

Advanced Skin Diseases Diagnosis Levaraging Image Processing

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***Abstract*: Air pollution affects human skin in many ways. Skin diseases are common in densely populated regions. These diseases have a devastating impact on people's lives by creating a huge need for the disease diagnosis. The proposed work on skin disease determination system aims for an accurate diagnosis leveraging image processing. The methodology outlined here aims to identify skin disease by scrutinizing the input image. The method involves filtering of the input provided to remove noise,conversion of image to a grayscale image, and image segmentation. Feature extraction is used to minimize the amount of data to be processed by the classifier. The SVM (Support Vector Machine) is then used in the image classification to identify the skin disease. The increased use of technology has led to an efficient and accurate way of diagnosis that aids in curing the disease more expeditiously. Using the proposed method skin diseases such as rosacea, melanoma, psoriasis and acne are identified with a high accuracy of 89%.**

Keywords—epidermis;segmentation; feature extraction; image classification.

Introduction :

Skin diseases are one of the most commonly seen infections among people. Due to the disfigurement and associated hardships, skin disorders cause lots of trouble to the sufferers [13]. Speaking of skin cancer, the facts and figures become more serious. In United States, skin cancer is the most common form of cancer. According to a 2012 statistics study, over 5.4 million cases of no melanoma skin cancer, including basal cell carcinoma and squamous cell carcinoma, are treated among more than 3.3 million people in America [20]. In each year, the number of new cases of skin cancer is more than the number of the new incidence of cancers of the breast, prostate, lung and colon in combined [24]. Research also shows that in the course of a lifetime, one-fifth of Americans will develop a skin cancer [19].

However, the diagnosis of skin disease is challenging. To diagnose a skin disease, a variety of visual clues may be used such as the individual lesional morphology, the body site distribution, color, scaling and arrangement of lesions. When the individual components are analyzed separately, the recognition process can be quite complex [6, 15]. For example, the well-studied skin cancer, melanoma, has four major clinical diagnosis methods: ABCD rules, pattern analysis, Menzies method and 7-Point Checklist. To use these methods and achieve a good diagnostic accuracy, a high level of expertise is required as the differentiation of skin lesions need a great deal of experience. Unlike the diagnosis by human experts which depends a lot on subjective judgment and is hardly reproducible, a computer aided diagnostic system is more objective and reliable.

By using well-crafted feature extraction algorithms and combining with some popular classifiers (e.g. SVM and ANN), current state of art computer aided diagnostic systems can achieve very good performance on certain skin cancers such as melanoma. But they are unable to perform diagnosis over broader classes of skin diseases. Human engineered feature extraction is not suitable for an universal skin disease classification system. On one hand, hand-crafted features are usually dedicated for one or limited number of skin diseases. They can hardly be applied to other classes and datasets. One the other hand, due to the diversity nature of skin diseases [6], human engineering for every skin disease is unrealistic.

One way to solve this problem is to use feature learning [4] which elim- inates the need for feature engineering and lets the machine to decide which feature to use. Many feature learning based classification systems have been proposed in past few years . However, they have been mostly restricted to dermoscopy or histopathology images. And they mainly focus on the detection of mitosis, an indicator of cancer. In recent years, deep convolutional neural networks (CNN) become very popular in feature learning and ob- ject classification. The use of high performance GPU makes it possible to train a network on a large-scale dataset so as to yield a better performance.

EASE OF USE :

The diagnosis of skin diseases can be done with much ease as the patient can get details of the disease without having to visit the doctor in person. This method is less time seeking therefore helps in the identification of the diseases quickly and the process is user friendly.

The Skin :

Human skin, except for palms and soles, is quite thin and of variable thickness. It has two layers: the epidermis (outer) and dermis (inner). Collagen and elastic components in the dermis allow it to function as a flexible barrier. The skin provides a unique shield which protects within limits against mechanical forces, or penetration by various chemical agents. The skin limits water loss from the body and guards against the effects of natural and artificial light, heat and cold. Intact skin and its secretions provide a fairly effective defence zone against micro-organisms, providing mechanical or chemical injury does not impair this defence. Provides an illustration of the skin and description of its physiological functions.

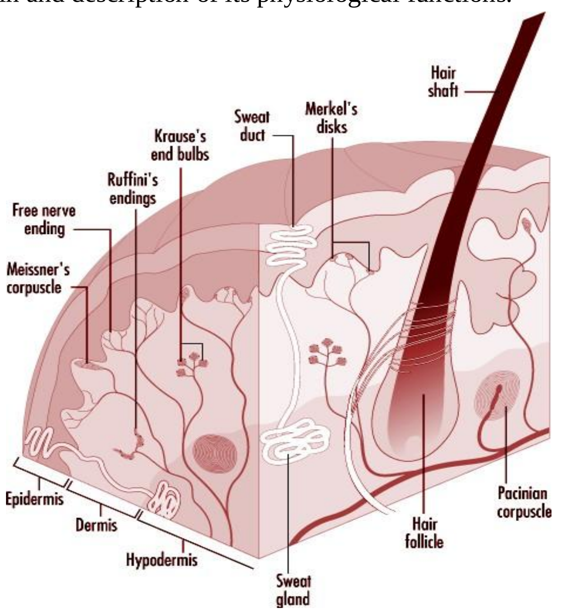


Figure 1.1 Schematic representation of the skin

The outer epidermal layer of dead cells (keratin) provides a shield against elements in the outside world. These cells, if exposed to frictional pressures, can form a protective callus and can thicken after ultraviolet exposure. Keratin cells are normally arranged in 15 or 16 shingle-like layers and provide a barrier, though limited, against water, water-soluble materials and mild acids. They are less able to act as a defence against repeated or prolonged contact with even low concentrations of organic or inorganic alkaline compounds. Alkaline materials soften but do not totally dissolve the keratin cells. The softening disturbs their inner structure enough to weaken cellular cohesiveness. The integrity of the keratin layer is allied to its water content which, in turn, influences its pliability. Lowered temperatures and humidity, dehydrating chemicals such as acids, alkali, strong cleaners and solvents, cause water loss from the keratin layer, which, in turn, causes the cells to curl and crack.

1. Literature review

Human skin, except for palms and soles, is quite thin and of variable thickness. It has two layers: the epidermis (outer) and dermis (inner). Collagen and elastic components in the dermis allow it to function as a flexible barrier. The skin provides a unique shield which protects within limits against mechanical forces, or penetration by various chemical agents, which cause several diseases such as rosacea, acne, psoriasis. Hence skin disease identification has become one of the most demanding and attractive research areas in the past few years. On one hand, this would be useful for dermatologists to decrease diagnostic faults, while on the other hand it can help as the early test bed for patients in rural areas where there is a dearth of good medical professionals.

Haralick R.M, Shanmugam K and Dinstein I, Textural features for image classification, IEEE Trans. Syst, Man, Cybern, 3 (6), 1973, 610–621.

Texture is one of the important characteristics used in identifying objects or regions of interest in an image, whether the image be a photomicrograph, an aerial photograph, or a satellite image. This paper describes some easily computable textural features based on gray-tone spatial dependancies, and illustrates their application in category-identification tasks of three different kinds of image data: photomicrographs of five kinds of sandstones, 1:20 000 panchromatic aerial photographs of eight land-use categories, and Earth Resources

Technology Satellite (ERTS) multispecial imagery containing seven land-use categories. We use two kinds of decision rules: one for which the decision regions are convex polyhedra (a piecewise linear decision rule), and one for which the decision regions are rectangular parallelpipeds (a min-max decision rule). In each experiment the data set was divided into two parts, a training set and a test set. Test set identification accuracy is 89 percent for the photomicrographs, 82 percent for the aerial photographic imagery, and 83 percent for the satellite imagery. These results indicate that the easily computable textural features probably have a general applicability for a wide variety of image-classification applications.

J. Arevalo, A. Cruz-Roa, V. Arias, E. Romero, and F. A. Gonzalez.

An unsupervised feature learning framework for ´ basal cell carcinoma image analysis.Artificial intelligence in medicine, 2015.

The paper addresses the problem of automatic detection of basal cell carcinoma (BCC) in histopathology images. In particular, it proposes a framework to both, learn the image representation in an unsupervised way and visualize discriminative features supported by the learned model.

J. Arroyo and B. Zapirain.

Automated detection of melanoma in dermoscopic images. In J. Scharcanski and M. E. Celebi, editors, Computer Vision Techniques for the Diagnosis of Skin Cancer, Series in BioEngineering, pages 139–192. Springer Berlin Heidelberg, 2014.

The incidence of malignant melanoma continues to increase worldwide. This cancer can strike at any age; it is one of the leading causes of loss of life in young persons. Since this cancer is visible on the skin, it is potentially detectable at a very early stage when it is curable. New developments have converged to make fully automatic early melanoma detection a real possibility. First, the advent of dermoscopy has enabled a dramatic boost in clinical diagnostic ability to the point that melanoma can be detected in the clinic at the very earliest stages. The global adoption of this technology has allowed accumulation of large collections of dermoscopy images of melanomas and benign lesions validated by histopathology. The development of advanced technologies in the areas of image processing and machine learning have given us the ability to allow distinction of malignant melanoma from the many benign mimics that require no biopsy.

C. Barata, J. Marques, and T. Mendonc¸a.

Bag-of-features classification model for the diagnose of melanoma in dermoscopy images using color and texture descriptors. In M. Kameland A. Campilho, editors, Image Analysis and Recognition, volume 7950 of Lecture Notes in Computer Science, pages 547–555. Springer Berlin Heidelberg, 2013.

The identification of melanomas in dermoscopy images is still an up to date challenge. Several Computer Aided-Diagnosis Systems for the early diagnosis of melanomas have been proposed in the last two decades. This chapter presents an approach to diagnose melanomas using Bag-of-features, a classification method based on a local description of the image in small patches. Moreover, a comparison between color and texture descriptors is performed in order to assess their discriminative power.

Methodology :

Input Image

The first and the most important step in the entire process is the collection of input images from the user, therefore the image should be processed to enhance the image quality. The figure 4 shows the image that is considered as input in this paper. The input given is an image of the disease melanoma. Input acquired from the user is analyzed and the corresponding disease is identified. In order to achieve accurate results the image is filtered.

Fig. 4. Input image

Pre-processing

In this step the input image is resized and then filtered in order to achieve high accuracy. The filtering process is done using an adaptive median filter to remove unwanted distortions such as noise. The input RGB image is then converted into a grayscale image in order to diminish the amount of information provided for each pixel [12], [1].

Figure 5 shows the grayscale converted image and figure 6 shows the output of the adaptive median filter which is used to remove noise from the input image.

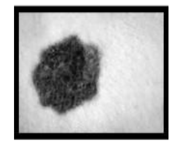


Fig. 5. Grayscale image Fig. 6. Filtered image

Flow chart for steps involved in skin disease diagnosis,

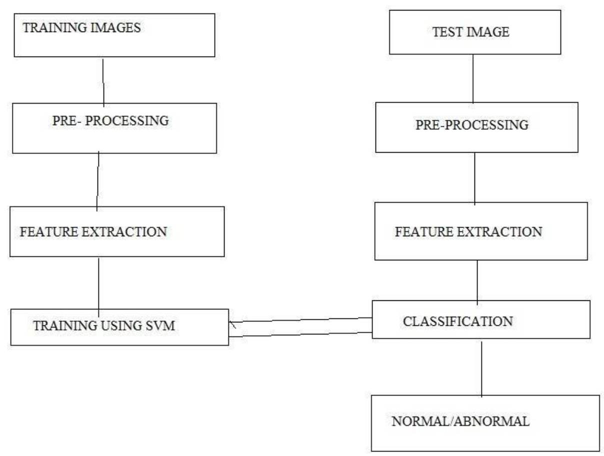
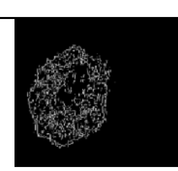


Fig. 2. Flowchart

Segmentation

The partition of an image into several parts is necessary in digital image processing and analysis of the image and a common technique used to achieve this is image segmentation which is based upon the pixel values and the pixel characteristics of the image. The image segmentation is done by separating the regions of contrast and by forming sets of pixels basing upon shape and colour. Image segmentation technique called thresholding is used to identify those tissue types in the images. Thresholding is a method to separate groups of objects in a scene.



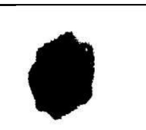


Fig. 7. Edge detected image Fig. 8. Segmented image

Feature extraction

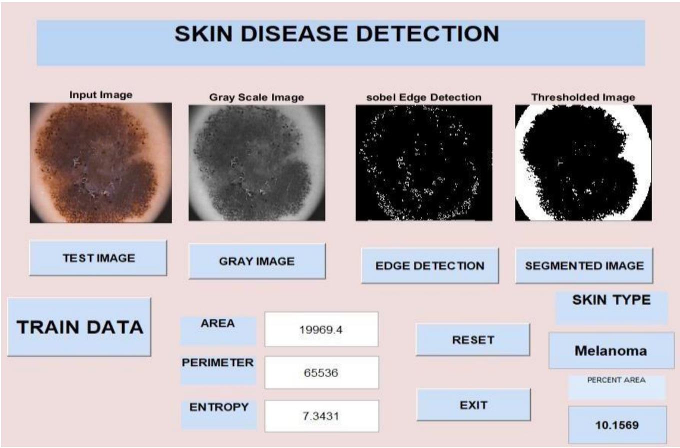
In this step the features of the segmented images are extracted, these features represent the relevant information of the image, thereby reducing the amount of information to be processed. In image processing feature extraction is essential in pattern recognition and in reducing the data to be processed by the classifier. Feature extraction is performed using GLCM(Gray Level Cooccurrence Matrix) [12]. This method uses a statistical method of texture analysis which uses spatial relationships of pixels in the gray-level co-occurrence matrix (GLCM) [9], which is also known as the gray-level spatial dependence matrix. The features such as autocorrelation, entropy, homogeneity and energy [10].

Classification

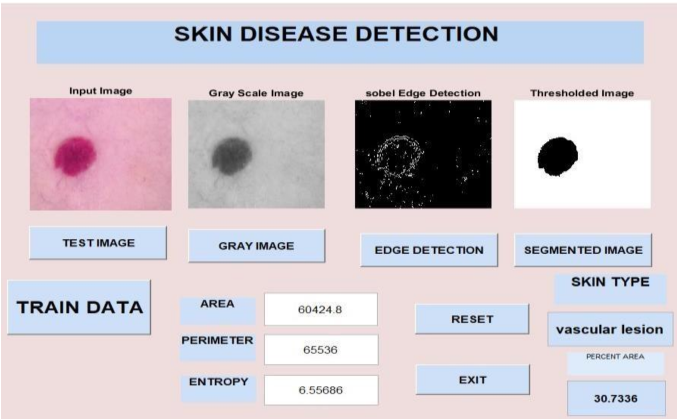
The features extracted are given as an input to the classifier. The classifier used in this paper is multi class SVM (Support Vector Machine) [2].SVM classifier is used to classify the input image as abnormal or normal, where in the name of the disease is displayed in case of abnormal and if the skin is healthy it is classified as normal. The errors in the output of the classifier are reduced using the structural risk minimization basing upon the principle of statistical learning theory [15]. The SVM classifier once trained can be used to categorize new data. But the classification is slow when applied to a large amount of data. The SVM algorithm chooses the best hyper plane to classify the input. To classify the given input linear kernel is used. kernel trick is used to achieve the best hyper plane results by mapping the current space to higher dimensions [11].

VI. RESULT

The output, that is the identified skin disease is displayed in the GUI (Graphical User Interface) under the classification button. The GUI has several fields that provide additional information such as entropy, area percentage of the spread of the disease which is calculated based upon the input image.



Skin disease identified as melanoma



Skin disease identified as vascular lesion

Advantages

1. Early detection: Advanced skin disease diagnosis allows for early detection of skin conditions, which can be critical in improving outcomes and reducing the risk of complications.

2. Accurate diagnosis: Advanced diagnostic techniques such as dermoscopy, confocal microscopy, and molecular diagnostics can provide more accurate and precise diagnoses of skin conditions than traditional methods.

3. Personalized treatment: With advanced diagnosis, clinicians can better tailor treatment plans to each individual patient's unique needs, ensuring the most effective treatment outcomes.

4. Reduced healthcare costs: Early detection and accurate diagnosis can help to reduce healthcare costs by preventing unnecessary treatments and hospitalizations.

5. Improved patient outcomes: Advanced skin disease diagnosis can lead to improved patient outcomes, including faster healing times, reduced scarring, and improved quality of life.

Overall, advanced skin disease diagnosis can have significant benefits for both patients and healthcare systems, including improved outcomes, reduced costs, and better use of healthcare resources

Applications

1. Dermatological disease diagnosis: Advanced diagnostic methods can help diagnose a range of dermatological diseases, including psoriasis, eczema, and acne.

2. Infectious disease diagnosis: Advanced diagnostic techniques can be used to diagnose infectious skin diseases such as herpes, syphilis, and fungal infections.

3. Monitoring treatment progress: Advanced diagnostic methods can be used to monitor the effectiveness of treatments for various skin conditions, allowing clinicians to adjust treatment plans as necessary.

4. Cosmetic dermatology: Advanced diagnostic techniques such as skin imaging can be used to assess skin quality, diagnose skin damage, and develop personalized treatment plans for cosmetic procedures such as laser resurfacing and chemical peels.

5. Genetic testing: Advanced diagnostic methods can be used to perform genetic testing to identify inherited skin conditions and to develop personalized treatment plans.

Overall, advanced skin diagnosis techniques have a wide range of applications, from diagnosing and treating skin cancer to developing personalized cosmetic treatment plans. These techniques can significantly improve patient outcomes and quality of life by providing accurate diagnoses and personalized treatment plans

Conclusion

The proposed work shows the improvement in identifying the melanoma skin cancer at different stages using image processing techniques based on active preprocessing, thershold and SVM classifier. The prime concern of the proposed work is to extract the skin image features i.e. area, perimeter and mean (R), mean (G), mean (B) and texture features. This enables in analyzing the melanoma spot analysis and guides for the direction of spread of the cancer. The features are normalized with respect to skin image size so that the features remain same if the image is varied in respect of it attributes. The main purpose is that the features should not vary for the same image at different orientation, size and location.

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