - who are required to conduct a massive search in a large unordered database, while deciding whether there is any similarity between the trademark submitted via application and the already approved marks [4]. Automation of the examination process using Artificial Intelligence with the supervision of trademark examiners can provide a solution for the above problem with greater ease and higher accuracy.

For example, VisionAPI [5] is a computer vision tool based on powerful machine learning models, that enables users to understand the content of an image by features extraction. VisionAPI also makes it possible to detect popular product logos within an image through the *logo detection* feature. However, we claim that VisionAPI's logo detection feature can not be used solely for the trademark examination process, since it is able to detect only popular logos from a closed set of images that is under the supervision of Google (and not under some state's patent office control). In addition, as we show in Fig. 1, VisionAPI manages to not only quickly be mistaken by a small attribute change (color change, for example), but also to point similarity to only a small set of logos (even one only), such that many other possible similar logos do not appear in the result list.

(a) Extremely well-known similar trademarks



(b) Stadt Brühl logo, extremely similar to Beats logo, incorrectly classified



(c) Stadt Brühl logo, after a color change, incorrectly classified

Fig. 1. VisionAPI's performance on extremely similar logos.

Another platform that provides image similarity search is LIRE [6–8], but it does not involve learning, thus we find it less suitable for finding similar abstract (deep) features, and therefore is less capable of finding visual and structural similarities in images.

Showkatramani et al. [9] utilized the usage of Convolutional Neural Networks (CNN) for the extraction of features that then were used by a variant of a nearest neighbor algorithm for finding trademarks with similar features. Another example is *TrademarkVision, trademark.vision1, trademark.vision2* which is a deep learning-based reverse visual search platform that identifies similar trademarks to a mark. However, despite the fact that the usage of deep-learning enables the detection of abstract features, the fact that the above systems are not based upon different similarity aspects or/and averages those aspects into a single list causes information loss - as will be explained next.

Although it seems that all the above systems provide a good solution for the *image similarity* problem, the formal definition of *trademark similarity* is far more complex [12] - trademarks are considered to be similar if they are *deceptively similar*. Thus, one can conclude that there may be several different metrics that the human eye uses to quantify similarities between trademarks - the main ones are the following: Visual similarity - *do the two trademarks look visually similar*?, Semantic/Content similarity - *do the two trademarks contain the same semantic content?* or Text similarity - *do the two trademarks contain similar text?*.

An improvement to the automatic examination process might be to examine the trademarks ordered by a range of similarity aspects. We use this separation in this work in order to focus on the best results from each category/aspect rather than searching through an unorderly mixture of them. We do so as we concluded that it is not feasible to average the different similarity aspects without losing information, as each of those represent a different domain of similarity, thus averaging all of the results will yield in a loss of accuracy and similarity precision. Since accuracy is the top restriction, we found the separate lists to be the optimal solution to the *trademark similarity* problem, even though there might be a bit faster ones.

2 Similarity Aspects

TradeMarker is an Artificial Intelligence based Trademarks Similarity Search Engine, that allows conducting simultaneously several independent search queries, each query examining a different similarity aspect. We next describe the work-flow of the system, as well as the different similarity aspects used by TradeMarker: Automated content similarity, Image/pixel similarity, Text similarity, and Manual content similarity.

2.1 Work-Flow

The system works in the following manner: After inserting the desired trademark image, the system performs said search queries and displays four independent output windows, corresponding to the four aspects mentioned above. In each of these windows, the most similar trademarks are presented in the order of their similarity to the input trademark. The work-flow of the system is presented in Fig. 2. As can be seen, Human-Computer Interaction is necessary in order to determine which of the trademarks are similar to the given mark, based on the ordered lists. However, this manual similarity check is minimized due to the ordered fashion in which the output is displayed.

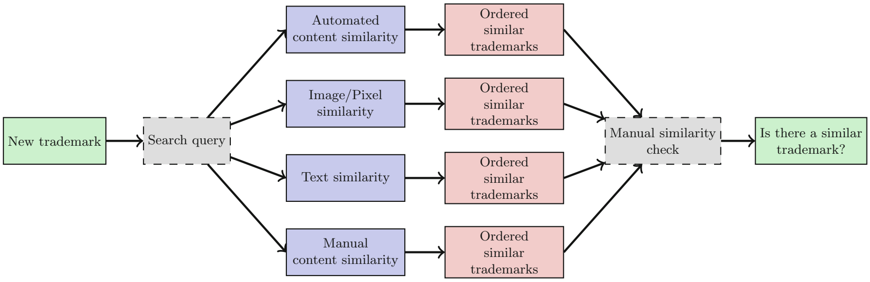


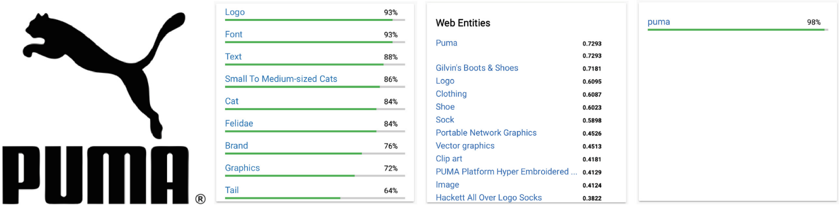
Fig. 2. The search engine performs four different search queries corresponding to the four similarity aspects of the system.

2.2 Automated Content Similarity

Similarly to the work presented by Showkatramani et al. [9] and TrademarkVision [10,11], the first similarity aspect, automated content similarity, uses machine learning models (e.g., such as Googles VisionAPI technology which helps derive insight from images using Google's pre-trained models), in order to extract features from images, and then find images with similar features. Automated content similarity may work as follows. First, extracting image attributes and their content as tags from a received image that represents a trademark, combined with the already approved trademarks from the database. Then, comparing the tags of the received trademark with the ones of the already approved trademarks, and finally displaying them ordered by similarity score. This similarity aspect is intended to find similar objects between the images, thus finding *semantic* similarities between the trademarks. Figure 3 presents an example of tag extraction that was made by Google VisionAPI.

2.3 Image/Pixel Similarity

The second aspect, image/pixel similarity, uses the platform provided by Clarifai's technology [13,14], in order to find visual similarities between images. It uses Computer Vision and Deep Learning techniques to display trademarks ordered by visual similarity to the input mark, based on pre-trained machine learning models. This similarity aspect is responsible for catching visual and structural similarities of the images.



(a) Input logo (b) Logo's labels (c) Logo's web (d) Logo's logos

Fig. 3. An example of tag extraction made by Google VisionAPI.

2.4 Text Similarity

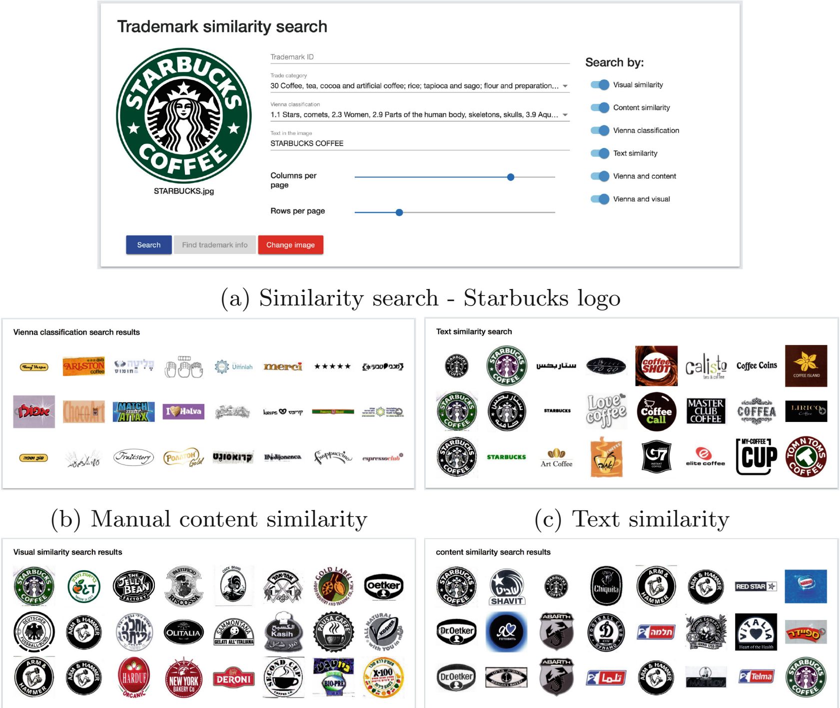
The third aspect, text similarity, orders approved trademarks by the similarity of the text they may contain to the text in the new trademark being examined. To quantify such text similarity, algorithms such as Dice's Coefficient, Levenshtein distance, Jaccard Similarity or Cosine Similarity can be used [15]. For example, the Dice's Coefficient algorithm returns a fraction between "0" and "1", which indicates the degree of similarity between the two strings (e.g., a first string refer to text that may appear in the examined trademark and the second string refers to the text that appear in each relevant approved trademark). Wherein "0" indicates completely different strings, "1" indicates identical strings. The comparison is case-insensitive. Naturally, this similarity aspect is in charge of finding textual similarities between trademarks.

2.5 Manual Content Similarity

The fourth aspect, manual content similarity, is the same as the existing examination trademark method. Namely, it allows a user (e.g., a trademark examiner) to manually classify the trademark with the desired tags from the Vienna Classification system [3], and then to go through all other trademarks that had already been approved and classified with the same tags. This method only reduces the amount of trademarks to examine, rather than the previous methods that present the trademarks in an ordered fashion. Thus, allowing the examiner to focus only on the most similar trademarks, and then to decide whether there is an already approved trademark that is similar to the input trademark.

3 Test Case

In Fig. 4 we present the performance of TradeMarker on Starbucks logo. The output of the tool is divided to the different similarity aspects. In this test case we present only the *first* 24 results, exactly as shown in the tool's four different windows. More results can be presented in the order of similarity by user's demand. In addition, we note that one can combine the output of Manual content similarity with the output of any other aspect by displaying the trademarks from that aspect with the same manual content that was given. Thus having the output trademarks with the given manual content, ordered by visual/text and (automate) content similarities.



(a) Similarity search - Starbucks logo

(b) Manual content similarity

(c) Text similarity

(d) Image/pixel similarity

(e) Auto' content similarity

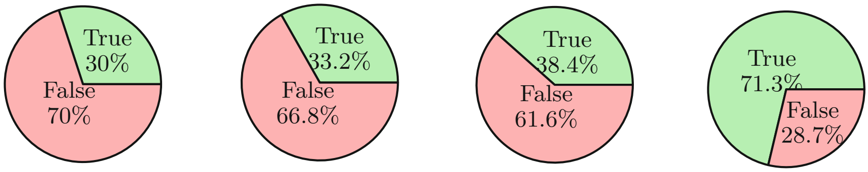
Fig. 4. TradeMarker's performance on Starbucks logo.

4 Evaluation

The Israeli Patent Office evaluated the performance of TradeMarker, and the results are shown in Fig. 5.

The test performed in the following manner. The examiners provided hundreds of pairs - test trademark and a counterpart similar trademark that is expected to show up after querying TradeMarker with the test trademark. We then decided on a threshold in which the expected counterpart trademark of a successful test trademark may reside. This is important, since if the expected trademark appears, but as the last result - it is practically impractical, as going through all trademarks to find similarities is not feasible in large databases, and specifically in the Israeli trademarks database, where there are more than 130 thousand registered trademarks.

We therefore found that going through 200 trademarks manually is reasonably representative but yet not too large amount of trademarks to examine.



(a) Only Manual content similarity aspect. The current examination method

(b) Only Auto' content similarity aspect

(c) Only Image/pixel similarity aspect

(d) TradeMarker, using all four similarity aspects in overlap

Fig. 5. The results of the search engines on the tests that were performed by the Israeli Patent Office. True is when a similar trademark has displayed in the first 200 results, given some trademark.

We note that without TradeMarker (only Manual content similarity), just 30% of the pairs were found to be successful, or in other words, in only 30% of the test trademarks the expected counterpart trademark was found in the first 200 similar trademarks. However, using TradeMarker we managed to elevate the success rate to more than 70%. We stress that not only that TradeMarker performed better than the current examination process in the tests by a factor of 2.5, it also was able to find similarities that the old system could not even detect. We estimate that in 10% of the searches the manual tagging is losing the ability to describe all the image features, as the Vienna Classification is bounded in about 150 categories.

5 Architecture

TradeMarker was built using the M.E.A.N stack architecture. Using Angular 6 for the front-end development, NodeJS and ExpressJS to build the back-end server and MongoDB as the database. As said previously, TradeMarker uses services provided by Calrifai and Googles Vision API for catching structural (visual) and semantic (content) similarity. These interfaces and the communication

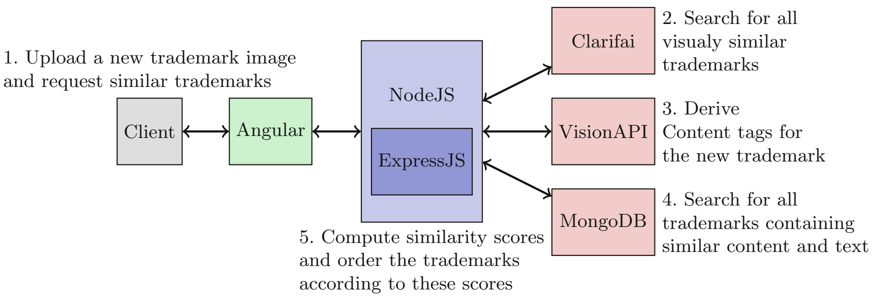


Fig. 6. The architecture of TradeMarker.

between the front and back-end of the system are done using a restful API. The architecture is summarized in Fig. 6.

6 Conclusion

Currently, trademarks examination is a long process that requires manually examining lots of unordered trademarks and the usage of techniques requiring experienced examiners. In this work we introduced several similarity aspects - Automated content similarity, Image/pixel similarity, Text similarity and Manual content similarity - on which we conduct search queries on. Automated and manual content similarities are responsible for catching semantic similarities, while image/pixel similarity is responsible for structural similarities, in contrast to text similarity that seeks for textual similarities and has no correlation to visual similarities. This separation made it possible to fully utilize the advantages of each aspect, as opposed to search through an unorderly mixture; just through one or an average of them, and thus suffer from a reduction in the significance of similarity between trademarks according to different aspects.

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