Content-based Image Retrieval System for clinical diagnosis of Pigmented Skin Lesions

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Summary

The screening process of skin cancer and the capacity of storing the digital images in recent years are rapidly increasing at an alarming rate. These digital image contains a lot of useful diagnostic information, which are not efficiently accessed and used. This requires a way to quickly and accurately find an access to these images, also known as content-based image retrieval (CBIR) system. The CBIR systems are developed based on text-based and visual features-based search techniques. A few content-based image retrieval (CBIR) systems were developed in the past to search pigmented skin lesions (PSLs) based on visual features from a set of dermoscopy images. Those CBIR systems were limited to specific categories of PSLs and employed non-effective visual features. In this paper, an improved CBIR (Derma-CBIR) system using deep learning algorithms for PSLs is proposed by defining effective visual color and texture features for retrieving skin lesions. The recall, precision and rank statistical metrics are utilized to test and compare the performance of CBIR systems. The Derma-CBIR system is tested on a dataset of total 240 lesions (20 images per category) achieved an average recall of 0.921, precision of 0.875 and rank of 0.081. The obtained results indicate that the Derma-CBIR is effective when compared with other state-of-the-art CBIR systems. As a result, it can be used to assist clinical experts for maintaining PSLs images.

Key words:

Skin cancer, Digital dermoscopy, Content-based image retrieval system, Color and texture features, Deep learning

1. Introduction

In recent years, the rapid development of multimedia technology and the capacity of digital images worldwide is growing at an alarming rate. Whether, it is medical informatics, bioinformatics or health-care domains, the capacity of digital images are increasing equivalent to several gigabytes images in one day. The digital image contains very useful information and it is needed to train the less experience experts. Since, these images are wildly distributed in the world, the information contained in the images cannot be processed efficiently in terms of access time. This requires a way to quickly and accurately find access to these images, also known as content-based image retrieval (CBIR) systems. However in the field of medical or computer vision, the development of CBIR system has become a very active area of research. In the past studies, the CBIR systems are developed in two basic domains such as text-based (T-IR) or visual-features (V-IR) based search the digital images.

Text-based image retrieval (T-IR) area is already explored by many researchers. In T-IR system, the experts defined many keywords to describe the content of an image. Then Query is text-based description of the image to match an exact match. However, there are many problems to develop a T-IR system for image-based information retrieval. First, the current studies about computer vision application are not automatically marked image, but must rely on manual annotation of the image. In that case, it is a time consuming task, but the manual tagging is often inaccurate or incomplete. Furthermore, the manual tagging is inevitable biased because different people have diverse interpretations of the same. Second, the image contains enrich visual features such as color or texture, which cannot often be objectively described in the text.

To overcome these problems, nowadays the content-based image retrieval (CBIR) systems based on visual features (V-IR) are developed. Compare to T-IR systems, the V-IR systems have capability to automatically search or tag an image based on certain features such as color, texture and shape. It noticed that the development of V-IR systems were completely different in terms of architecture. In V-IR systems, the query will be based on the similarity of the image visual features. The users have to select one or more images of representative examples to construct a query and afterwards, the system looks for similar examples based on the visual content. Then the system is arranged quite similar images according to the similarity index. This is so-called an image-retrieval by example or query-by-image example.

Core development of visual-features based CBIR systems is the image feature database. Image features are extracted either from the image itself or it can be obtained through user interaction for computing the similarity between images. The relationship between the user and the system is two-way. In the first way, the user can make a query to request the CBIR system, the system returns the query

Manuscript received May 5, 2017
Manuscript revised May 20, 2017

results based on the query requirements. In the second way, the users can query results by relevance feedback to improve search results.

The visual-features based CBIR systems are also developed in the field of medical such as skin cancer. In this paper, the visual-features based CBIR system is developed for large-scale pigmented skin lesions (PSLs) when diagnosis the skin cancer by digital dermoscopy. This system is known as Derma-CBIR for automatic tagging the images that are obtained during screening process.

The rest of the paper is divided into different sections. In the section 2, the related approaches for CBIR systems based on dermoscopy images are presented. Whereas in section 3, the utilized dataset and the proposed Derma-CBIR system were detailed described. After this section, the section 4 described the results and finally, the paper concludes in section 5.

2. Background

Content-based image retrieval (CBIR) systems [1] are extensively studied in past decades for indexing, searching and retrieval of digital images. In the field of computer vision, CBIR is one of the most active research areas. The availability of large amount of data through WWW [2] created the need to manage these datasets. The automatic annotation of these data sets by CBIR systems is performed by extraction of visual features [3] from images that are indexed into a database. If a user wants to search an image then the system outputs the most alike images by matching features of the query image with those of the images in the database. These CBIR systems are required by users of different domains such as medicine, architecture, remote sensing and crime prevention. In all these domains, there are two main frameworks developed for CBIR systems, which are text-based and visual content-based [4]. In text-based retrieval systems, the images are manually annotated by text description, while in visual CBIR systems, the images are indexed by their visual content such as color, shape and texture information. In practice, the CBIR systems are mainly developed based on these visual content-based features [5]. Unfortunately, the extraction process of these visual features from digital images is a challenging task.

New methods are proposed continually to develop CBIR systems by using visual features that are recognized by a classifier to match with the query image to obtain similar results. In particular to medical domains [6], the query image is recognized by showing some clinical attributes of the matched image. These clinical attributes are further utilized by a medical expert to effectively diagnose the patients. To take maximum benefit by medical experts [7], the CBIR system is provided access to practitioner as well as an expert through internet services. These systems are developed by using image visual features and the extraction of features is one of the difficult steps. Therefore, the primary aim of this paper is to extract and classify the visual features in an effective manner.

In the literature, a number of CBIR systems [8-17] have been proposed in the field of medical domain. In particular, there are systems that focus on CBIR [11-18] in the domain of dermatology. However, these CBIR systems are not developed by using perceptually-oriented or uniform color spaces but they utilize non-uniform color space such as RGB, CIELAB or HSV and the color and texture features are not effectively extracted. These CBIR systems are mainly focused on texture features but not on color features.

In this paper, an effective CBIR system is developed, which we refer to as PCBIR based on visual content such as color and texture features that are extracted in a perceptually-oriented (P) color space for searching every major category of PSLs.

Image feature extraction and expression is the basis of the content -based image retrieval technology. Broadly speaking, the image feature comprises a text -based feature (such as keywords, comments, etc.) and visual features (such as color, texture, shape and surface of the object, etc.) categories. Because text -based image feature extraction in database systems and information retrieval field has in-depth research, this chapter introduces us to extract and express the image visual features.

Visual features can be divided into general areas relevant visual features and visual features. The former is used to describe features common to all the images , and the image independent of the particular type or content , including color, texture and shape ; latter described based on some a priori knowledge of the image content (or hypothetical) on closely related to the specific application , such as a human fingerprint characteristic facial features or the like. As the field relevant to the main part of the image feature pattern recognition research scope and involve many specialized areas of knowledge , in which we will not go into details , but only consider the common visual features.

For a particular image features, usually there are many different methods of expression. Due to the subjective understanding of the vastly different people, a feature does not exist for the expression of a so-called good. In fact, the image characteristics expressed in different ways from different angles characterize the nature of some of the features. In this chapter, we introduce the practice that proved to be more effective image search feature and a corresponding expression methods. 1,2,3 sections of this chapter , we will introduce the color, texture and shape features of the image, is described in Section 4 contains information on the image feature space , the latter section outlines the multidimensional indexing techniques and technologies to reduce the dimension.

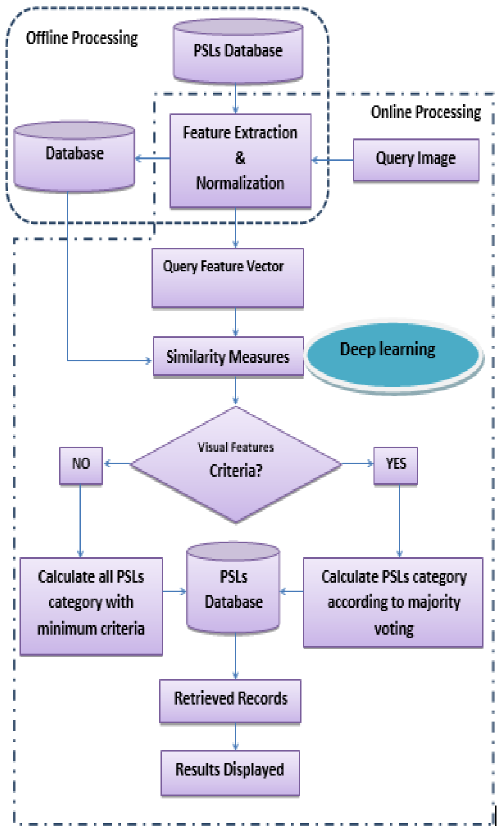

Fig.1 the systematic flow diagram of proposed Derma-CBIR system for pigmented skin lesions (PSLs) when diagnosis through dermoscopy images.

3 Material and Method

3.1 Acquisition of dataset

The performance of the proposed Derma-CBIR system for image-visual features based searching is tested on a dataset of 240 dermoscopy images. In this dataset, the distribution of each category is as follows: melanomas, atypical nevi, benign nevi, congenital nevi, blue nevi, lentigo, seborrhoeic keratosis, melanocytic nevus, actinic keratosis (AK), basal cell carcinoma (BCC), squamous cell carcinoma (SCC) and merkel cell carcinoma (MCC). Each category contains 20 images. These images are mostly selected from the EDRA Interactive Atlas of Dermoscopy [19], while some are acquired from various online sources.

3.2 Methods

The systematic diagram of the proposed Derma-CBIR system is shown in Fig.1. In this figure, four major types are displayed such as color and texture features extraction, normalization the visual feature vector and finally searching features through deep learning algorithm. These processing steps are explained in the subsequent subsections.

3.3 Color Features

The dermoscopy images are captured through digital camera so these images contain colors. The extraction of color features played an important role in a wide range of image retrieval systems mainly due to the color of an object or scene and often contained in the image is very relevant. Moreover, compared with the other visual features, the color characteristics of an image is provided high robustness to classify objects. There are number of problems to extract perfect color features. First, the appropriate color space is need to describe the color feature. Second, to extract color features, there is a need to adopt some methods, but also to define a similarity (distance) standard used to measure the image of similarity between the colors. In this paper, the color histogram and color moments are used to define color features from dermoscopy images.

Color histogram is described the color characteristics of the image retrieval system and do not care about which the spatial position of each color, i.e., does not describe the object or objects in the image. The color histogram is particularly suitable for those images, which is difficult to describe the automatic segmentation. Of course, the color histogram is based on the type of color space and the coordinate system. The common color space is RGB color space, because the majority of the digital image in this color space is expressed. However, the RGB spatial structure does not meet the people on the subjective judgment of color similarity. Therefore, it was preferred to use CIELuv, CIELab or HSV color spaces. The HSV histogram is used in this paper and it represents the components such as three color (Hue), saturation (Saturation) and a value (Value).

Necessary to calculate the color histogram of color space is divided into several small color interval between each cell into a bin of the histogram. This process is called color quantization (color quantization). Afterwards, the number of pixels are calculated between the color of each cell falls within the color histogram can be easily obtained. There are many ways to quantify color, such as vector quantization, clustering methods or neural networks. For the common practice, it is to be divided evenly for each component color space (dimensions). In contrast, taking into account the clustering algorithm is a color image wherein the distribution of the entire space, thereby avoiding some of the bin number of pixels in the event of very sparse, more efficient quantization. Further as dermoscopy images are in the RGB format and the HSV space histogram, the pre-established lookup table (look-up table) from the quantization of the quantized RGB to HSV space is calculated. Experiments show that this method does not reduce the color histogram retrieval results. Indeed, those values by ignoring the smaller bin, the sensitivity of the color histogram of the noise is reduced, and sometimes make better retrieval results.

Another very simple and effective way is to use color moment. This method is the mathematical basis for any distribution of colors in an image can be represented by its moment. In addition, due to the color distribution information mainly concentrated in the low-order moments, so using only colors the first moment (mean), second moment (variance) and third moment (skewness) is sufficient to express the color distribution of the image. Compared with the color histogram, another advantage of this approach is that the features do not need to be quantified.

3.4 Texture Features

A texture feature is not dependent on visual characteristics or the color image that reflects the luminance homogeneity phenomenon. It is an inherent characteristic of all common surfaces, such as clouds, trees, tiles, fabrics, etc. and it has its own texture features. Texture contains important information about the surface structure of the organization and arrangement of their links with the surrounding environment. Because of this, the texture features have been widely used in content-based image retrieval systems. The users can submit images contain some texture to find other images containing similar texture. The pattern recognition and computer vision areas suggested that there is a great importance of use of texture features for pattern analysis. It has made significant achievements in the past three decades. In this paper, there are Tamura texture feature and directional features on a wavelet transform utilized.

3.5 Combine Visual Features

The extracted color and texture features are combined into a single feature vector of each image in the dataset and the query image. Afterwards, a normalization step is performed by min-max normalization technique to equalize the range of features to [0,1]. For each PSLs lesion, this normalized feature vector is calculated and stored in a dataset. Furthermore, these feature vectors of each lesion are utilized to search and retrieve the most similar records of a query image.

3.6 Search Visual Features

For searching the visual content, the deep learning algorithm is used. The recurrent neural network (RNN) model with three layer architecture was used in this paper to search the query images. The RNN [20] model used in this study due to a use of feedback loop. In RNN model, the output from step n-1 is fed back to the net to affect the result step n, and so forth for each subsequent step.

In order to describe the RNN model, let us consider an environment in which the hidden states should be used to determine the previous classification in a serious. In each subsequent step, that hidden state is combined with the new step’s input data to produce a) a new hidden state and then b) a new classification. Each hidden state is recycled to produce its modified successor. This behavior can be observed in RNN model that is best fitted for CBIR system.

4. Experimental Results

The proposed Derma-CBIR system for searching all categories of pigmented skin lesions (PSLs) is implemented in MATLAB 2012 on Intel(R) Core (TM) i7-3317 CPU @ 1.7GHz, 8 GB RAM and Windows 8, 64-bit operating system. In total, there are 240 images in this PSLs dataset.

All image sizes are decreased to (600 × 600) pixels and then (250 × 250) pixels areas are automatically selected from central position and stored in a dataset before feature extraction step. In the query matching mode, top n-ranked images are retrieved with maximum votes to support the dermatologist in clinical decision making. This query matching step is capable of searching and matching the given query image with the stored features’ dataset of 240 PSLs lesions. These 240 PSLs images consist of 20 lesions per category of melanoma.

In the first step, all 240 image's features are extracted and stored in a file to test the performance of proposed PCBIR system. To recognize the query image, a supervised learning algorithm (RNN) is utilized. To test the performance, the 50% lesions are used to train the RNN classifier and 50% are used to test this classifier on a 240 dermoscopy images.

To measures the performance of Derma-CBIR system, the precision, recall and rank metrics are calculated. In fact, these metrics are used in many content-based image retrieval systems to interpret and characterize different aspects of the system. The mathematical description of these metrics is defined as follows:

Precision (PVs) = Number of relevant PSLs retrieve / Number of all PSLs retrieved (1)
Recall (RVs) = Number of relevant PSLs / Number of all relevant PSLs (2)
Afterwards to calculate the overall PCBIR system performance, the rank metric is defined as:
Rank (RNs) = 1/NNr (sum (Ri)- Nr(Rr+1)/2) (3)

Where Ri is the rank at which the ith relevant image is retrieved, N the number of images in the database and Nr is the number of relevant images. The rank measure (RNs) equals 0 for perfect performance and approaches 1 as performance worsens. These recall values (RVs), precision values (PVs) and rank values (RNs) are used to describe the overall performance of content-based image retrieval systems. For calculating effectiveness of the retrieval, the average values are commonly calculated.

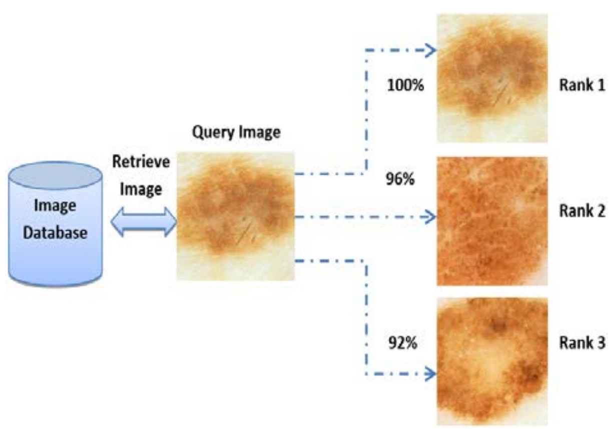

Fig. 2 dermoscopy image query matching results of PCBIR system with top n-ranked images based on maximum similarity when performed on PSLs lesions.

The performance of PCBIR system on 240 PSLs (12 categories) is shown in Table 1 by using recall values (RVs), precision values (PVs) and rank values (RNs) metrics. As displayed in Table 1, the proposed PCBIR system has obtained average recall values (RVs) of 0.921, precision values (PVs) of 0.875 and rank values (RNs) of 0.081. These experimental results indicate that the PCBIR has obtained more than 90% accuracy. Compared to melanoma PSLs, the other non-melanoma lesions such as SK, MNs, AK, BCC, SCC and MCC have obtained significant results such as (RVs: 0.830, PVs: 0.760 and RNs: 0.081), (RVs: 0.961, PVs: 0.802 and RNs: 0.076), (RVs: 0.804, PVs: 0.721 and RNs: 0.073), (RVs: 0.852, PVs: 0.801 and RNs: 0.083), (RVs: 0.912, PVs: 0.871 and RNs: 0.080) and (RVs: 0.834, PVs: 0.762 and RNs: 0.087), respectively. Similarly in case of Melanocytic Nevus (MNs), more than 96% accuracy is obtained in terms of recall values. As a result, overall Derma-CBIR system has obtained results, which are better than state-of-the-art content-based image retrieval systems for dermoscopy images.

To compare the PCBIR with other state-of-the-art CBIR systems, we have selected two CBIR systems such as Hedde et al [17] and Baldi et al [18]. These comparisons results are demonstrated in Table 3. In this table, the Balid et al CBIR system is achieved good recall: 0.787, precision: 0.474 and rank: 0.429 values compare to Hedde et al CBIR system. However, these statistical are below than average if compared to proposed Derma-CBIR system. The proposed Derma-CBIR system is effective in retrieving dermoscopy images of PSLs. This Derma-CBIR system is unique because it has been tested on 12 classes of PSLs on a total dataset of 240 images with 20 lesions per category. The overall Derma-CBIR system can provide support to dermatologists by improving their diagnostic accuracy. Moreover, this system can be suitable for training less experienced dermatologists and students because it has capability to browse large numbers of matching PSLs with effective visual features. In this paper, color features are more dominant compared to texture because in some of the dermoscopy images, the patterns of lesion is not clear due to dermoscopy-gel or different view of angles. An example of Derma-CBIR system is shown in Fig. 2.

To classify visual features, RNN classifier is utilized and the performance is calculated using statistical metrics such as average recall values (RVs), precision values (PVs) and ranking values (RNv). The obtained results indicate that this CBIR system is effective compared to state-of-the-art systems. The average value of recall of 0.921, precision of 0.875 and rank of 0.081 on this dataset are obtained. These results specify that the proposed CBIR system has gained higher level of accuracy. The Derma-CBIR system was also compared with other two state-of-the-art CBIR systems. The proposed PCBIR system is effective compare to these two state-of-the-art CBIR systems as shown in Table 2.

The primarily goal of the Derma-CBIR system is to retrieve PSLs images with visually similar color and texture features to match with the query image. In many cases, there are PSLs in the database, which are visually similar to the query lesion but belonging to a different diagnostic category. This indicates that the dermatologists can use it to make final decision about diagnosis of the PSL. A graphical user interface (GUI) is developed to help less experienced dermatologists that can search a query image with pre-stored images of patients. This GUI interface has been shown in Fig. 3. The installation of this GUI of CBIR system is very easy in any medical hospital because it only needs a computer to search the query image by checking visual features. It is possible because the RNN classifier has capability of adding new features without effecting on the previous classification results.

Although, this CBIR system is developed based on desktop application, it can be augmented by adding web services as well. This Derma-CBIR system can be also accessed online and other researchers can also submit their images for identification. To do this, we need to develop a simple web page, which a user can upload query-by-example image and submit to this tool and it will search through dataset.

Table1: The average values of recall values (RVs), precision values (PVs) and rank values (RNs) of the proposed 12 types Derma-CBIR system

Class	Lesions Type	RVs	PVs	RNs
1	MMs	0.934	0.862	0.087
2	ANs	0.702	0.714	0.074
3	BNs	0.854	0.801	0.087
4	CNs	0.940	0.792	0.081
5	BNs	0.874	0.781	0.075
6	LNs	0.921	0.836	0.080
7	SK	0.830	0.760	0.081
8	MNs	0.961	0.802	0.076
9	AK	0.804	0.721	0.073
10	BCC	0.852	0.801	0.083
11	SCC	0.912	0.871	0.080
12	MCC	0.834	0.762	0.087
On average		0.921	0.875	0.081

Table 2: The average recall values (RVs), precision values (PVs) and rank values (RNs) of the other state-of-the-art CBIR systems for dermoscopy images

No.	Cited References	RVs	PVs	RNs
1	[17] by Hedde et al	0.765	0.553	0.528
2	[18] by Baldi et al	0.787	0.474	0.429

5. Conclusions

The experimental results indicate that the Derma-CBIR system is an effective tool for providing decision support option to experience as well as less experienced dermatologists. A Graphical User Interface (GUI) is also designed to demonstrate the proposed system. This GUI is user friendly, easy to use and automatically match the query image. The proposed PCBIR system can be enhanced by adding more training data and an integration of web-based interface. In recent years, many researchers have developed content-based image retrieval (CBIR) systems for various medical imaging modalities. However, these CBIR systems required more attention to add new methods or technologies that increase their performance. The optimizations and integration of new techniques are needed to develop an effective application for medical experts. Moreover, the comparisons with other state-of-the-art CBIR systems indicate that the Derma-CBIR system is having effective results when search images by using visual content.

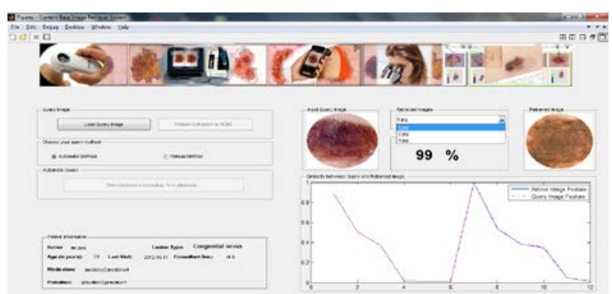

Fig. 3 A graphical user interface (GUI) for the development of Derma-CBIR system for automatic tagging of dermoscopy image

Acknowledgments

The author would like to express their cordial thanks to the department of Research and Development (R&D) of IMAM, university for research grant no: 360905.

References

[1] F. Long, H. Zhang, D.D. Feng, Fundamentals of content-based image retrieval, Multimedia Information Retrieval and Management, Springer Berlin Heidelberg (2003) 1–26.

[2] Y. Liu, D. Zhang, G. Lu, W.Y. Ma, A survey of content-based image retrieval with high-level semantics, Pattern Recognition 40 (2007) 262–282.

[3] S.M. Lew, N. Sebe, D. Chabane, J. Ramesh, Content-based multimedia information retrieval: state of the art and challenges, ACM transactions on Multimedia Computing, Communications and Applications 1551–6857 (2006) 1–19.

[4] J.C. Pereira and N. Vasconcelos, Cross-modal domain adaptation for text-based regularization of image semantics in image retrieval systems, Computer Vision and Image Understanding 124 (2014) 123–135.

[5] T. Deselaers, D. Keysers, H. Ney, Features for image retrieval: an experimental comparison. Information Retrieval 11 (2008) 77–107.

[6] H. Muller, N. Michous, D. Bandon, A. Geissbuhler A, A review of content-based image retrieval systems in medical applications-clinical benefits and future directions, International Journal of Medical Informatics 73 (2004) 1–23.

[7] H.C. Cho, L. Hadjiiski, B. Sahiner, H.P. Chan, M. Helvie, C. Paramaqul et al, Similarity evaluation in a content-based image retrieval (CBIR) CADx system for characterization of breast masses on ultrasound images, Medical Physics 38 (2011) 1820–1831.

[8] M. Tarjoman, E. Fatemizadeh, K. Badie, An implementation of a CBIR system based on SVM learning scheme, Journal of Medical Engineering & Technology 37 (2013) 43–47.

[9] S. Murala, R.P. Maheshwari, R. Balasubramanian R, Local tetra patterns: a new feature descriptor for content-based image retrieval, IEEE Transactions on Image Processing 21 (2012) 2874–2886.

[10] H.C. Akakin, M.N. Gurcan, Content-based microscopic image retrieval system for multi-image queries, IEEE Transactions on Information Technology in Biomedicine 16 (2012) 758–769.

[11] M. Zortea, T.R. Schopf, K. Thon, M. Geilhufe, K. Hindberg, H. Kirchesch et al, Performance of a dermoscopy-based computer vision system for the diagnosis of pigmented skin lesions compared with visual evaluation by experienced dermatologists, Artificial Intelligence in Medicine 60 (2014) 13–26.

[12] A. Baldi, R. Murace, E. Dragonetti, M. Manganaro, S. Bizzi, Automated content-based image retrieval: application on dermoscopic images of pigmented skin lesions, Skin Cancer, Current Clinical Pathology (2014) 523–528.

[13] M.M. Rahman, P. Bhattacharya, An Integrated and Interactive Decision Support System for Automated Melanoma Recognition of dermoscopic images, Computerized Medical Imaging and Graphics 34 (2010) 479–486.

[14] W.V. Stoecker, M. Wronkiewiecz, R. Chowdhury, R. J. Stanley, J. Xu, A., Bangert et al, Detection of granularity in dermoscopy images of malignant melanoma using color and texture features, Computerized Medical Imaging and Graphics 35 (2011) 144–147.

[15] K. Bunte, M. Biehl, M.F. Jonkman, N. Petkov, Learning effective color features for content based image retrieval in dermatology. Pattern Recognition 44 (2011) 1892–1902.

[16] L. Ballerini, X. Li, R.B. Fisher, J. Rees, A query-by-example content-based image retrieval system of non-melanoma skin lesions, Medical Content-Based Retrieval for Clinical Decision Support, Lecture Notes in Computer Science 5853 (2010) 31–38.

[17] H.H. Bosman, N. Petkov, M.F. Jonkman, Comparison of color representations for content-based image retrieval in dermatology, Skin Research and Technology 16 (2010) 109–113.

[18] Alfonso Baldi, Raffaele Murace, Emanuele Dragonetti, Mario Manganaro, Oscar Guerra, Stefano Bizzi and Luca Galli, Definition of an automated Content-Based Image Retrieval (CBIR) system for the comparison of dermoscopic images of pigmented skin lesions, BioMedical Engineering OnLine 8 (2009).

[19] G. Argenziano, H.P. Soyer, G.V. De, D. Piccolo, P. Carli, M. Delfino et al, Interactive atlas of dermoscopy CD. Milan: EDRA Medical Publishing and New Media, 2000.

[20] S. Ravuri and A. Stolcke, "A comparative study of recurrent neural network models for lexical domain classification," 2016 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), Shanghai, 2016, pp. 6075-6079.

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