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SOFT COMPUTING APPROACH BASED MELANOMA DETECTION TECHNIQUES: A REVIEW

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ABSTRACT

Skin disease is the world's fourth largest cause of non-fatal diseases impacting 30-70% of populations and it is widespread across geographies and ages. In the United States, skin disease is the primary form of skin cancer. Skin disease is one of the most prevalent health issues. Over the years hepatic melanoma diagnosis is a complex field of research. Nevertheless, dermatologists usually have low supplies and the consultation costs are high, particularly in rural areas. Dermatoscopy is a widely used diagnostic method that enhances the detection of skin lesions, as it provides important lesion information that can be useful for the clinician and an automated alert tool. Diagnostic systems operated by computers need sophisticated image processing algorithms to provide statistical representations of suspended areas. In this article we have analysed the current technological advancements used in computer-aided skin lesion diagnostic techniques. The stages include the pre-processing of dermoscopic images, segmenting, feature selection and classification of specific characteristics and relegation of skin lesions. © 2012 Published by Elsevier Ltd. Selection and/or peer-review under responsibility of Global Science and Technology Forum Pte Ltd

KEYWORDS

Skin lesions, Melonoma, Dermatoscopy, Segmentation, Features, Clasifications.

1. INTRODUCTION

Melanoma is one of the critical skin diseases. The reports reveal that the melanoma is detected in benign state for quarter cases and rest cases are detected with malignant (Wang et al., 2011).

Precise early-stage identification of melanoma can significantly increase patient survival rates. Conversely traditional way to detect melanoma requires enormous specialization in skin diseases, which needs inter-observer variations for each patient (Abbas et al., 2016; Burrioni et al., 2004). Certainly it's a demand to develop an automatic system for melanoma detection which will help the pathologist to diagnosis of the skin diseases with higher accuracy (Celebi et al., 2008).

The strategy of dermoscopy was developed for the melanoma analysis and detection. Dermoscopy is a noninvasive way of imaging the skin, in which magnification and illumination is performed for defected skin region to improve clarity of the spots.

Due to which visual effect of skin lesion by removing surface reflection is improved (Barzegari et al., 2005; Iyatomi et al., 2008). Due to several challenges automatic melanoma detection using dermoscopic images becomes a complex process (Rubegni et al., 2001). Dermoscopic images have low contrast so it's very difficult to accurately segment skin lesions and normal skin region. The melanoma and non-melanoma lesions have same tissue intensity which makes difficult to differentiate between

melanoma & non-melanoma lesion (Celebi et al., 2007b; Alcon et al., 2009). Variations of skin conditions like skin colour and natural hairs between different patients make the different melanoma appearance (Kasmi et al., 2016).

Skin is the most astronomically enormous component of the human body. The skin is complex structure which consists of different layers viz. subcutaneous layer, dermis and epidermis layers. Skin's three main functions are Auspice, Sensation and Thermoregulation (Zhou et al., 2010). Stratum corneum is the upper layer of epidermis which is protective in nature and optically neutral with differing thicknesses (Garnavi et al., 2012; Abbas et al., 2013a; Abbas et al., 2013b; Greenland, 2008).

Basal layer of the epidermis includes melanocytes. Melanocytes create the skin pigment called melanin which provides the skin's bronze or brown colour. The extent to which the UV rays absorb depends on melanocyte concentration. Figure.1 represents different layer in internal skin structure (Yu et al., 2017).

Dermis is the middle layer of skin consisting of blood vessels, filters, antibodies, collagen fibers and nerve ends. It provides strength and elasticity to skin (Omar et al., 2015; Amelard et al., 2015; Oliveira et al., 2016; Dalila et al., 2017).

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Figure 1: Internal Skin structure with different layers

2. MATERIAL AND METHOD

Worldwide, a lesion of the skin contributes to serious disease. Early melanoma detection using dermoscopic images drastically augment the mortality rate. Accurate melanoma detection is enormously difficult due to tissue similarity and uneven contrast in images etc. Hence, accurate automated skin cancer identification is very useful to increase pathologist's precision and performance. Image processing based technique are employed to overcome above challenges. The overall flow of automated system consists of following steps as illustrate in Figure 2.

- Preprocessing
- Feature extraction
- Segmentation
- Classification

Figure 2: Automated skin lesion detection system

By reducing artefacts, preprocessing techniques improves the image quality. Extraction and selection of the feature provides the evaluating vectors on which the segmentation of the image is centered (Sadeghi et al., 2011; Olugbara et al., 2015). Segmentation divides pixels into zone and thus determines tissue boundaries. Segmentation is followed by regions being classified or labeled into tissue types. Precise segmentation of dermoscopic images as per the tissue type has become significant. In skin cancer research it is effective in diagnosis, treatment planning (Kasmi and Mokrani, 2016; Khalid et al, 2016). Changes in skin tissue structure can be used to define and interpret physiological processes, and to describe disease in large measure.

2.1 Feature Extraction

The feature extraction is technique used to mine the important features from an image which will be helpful for purpose of the application undertaken. In early detection of melanoma shape, colour, texture of skin lesions and geometrical features are used as important features. Several studies have been performed for the extraction of features from segmented region (Celebi et al., 2013; Zortea et al., 2017). This sub-section offers insight into the various features of dermoscopic images that have been identified for melanoma detection till date. Figure 3 below shows a summary of the groups of features used for melanoma detection.

2.2 Segmentation

Segmentation refers to division of dermoscopic image into different areas that contain every pixel having same attributes. Performance of medical image analysis relies on the consistency of segmentation and the accurate segmentation of the image is usually very difficult (Okuboyejo et al., 2013; Schaefer et al., 2011; Xie and Bovik, 2013). Manual detection of boundaries includes the dilemma root due to tumor overlapping. Hence increased knowledge of lesion characteristics must be considered for accurate

segmentation. Additionally, the classification process would be less affected by boundary errors (Garnavi et al., 2011; Zortea et al., 2011).

The possibilities for an early screening system focused on a computer based evaluation of dermoscopic images are currently highly ecstatic (Khuwuthyakorn et al., 2010; Yang et al., 2013a). Segmentation is an automated process for developing a strong computer aided framework for early precautionary skin lesions analysis. This offers remarkable research scope to have a computer-based framework for analysis of dermoscopic images (Meckbach et al., 2014; Flores and Scharcanski, 2016; Bozorgtabar et al., 2016).

Figure 3: Feature distribution used in Dermoscopic distribution

2.3 Classification

Skin disease can be caused due to allergies, certain conditions, genetic makeup, irritants and immune problems (Hussain et al., 2016; Ahn et al., 2017). These skin diseases are classified into different categories based on appearance & clinical diagnosis are shown in Figure. 4 and Figure 5.

Figure 4: Tree-structure that divides the diagnoses up into groups based on appearance and clinical similarity

The dermoscopic images can be classified into nine different diagnostic categories depicted as below

- 1) Melanoma
- 2) Basal cell carcinoma
- 3) Actinic keratosis
- 4) Vascular lesion
- 5) Squamous cell carcinoma
- 6) Benign keratosis
- 7) Melanocytic nevus
- 8) Dermatofibroma
- 9) None of the others

3. COMPARATIVE ANALYSIS

3.1 Segmentation Techniques

Segmentation is the method of separating an image into various regions. In medical imaging, segmented regions ensemble specific tissue types, pathologies, organ or other biologically relevant structures (Thompson and Jeyakumar, 2016; Masood et al., 2013; Pennisi et al., 2016). Low contrast, noise and other inconsistencies in imaging makes medical image

segmentation difficult. Many image processing and computer vision techniques for segmentation of images have been specifically developed for computation of medical images (Dalila et al., 2017).

Table 1 focuses on various techniques used by researchers to analyze the dermoscopic images using different image segmentation techniques (Celebi et al., 2007a; Fan et al., 2017; Gomez et al., 2008). Many dermatologists prefer ABCD criteria to classify melanoma from normal skin. It has been shown that it is easy to learn and estimated easily and it is trustworthy method which provides additional intent and accurate diagnosis of melanoma (Okuboyejo et al., 2014a; Premaladha et al., 2016; Ahn et al., 2015).

Figure 5: Skin Disease classification

Table 1: Segmentation Methods for Dermoscopic images.					
Processing category	Segmentation Method/s	No. of Processing Images	Evaluation Metric	Performance measure	Research Outcome
Soft Computing Based Approach	Cooperative Neural Networks	100	Greylevels:0.16	NA	<ul style="list-style-type: none"> Bulky and Difficult to examination Minimum awareness serves an objective function Effective segmentation Supervised learning is used Non-uniform illumination case sensitive
	Evolution Strategies	111	Error Rate Min 45 to 84.71%	15min	
	Fully Convolution Residual Network	900 Training + 350 Testing	0.911 Sensitivity 0.97 Specificity	0.52 Sec	
	CNN	900 Training + 379 Testing	0.847 JI	0.14 Sec	
	Dynamic Programming	240	BCC: 9.0% MCC: 7.02%	12.65 Sec	
	Improved Dynamic Programming	100	Sensitivity:94.64% Specifitivity:98.14	2.5 Sec	
Deformable Models	Chan-Vese	408	Subjective Evaluation	49.12 min	<ul style="list-style-type: none"> Simplify analysis by reducing pixels Conserve satisfactory structure
	Region Based Active Contours	175	Error Predictor Single Contour- 8.38 % Multi Contour- 4.32 %	17.89 Sec	
	Mean Shift GVF	100	86% SE; 99% SP	NA	
Fusion Based Technique	Thresholding + dynamic Contour	250	FPR: 3.03% GT and SI differ in 10.82%	NA	<ul style="list-style-type: none"> Evade post processing Robust segmentation
	dynamic Contour	152	Sensitivity- 90.07% Specificity- 99.11% Error rate-15.60%	NA	
	HCA+ Region Based Method	100	TPR-94.25% FPR- 3.56% EP- 4%	9.52 Sec	
	Fusion Thresholding	90	8.79% XOR	0.1s	
Region Based Methods	Region Merging	60	DR93.06- 94 Negative PR 3.03	NA	<ul style="list-style-type: none"> Rigidity in seed point selection
	Iterative Stochastic Region Merging	60	Segmentation Inaccuracy- 9.16-10 %	6 sec	<ul style="list-style-type: none"> Merge intense effects severer edges and shadowy images
Thresholding Based Methods	Thresholding	426	Precall. 84.5% Recall;88.5% Sensitivity: 93.9% Precall,93.8%	NA	<ul style="list-style-type: none"> Non expensive to compute Threshold selection is important

3.2 Classification Techniques

A quick summary of the well-known segmentation techniques is explained. Similarly various classification techniques used in computer-aided melanoma demonstrative frameworks is explained. The Figure. 6 illuminates various soft computing based Classification approaches used in Skin lesion detection.

3.3 Skin Lesion detection system

For prompt diagnosis and treatment planning early detection and segmenation of skin lesions is essential. Early detection is crucial to increase the survival rate of patients. During manual detection processing time, dermatologist intra- and inter-observer differences makes unproductive system (Zhao et al., 2017; Aksac et al., 2017). This challenge occurs in

manual detection system leads to develop an accurate and automatic system (Zhang et al., 2017). To overcome this issue, we reviewed the various techniques and approaches used for detection and classification of skin lesion/s (Yang et al., 2013).

In machine learning approach features plays an important role to develop effective system. Generally color, Texture, shape, asymmetry and border are important features considered during previous research work (Borji et al., 2015). To compute performance of various classification algorithm sensitivity, specificity, accuracy, false prediction value and Mathews' correlation coefficient (MCC) are considered (Dubey et al., 2015; Celebi et al., 2015; Okuboyejo et al., 2014b). Table 2. Shows Comparative Analysis of Skin Disease Detection Approaches where feature extraction & performance of algorithm are elaborated

Table 2: Comparative Analysis of Skin Disease Detection Approaches

Author	Year	Segmentation method	Feature Extraction	Classification	Remarks	Sensitivity (SEN)	Specificity (SPE)	Accuracy (ACC)
Q. Abbas et al	2016	Circular center of each PSL	Colour & Texture	MV-SVM	This classifies seven types of skin lesion	94.04	84	93.30
Marco Burroni et al	2004	Laplacian filter+ zero crossing algorithm	Geometry, colors textures and islands of color	KNN	Uses 4 computation analyzer to compute PSL in different dermatological units.	98%	79%	NA
M. Barzegari et al	2005	Laplacian filter+ zero crossing algorithm	Lesions were excised and examined histologically	KNN	Skin lesion score was found in range of 1-10.	NA	98.90	90
H. Iyatomi et al	2008	Clustering + Region Growing	Color, Texture Symmetry, Border,	ANN	Web server is established on the Internet	85.9%	86%	NA
M.E. Celebi et al	2008	Region Growing+ Region	Shape, Color, texture	SVM	Shape & texture features are computed and processed using feature Selection algorithm (CFS, MIFS and ReliefF)	93.3%	92.34%	NA
J.F. Alcon et al	2009	Threshold	Color, Texture Asymmetry, Border	Bayesian	Correlational features are selected	94%	68%	86%
Y. Zhou et al	2010	Normalized Cut	Border Irregularity	Discriminant Analysis	Centroid distance is influential to distinguishing border irregularity	74.2%	72.6%	NA
Abuzagheh et al	2012	Global thresholding + adaptive histogram thresholding	Radix 2-FFT	SVM+ RF+ LMT+ HNB classifiers	Feature selection was done by gain ratio technique	NA	NA	91.26% AUC 0.937
Q. Abbas et al	2013	450 × 450 ROI	Color Multi-scale Texture	ML-SVM ML-KNN	Color-texture features matches dermatologist opinion	89.2%	93.75%	NA
Q. Abbas et al	2013	Thresholding +Improved Dynamic Programming	Asymmetry, Border Irregularity, Color, Differential Structures	SVM	Sequential floating in forward approach, ABCD features used in investigative system	88.2%	91.3%	NA
S. Greenland et al	2015	Laplacian filter+ zero crossing algorithm	Global & local variables	Random Forest & probabilistic classifiers are used	CFS subset evaluation	NA	NA	84.16%
R. Amelard	2015	450 × 450 ROI	High level Intuitive Features	AdaBoost MC LIBSVM	accuracy was find for different optimization function	NA	NA	83.59%, 81.36%, 81.17%
Abuzagheh et al	2015	Sparse Field level-set method (Otsu thresholding) using Active Contour	2-FFT & 2-DCT	Using LIBSVM integrated software	Different level classifiers are Compared	NA	NA	Benign 96.3% Atypical 95.7% Melanoma 97.5%
Q. Abbas et al	2016	Chan-Vese	Asymmetric Border Irregularity Color	Using SVM	chronological forward selection CASH features are extracted	NA	NA	74.36%
FekracheDalila et al	2017	Segmentation using Ant Colony	Texture Features Shape Color	Using KNN & ANN	Using Relief algorithm 12 feature Extracted & selected in this approach	NA	NA	KNN 85.22% ANN 93.60%
L. Yu et al	2018	Fully Convolutional Residual Network	Differential Structures Asymmetry, Border, Color,	Deep Residual Network	Using Residual learning avoid the partial training data limitation	0.547	0.931	0.855
R. Kasmi et al	2019	Intrinsic Geometry active contour	Asymmetric Border Irregularity Color disparity Structures	Total dermoscopy score	Using Differential Structures geometric properties are extracted	0.912	0.958	0.94
Josep Quintana	2019	Fully Convolutional Neural Network	ABCD	Performance Time	Different level classifiers are Compared, Residual Training is used to ignore training rate of algorithm	0.568	0.968	0.85
R. Amelard	2018	SVM Library (LIBSVM)	High level Intuitive Features	Accuracy	Accuracy was calculated with optimization function variance	Accuracy in between 80-85%		
P.G. Cavalcanti	2018	ANT colony based optimization & Segmentation	Texture Features	Accuracy	Accuracy was calculated	Accuracy in between 85-93 % for ANN & KNN

Figure 6: Classification techniques used for skin lesion detection

4. CONCLUSION

Skin cancer is the globe's most common cancer, with melanoma the largest. Dermoscopy is a technique for skin imaging that has shown improvement in skin cancer diagnosis relative to unassisted visual inspection. Nevertheless, physicians should be properly trained to incorporate these developments. Skin and subcutaneous diseases are estimated to affect nearly 1.9 billion people at all times and remain the world's 4th largest non-fatal disease cause.

The lack of dermatologists, which means long waiting and prompting patients to receive dermatological services from physicians are restricting their access to dermatological treatment. In Manual diagnostic the overall accuracy was found in between 25 % to 70 %. This moderate diagnostic findings will causes due to over- and under-referrals, delays in precaution and diagnosis and treatment error. This review paper provides a details review of skin cancer detection techniques.

Digital dermoscopy is a commonly used non-invasive method combining visual magnification with exceptional imaging techniques to offer an enhanced dermoscopic image for clinical melanoma diagnosis. Dermatologists already prefer this method routinely for several decades to study human skin's surface structure that is invisible to the naked eyes. This diagnostic process, however, is time-consuming and highly subjective, and a dermatologist needs a lot of experience. Because of the difficulty of melanoma treatment at later stages, researchers are trying to develop an effective, non-invasive, computer-aided automated system to make its diagnosis quicker and easier

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