A Supervised Quantification of the Color Names Characterizing the Visual Component Color in the ABCD Dermatological Criteria for a Further Melanoma Inspection

Jinen Daghrir[1,2], Lotfi Tlig[2], Moez Bouchouicha[3], Noureddine Litaiem[4], Faten Zeglaoui[4] and Mounir Sayadi[2]

[1]*Université de Sousse, ISITCom, 4011, Hammam Sousse, Tunisia*

[2]*Université de Tunis, ENSIT, Laboratory SIME, Tunisia*

[3]*Aix Marseille Univ, Université de Toulon, CNRS, LIS, Toulon, France*

[4]*University of Tunis El-Manar, Faculty of Medicine of Tunis, Department of Dermatology, Charles Nicolle Hospital, Tunis, Tunisia*

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Abstract: Digital imaging is widely used for creating automated systems for medical purposes such as the diagnosis of certain kinds of diseases. One typical use of these computer vision diagnosis systems in dermatology is the inspection of melanoma skin cancer, which is one of the most fatal skin cancer. For the early detection of melanoma, a lot of systems have been proposed. Most of them use some visual features through image processing methods, such as color processing and border and texture inspection. Color variation is a good clue to differentiate melanoma and benign lesions. Thus, it is important to process skin lesion images to extract the various colors. The paper presents a new method that extracts the different color names from a skin lesion in a supervised way based on observed skin condition types. These features can ensure accurate melanoma detection with other types of features. To demonstrate the effectiveness of our suggested representation, we construct a prediction system for inspecting the malignancy of skin lesions. The experimental results show a consistent improvement in the prediction performance against other color representations.

1 INTRODUCTION

Skin cancer is the uncontrolled growth of abnormal skin cells. It is caused by unrepaired DNA damage that activates mutations or genetic defects, which stimulate the skin cells to rapidly multiply and form malignant tumors. Among the three main types of skin cancer, two of them are frequently diagnosed, which are Basal and Squamous cell carcinoma. These are considered non-melanoma skin cancer and not life-threatening (Khazaei et al., 2019). However, melanomas, which is the deadliest form of skin cancer, are less common but they represent the most fatal cancer since they can quickly spread to other parts of the body. A melanoma arises through a malignant transformation of melanocytes which are derived from the neural crest neoplasia (Dimitriou et al., 2018) causing about 60,000 cancer deaths in 2018 (Khazaei et al., 2019). It represents as 0.7% of all cancer deaths. The incidence rate from 1973 to 2009 shows a rise in the number of cases (Heinzerling and Eigentler, 2021) which is particularly worrying. A particular interest in creating automated systems for melanoma inspection has been the challenge of the healthcare management community. It is now crucial to use supportive imaging to identify melanomas at an early stage when the odds of curing it are completely high, thereby reducing mortality (Khazaei et al., 2019).

Computer-Aided Diagnosis (CAD), has been designed to improve and facilitate a quick and accurate diagnostic process based on strategies invented by physicians. One widely used clinical clue is the ABCDE signs, which is a useful indicator for melanoma. The ABCD rule (Stolz et al., 1991) of dermatoscopy, based on multivariate analysis of only four criteria was introduced by Stolz et al. and expanded to ABCDE in 2004. The rule represents an analytical method for the evaluation of melanocytic

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lesions that clinicians and the general public can utilize to help detect melanoma (Abbasi et al., 2004). Melanoma often manifests some or all of the ABCDE features, namely asymmetry (A), border irregularity (B), color variability (C), diameter greater than 6 mm (D), and evolution (E) or change in the color or size (see Fig. 1). The color variability means that the colors of a skin lesion are not uniform. Since most benign lesions mainly contains one color, often a single shade of brown, having a variety of colors is a warning signal as given by Fig. 1. Melanoma can contain different shades of brown, black, red, white, or blue colors. Due to the sensitivity of the ABCDE rule, physicians tend to use other new features to recognize melanoma. The blue-black color is one of these features. It is defined by the presence of a combination of blue and black pigmented areas involving at least 10% of the lesion surface (Argenziano et al., 2011).

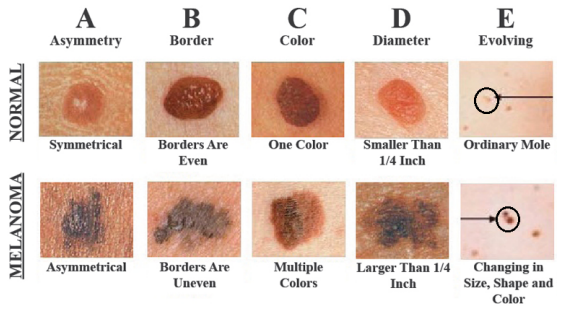

Figure 1: ABCDEs of detecting melanoma: Aspects and differences between benign and malignant skin lesions.

While some melanomas begin within an atypical mole, though it can be hard to observe the different colors in an atypical mole. However, it may be amelanotic, not having any of the skin pigment that typically turns a mole brown or black. Thus, defining the different colors in a skin lesion is not a straightforward process. Accordingly, it becomes harder to recognize the melanoma. Even dermatologists will not be able to examine it by the naked eye which can lead them to remove a portion of a mole for examination in a lab, which can delay diagnosis. The automatic inspection of melanomas is composed of a variety of steps including preprocessing, extraction of the region of interest, post-processing, and lesion inspection, which are the various steps of a classical pattern recognition system, including image acquisition, image processing, segmentation, characterization, and classification of the lesion in question (Maglogiannis and Doukas, 2009a).

One important step is skin lesion characterization, which consists in extracting a set of relevant and discriminative primitives that can describe precisely a skin lesion. These characteristics must ensure non-redundancy, relevance, discrimination, and robustness to noise.

The ABCD rule is widely used in automated computer diagnosis systems, which investigates the asymmetry, the border, the color, and the diameter or differential structures (Maglogiannis and Doukas, 2009a). Other features can be employed like the seven-point checklist (Spalding, 1993) which contains three major aspects (change in size, shape, and color) and four minor aspects (diameter, inflammation, crusting or bleeding, and sensory change). These criteria can be quantitatively determined by the change of the texture, color, and structure of the skin lesion. A lot of studies have been introduced to examine the color characteristics inside a lesion and to define the number of colors. Skin diseases are restricted to only six defined colors, for which the color name features are extracted to achieve accurate inspection under any illumination condition.

A lesion may include light brown, dark brown, black, red, white, and slate blue (Maglogiannis and Doukas, 2009b). Nevertheless, the lesion can be amelanotic in some cases. Thus, these color names become worthless for melanoma inspection, and other degrees of colors should be examined. Besides, the human perception of color is very complex, as men and women can differently describe a color. Women can distinguish even the tiniest differences between two colors, contrarily to men who see them identical. Hence, learning about the different color shades which can differentiate that a malignant and benign lesion is not easy, Hence, learning about the different color shades which can differentiate that a malignant and benign lesion is not easy, so our main contribution is to build a machine learning-based method to extract the most relevant color names. This color representation will be used then for skin lesion classification. Our aim is to design a low-dimensional representation that can efficiently detect the different colors in a skin lesion, more specifically the black and blue color which has been proved that it is an accurate clue for melanoma inspection.

This paper is organized as follows. In the next section, the most color features used in the literature for melanoma inspection are reported. After that, we present the way to define the color names using machine learning and use them to classify skin lesions. Then, we introduce the conducted experiments and the results evaluating the classification process. So the conclusions and future work are drawn in the last section.

2 RELATED WORK

Classifying skin lesions addresses the problem of defining skin lesions as malignant or benign. The classification process is led by some visual clues that characterize a skin lesion. These features differentiating malignant and benign lesions should be quantified and should have a high probability of being true classified. More essentially, when detecting melanoma, the decrease in false negatives (misclassified malignant lesions) is critical.

Examining the shape, color and texture have been the consideration of many researchers. The color of a lesion is considered as a crucial criterion for melanoma inspection. This is because the blue-black rule has also proved to be a good practice in the diagnosis process (Argenziano et al., 2011) in addition to the fact that the ABCD rule defines the most used and accurate clue for dermatologists. The color features have been examined on different color representations, such as Red, Green, Blue (RGB), HSV (Hue, Saturation, Value) or the spherical coordinate LAB average and variance responses for pixels. The color inconsistency is quantified by calculating the minimum, maximum, average and standard deviations for each channel (Menzies et al., 2005; Maglogiannis and Zafiropoulos, 2004a; Maglogiannis and Zafiropoulos, 2004b). In (Manousaki et al., 2006), the authors used the color texture for determining the nature of skin lesions by measuring the lacunarity in the distribution of colors. Furthermore, in (Yang et al., 2018), the authors have tested the color SIFT (Abdel-Hakim and Farag, 2006), which examines the color texture. Another interesting yet simple method is to examine the color variegation in a lesion by calculating the variance of the local average color (Zhang et al., 2003). Examining the uniformness of the tumor color, it can be quantified by comparing the colors inside a lesion and the healthy skin colors as in (Claridge et al., 2003). In (Yang et al., 2018), Yang et al. put forward clinical skin lesion diagnosis using a representation inspired by dermatologists, where the color is introduced by two representations, defining the different color names and the continuous color values of lesions, which indicates for each pixel the probability of belonging to a color bin.

3 PROPOSED METHOD

As a CAD system, many frameworks based on image processing have been proposed and have proved their efficiency in melanoma inspection. In the literature, a large variety of classification methods have been adopted: KNN, SVM, ANN, etc. (Magalhaes et al., 2021; Melbin and Raj, 2021a). In the last decades, regarding the evolution of Convolutional Neural Networks (CNN), CAD systems have become more and more oriented into the implementation of semantic techniques called Deep Learning (DL) (Gonzalez-Diaz, 2018; Saeed and Zeebaree, 2021). When using DL, the low-level features discriminating malignant and benign lesions are automatically extracted. This representation has shown a limitation in some cases. Thus, it is important to extract hand-crafted features that have been used and proved by dermatologists for the diagnosis process. Generally, these primitives represent only the ABCD rule that describes the color, the border and the texture to find some differential structures (Daghrir et al., 2020). The color of the lesion is still a crucial criterion for diagnosing melanomas. It represents a variety of colors. Moreover, dermatologists have proposed other important rules for diagnosing melanomas like the blue-black rule (Argenziano et al., 2011) and the ugly duckling (Grob and Bonerandi, 1998). The blue-black rule is defined as the presence of the blue and black color in a lesion surface (Daghrir et al., 2020). Thus, extracting color features is extremely important in melanoma inspection. For instance, some systems represent the color by defining the Color Name (CN) features which are linguistic color labels representing different colors in a skin lesion. As discussed above, we can notice that the color is with a high sensitivity in the whole melanoma CAD system. In this work, we suggest a new color feature extraction method.First we determine the different color names of skin lesions. Second,we search is a selection step the most pertinent color names that ensure accurate melanoma detection. The overall implementation of the extraction process is given in (see Fig. 2). To demonstrate the effectiveness of our proposed method, we test the selected features on a set of skin lesion images (see Fig. 3).

3.1 Supervised Color Name Extraction

Skin lesions may contain many different colors regarding the healthy skin color, the kind of the skin disease, the stage of the disease, etc. Thus, it is important to choose which colors are more likely to be present in a skin lesion. Melanomas may mainly include six colors. These colors can be presented with different degrees. For an effective color name representation, we extract the dominant six colors from a set of images using the K-means algorithm. Centroids for the algorithm initially depend on the six considered colors: light brown, dark brown, black, red, white, and

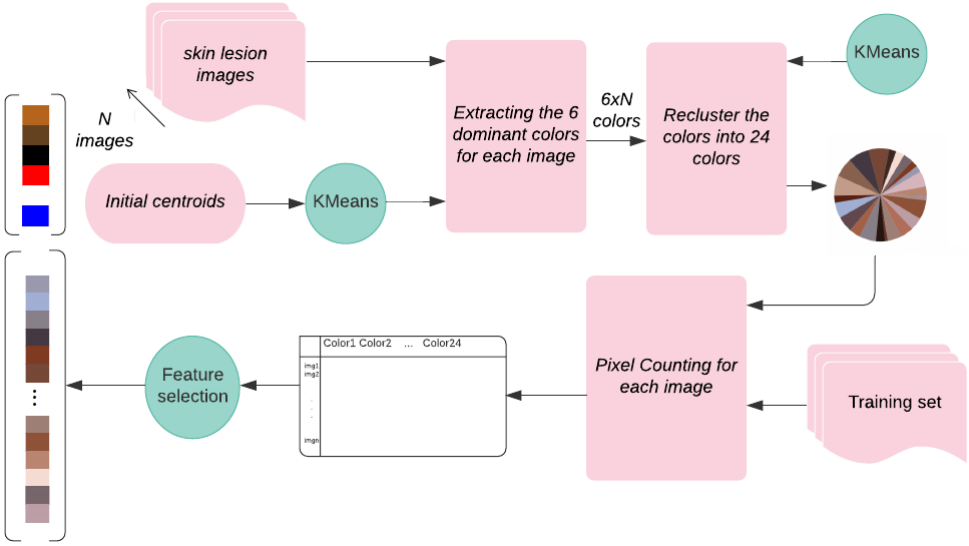

Figure 2: Layout architecture of method of extracting color-names.

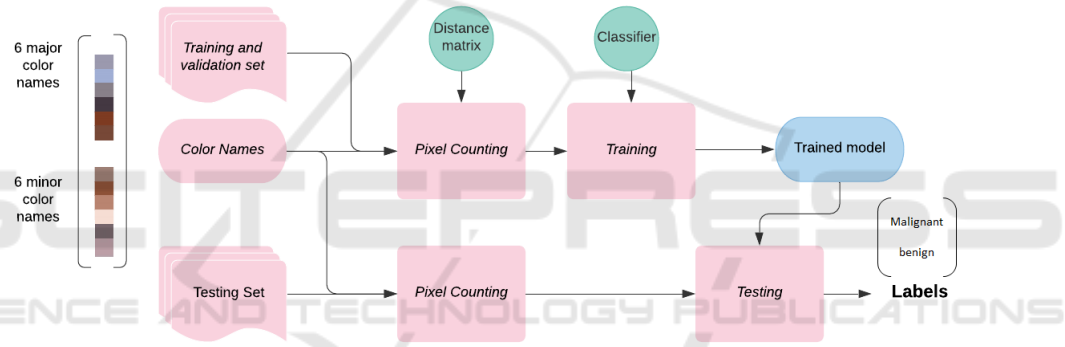

Figure 3: Layout architecture of evaluating extracted color names.

slate blue. K-means iteratively minimizes the intra-class and maximizes the inter-class distances to create a final partition of image pixels into six groups. Each input pixel is characterized by three intensities in the RGB color space. When convergence is reached, six centroids will be assigned for each color. For more details about K-means clustering, please see (Melbin and Raj, 2021b). Gathering all the extracted colors will serve then to do clustering one more time to finally extract the 24 major colors, which are displayed in the pie chart shown in Fig. 4. We assume that for each color four instances are adopted. After identifying, the major 24 colors associated with skin lesions, the process of preserving only those which guarantee an effective representation of lesion color names is done using feature selection, which is a trend in a lot of machine learning systems. We use the infinite Feature Selection (inf-FS) (Roffo et al., 2015) which is a feature selection method that performs a ranking step in an unsupervised way, followed by a cross-validation strategy to select only the most repre-

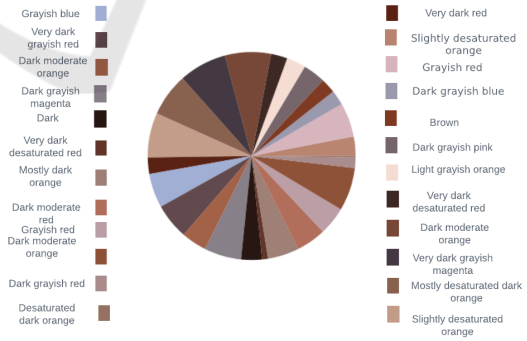

Figure 4: The most dominant 24 colors extracted from a set of images.

sentative features. Ranking individually the relevancy of features is done utilizing class labels: malignant or benign. On the other hand, using a distance matrix, we define how the 24 various color values frequently occur in the lesion (see Fig 3). In the processed image, every pixel value is assigned to the nearest color

name regarding the distance of its intensity. Finally, by counting the pixels of each color name and applying the inf-FS procedure, the suggested process generates a ranked features that refer to their characterization relevance. The six major colors found after applying the feature selection, affirm the efficiency of the black-blue clue proposed by physicians in inspecting the malignancy of skin lesions. The slight blue and black colors are highly ranked (see figure3).

3.2 Classifying Skin Lesion using Color Name Features

After extracting the most relevant color names, the skin lesion classification is implemented. The most attractive feature of this process is to evaluate the importance of using only the best-ranked color names. Generally, using them would be more accurate in classifying skin lesions. However, counting the pixels for the best color names using the distance matrix will create an unfair distribution since some pixels have different yet distant colors regarding the best color names. These pixels will be assigned anyway with the nearest color name, so it is crucial to disturb the pixels partitioning by using alternative color names. It would be more appropriate to use the six worst color names for that purpose. For the classification task, we have use the K-Nearest Neighbor (KNN) algorithm (Coomans and Massart, 1982). This method demonstrates a high classification accuracy especially when using a low-dimensional representation.

4 EXPERIMENTS AND RESULTS

The experiments are conducted using the ISIC2017 (International Skin Imaging Collaboration) dataset (Codella et al., 2018). The images are split into three sets, the training set which is used for ranking the color names and for training the KNN, and the validation and testing set which are used to evaluate the performance of our color name extraction method. We have also used the SD-198 (Sun et al., 2016), which contains 198 skin diseases represented by 6,584 images. The authors provide two split strategies. We have used the fifty split, which contains 3,292 training and 3,292 testing images. The SD-198 dataset was trained in (Yang et al., 2018) by using different low-level features describing the three visual components: texture, color, and border. We compare our proposed color name extraction method with the other color features used in the literature. To demonstrate the performance of any classification task, the accuracy is basically introduced, which is the fraction of correctly classified points and the total number of points.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

where TP = True positive, FP = False positive, TN = True negative and FN = False negative.

However, in some cases, accuracy does not really indicate the relevancy of the system. For example when evaluating a binary classifier, one class having positive labels can appear in the validation set more than the other one having negative labels. Thus, to overcome this class imbalance problem, sensitivity, specificity and balanced accuracy are defined to efficiently evaluate the classification task. The sensitivity known also as recall, measures the proportion of actual positives that are correctly identified.

$$Sensitivity = \frac{TP}{TP+FN} \quad (2)$$

Nevertheless, specificity measures the proportion of actual negatives that are correctly classified.

$$Specificity = \frac{TN}{TN+FP} \quad (3)$$

As a consequence, balanced accuracy, which is the arithmetic mean of both sensitivity and specificity metrics will properly introduce the pertinence of malignancy inspection.

$$Balanced\ accuracy = \frac{sensitivity+specificity}{2} \quad (4)$$

In the experiments, we first find the best color names introducing the best representative features and we use the validation data set to gain insights into what the optimal hyperparameter K is. Therefore, we suggest three scenarios to demonstrate the performance of the extracted color names using the validation data. The first, called Scenario A, illustrates the use of the six major and six worst color names. The second named Scenario B, is defined as the use of only the best color names. On the other hand, we use all the 24 color names for scenario C.

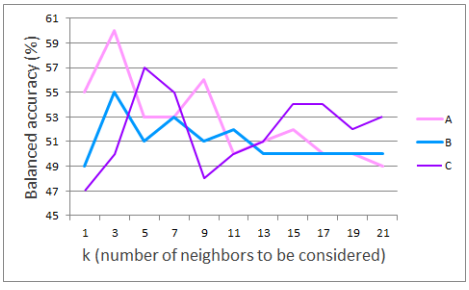

Figure 5: Balanced accuracy using different scenarios with various values of K on validation set.

Table 1: Balanced accuracy using different scenarios applied on testing set.

	Scenario A	**Scenario B**	**Scenario C**
Accuracy(%)	**77.7**	77	62.7
Sensitivity(%)	17.4	11.6	**26.7**
Specificity(%)	87.7	**88.1**	68.8
Balanced accuracy(%)	**52.6**	49.8	47.7

Generally, when the number of classes is odd, hyperparameter K must be even. Thus, by generating the model on different even values of K and checking their performance, we will understand which number of neighbors should be considered in the testing process. In Fig. 5, we can say that the classifier does a little better when using a small number of K with a small number of color names. However, for the third scenario, when the number of Ks is higher, balanced accuracy is higher than when applying the other scenarios. The experiments show also that when using the proposed color name combination the balanced accuracy is higher than using the other scenarios.

Now, we have test the performance of the KNN using the three scenarios as well, with K=3 (Table 1). Based on balanced accuracy, it is obvious that scenario A achieve the best performance. Finally, the disturbing strategy reports the best classification performances so far referring to the other scenarios. It is evident that adding further color names is generally useful. With the three scenarios, balanced accuracy is somewhat minimal, probably because we train the classifier with an unbalanced dataset having a limited number of features.

We compare the extracted color names with other several hand-crafted color features used in the state of the art. Table 2 reports the prediction performance of using various representations using KNN with k=3. As we have a limited and unbalanced dataset, we use the 5-Fold Cross Validation strategy to report how well the representations are working. Thus, five accuracies as well as their mean using the colorSIFT, CH (Color Histogram), and our proposed method (SCN) are reported. It is obvious that all the color representations succeeded in accurately diagnosing melanoma. Nevertheless, the best representation is the proposed one, which reaches about 75% accuracy with only 12 features, unlike the other used representations.

Convolutional Neural Networks (CNNs) have been widely used in the literature to automatically characterize skin lesions, for their notable performance. Therefore, in a previous research work(Daghrir et al., 2020), we have used a CNN followed by a fully-connected layer with a softmax activation function to classify malignant and benign lesions on the ISIC2017 dataset. The extracted features achieve an 85.5% accuracy, about 8% greater compared to the achievement of our proposed features (77.7% accuracy in Table 1). This result shows that our proposed method can reflect the comprehensive medical information relating to the black-blue feature. As a result, when using other different features describing also the color, texture, and shape of the lesions, our suggested color name features will be more relevant.

We compare also our proposed color name extraction using the SD-198 dataset. Thus, the whole process was tested using 198 skin diseases. A set of the most present 24 colors and their ranks in identifying the type of the disease are extracted. In table 3, we report the accuracy of using different color features proposed and used in (Yang et al., 2018), as well as the color-based features extracted using our proposed method. It is shown that our method does not perform well, it achieves only 5.58% accuracy. It fails in recognizing the different skin diseases, mainly because of the variability and the specificity of the skin diseases. In (Yang et al., 2018), the authors also have compared the classification performance using deep features derived from fine-tuned CNNs. Mainly, a CNN achieves an accuracy of 53.35% in classifying the 198 skin diseases, which is incomparable with the use of our proposed color-based features.

Although, the use of more than 12 color names (all the 24 extracted color names) slightly improves the accuracy to 5.99% using KNN. This can somehow prove the efficiency of our proposed method in precisely identifying melanoma since it manifests the presence of a very limited number of colors(generally 6 colors). However, 198 skin diseases might be characterized by a huge number of color names.

Thus, the huge number of skin diseases in a dataset, limits the performance of our method, as it is shown in Table 3, 5.58% against 52.6% accuracy for recognizing 198 skin diseases, compared to the use of the ISIC2017.

5 CONCLUSION

In this paper, we have presented a new method of color name extraction in a supervised way using feature selection to rank the extracted color names. The application of the extracted color names has been

Table 2: Accuracy using different validation Folds with different color representations on the ISIC2017 dataset.

Accuracy	Fold1	Fold2	Fold3	Fold4	Fold5	Mean	Dimension
SCN	0.78	0.76	0.77	0.78	0.67	0.75	12
CH	0.71	0.78	0.75	0.77	0.63	0.72	255
colorSIFT	0.69	0.71	0.75	0.71	0.62	0.69	10000

Table 3: Accuracy using different representations and classifiers on the SD-198 dataset.

		Accuracy	
Features	Dimension	KNN	SVM
CH	256	12.33	4.19
CN	21000	20.03	20.23
colorSIFT	21000	21.29	22.51
CN-L	21000	42.50	38.91
CCV-L	21000	42.80	40.13
SCN	12	5.58	4.73

proved utilizing a classifier with three different partitions. These color names are mainly extracted to classify skin lesions for more accurate inspection of melanomas, which are considered as the most fatal skin cancer. The proposed method has shown a notable performance for diagnosing melanomas. A comparison of different handcrafted features is presented as well, which proves the efficiency of our color name features against the state-of-the-art color representations. Accordingly, using only our proposed color-based features shows a promising result compared to automatically extracted features using deep learning. However, our proposed representation method shows a limitation when using a benchmark dataset that contains several skin conditions. Thus, these color names can be further used with other hand-crafted features and more sophisticated machine learning models to inspect melanomas to ameliorate the diagnosis process. Fuzzy features of color names could be also introduced in future work.

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