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A Survey on Computer Vision Based Diagnosis for Skin Lesion Detection

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Abstract— For skin lesion detection pathologists examine biopsies to make diagnostic assessment largely based on cell anatomy and tissue distribution. However in many instances it is subjective and often leads to considerable variability. Whereas computer diagnostic tools enable objective judgments by making use of quantitative measures. The basic three steps are there to achieve the results i.e. 1) image processing 2) Feature extraction 3) Classification. Step 1 deal with noise reduction artifacts removing, step 2 deals with extracting variety of information fro the processes image for accurate detection and step 3 deals with results that say various types of skin lesions. In this paper we are showing the process of it and also discussed some clinical diagnosis methods which is being incorporated with the tool for detecting the type of lesion

Index Terms— ABCD Rule, Computer Vision Based Diagnosis, Classification, Feature Extraction Melanoma, Skin Lesion.

I. INTRODUCTION

Skin cancer is one of the major health problems. and it is cause of death in almost eighty percentage of the cases if its not being diagnose at early stages. Fortunately, the recent advances in medicine have significantly increased the possibility of curing cancer. However, the chance of curing cancer primarily relies on its early diagnosis and the selection of its treatment depends on its malignancy level. Therefore, it is critical for us to detect cancer, distinguish cancerous structures from the benign and healthy ones and identify its malignancy level. Skin cancer can be generally classify in two types i.e. 1) Non-melanoma. Melanoma skin cancer (NMSC) and 2) Melanoma skin cancer (MSC) The critical factor in assessment of patient prognosis in skin cancer is early diagnosis. There are many methods to diagnose non-melanoma skin cancer (NMSC)[1],[2],[3],[4] such as physical and clinical examination, biopsy, molecular markers, ultra sonography, Doppler, optical coherence tomography, dermoscopy, spectroscopy, fluorescence imaging, confocal microscopy, positron emission tomography, computed tomography, magnetic resonance imaging, terahertz imaging, and electrical impedance. All these methods have different accuracy rates, sensitivity and specificity in diagnosing NMSC. Melanoma skin cancer is divided into: superficial spreading melanoma, nodular melanoma, lentigo maligna melanoma and acral lentiginous melanoma. More than 60,000 people in the United States were diagnosed with invasive melanoma in recent years, and more than 8000 Americans died of the disease.[5] Over the last two decades, a tremendous amount of research work has been conducted for automated skin cancer diagnosis. This is partly because automated skin cancer diagnosis holds great promise for large-scale use in the advanced skin cancer treatment and partly because automated skin cancer diagnosis is not a straightforward task, with a number of challenges to be overcome. The first challenge is the noise elimination in the task of determining the focal areas in the image. In the case of focusing on the properties of nuclei/cells in the image, the second challenge is the nucleus/cell segmentation. This is challenging because of the complex nature of the image scenes (e.g., touching and overlapping cells) and the noise (e.g., stain artifacts). The third challenge is the feature selection to represent a cell/tissue in the task of cellular or tissue-level property quantification. The features should provide distinguishing quantitative measures to automatically diagnose the cancer. The last important challenge is the system evaluation in the task of diagnosis. Due to the limited amount of available data, there might be a considerable amount of bias if the system evaluation is not conducted properly. In this paper, we present a systematic survey on the computational steps to automatically diagnose skin cancer by using various images such as stain images of biopsy, dermoscopy images, skin camera images etc In each step, we explain the techniques, address the challenges, and discuss the remedies offered by these techniques to overcome the challenges.

II. OVERVIEW

In this paper, we focus on the following problem. We are given an image of a skin tumor. The goal is to automatically decide Type of cancer i.e melanoma or non -melanoma by examining various properties of lesion



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The automated skin cancer diagnosis is based on (i) extracting information from the images of and (ii) examining this information by using either statistical analysis or machine learning algorithms. The skin cancer diagnosis consists of three main computational steps: preprocessing, feature extraction, and classification. The aim of the preprocessing step is to eliminate the background noise and improve the image quality for the purpose of determining the focal areas in the image. This step also comprises nucleus/cell segmentation in the case of extracting cellular-level information. The preprocessing becomes the most important yet difficult step for a successful feature extraction and diagnosis.[22] After preprocessing the image, features are extracted for further accuracy of classification of lesion. Feature extraction focuses on quantifying the properties of skin lesions for a single skin lesion the morphological, textural, fractal, color, pigmentation and/or intensity-based features can be extracted. fractal, and/or topological features can be extracted. The aim of the classification step is (i) to distinguish benignity and malignancy or (ii) to classify different malignancy levels by making use of extracted features. This step uses statistical analysis of the features and machine learning algorithms to reach a decision. An overview of these three steps is given in Fig.1. In the following sections, we will study each of these steps in detail.

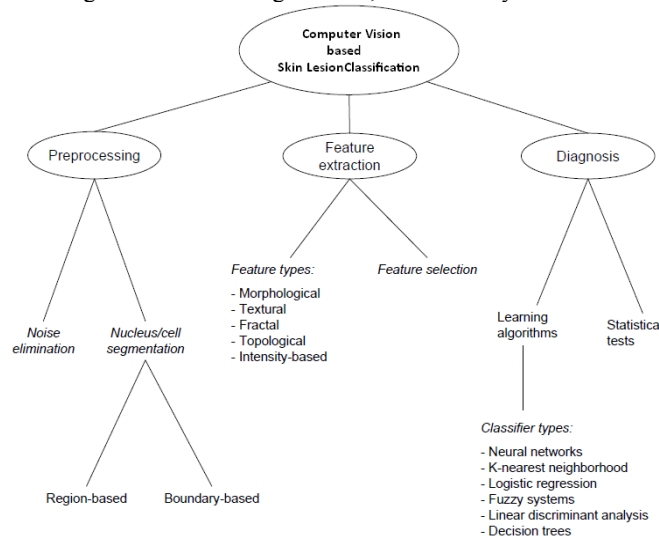


Fig 1 Overview of the computational steps

III. PREPROCESSING STEP

The main aim of the preprocessing step is to determine the focal areas in the image. Due to a considerable amount of noise in the images, it is usually necessary to reduce the noise prior to the focal area identification. Also some artifacts has to be removed.

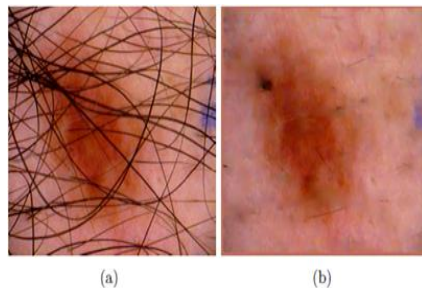


Fig 2 a) Dermoscopic images with many occluding hairs b) the results from in painting

A. Artifact Detection

Dullrazor [6] represents the seminal work in dermoscopic artifact removal. It identifies dark hair by a morphological closing operation. The pixels in the resulting mask are then further examined to ensure they are 'hair-shaped' by identifying long, thin, straight shapes. Regions which are not long and thin are rejected as hair pixels. A similar approach has been employed more recently in [7], and a modified approach, which accounts for the curvature of the resulting pixels in the hair mask, is presented in [8].



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B. Artifact Removal

Dullrazor uses linear interpolation to estimate the underlying colour of artifact pixels [6]. Other methods to estimate values for artifact pixels include auto-regressive as well as band-limited techniques [9], masked median filtering [10] and in painting [11].

IV. FEATURE EXTRACTION

A. ABCD features

For melanoma skin lesion detection ABCD features are used most widely by the dermatologist here we are describing the same for computer vision diagnosis software. ABCD feature is the important information based on morphology analysis of image dermatoscopic lesion. ABCD feature is Asymmetry, Border Irregularity, Color Variation and Diameter features. The melanoma lesions usually have morphology characteristics such as asymmetrical characteristic, irregular edge of the lesion, different color composition, and a large diameter. Asymmetry feature consist information of asymmetry and lengthening Index of the lesion. Border Irregularity feature consist information of Compactness Index, Fractal Dimension, Edge Abruptness, and Pigmentation Transition from the lesion. Color homogeneity feature consist of Color Information Homogeneity and the correlation between Photometry and Geometry of the lesion. Diameter extraction is diameter of the lesion. ABCD feature extraction is one of the process to extract the important feature. The results of this process are used to distinguish melanoma or non melanoma. There are four important features i.e. Asymmetry, Border Irregularity, Color Variation, and Diameter.

1. Asymmetry feature

There are two value of asymmetry feature i.e. Asymmetry Index (AI) and Lengthening Index. Asymmetry Index value is computed with the equation (1)

$$AI = \frac{1}{2} \sum_{k=1}^2 \frac{\Delta A_k}{A_L}, \quad (1)$$

k is major and minor axis, ΔA_k is non-overlapping area of lesion.

2. Border Irregularity

There are four value of border irregularity feature i.e. Compactness Index, Fractal Dimension, Edge Abruptness and Pigmentation Transition.

Compactness Index

Density index (Compactness Index / CI) is the measurement of the most popular form of barrier which 2D objects estimate unanimous. However, this measure is very sensitive to noise along the boundary term amplified by the square of the perimeter

$$CI = \frac{P_L^2}{4\pi A_L}, \quad (2)$$

PL is perimeter lesion.

To find PL value, use the surgery Robert edge detector to detect edges. Robert is a differential technique, the differential in the horizontal direction and the differential in the vertical direction, with the added conversion process after the differential binary. Binary conversion technique proposed is the conversion to level the distribution of a binary black and white. Filter kernel used in Robert's method is:

$$H = \begin{bmatrix} -1 & 1 \end{bmatrix} \text{ and } V = \begin{bmatrix} -1 \\ 1 \end{bmatrix}$$

Pigmentation Transition

This important feature explains transition of skin pigmentation between the lesion and surrounding skin. Sharp edge is steep dangerous when fading slowly, do not indicate a dangerous lesion. For that, we consider component before (i, j) of the original color image as the only three components are weighted the same color. Then we estimate the gradient magnitude of intensity component *lum* along the boundary before C of the skin lesion.



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We obtained a set of gradient magnitude value of K , $e(k)$ ($1 \leq k \leq K$, where K is the limiting sample size) that describes locally the transition between the injury and setting points of skin on each side. To describe more globally, we use the mean m_e and variance v_e of the gradient magnitude values $e(k)$ which describes the level of steepness and global variations.

$$lum(i, j) = \frac{1}{3}[r(i, j) + g(i, j) + b(i, j)] \quad (3)$$

$$m_e = \frac{1}{K} \sum_{k=1}^K e(k), \quad v_e = \frac{1}{K} \sum_{k=1}^K e^2(k) - m_e^2. \quad (4)$$

3. Color Variation

One early sign of melanoma is the emergence of color variations in color. Because melanoma cells grown in grower pigment, they are often colorful around brown, dark brown, or black, depending on the production of melanin pigment at different depths in the skin. To limit further diagnosis, the color variation in a lesion described by Ch color homogeneity and the correlation between the geometry and photometry.

Color Homogeneity

Luminance histograms of injuries are divided into three equal-length intervals. Intervals that relate to the three smallest Luminance values defined dark area in the intermediate level to relate to others from injury and is not involved in the quantification of color. Then, the color homogeneity is described as a transition zone of lighter / darker zone and the zone darker / lighter zone when the scan cuts horizontally and vertically.

Correlation between Photometry and Geometry

This attribute evaluates the distribution of color on the lesion. Including an explanation of the evolution of the color levels of the barrier centroid GL lesion. This value is larger for non-dangerous injury because it has a target aspect, whereas small values indicate danger.

$$C_{pg} = \frac{1}{A_L} \sum_{p \in L} \frac{(lum(p) - m_l) \cdot (d_2(p, G_L) - m_d)}{v_l \cdot v_d}, \quad (5)$$

m_d and v_d are mean and variance of distance d_2 , m_l and v_l are related to luminance

4. Diameter

Melanoma tend to grow larger than common moles, and especially the diameter of 6mm. Because the wound is often irregular forms, to find the diameter, drawn from all the edge pixels to the pixel edges through the mid-point and averaged.

Compute Total Dermatoscopic Value (TDV)

After the value of four components is found, then calculate TDV (Total Dermatoscopic Value). To get the TDV values, the formula is obtained as follows:

$$TDV = A \cdot 1,3 + B \cdot 0,1 + C \cdot 0,5 + D \cdot 0,5 \quad (6)$$

Then the value obtained has the following conclusion:

- 1,00 - 4,75 – benign skin lesion
- 4,75 - 5,45 – suspicious
- More than 5,45 – melanoma

For the lesions other than the type of melanoma i.e. non melanoma type RGB color features are being extracted which is as same color features of ABCD and other than color the texture features is being extracted to get proper diagnosis of skin lesion.

Textural features

Texture is a connected set of pixels that occurs repeatedly in an image. It provides information about the variation in the intensity of a surface by quantifying properties such as smoothness, coarseness, and regularity. To describe textural features, the two most widely accepted models are those that use the co-occurrence and run-length matrices. The co-occurrence matrix quantifies the various textural features such as correlation, contrast and angular second moment [12] by making use of the spatial dependency between the gray-level pixel values. The co-occurrence matrix C , computed on a gray-level image P , is defined by a distance d and an angle μ . $C(i; j)$ is the



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number of times that the gray value i co-occurs with the gray value j in a particular spatial relationship defined by d and θ ; mathematically,

$$C(i, j) = |\{m, n\} : P(m, n) = i \text{ and}$$

$$P(m + d \cdot \cos \theta, n + d \cdot \sin \theta) = j$$

There are also other methods to extract textural features. One of such methods uses wavelets representation which discriminates several spatial orientations in the image [13]. For instance, Weyn et al. compute wavelets by passing the image through a set of iterative low/high-pass filters and use the energies of the filtered images as the textural features [14]. Another method makes use of the complexity curve of a binary image which is obtained by computing the number of black-to-white transitions observed in the image [15].

V. CLASSIFICATION

After determining an appropriate set of features, the next step is to distinguish the malignant structures from their counterparts. In this step, a region of interest of lesion image is assigned to one of the classes of cancerous, benign, or healthy. As a part of diagnosis, it is also possible to classify the malignancy level of the tissues (i.e., grading). In this case, the classes are the possible grades of the cancer of interest. For diagnosis, one group of studies employs a statistical test on the features [17], [18]. All these studies examine whether or not a significant difference exists in the value of at least one feature of interest for different classes. However, for the images, the results of statistical tests should be interpreted with an extra caution for the following reason. Statistical tests assume independent samples and lead to conclusions accordingly. On the other hand, the data set consists of different tissue images taken from the same patient, which are not independent, and this may cause misleading and confusing results. Another group of studies uses machine learning algorithms to learn (from data) how to distinguish the different classes from each other. Among those algorithms are the neural networks, k-nearest neighborhood algorithm, [20] logistic regression method, fuzzy systems, linear discriminate functions, and decision trees neuro fuzzy algorithm and adaptive neuro-fuzzy inference system (ANFIS) algorithm [19]

A. Evaluation of the classification system

In general, a classification system should have two stages: (i) training the classifier to learn the system parameters and (ii) testing the system to evaluate the success of the classifier. Since there is a limited amount of available data in training, it is very important to test the system with extra data. However, it is an issue how to use this limited amount of data in both training and testing. More data used in training lead to better system designs, whereas more data used in testing lead to more reliable evaluation of the system. Evaluating the system according to the success obtained on the training set brings the risk of memorization of data and obtaining over-optimistic error rates. To circumvent the memorization problem, the system should be evaluated on a separate data set that is not used in training the system. For that, one approach is to split the data into two disjoint sets and use these sets to train and test the system.

For a given sample, a diagnostic system can lead to one of the four possible categories:

- True positive (TP): the diagnostic system yields positive test result for the sample and the sample actually has the disease,
- False positive (FP): the diagnostic system yields positive test result for the sample but the sample does not actually have the disease,
- True negative (TN): the diagnostic system yields negative test result for the sample and the sample does not actually have the disease,
- False negative (FN): the diagnostic system yields negative test result for the sample but the sample actually has the disease,

By using the number of samples that fall into these categories, *sensitivity* and *specificity* are defined to assess the success of the diagnostic system. Sensitivity is the probability of a positive diagnosis test among persons that have the disease and it is defined as,

$$\text{Sensitivity} = \frac{\text{number of TP}}{\text{Number of TP} + \text{number of FN}}$$

Specificity is the probability of a negative diagnosis test among persons that do not have the disease and it is defined as



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Specificity = $\frac{\text{number of TN}}{\text{Number of TN} + \text{number of FP}}$

The aim is to design diagnostic systems that lead to both high sensitivity and high specificity. The numerical measure in terms of both sensitivity and specificity is obtained by calculating the area under a Receiver Operating Characteristic (ROC) curve [21]. ROC curves plot the sensitivity versus one minus the specificity; the greater the area under these curves, the better the systems.

VI. CONCLUSION

In this review, we investigate the computational steps to automatically diagnose cancer by making use of various types of images. There are primarily three steps: preprocessing, feature extraction, and classification. For skin cancer mostly Textural, intensity-based and color features are being used for diagnosis. In the preprocessing step, the focal areas determined. This comprises to eliminate the noise and improve the image quality. Although, different techniques such as filtering and mathematical transformations show different levels of success in noise reduction, the problem of noise elimination has not been entirely solved. In the case of diagnosis at the cellular-level, this step also includes cell segmentation. The segmentation is achieved either by finding their boundary points or by differentiating the pixels of cells. Next is the feature extraction step. This step quantifies the properties of the biological structures of interest; extracting features such as color variation of lesion, texture, and pigmented structures bubbles dots etc. this will help to find out the difference between nevi and skin lesion.

- The **morphological** features provide information about the size and the shape of a nucleus/cell.
- The **textural** features provide information about the variation in the intensity of a and quantify properties such as smoothness, coarseness, and regularity.
- The **fractal-based** features provide information on the regularity and complexity of a cell/tissue by quantifying its self-similarity level.
- The **intensity-based** features provide information on the intensity (gray-level or color) histogram of the pixels located in a nucleus/cell.

After feature extraction, the next step is to distinguish benign and malignant structures as well as to classify the type of skin lesion. The important challenge is to evaluate the reliability of the designed diagnostic systems because of a limited amount of available data. This limited amount of data should be used both to learn the system parameters and to estimate the system reliability. The improper use of an evaluation method, however, may lead to biased and misleading results. For example, if the system performance evaluation is not done by using independent samples, overoptimistic results might be obtained. The numerical comparison of different studies is important to identify and avoid such biased and misleading results. For that, it is essential to form a benchmark of data sets that include biopsy samples taken from a large number of patients and examined by different pathologists.

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