

A 3D RECONSTRUCTION AND MONITORING TECHNIQUE FOR COMPUTERIZED DERMOSCOPIC SKIN LESION CLASSIFICATION

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Abstract— This paper highlights a non-invasive 3D reconstruction and monitoring technique for early detection of melanoma. Melanoma is life threatening when it grows beyond the dermis of skin. Hence, depth is an important factor to diagnose melanoma. The computer aided monitoring system empowers and motivates the user to actively manage their skin health status by collecting, processing and store information of skin lesion through classifications. In this paper introduces a 3D segmentation method, which is an energy minimization based method designed to segment individual objects in 3D satisfying certain size and shape properties. Different feature set combination is considered and performance is evaluated. Experimental results prove that the proposed computerized dermoscopic system is efficient and can be used to diagnose varied skin lesions.

Keywords— 3D lesion reconstruction, 3D features and tumor depth estimation, 3D segmentation, skin lesions, melanoma, Bag of Features, Adaboost algorithm, Support Vector Machine.

INTRODUCTION

The world health organization reports a rapid increase of skin cancer cases [20]. Skin cancer can be broadly classified as melanoma and non-melanoma type. About two to three million cases of non-melanoma cancer and 132,000 melanoma cancers are reported annually worldwide [5]. The computer aided diagnostic systems are also referred to as "Computerized dermoscopy". Computerized dermoscopy systems primarily constituted of five components A) Dermoscopy image acquisition of skin lesions, B) Region of interest identification or segmentation of skin lesion, C) Feature Extraction D) Feature selection and E) Decision making mechanisms achieved through machine learning techniques. Numerous studies published lay emphasis on the segmentation or region of interest identification. Digital image processing plays a vital role in the area of research and has opened a wide range of new research prospects. Image processing is a profound key that can modify the outlook of many designs and proposals. Digital image processing refers to the automatic processing of digital image by means of digital computer. The basic steps involved in image processing are image acquisition, pre-processing, segmentation, enhancement of image, image compression, and restoration. In this, image segmentation has become a very significant task in today's scenario [14]. Segmentation is usually the primary step in any computer aided analysis of images. The segmentation process converts an image into more easy and meaningful way to analyze. It is typically used to extract boundaries and curves in the images. Application areas of segmentation includes content based image retrieval, locating, biometric recognition, detection of tumors, tissues in medical field.

Melanoma is typically a type of skin cancer. Of all types of skin cancer known, melanoma is the deadliest type and the highest mortality rates are reported from patients suffering from melanoma. Melanoma cancer occurrences are predominantly reported in the skin but occurrences in the eyes, nasal passages, throat, brain etc. are also known. In the research presented here melanoma cancer of the skin is considered. To diagnose melanoma of the skin a physical examination by a dermatologist and a biopsy is generally carried out. Post confirmation, the doctors proceed to identify the stage of the melanoma skin cancer to initiate the relevant treatment. Stages of melanoma are described through various scales like Clarke scale, Breslow scale, Tumor Node and Metastases (TNM) scales. The Clarke and Breslow scale basically define the measure of the depth of the tumor i.e. how deep the tumor has gone into the skin. A normal skin anatomy is shown in Fig.1 (a). The T stages of melanoma defined by Cancer Research UK [7] to measure type and size of tumor.

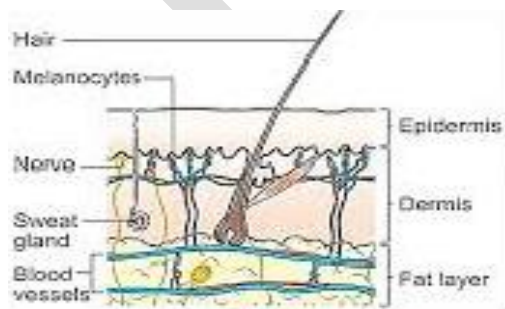


Fig 1(a)

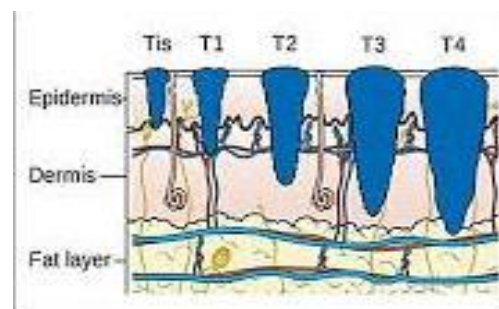


Fig1(b)

FIGURE 1. Anatomy of the skin (a) and T Stages of melanoma (b). Based on the depth of the primary tumor the stage of melanoma is identified. (Note: Depth and dimension of tumor may vary from case to case. Figure only intends to highlight the significance of tumor depth in melanoma diagnosis) (Source: Cancer Research UK).

“Tis” represents an initial stage of melanoma and the tumor is on the epidermis (i.e. top layer of the skin). The primary tumor T1 is of depth is less than 1 mm and is still in the epidermis. Primary tumor T2 has grown into the dermis of the skin and its depth ranges from 1mm to 2mm. Size of the tumor is T3 if its measured depth is 2mm to 4 mm thick and is still localized to the dermis. When the growth depth of a primary tumor is greater than 4mm and is beyond the dermis then it is said to be of T4 size. Based on how far the cancer is spread and the size of the tumor melanoma cancer is classified into five stages[7].

Stage 0: It is the initial stage referred as in-situ melanoma. Occurrences of abnormal melanocytes are observed in the top layer of the skin. Melanoma detected in this stage is 100% curable.

Stage 1: The tumor in this stage has spread into the skin but limited to the epidermis layer. No spread into the lymph or other parts of the body are detected. The tumor growth depth is between 1mm to 2mm and can exhibit ulceration (i.e. breakage of the skin). At this stage through surgical procedures the patients can be cured.

Stage 2: Melanoma tumor is 2mm to 4mm in size and can exhibit ulceration. No spread to lymph nodes or other parts of the body. Cure is possible through surgical procedures.

Stage 3: Tumor is more than 4mm deep and can exhibit ulceration. Cancer is spread to the lymph nodes but is still localized. Advance surgery and post-surgical care required. Survival rate is less.

Stage 4: The tumor is more than 4mm deep and has spread to other organs and lymph nodes. Treatment at this stage is expensive and life threatening as the cancer has spread from its primary tumor site. Low survival rates amongst patients.

Based on the above discussion it is clear that the depth of the tumor is a critical parameter for diagnosis and identification of the cancer stage. Early detection of melanoma (Stage 0 and Stage 1) is the solution to reduce mortality rates amongst patients suffering from melanoma skin cancer. This computerized dermoscopy system to aid early detection of melanoma is presented considering the 3D reconstruction of the lesion. The 3D reconstruction enables to estimate the relative depth of the primary tumor.

A non-invasive computerized dermoscopy system to aid diagnosis of skin lesions is proposed method. A 3D segmentation of the 2D dermoscopic skin lesion images. To reconstruct the 3D skin lesion initially a depth map is derived from the 2D dermoscopic image. The depth map data is fit to the 2D surface to achieve 3D skin lesion reconstruction. The 3D skin lesion is represented as structure tensors. Using the 2D skin lesion data colour, texture and 2D shape features are extracted. The 3D reconstructed skin lesion data issued to obtain the 3D shape features. The 3D shape features encompass the relative depth features estimated. To highlight and study the significance of the features, feature selection methods are considered. For decision making, three different multiclass classifiers have been considered and their performance is compared and studied. The proposed computerized dermoscopy system relies on bag-of-features (BoF), AdaBoost and Support Vector Machine (SVM) for decision making[18]. The patient monitoring is done by sending the output dermoscopic images to the doctor's mail and thereby real time monitoring of patient can be done accurately and can prevent form death of the patient.

RELATED WORKS

A Multi Parameter Extraction and Classification System(MPECS) is proposed to detect early melanoma[12].A six phase approach is[11]adopted to extract the colour,texture and shape features. Classification of three skin lesion types, namely “Advanced Melanoma”,”Non-Melanoma,”Early Melanoma” is achieved and not explained about the accurate depth of the tumor.into benign or malignant types. The use of classical clinical algorithms such as ABCD (Asymmetry, Border, Color and Diameter) [8], ABCDE(Asymmetry, Border, Color, Diameter and Evolution) [9],Menzies method [10] and the seven-point checklist [11] is adopted by for the diagnosis of melanoma skin lesions. An improvement of 5_30% is achieved by using dermoscopy and classical clinical algorithms when compared to the examination carried out by the naked human eye [12]. The skill of the dermatologists is also critical to achieve accurate diagnostic performance considering dermoscopy images [13], [14].Considering the varied type of melanoma, non-melanoma skin lesions and dependency on the skill level of dermatologist, accurate diagnosis of melanoma is still a problem.

A. Saéz et al. [19] consider that each dermoscopic image represents a Markov model. The parameters estimated from the model are considered as the features of the skin lesion. Classification is performed to identify the globular,reticular and homogeneous patterns in the pigmented cell. Saéz et al. [19] have obtained the dermoscopic images from Interactive Atlas of Dermoscopy [4].Based on high-level intuitive features (*HILIF*) and *SVM* classifiers the diagnosis of melanomas and non-melanoma skin lesions is presented in [4]. In addition to the *HILIF* features, low-level features and their combinations are also considered. In [2] a novel equation to compute the exposure time for skin to burn is introduced A threshold based segmentation, hair detection and removal techniques is considered as the pre-processing steps in the image analysis module. Shape, color and texture features are extracted to define the skin lesion images. A two level *SVM* classifier is used to identify the benign, atypical and melanoma moles from the *PH2* dataset [18]. The importance of considering global and local features in computer aided diagnosis methods is discussed in [7]. Use of color and texture features (global and local) to identify melanoma and non-melanoma images from the *PH2* dataset is presented. The use of, *SVM*, AdaBoost and BoF classifiers adopted for decision making. Based on the related works reviewed it is observed that limited work is carried out

considering 3D reconstruction, depth estimation and 3D shape features of skin lesions which is critical to diagnose melanoma skin cancer. The state of art works carried out so far predominantly consider only binary decision making mechanisms. In this paper, considers a 3D reconstruction of skin lesion images to estimate depth of the tumour and adopt multiclass decision making mechanisms.

PROPOSED WORK

The proposed computerized dermoscopy system is to aid early detection of melanoma, additionally, the proposed system can also be adopted to diagnose different skin lesions types and the monitoring of patient done by sending the dermoscopic image to the doctor for verification thereby the patient take treatments early as possible. The dermoscopic image dataset is considered to consist of training and testing data. Segmentation is performed obtain the region of interest or skin lesion to be diagnosed. A depth map is extracted from the 2D dermoscopic image. Depth map is used in constructing a 3D model corresponding to the dermoscopic image. The 3D model is represented as a structure tensor. A comprehensive feature set considering the 2D shape, 3D shape, color and texture are extracted per image. A feature selection method to understand the significance of features extracted on decision making is incorporated. For decision making, most of the related works consider binary classification mechanisms. The proposed system considers a multiclass classification mechanisms for decision making, enabling its applicability to diagnose a wide variety of skin lesion images. The computer-aided monitoring system that empowers and motivates the users to actively manage their own skin health status by collecting, processing and store information of skin lesions through its automatic classification. This solution is not intended to perform a skin cancer diagnosis, but rather alert the users to the presence of risk signs and take them earlier to the doctor. Dermoscopic images used for evaluation are obtained from CDROM of Dermoscopy and PH2 dataset.

PROBLEM FORMULATION

Let $I = \{I_0, I_1, \dots, I_n\}$ represent a set of n dermoscopic images. Let $C = \{C_0, C_1, \dots, C_m\}$ represent a set of classes of the dermoscopic. The set I consists of images used for training and testing. Each image I_n is represented by a feature set F_n . The training data is represented as $R = \{(F_1, C_2), (F_2, C_2), \dots, (F_r, C_r)\}$

Similarly the testing data vector can be as $T = \{(F_1, C_1), (F_2, C_2), \dots, (F_t, C_t)\}$. C_t represent the unknown classes and F_t represent a set of features extracted from the images whose class is to be identified. Let D represents the decision making mechanism such that $D(F_r) = C_r$. The goal of proposed system is $D(F_t) = C_t$ i.e. features of image can be need to diagnosed.

3D SEGMENTATION

Image segmentation is a fundamental problem in computer vision and most of the statistical analysis in several applications. For example identification of cells in microscopy images is one of the major challenges in computational biology. Single-cell analysis of brain cells, bacteria or tumors leads to a better understanding of fundamental biological processes and to a more precise treatment of diseases. A variety of methods were proposed to segment cells in tissue sections and cell cultures and several software packages utilize these results for further statistical analysis. Recent studies in biotechnology show that cells cultured in a 3-dimensional microenvironment mimic disease physiology more precisely than those cultured in 2-dimension[2]. To study cell-cell interactions and create predictive models, different cell types are often mixed and 3-dimensional co-cultures and organoids are grown. The segmentation of such mixed 3D cell populations at the single-cell level is a great challenge, especially when their morphology shows high diversity. Although recent advances in light microscopy and assay preparation where made possible to successfully use these models for drug development and clinical applications, there is a great need for advanced segmentation methods to most precisely and cost effectively analyze these large-scale (often 10-100 TB) image data sets.

3D LESION SURFACE RECONSTRUCTION

3D reconstruction is essential to estimate depth of the skin lesions. Techniques like stereo vision, structure from motion, depth from focus, depth from defocus etc. are used to estimate depth considering multiple images. Using constrained image acquisition techniques like active illumination and coded aperture method's, depth can be estimated using single images. The varying or unknown dermoscopic data acquisition parameters/settings used and the non-availability of multiple images render these mechanisms ineffective. In [20] a novel technique to estimate depth, considering a single image obtained from unconstrained image data acquisition techniques is described. The proposed computerized dermoscopy system adopts this technique to estimate the depth in dermoscopic images. Depth map obtained is fit to the underling 2D surface to enable 3D surface reconstruction. The 3D surface

constructed is represented as structure tensors. The 3D surface reconstruction results considering two melanoma and one blue nevus skin lesion images is shown in Fig.2

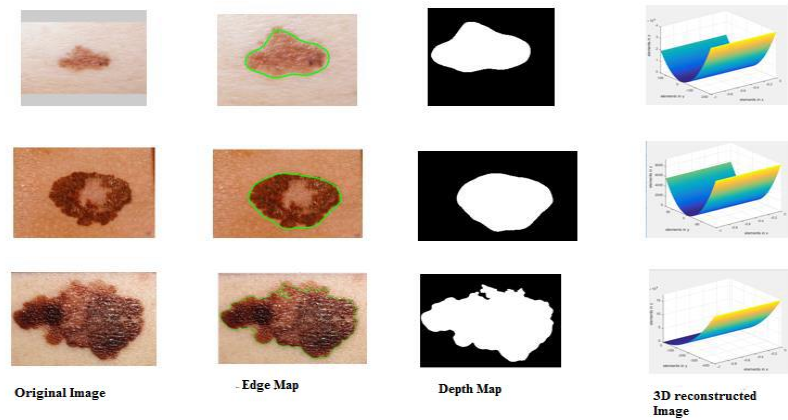


Figure 2: The 3D lesion surface reconstruction technique. The original image is shown in column 1. The edge map used to compute the defocus is shown in column 2. Sparse and the resultant depth map is shown in column 3-4. The structure tensor T representing the 3D lesion surface is shown in the last column.

FEATURE EXTRACTION

Characteristics of the skin lesion images are represented as features. In this paper color, texture, 2D shape and 3D shape features are considered. Accurate and robust feature representation is essential as they directly affect the performance of the skin lesion classification.

COLOR FEATURE EXTRACTION

Color characteristics are often used by dermatologists to classify skin lesions.[7] According to dermatologists, skin lesions are characterized by variegated coloring[10]. The variegated coloring induces high variance in the red, green and blue color space. Red, green and blue component data of the pixels in the segmented skin lesion is stored as vectors. The mean μ and variance σ of each channel is computed. Mean, variance are represented as μ_R, μ_G, μ_B and $\sigma_R, \sigma_G, \sigma_B$. To capture complex non-uniform color distributions within the skin lesion, mean ratios of the mean values is computed.

TEXTURE FEATURE EXTRACTION

To extract the texture features the segmented skin lesion image is converted to grey scale. Haralick-features [20] are adopted to obtain the texture characteristics of the skin lesion. Considering applicability of the proposed computerized dermoscopy system to classify even low quality skin lesion images, Haralick texture features are considered. Texture features are computed using gray-tone spatial-dependence matrices, i.e. $G_s^{(0)}(x,y)$. The energy feature is computed by using

$$E^{(0)} = \sum_{x,y} G_s(x,y)^2$$

CLASSIFICATION

Skin lesion classification is the final step of proposed computerized dermoscopy system. In this work presented here, three different classes of classifiers i.e. SVM [8,9], AdaBoost[20] and the recently developed Bag-of-features (BoF)[13,17] classifiers are adopted. The classifiers adopted are also referred to as decision making mechanisms D . Classification broadly involves two phases namely training and testing. In the training phase the classifiers learn from the training set R . Feature properties with respect to the classes are derived in the training phase. In the testing phase we wish to classify test data T . Based on the feature properties observed in training, the decision making mechanisms D classifies a test image represented by feature set F_t as the resultant class C_t . Skin lesion data is complex in nature and cannot be considered as a global model. In the BoF decision making mechanism, skin lesion data is considered

as a combination of individual feature models rather than the complete feature set. The BoF classifier exhibits promising results when adopted for complex image analysis. Therefore, the BoF classifier was deemed applicable to solve our skin lesion classification problem. The capability to train a strong classifier from a combination of weak classifiers and appropriate feature selection capabilities exhibited by the AdaBoost algorithm. SVM classifiers are robust, [9] simple to implement and provide high degree of classification accuracy. Recent works for skin lesion classification [14], [2], [4], [7] prove the ability of SVM classifier for decision making. A Gaussian radial basis function (RBF) kernel is considered in the proposed computerized dermoscopy system. The RBF kernel assists in deriving complex relations between the skin lesion classes and complex nonlinear skin lesion data represented as a feature vector space. A linear kernel is a special case of the RBF kernel, hence SVM classifier is chosen in the proposed method.

EXPERIMENTS AND RESULTS

In this section experimental studies conducted to evaluate the performance of the proposed computerized dermoscopy system [7]. The proposed system was implemented on MATLAB. The dermoscopy data used in the experiments where considering the performance of the three classifiers proposed, comparisons with existing systems and the experiments based on the 3D reconstruction algorithm proposed for depth estimation.

ASSESSMENT OF BoF, AdaBOOST AND SVM CLASSIFIER

The BoF classifier considers a block size of 50 and the number of histogram bins is set to 25. The k-means clustering algorithm is adopted to obtain visual words the KNN employed, considers Euclidean distance and the number of neighbors is set to 10. Inclusion of shape features to color and texture improve performance considering the BoF classifier. Results considering ATLAS dataset show that color and texture information alone considered in D2EX2 is insufficient to classify skin lesions. Considering shape feature improves performance of the BoF classifier observed in D2EX1, D2EX3 and D2EX4. The AdaBoost classifier considered is built using 10 weak classifiers [6]. Number of bins is set to 50. This configuration is established based on a number of iterations to obtain best performance. Results obtained prove that the SVM classifier exhibits better generalization performance on increasing the feature vector when compared to the other classifiers. Observe results of D1EX1, D1EX4 against D1EX2 and D1EX3. A marked performance improvement considering the proposed 3D shape feature inclusion is reported on PH2 dataset. Similar performance improvement is reported considering ATLAS dataset. Sensitivity, specificity and accuracy are described in terms of TP, TN, FN and FP.

True positive (TP) = the number of cases correctly identified as patient

False positive (FP) = the number of cases incorrectly identified as patient

True negative (TN) = the number of cases correctly identified as healthy

False negative (FN) = the number of cases incorrectly identified as healthy

Sensitivity: The sensitivity of a test is its ability to determine the patient cases correctly. To estimate it, we should calculate the proportion of true positive in patient cases. Mathematically, this can be stated as:

$$\text{Sensitivity} = TP / (TP + FN) = (\text{Number of true positive assessment}) / (\text{Number of all positive assessment})$$

Specificity: The specificity of a test is its ability to determine the healthy cases correctly. To estimate it, we should calculate the proportion of true negative in healthy cases. Mathematically, this can be stated as:

$$\text{Specificity} = TN / (TN + FP) = (\text{Number of true negative assessment}) / (\text{Number of all negative assessment})$$

Accuracy: The accuracy of a test is its ability to differentiate the patient and healthy cases correctly. To estimate the accuracy of a test, we should calculate the proportion of true positive and true negative in all evaluated cases. Mathematically, this can be stated as

$$\text{Accuracy} = (TN + TP) / (TN + TP + FN + FP) = (\text{Number of correct assessments}) / (\text{Number of all assessment})$$

The tradeoff between specificity (SP) and sensitivity (SE) have introduces a cost function C for evaluating the performance. The cost function C is defined as

$$C = \frac{K_{FN}(1-SE) + K_{FP}(1-SP)}{K_{FN} + K_{FP}}$$

Where K_{FN} and K_{FP} are constants and $K_{FN} = 1.5 \times K_{FP}$. K_{FN} and K_{FP} represents false negative (FN) and false positive (FP). In the experimental results $K_{FN} = 1.5$ and $K_{FP} = 1.0$ is considered

Table 1: Experimental result from Adaboost

Exp	SE	SP	C
D1EX1	94%	97%	0.049
D1EX2	96%	98%	0.029
D1EX3	96%	98%	0.028
D1EX4	94%	97%	0.049

Table 2: Experimental result from SVM

Exp	SE	SP	C
D1EX1	80%	97%	0.136
D1EX2	96%	91%	0.448
D1EX3	97%	94%	0.271
D1EX4	98%	99%	0.013

ASSESSMENT OF 3D SKIN LESION RECONSTRUCTION TECHNIQUE

A major goal of the proposed computerized dermoscopy system is to aid early detection of melanoma i.e. in-situ melanoma. Diagnosis can be efficiently achieved using the 3D reconstruction technique proposed. The 3D data / tensor provides useful insight to analyze relative depth of melanoma cancer skin lesions. The International Skin Imaging Collaboration (ISIC):Melanoma Project introduced in recent times, is an academia-industry partnership providing dermoscopic data for melanoma diagnosis [16]. A large number of societies have collaborated together in the ISIC: Melanoma Project. Data provided is by far the most comprehensive set of publicly available melanoma skin lesion images [13]. A total Clinical/ diagnosis data corresponding to each skin lesion image is also available. Though actual depth (currently obtained using invasive biopsy) cannot be computed, accurate estimates can be obtained by using the proposed technique. The relative estimated depth is a critical feature for identification of in-situ melanoma. In addition, 3D features extracted using the 3D reconstructed skin lesion improve overall system classification performance as reported in the previous section.

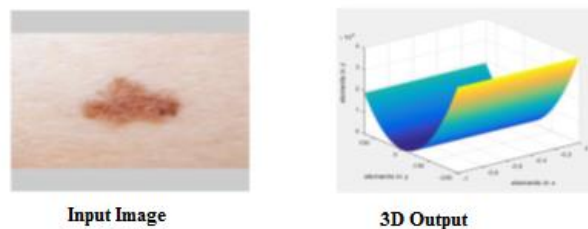


Figure 3: Melanoma follow up image and its estimate depth

From figure 3 the relative depth of the tumor is 0.02mm and the melanoma at this stage is 100% curable. Only occurrence of abnormal melanocytes are observed in the top skin layer. The tumor in this stage has spread into the skin but limited to the epidermis layer. No spread into the lymph or other parts of the body are detected. Dermoscopic images is consider to further assess performance of the proposed 3D reconstruction technique. An in-situ melanoma image and the corresponding relative estimated depth is shown in the figure

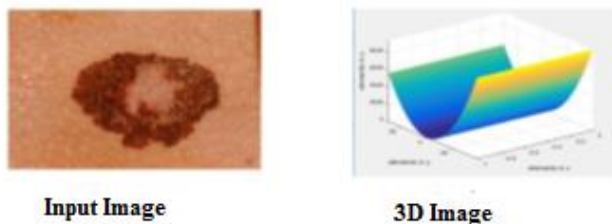


Figure 4: Input melanoma and its 3D reconstructed depth projection

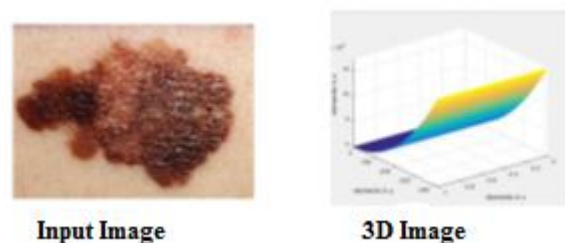


Figure 5: Severe melanoma and its 3d projection

At this stage the relative depth of the tumor is in between 0.6mm and can exhibit ulceration and will not spread through any part of the lymph. From figure 5, at this stage the tumour is cure only through surgical measures. The tumour depth is of about 1.5mm in growth and has spread to other organs and lymph nodes, treatment at this stage is expensive and can be removed only through surgical measures hence from the above discussions it is clear that depth is an important parameter for diagnosing and identification of cancer. The input image is send to the doctor then he can continually monitor the patient and can detect the melanoma at its early stage and thereby life threatening will not be occurred.

CONCLUSION

Amongst all the skin cancers known, melanoma accounts for the majority of deaths reported. Melanoma is curable if diagnosed early. Use of noninvasive computerized dermoscopy techniques to diagnose skin lesions is commonly adopted. Identifying depth of the melanoma tumor into the skin is essential to ascertain the stage of cancer. Existing computerized dermoscopy techniques lay marginal or no emphasis on depth for diagnosis. Here introduce a computerized dermoscopy system in this method that incorporates depth estimation. A 3D skin lesion reconstruction technique using 2D dermoscopic images is proposed. Segmentation is achieved using the adaptive snake technique. The 3D reconstruction is achieved by fitting the depth map estimated to the underling 2D surface. Color, texture and 2D shape features are extracted. Based on the 3D tensor structure constructed, depth and 3D shape features are extracted. Feature selection to study the effects of features and their combinations on decision making is proposed. For decision making BoF, AdaBoost and SVM classifiers is applied. Experimental study is conducted using the PH2 and ATLAS datasets. Results considering different feature combinations and BoF, AdaBoost, SVM classifiers is presented in this paper. The SVM achieves best classification scores of SE = 96% and SP = 97% on PH2 dataset. The SVM classification score of SE = 98% and SP = 99% on Atlas datasheet. In view of the results, it is concluded that inclusion of 3D shape features proposed (that include the estimated depth features) enhance performance aiding accurate diagnosis of varied skin lesion types. The computer-aided monitoring system that empowers and motivates the users to actively manage their own skin health status by collecting, processing and store information of skin lesions through its automatic classification. The analyzed skin lesion can be submitted on the database as a new checkup of a previously analyzed mole. This way the user is able to compare the results with previous examinations and check if significant changes appeared.

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