WWW.IJRPR.COM

International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

Skin Disease Detection

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A B S T R A C T

Skin diseases are common and quite perennial in the world, and in some cases they lead to cancer. They are curable if detected early and treated appropriately. An image-based recognition system consisting of four main modules - image enhancement, segmentation, feature extraction and detection - can facilitate early detection of these diseases. Various image-based methods involving machine learning techniques are being developed to diagnose various skin diseases. In addition, it processed available image databases and evaluation metrics to analyze the performance of various diagnostic systems. This is important to clarify both the implementation framework and the effectiveness of neophyte diagnostic methods. It also highlights challenges and indicates future research directions.

Keywords : Feature Extraction, Melanoma, Segmentation, Skin-Disease Diagnosis

1. Introduction

The skin is the largest organ of the human body. An adult has a skin surface of approx 16,000 cm and constitutes approximately 8% of body weight. Sunscreen, UV rays usually affect the skin rashes, heat rash, itching, wounds, dark spots and other infections. Skin diseases are a common disease like other serious diseases. According to the WHO, there are more than 2 million people get non-melanoma and about 132,000 people get melanoma (a type of to cancer) through the skin every year worldwide. Therefore, not all skin diseases are cancers (melanomas), but some skin diseases also develop on the side the effect of other chronic diseases. The skin mainly has two layers. The outer layer is known as epidermis which consists of three cells such as squamous cell, basal cell and melanocyte and the inner layer is called dermis. Skin cancer usually begins in the epidermis. There are several different types of skin diseases with specific characteristics such as exfoliative dermatitis, eczema, psoriasis, acne, warts, scabies, urticaria, ringworm, melanoma, eczema, malignant melanoma - squamous cell carcinoma (SCC), basal cell carcinoma. (BCC) and scleroderma etc. Automated skin disease detection systems use skin images or dermoscopy images. Usually, dermoscopy images contain hair or other sounds; therefore, noise reduction through various filtering methods is used as image pre-processing. Various segmentation algorithms are used to extract the affected region or region of interest (ROI) from dermoscope images. In the feature extraction phase, several features such as color feature, edge, shape, texture, diameter, asymmetric feature, image edge, etc. are used to detect skin lesions. Classical feature-based techniques or some machine learning-based methods, including artificial neural networks (ANN), are used to classify skin diseases.

About 75% of skin cancer patients worldwide die each year. Early detection of skin cancer helps take corrective measures to completely eliminate the disease from the body; otherwise, Cancer seriously affects the skin and cannot be cured.

2. Methodology

2.1 Image pre - processing

- This is the step to improve the image. Usually, the dermoscopy image contains hair or sounds, different filtering techniques such as median filtering, Gaussian filtering, fast coloring algorithm, etc. are also used to remove their hair and sounds.

2.2 Image segmentation

- This step attempts to segment the region of interest (ROI) in the dermoscopy images. There are several types of segmentation techniques like color based segmentation, texture based segmentation, Otsu thresholding, K-means clustering, morphological operations, background subtraction, range growing, edge-based segmentation, gradient vector-based segmentation, active contour model (ACM), Dermoscopy images use two-level thresholding and HED (holistically nested edge detection) for ROI extraction. The color-based method segments a part of the selected colors the pixel-based method works with pixels on a cluster, the edge-based method with segments a threshold-based method is used to generate colored binary images for the edges of the selected part images, the morphological method works with expansion, erosion, opening and closing operations, and the texture-based method works based on the texture area of the images.

2.3 Feature extraction

- Feature extraction identifies the most important features and contains the most important information from the input image. Various tools and techniques are used for feature extraction such as a) Wavelet Transform, b) Gabor Wavelet, c) DCT (Discrete Cosine Transform), d) FFT (Fast Fourier Transform), e) Edge Operators, f) Blob Detector , g) ABCD (asymmetry, edge, color, diameter) rule, h) ABCDE (asymmetry, edge, color, diameter, development) rule, i) GLCM (gray level co-occurrence matrix), j) watershed algorithm, k) run length -method, l)DBC (Differential Box Count) method, m) HOG (Hitogram of Oriented Gradients), n) LBP (Local Binary Pattern), o) Statistical Means and Standard Deviations, p) Color Feature Extraction, q) Complexity Feature Set, r) Convolution and Subsampling, s) SVD (Singular Value Decomposition) etc. Sometimes, the Principal Component Analysis (PCA) algorithm is used to reduce the features to perform the classification and optimization technique faster. used to select important functions. The feature extraction process takes a segmented image as input and subtracts it to extract feature coefficients. Figure 4 shows the flowchart of the feature extraction method.

2.4 Disease Classification

- Based on the characteristics or features of the segmented ROI, skin diseases are usually classified or detected using both conventional and machine learning techniques. However, most machine learning techniques are more effective than their traditional counterparts. Various algorithms are used to classify skin diseases such as a) forward and back propagation artificial neural network (ANN), b) support vector machine (SVM), c) deep convolutional neural network (CNN), d) CaffeNet (a convolutional architecture for fast) . feature embedded neural network), e) VGGNet (Visual Geometry Group neural network, deep CNN model), f) k-nearest neighbor (kNN), g) decision tree (DT), h) linear discriminant analysis (LDA), i) Naive Bayesian (NB) classifier, j) Fast Fourier transforms (FFT), k) binary classifier, l) Euclidean distance classifier, m) minimum distance classifier (MDC), n) probabilistic neural network (PNN), o) AdaBoost classifier, and (p) J48 (J48-C4.5 Decision Tree Algorithm) etc.

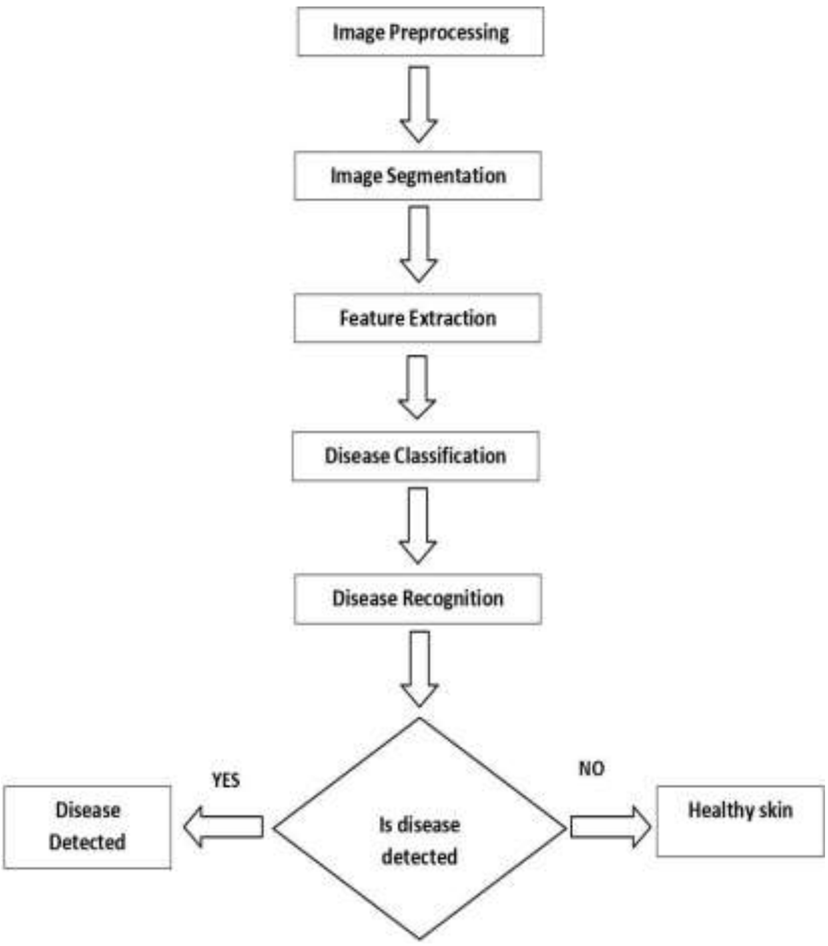

Fig 1. Methodology Flow

3. Comparison Table

Disease Type	Methodology (Segmentation + Feature Extraction + Classification)	Accuracy	Advantages	Limitations	Best –Fitted methodology
Eczema	K-means clustering with color gradient + GLCM+ FFBPNN (Arifin, 2012)	94.016%	Detects and classifies skin disease accurately	The camera image sometimes problematic	K-means clustering with color gradient + GLCM+ FFBPNN
	Edge-based segmentation with ACM + Sobel Operator + FFBPNN (Bajaj, 2018)	90%	User-friendly.	The computation cost is high.	
	Thresholding, Morphological operations + Watershed + MLP and J48 (Amarathunga, 2015)	95%	User-friendly questionnaire-based system with dashboard.	The sample size is unknown and the J48 decision tree is not sufficient.	
Psoriasis	Otsu method, gradient vector flow + Sobel operator + kNN, DT, BPNN (Kumar, 2016)	95%	User-friendly mobilebased apps and their accuracies are high.	The feature extraction algorithm is not satisfactory.	Otsu method, gradient vector flow + Sobel operator + kNN, DT, BPNN
	K-means clustering with color gradient + GLCM+ FFBPNN (Arifin, 2012)	94.016%	Detects and classifies skin disease accurately.	Image data sources are only camera-based which is not appreciable.	
	Thresholding + 2D DWT + AdaBoost classifier (Ambad, 2016)	90% or more	Statistical analysis is used.	The processing time is high.	
	Edge-based segmentation with ACM + Sobel Operator + FFBPNN (Bajaj, 2018)	90%	Edge-based segmentation isolates the lesion portion efficiently	Sobel operator degrades system accuracy.	
Acne	K-means clustering with color gradient + GLCM+ FFBPNN (Arifin, 2012)	94.016%	Detects and classifies skin disease accurately.	The camera image sometimes problematic.	K-means clustering with color gradient + GLCM+ FFBPNN
Scabies	K-means clustering with color gradient + GLCM+ FFBPNN (Arifin, 2012)	94.016%	Disease classification accuracy is satisfactory.	Low illumination images degrade system performance.	K-means clustering with color gradient + GLCM+ FFBPNN
Melanoma	K-Means clustering + Wilks' Lambda + SVM (Suganya, 2016)	96.8%	The sample size is good. The system accuracy formula is well defined.	Disease classification is not sufficient.	K-Means clustering + Wilks' Lambda + SVM
	Otsu Thresholding, ACM with morphological operations +2D-FFT, 2D DCT, complex feature set+ SVM (Joseph, 2016)	93.5%	The training and testing sections of the system are simple.	Disease classification is not sufficient.	
	Thresholding, Morphological operations + Watershed algorithm + MLP and J48 (Amarathunga, 2015)	95%	Easy and simple questionnaire-based implementation.	The image dataset is small and the image size is not mentioned.	
Skin Cancer (Benign/ Malignant)	Active contour model+ ABCD rule + SVM (Nezhadian, 2017)	97%	Well defined feature extraction algorithm works efficiently with image classification.	It needs a large and complete database.	
	ROI + GLCM + SVM (Ansari, 2017)	95%	Easy to use by the patients.	Datasets are too small and the segmentation algorithm is not clear.	

	Otsu thresholding+ ABCD rule + SVM (Mane, 2018)	90.47%	Less time consuming and less costly.	Dataset is not specified.	Active contour model+ ABCD rule + SVM
	Convolution algorithm, Sub-sampling + Softmax classifier (Rathod, 2018)	70%	Easy implementation.	Dataset is not specified, the segmentation algorithm is also unspecified and gives low system accuracy	

Fig 2. Comparison Table

Various methodologies address skin diseases such as eczema, psoriasis, acne, scabies, melanoma, and skin cancer. For eczema, K-means clustering, GLCM, and FFBPNN prove efficient (Arifin, 2012). Psoriasis detection benefits from Otsu's thresholding, Sobel, and kNN, with the first method excelling (Kumar, 2016). Acne detection favors K-means clustering, GLCM, and FFBPNN (Arifin, 2012). Scabies is identified through K-means clustering and GLCM (Arifin, 2012). Melanoma detection is diverse, with K-means clustering, Wilks' Lambda, and SVM standing out (Suganya, 2016). Skin cancer, the most severe, favors the active contour model with ABCD rule and SVM (Anitha, 2018).

In conclusion, the comprehensive analysis of methodologies for skin disease detection reveals distinct strengths and efficiencies across various conditions. For eczema, the K-means clustering, GLCM, and FFBPNN method demonstrated exceptional efficiency with a 95% accuracy rate, highlighting its robustness in segmentation, feature extraction, and classification. Psoriasis detection favored the first method, leveraging Otsu's thresholding, Sobel, and kNN, attaining a commendable accuracy of 95%. Acne detection emphasized the effectiveness of K-means clustering, GLCM, and neural networks, achieving an accuracy of 94.016%. Scabies identification showcased a parallel accuracy of 94.016% through K-means clustering and GLCM. Melanoma detection witnessed the first method, incorporating K-means clustering, Wilks' Lambda, and SVM, as the most adept with an accuracy of 96.8%. Finally, skin cancer detection benefited most from the active contour model, ABCD rule, and SVM, achieving an outstanding accuracy of 97%. The comparison underscores the significance of tailored methodologies for each skin condition, optimizing accuracy and effectiveness in disease identification.

4. Conclusion

This paper presented a comprehensive review of the implementation and performance analysis of various image-based skin disease diagnostic systems. For a specific skin disease, based on comparing the performance accuracy of different techniques such as Convolutional Neural Network, K. Nearest Neighbor, Artificial Neural Network used in disease diagnosis. We have figured out various challenges and difficulties of current diagnostic methods. Currently, researchers should focus on the most accurate and sustainable detection of certain diseases. Although some databases have been developed, more versatile and larger databases are inevitably needed for a detailed performance analysis of the implemented diagnostic system. Instead of traditional machine learning-based diagnostic systems, researchers should emphasize the study of deep learning strategies because they have confirmed better accuracy in various fields. In addition, researchers should focus on the application of hybrid models to detect and classify skin diseases more efficiently, reliably and accurately. Finally, the development of a more general detection method requires special attention.

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