Skin Cancer Detection by FCM & Classification of Dermoscopy Images using SVM

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Abstract— Melanoma, one type of skin cancer is considered the most dangerous form of skin cancer occurred in humans. However it is curable if the person detects early. To minimize the demonstrative error affected by the complexity of visual interpretation and subjectivity, it is necessary to develop a technology for computer aided image analysis. This paper presents a methodological approach for the categorization of brunette skin lesions in dermoscopic images. Firstly, the image of the skin to remove unwanted noise and edges, and then the segmentation process is performed to extract the affected area. For detecting the melanoma skin cancer, the GLCM, Thresholding algorithm that segments the lesion from the entire image is used in this study. Feature extraction is then performed by underlying various dermatology rules. After extracting the features from the lesion, feature selection algorithm has been used to get optimized features in order to feed for categorization stage. Fuzzy C-means (FCM) is a method of clustering which allows one piece of data to belong to two or more clusters. Segmentation is performed by using Fuzzy Clustering Means because it has robust characteristics for uncertainty and can retain much more information than hard segmentation methods. Support vector machine has been used as a classifier to classify melanoma and non-melanoma. Experiments have been tested on well-known dataset dermis that is freely available on the Internet. The proposed method has been compared with state of the art methods and shows better performance in comparison to the existing methods.

Key words: Skin Cancer Detection, FCM, Dermoscopy, SVM

I. INTRODUCTION

Melanoma is the most dangerous form of malignant growth worldwide with highest rates in New Zealand and Australia. Early identification of disease of melanoma would aid in reducing mortality rates as well as the treatments costs. Recently, skin cancer specialists are comes to using Computer Aided Diagnosis (CAD) systems as a decision support tool for early detection of melanoma. Thus, a real-time image processing based CAD system in the form of a low-cost easy handheld device dedicated for melanoma detection is needed in the primary care. However, developing such image processing based system is so challenging because of its complicated computations.

Today the most important problem in health and medicine context is cancer. Earlier identification and timely treatment are very effective to improve and survival so image processing as a decisive tool can help the physician to identification cancer early. Mechanism for image processing is a simple and non-invasive method to detect cancer cells so that it accelerate earlier diagnosis and increase rate of survival. Earlier diagnosis and timely treatment lead to improve and survive cancer patients. Cancer are based on interference type such as surgery, radiotherapy and chemotherapy, the studies showed that new algorithms such as image processing have been successful for diagnosis and categorization of cancers [1]. Melanoma is less common than some other types of skin cancer, but it is more likely to grow and spread. Skin tumor such as other tissue tumors may be malignant or benign. Their nature and status are very different in skin cancer so that they may soft or hard, loosing or moving, shallow or deep as respects their shape and size may not be consistent [2]. Cancer especially melanoma is a skin disease which thousands of patient die in world annually. 50 -60 % of identification cancers are related to skin and malignant melanoma is the most aggressive type of skin cancer that is very fatal [3]. It is important to note that melanoma is a treatable disease if it is identification early. Studies showed that earlier diagnosis leads to improve 80-96% of patients [4]. Earlier identification of cancer is so important that studies showed probability of other cancers occurrence by skin cancer. Earlier diagnosis of melanoma can dramatically prevent the death cause by malignant cancers. There are two major problems to identification the disease: 1) because of ignoring skin lesions or lack of access to dermatologist, skin lesions change from benign to malignant 2) because of similar symptoms, skin lesions are not identification correctly. For example melanoma and Clarke are two similar skin lesions but melanoma is recognized as a killing and malignant cancer and Clarke a benign skin lesion. Recently many systems and algorithms were designed to identification malignant or benign lesions by dermoscopy.

In this paper we describe the system. Its general workflow of automatic system for skin lesions section 1.In Section II, we describe the image existing papers and techniques describe and using in this system flow. In Section III, we describe the pre-processing, Segmentation, feature extraction process, where image representation are produced and later used to separate between healthy and lesion areas, we explain how to describe the features according to the skin lesions criteria, where computable illustration for the lesion areas gets created. The finally explaining about the Experimental results and conclusion explained in Section IV.

II. LITERATURE REVIEW

In the literature, several researchers have focused on developing CAD systems for skin cancer detection. In treatment based hospitalized, to detect the melanoma tissues, patients generally undergo a skin examination using the skin surface microscopy techniques commonly known as dermoscopy [9]. To measure the severity of skin deformation, physicians often use scoring type such as the ABCD rule [10] or the 7-point checklist [11] for diagnosis and detection of melanoma. As Image processing techniques, the contributions of different papers in the literature are in image pre-processing, segmentation, feature extraction and categorization. For pre-processing of melanoma images, many type proposed in the literature focused on removing

noises and contrast enhancement. Once such type, named Dullrazor, was introduced by Lee et al. [8] to remove various and image artefacts. It is one of the most widely known software based in dermoscopic images [6]. With a similar objective, Abbas et al. [12] proposed a matched filtering with first Gaussian method for hair detection/removal. This method shows accurate results, but the multitude of parameters complicates its implementation. Applied on 80 dermoscopic images, the method shows a detection accuracy of 93.5%. Barata et al. [13] used a bank of directional filters and Partial Differential Equation (PDE)-based interpolation for hair detection and inpainting, respectively. Then, the authors applied a bank of directional filters and connected component analysis to detect the lines of pigment network. Recently, Koehoorn et al. [14] refered a new approach based on thresholding set decomposition and morphological analysis using gap-detection by multi-scale skeletons. They applied their method on more than 300 skin images and compared visually in their results to the literature. They also compared the execution time of these type. Mirzaalian et al. [15] proposed an alternative approach to identify hair in dermoscopic images using the measurement of turbulence quaternion [16] and dual matched filters for hair detection and suppression. On a database of 45 dermoscopic images and 95 synthetic images, the results obtained are, for segmentation, 86 and 85% of accuracy for dermoscopic and synthetic images, respectively.

Once the pre-processing step is completed, the next challenging task is the segmentation of melanocytic lesions from the processed images. It refers to separate an image into disjoint homogeneous regions respecting some properties such as luminance, colour and texture. This procedure is elaborate in Celebi et al. [17] and completed in [7], where the authors classified several type of image segmentation explored in the literature into various categories such as histogram thresholding, clustering, edge based etc. They also compared the recent edge detection type (50 type), and concluded that half (25/50) of them use smoothing filters, and those based on thresholding are inherently robust against noises. The authors noted that two type, clustering (19/50) and thresholding (18/50), are the most popular segmentation type. Previously, Celebi et al. [18] used the Otsu thresholding method for lesion localisation. In Capdehourat et al. [19], Colour-based Otsu method was also used, which is simpler and significantly faster for some cases. Safi et al. [20] used a total variation method developed by Li et al. [21], which is the generalisation of Chan and Vese model [22]. The main idea is to minimise the convex energy of the image. The results of these type are very encouraging. In a similar kind of study, an extension of Chan and Vese model to differentiate the melanoma and non-melanoma cases in skin cancer images is explored and presented in [23].

The feature extraction step plays a crucial role in CAD systems, because the categorization and diagnosis depends on the types of features extracted and their discriminating power. There are several feature extraction type in skin cancer research as in [20], where the authors used the idea of the Asymmetry, Border, Color, Diameter, Evolving (ABCDE) rule for extracting the image's features from the regions of interest (ROIs). In this rule, A is asymmetry, B is border, C stands for colour, D is diameter and E is elevation or evolving (less used in clinical treatment). A set of features are extracted by Celebi et al. [18] from multiple operators describing the shape such as asymmetry and compactness of the lesions, and colour features computing several statistical measures over channels and colour spaces. They also used textural features, where grey-level co-occurrence was employed. Multi-scale roughness descriptors were used by Clawson et al. [24], Capdehourat et al. [19] and Arroyo and Zapirain [4], where the authors computed important statistical features as variance, Hessian matrix and entropy. In [4], they extracted Gaussian features using different values of σ and spectral texture features. To select the best features, a decision tree by means rule was implemented to obtain the 23 most significant features from a total of 80 extracted features. Similarly, Barata et al. [9] compared the global/local texture and colour features to classify skin lesion. For smart-phone-based real-time systems, Abuzaghleh et al. [25] proposed fast Fourier transform (FFT) mixed with discrete cosine transform (DCT) applied on colour and shape for feature extraction.

Categorization is the last step in the typical work-flow for the computerised analysis PSL images. The categorization performance is often measured in terms of accuracy, sensitivity and specificity. The computation of these metrics is mostly used to compare the results. The most used categorization and often explored by radiologist on ABCD criteria is scoring system by thresholds [6, 19], where the score is computed following the value and the weight attributed to each feature (see Table 1). They also used a 7-point checklist, which is another scoring system. The scores were divided into two parts, i.e. major criteria (atypical pigment network, blue-whitish veil and atypical vascular pattern) and minorcriteria (irregular streaks, irregular pigmentation, irregular dots/globules and regression structures). The major criteria received twopoints and those lying under minor criteria were awarded one point[6, 19]. The categorization is also done by thresholding for 7-point checklist. In the literature, Maglogiannis and Doukas [26] enumerate many classifiers explored in different categorization type used in dermoscopy such as Support Vector Machine (SVM), artificial neural network, K-nearest neighbours, discriminant analysis),decisions trees, K-means, Bayesian classifiers and regression analysis. Celebi et al. [18] used SVM classifier on a database of 564 images, with a proportion of 15.6% melanoma and 84.4% benign, an area under the ROC of 0.9662 is obtained as results.

Capdehourat et al. [19] applied their approach on 655 images of melanocytic lesions: 544 benign lesions and 111 malignant melanoma. The result obtained is 89% of specificity and 95% of sensitivity using AdaBoost / C5.4 approach. They compared their method with ABCD rule and 7-point checklist. The objective of Arroyo and Zapirain [4] is to detect typical and atypical networks, using high-level design which is composed of two main blocks, the machine learning process and the searching of pattern structures. They used C4.5 algorithm on 220 images (120 without reticular pattern and 100 with such structure), the sensitivity is 86% and the specificity is 81.67%.

Recently, Codella et al. [27] combine deep learning, sparse coding and SVM learning algorithms. On a database of 2624 skin images from International Skin Imaging

Collaboration (ISIC) archive database, a two-fold cross-validation is applied for categorization. The result obtained shows 93.1% of accuracy, 94.9% of sensitivity and 92.2% of specificity. One of the drawbacks of Codella et al. [27] study is that they chose a particular set of lesions for their approach which can be considered as statistically biased. Barata et al. [28] used four algorithms to extract colour constancy (Gray World, max-Red Green Blue (RGB) color model, Shady of Gray and General Gray World). SVM classifier with the $\chi 2$ kernel is used for categorization on two different databases, PH2 and Interactive Atlas of Dermoscopy (Skin Database) (EDRA).

The results obtained show the best performance on PH2 database, with an accuracy of 84.3%, a sensitivity of 92.5% and a specificity of 76.3%. Abuzaghleh et al. [25] used colour and shape geometry features using Fast Fourier Transform and DCT. SVM classifier is used on PH2 database for 75% for training and 25% for test. The results showed an accuracy of 90.6%. From the aforementioned type, most of the developed type consider only local or global features [4, 18, 24], and in other cases the authors used some special descriptors such as colour [28], pigment network and border irregularities [19]. In addition to that the majority of developed type is based on ABCD rule or 7-point checklist type, which is more visual scoring system than CAD system. For a fair comparison amongst the studies the database should be the same, which is not the case for many of these studies. Thus, from the literature, we suggest, three main items to aid the comparison of different proposed type:

1) The use of public databases, which could in addition to their private database.
2) The highlighting of all parameter details.
3) The results validation using statistical type such as cross-validation.

Despite the several developed approaches, to our knowledge, there is no CAD system available for medical doctors that can perfectly discriminate melanoma. Thus, there is a need to explore new directions in skin cancer detection. In the current paper, we explore a set of features describing the local characteristics such asdots and network pigments, using LBP operator and global characteristics such as border irregularities and asymmetry, exploring multiresolution analysis using wavelet and curvelet transforms.

As evident from the literature, the detection of melanoma is avery challenging task in dermoscopic images. Thus, in the current paper, we present an approach to distinguish between the benign and malignant lesions. Multiresolution techniques, e.g. wavelet and curve let provide shape representation of lesions by finding the borders and streaks in skin cancer image, while LBP operator is proposed to find all the local variations in colour and skin pigments. This paper presents an automatic set of features describing benign and malignant lesions. It aims at performing also between common, atypical and melanoma cases. The approach is performed and validated on a free public dataset of 200dermoscopic images and all details are highlighted. Two comparisons are done, intermediary one which is performed between different combinations of textural and structural features, then, we compared the obtained results to the ones achieved in the literature using the same public database.

III. SYSTEM DESIGN

In this research, we aim to propose an intelligent automated method for identification of the type of skin lesions using machine-learning techniques. Two types of texture feature have been used to perform categorization of melanoma and non-melanoma. First local information through Local Binary Pattern (LBP) on different scales and Gray Level Co-Occurrence Matrix (GLCM) at different angles has been extracted as a texture features. These features are robust due to scale invariant property of LBP and rotation invariant property of GLCM features.

The multitude of skin cancer lesions, benign and malignant, complicates the recognition of skin cancer. In addition to that, melanoma is developing randomly in different directions. Finding the best descriptor to discriminate melanoma is one of the challenging tasks in medical image processing. In the current paper, we present a set of perceptive features obtained from different descriptors to distinguish between benign and malignant cases as elaborate in experimental work. An elaborate statistical analysis of the used database is also reported. The methodology can be divided into two stages, i.e. computation of features (structural and texture) and fusion of features. Global information of different colours channels has been incorporated through four different moments extracted in various different color spaces like RGB, grey scale conversion etc., Experiments have been tested on well-known dataset dermis that is freely available on the Internet. The proposed method has been state of the art type and shows better performance in comparison to the existing type.

In order to improve the accuracy of feature extraction, eight different pre-processing algorithms were used. The algorithms used were converting to grey scale image, sharpening filter, median filter, smooth filter, binary mask, and RGB extraction, and histogram and sobel operator. The RGB values of the images are extracted before converting it into a gray scale image and set to thresholding value. Sharpening filter is applied to the gray scale image in order to sharpen the details of the infected region. The number of components of the skin affliction was extracted from the image using the Euler value. For the categorization use GLCM (Gray Level Co-occurrence Matrix) and LBP (Local Binary Pattern).

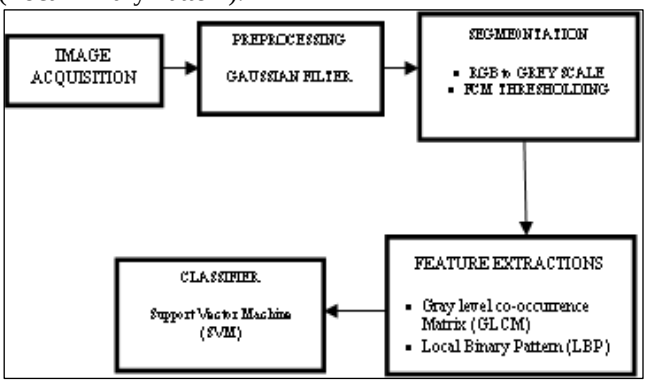

Fig. 1: Block Diagram of proposed system

A. Image Acquisition

The images for this research were obtained from dermquest website online skin diseases gallery

https://www.dermquest.com/. A total of different image samples were used with 40 pre-identification as malignant (cancerous) and the other 40 as benign (noncancerous). An example of our acquired images is shown below in Fig. 2.

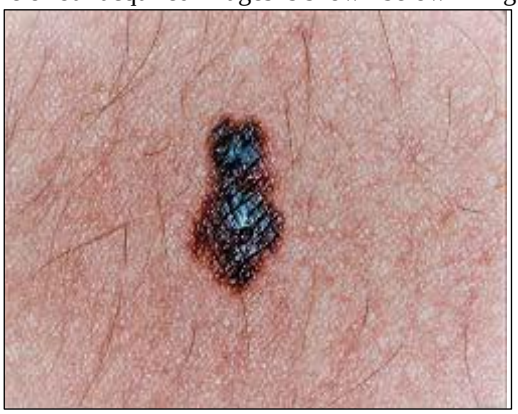

Fig. 2 Sample Acquired Image

B. Pre processing

1) The first step in pre-processing is the enhancement of the image by modification of both Contrast and Brightness (reduce light illumination). Contrast is described as the modification in colour or luminance that marks an object making it distinct and unique in the image. The higher the difference between a pixel and its neighbours the higher the contrast is in that area.

Brightness can be described as the sensitivity produced as a result of the luminance of a visual mark. In image processing of pixels, a bright pixel is characterised by a higher value [16]. We therefore modified our images by applying a scale factor and delta to the scaled values to perform enhancements 2) Colour Space: The grey scale conversion colour space, unlike the RGB (Red, Green and Blue) colour space which is the format of the acquired image from a standard camera, is a cylindrical colour space. The Hue values are across a circle. So, after completing one rotation across the circle, we get the same colour i.e. the Hue values at 0 and 360 represent the same colour as illustrated in Fig 3 below.

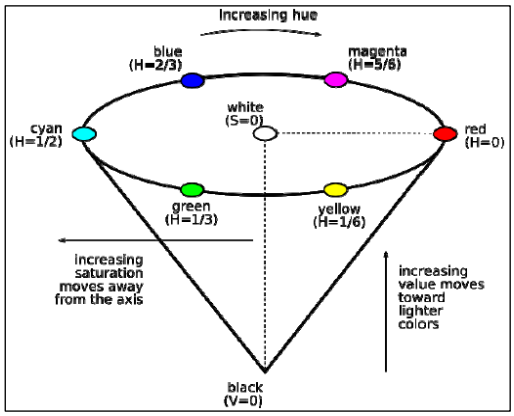

Fig. 3: RGB into Grey Scale Conversion

Grey scale conversion thresholding method usually gets better information for image processing. This is because it splits color data (Chroma) from intensity or lighting (Luma). Therefore, generating a histogram or thresholding procedures is likely using only saturation and hue as a result of the value being divided through color data splitting. We used the first channel which represents luminance is the Grey scale conversion format converted images. This format of the image is also a type of grayscale that makes it possible to extract contours by double thresholding.

C. Segmentation

We use morphological technique, which is derived from graph cuts for image segmentation in this research. The preliminary identified information about the foreground and the background is represented by the user in a rectangular selection around the region of interest. External pixels separating this selection are treated as recognized background while the internal pixels are identified as unknown. We therefore want to create a model from this information that can be used to conclude if the unknown pixels represent either background or foreground. In this method we are using FCM thrsholding method are used to segment the melanoma images.

D. Feature Extraction

Within the morphological algorithm, generating K modules of Different Gaussian Mixture Models (GLCM) for the two sections (background or foreground) achieves this. The parameter to the GLCM, LBP algorithm is the number of variable, K, to use and the first cluster, C1.

1) Initialize first fuzzy cluster, C1 = Unknown ∪ Foreground
2) Calculate the mean, μ1, and the covariance matrix Σ1of the variable C1
3) For i = 2 to K do
4) Find the variables, Cn, with the largest eigenvalue and its associated eigenvector en
5) Split Cn into two sets along the mean values projection on the eigenvector, Ci = {x ∈ Cn: enTzn ≤ enTTμn} and update the original Variables Iteration with the other half Cn∗ = Cn−Ci
6) Compute μn∗, Σn∗μi and Σi

E. Classification

The segmentation results are used to identify the largest contour to derive its features. The features we are interested in extracting from the contour are geometric Circularity and SVM. We find all the contours by using the read to define a threshold to eliminate smaller contours and sort the contours by sizes and it was used to find the given images are melanoma or not from the dataset images.

IV. RESULT AND DISCUSSIONS

The proposed method elaborate in Section 4 is applied on the various dermoscopic images from database. This database contains multiple non-melanoma (benign) and melanoma (malignant) images. The categorization is performed using SVM classifier with the 4 type, 85% of the database is used for training and 15% for test. A random sampling cross-validation method is applied to validate the obtained results, where a thousand (1000) combinations of training and test sets are chosen randomly from the database.

Recently, significant progress has been made in statistical learning theory and machine learning. The problem of learning is much better understood thanks for the work of several researchers, and algorithms with high categorization

accuracy such as SVM have been developed and successfully applied to many problems. Traditional approaches from statistics failed to address the problem of "the curse of dimensionality". However, SVM tries to minimize the empirical error while controlling the complexity of the mapping function

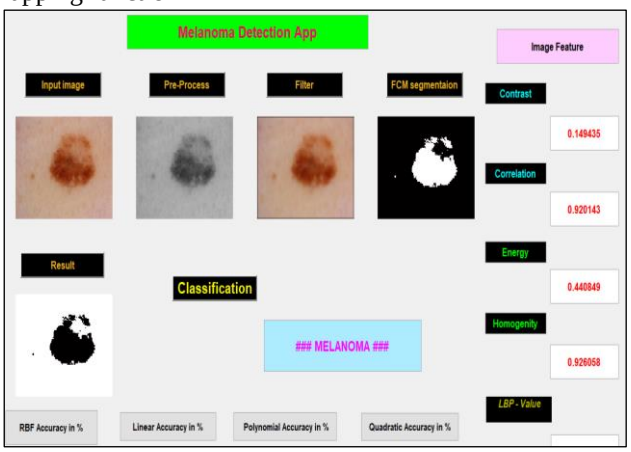

Fig. 4: GUI design and output for melanoma detection

Thus, each image is used in average number of times for training and number of times for tests. An unbiased standard deviation (Std) for the thousand combinations is also computed for the three performance metrics (sensitivity, specificity and accuracy) elaborate. Fig 4 describes the final GUI result skin cancer detection.

Several tests have been performed for the skin lesion images. One and two hundred feature vectors are extracted from each of them, within which 20% are reserved as testing samples, while the remaining data set are used for training. The average accuracy from 10 experiments (to reduce the variance from different experiments) for 100 and above feature vectors is about 80%, while the accuracy for feature vectors is about 70% for determining the benign and malignancy of any given images. The texture information in the skin lesion images has much lower frequency than those in the benchmark textured images. This results in larger window size. Analysis of the skin lesion images tells us that the real lesion.

However, for our experiments, all feature vectors were assigned labels based on whether the whole lesion image is classified as benign or malignant. Experiments results show better categorization accuracy when using skin lesion images from TLM modality, which confirms our observation. New experiments are designed to solve this problem by discard the background feature vectors, which will improve the categorization performance.

V. CONCLUSION

In this paper we described a SVM and texture classification algorithm for early melanoma detection. All the experiments were done using a simple texture feature –SVM features. We tested the algorithm on a benchmark binary texture categorization problem, and select the optimal window polynomial kernel for SVM based on performance analysis. After following the same performance analysis routine. Using this set of parameters we did experiments using pairs of skin lesion images with no disputable class label. The average accuracy for the binary categorization (LBP) is about 70% when 200 feature vectors are selected from each image. Future study look at whether more advanced texture feature extraction algorithms, such as the multi-channel filtering based texture feature extraction will improve the categorization accuracy for early melanoma detection.

Performance comparison will be studied between SVM-based texture categorization and the most popular data mining algorithm, decision-tree based texture categorization, in both spatial and frequency domain. Compared with various methods RBF, Linear, Polynomial and Quadratic accuracy is better than existing methods.

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