Research Directions for Skin Disease Identification using Image Processing and Machine Learning

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Abstract— *Skin disease is a common issue faced by many in our society. It often decreases the quality of life and may lead to a disability. Recent AI advancements offers to help people with poor access to skin disease specialists, by identifying skin diseases. An artificially intelligent skin disease identifier will provide the opportunity of an early treatment and a timely recovery to people lacking access to skin disease specialists. AI techniques, including image processing and machine learning, have been explored by researchers in recent decades to intelligently identify skin diseases. This paper presents an in-depth review of the image processing and machine learning techniques used thus far. The aim of this review is to facilitate better and improved approaches.*

Keywords— **image processing, machine learning, skin diseases, classification**

I. INTRODUCTION

The World Health Organization (WHO) stated that skin diseases are very common in our society today. It has been estimated that around 30% to 70% of the population have fallen victim to skin diseases (Hay et al., 2014), irrespective of race and gender. A research presented in (Feldmeier, 2009) concluded that skin diseases are more prevalent in the at-risk subpopulation which refers to the low-income and ageing population. In addition, skin diseases are well known to contribute to disability worldwide (Karimkhani et al., 2017). According to a research summarized in (Perera et al., 2015), skin diseases were commonly faced by individuals in both semi urban and urban areas at 47.6% and 32.9% respectively in Sri Lanka. Recent advancements in AI provides an opportunity for the automated identification of skin diseases, especially in areas that lack trained and qualified skin specialists.

Prior to the widespread adoption of computationally intensive AI techniques such as complex image processing algorithms and machine learning, researchers attempted to automate the identification of skin diseases using knowledge-based image analysis with the guidance of expert dermatologists (Dhawan, 1988). Distinctive features including thickness, size, colour, margin, boundary and surface characteristics were taken into consideration along with the patient's history information. With the subsequent improvement in computer processing power, researchers implemented complex image segmentation algorithms to extract the regions of skin lesions based on an image feature such as gray-level. However, gray-level based segmentation disregarded sections with varying textures, thus proving inefficient. As significant variations in colour hues existed in skin disease images, researchers proposed and implemented a colour and texture based image segmentation algorithm, obtaining better results than gray-level based segmentation (Dhawan, 1992). The concept of image feature extraction and selection, and classification with machine learning algorithms to identify skin lesions was eventually introduced. The research done using a simple, easy-to-implement KNN classifier delivered promising results (Ganster et al., 2001). Subsequently, researchers experimented with various other image processing and machine learning algorithms with increasing complexity, aiming to improve the efficiency and accuracy of digital skin disease images. However, the fundamental steps taken remained same.

Automated image-based skin disease identification via classification consists of five fundamental steps namely image pre-processing, segmentation, feature extraction, feature selection, and classification. With the accessibility of computers having improved performance, various complex algorithms have been tried and tested. However, there is still room for improvement.

This paper aims to explore the trends and techniques adopted by researchers presently, analysing the pros and cons. The paper is organised as follows. Section II discusses various AI techniques used by researchers for image-based skin identification. Section III discusses the findings presented in the literature review. Section IV presents concluding remarks regarding possible developments that can be explored by future researchers.

II. LITERATURE REVIEW

This section provides an in-depth insight into various techniques and algorithms used by researchers along with the findings obtained, and the techniques yet to be implemented. The five fundamental steps –pre-processing, segmentation, feature extraction, feature selection and classification– are discussed below.

A. Image Pre-processing

The primary purpose of pre-processing is to enhance image features, which can be done by removing noise and redundancy, as well as unwanted artefacts such as hair. However, it is crucial to avoid significant alteration.

1) Image Restoration: There are several image pre-processing techniques that can be applied to restore images which eliminates noise and blur. Spatial filtering is typically preferred for background noise reduction of skin lesion images (Jamil and Khalid, 2015). It involves using masks to change pixel intensities according to the intensity values of neighbouring pixels. Background noise are of four main categories – Gaussian, Salt and Pepper, Poisson and Speckle (Hoshyar et al., 2014). Spatial filters consist of linear and non-linear filters. Linear spatial filters, often used in skin lesion images, are of two forms - low pass and high pass. Low pass filters replace pixels values with the average values of neighbouring pixel values. Thus, reducing noise by blurring the images. However, the edges are not maintained as fine details are lost. Commonly used low pass filters include mean filter, weighted average filter and Gaussian low pass filter. On the contrary, high-pass filters are used to reduce blur by sharpening and edge enhancement via enhancing contrast between adjoining areas with similar luminance levels. Unwanted artefacts such as hair from skin lesion images can be removed using inpainting and morphological operators (Salido and Ruiz, 2017). Non-linear spatial filters such as median filter can also be used for noise reduction while preserving the edges.

2) Image Enhancement: Image enhancement plays a crucial role in segmentation accuracy. Issues such as uneven illumination, which results in shadows, need to be resolved. Uneven illumination corresponds to the low spatial frequency component, whereas texture and pigmentation corresponds to the high spatial frequency component. Thus, removing the low spatial frequency component will rectify uneven illumination (Fernandez Alcon et al., 2009). Linear and non-linear contrast enhancement techniques are widely used (Jamil and Khalid, 2015). Linear contrast enhancement refers to contrast stretching. The gray-levels are stretched to spread over the 256 gray levels. Linear contrast enhancement techniques include min-max linear contrast stretch, percentage linear contrast stretch, and piecewise linear contrast stretch. Conversely, non-linear contrast enhancement typically refers to histogram equalization. Non-linear contrast enhancement techniques include histogram equalization, adaptive histogram equalization, homomorphic filtering and unsharp masking. Image scaling can be applied when the images are of varying sizes. Colour space transformation is also crucial. Several colour spaces exist including RGB, HSV and CIE-LAB, however, there are several factors to consider. RGB consists of red, green and blue spectral wavelengths. However, colour information cannot be separated from luminance. On the contrary, HSV separates colour information from luminance. CIE-LAB provides uniformity.

B. Segmentation

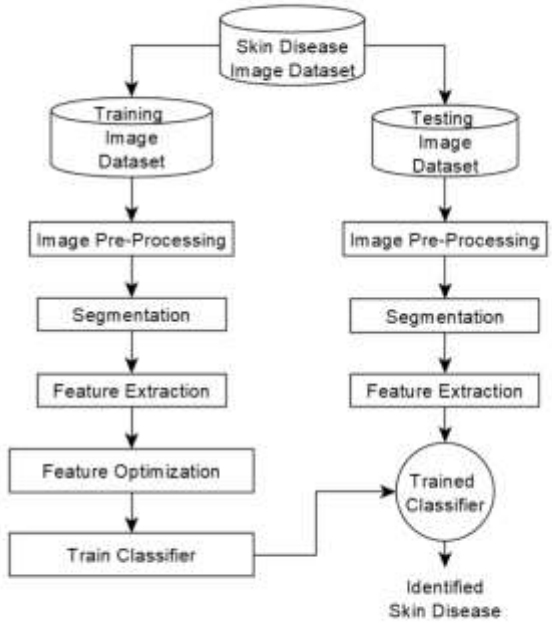

Figure 1. General System Architecture for Automated Skin Disease Identification
Source: Author 2019

Segmentation is used to separate the skin lesion using image properties such as texture, edge or pixel intensities. There are two forms namely gray scale segmentation and histogram based segmentation (Sharma and Lal, 2017).

1) Gray scale segmentation: Gray scale segmentation includes edge-based segmentation, region growing segmentation and threshold-based segmentation. Edge-based segmentation is unreliable in the presence of noise and the threshold selection may vary. Region growing segmentation involves the selection of seeds and thresholds with which the pixels surrounding the seeds are compared with to determine whether to be included to the segmented region of interest. Threshold-based segmentation involves a global threshold with which the pixels belonging to the region of interest are determined. However, determining the threshold can be challenging.

2) Histogram-based segmentation: Histogram-based segmentation utilizes the image histogram to determine the gray level to be used for grouping pixels into regions of interest. The peaks and valleys play a key role in histogram-based segmentation. Histogram-based segmentation techniques used for skin lesions includes histogram peak technique, histogram valley technique and adaptive histogram technique. Histogram peak technique involves obtaining two peak values corresponding to the background and skin lesion, then setting the threshold halfway between the obtained peaks. As with the histogram peak technique, histogram valley technique obtains the two peaks, however the gray level corresponding to the lowest valley between the two peaks are thresholds (Castleman, 1995).

Several other segmentation techniques can be used such as colour-based segmentation, discontinuity-based segmentation and border segmentation (Olugbara et al., 2018). Some techniques combine two or more aspects such as watershed algorithm which combines both region- and edge-based segmentation (Hanbury, 2009).

C. Feature Extraction

Feature extraction is performed to extract properties that can be used to characterize the skin lesion. With respect to the classification of skin lesions, texture, colour and shape features are typically considered.

1) Texture Features: Texture describes homogeneous patterns. Texture feature analysis can be done to derive the spatial arrangement of the pixels in the neighbourhood, which cannot be sufficiently described by the intensity or colour properties (Okuboyejo et al., 2013). The analysis can be performed using techniques such as co-occurrence matrices to capture texture features such as energy, entropy, contrast and correlation. Other texture features include coarseness, directionality, regularity and roughness. Gray Level Co-occurrence Matrix (GLCM) is a widely used statistical method for texture analysis, which considers the spatial relationship of pixels in various directions {0^{O}, 45^{O}, 90^{O}, 135^{O} } (Islam et al., 2017). The co-occurrence matrix can be used to extract several texture features. However, as many features are correlated, only energy, contrast, correlation and homogeneity are generally considered.

2) Colour Features: Colour feature extraction involves the examination of colour spaces. Certain skin lesions can be characterised by existence of certain colours such as white, black, red, light-brown and dark-brown (Zaqout, 2016). Other colour features such as colour moments, which includes mean, standard deviation, variation, and skewness, can be extracted from lesion regions over several colour spaces – RGB, HSV, YCbCr, NTSC, CIELAB and CIELUV (Sumithra et al., 2015). A colour histogram can also describe the colours present in an image, representing the frequency of each colour. Considering an RGB histogram, a number of bins – for example, 16, can be set for each channel (R, G, B), which will result in 16^3 features (4096). However, variations in image colour will negatively impact classification with colour histogram.

3) Shape Features: For skin lesions such as melanoma, asymmetry score of the segmented lesion can be taken into consideration. Other shape features include area, diameter and perimeter (Chatterjee et al., 2015). The compactness can be measures using the calculated area and perimeter. Radial variance can be used to determine the border irregularity (Esgario and Krohling, 2018).

D. Feature Selection

Feature selection results in the reduction of the extracted feature vector dimensionality. It identifies and removes features that do not affect the accuracy of the prediction model. Over the years, researchers have failed to optimize the extracted features for skin disease classification. However, researchers who have recently explored the concept have obtained satisfactory results. The three classes of feature selection are namely filter method, wrapper method and embedded method (Liu et al., 2010).

1) Filter Methods: Filter methods utilise a statistical measure to assign scores to features. The features are then retained or removed based on their scores. However, as the relationship between features and targets are generally not considered, dependent feature variables may be present in the subset. Thus, affecting the efficiency of the classifier. Filter methods include information gain, chi-square test and Fisher score.

2) Wrapper Methods: Wrapper methods approach feature selection as a search problem. Different combinations of features are evaluated with a classifier, and a score is assigned based on the resulting accuracy. Wrapper methods include sequential selection algorithms and nature-inspired algorithms such as genetic algorithms and particle swarm optimization (Brezočnik et al., 2018).

3) Embedded Methods: Embedded methods involve embedding feature selection within the prediction model while being created. Machine learning algorithms used for prediction need to be redesigned to incorporate feature selection. Common embedded methods are regularization algorithms such as LASSO and ElasticNet.

E. Classification

Classification, the final step, is the process of training a classifier to predict the skin disease class. With recent advancements in machine learning, various machine learning algorithms have been used for classification of skin diseases over the past few decades.

1) Support Vector Machine (SVM): A system was proposed to intelligently segment and classify pigmented skin lesions in skin images using a Support Vector Machine (SVM) classifier in (Maglogiannis et al., 2006). The system was used to determine whether the lesion was malignant melanoma or dysplastic nevus. Image processing techniques were implemented to segment the skin lesion using local thresholding, extract certain features including border, colour and texture features using gray-level co-occurrence matrix (GLCM), Angular Second Moment (ASM), and border symmetry.

Another group of researchers proposed an SVM based system to identify leprosy, vitiligo, and tinea versicolor using Local Binary Patterns in (Das et al., 2013). LBP based texture features and frequency domain features were considered for classification. The open source SVM classifier, LIBSVM, was used with Radial Bases Function (RBF) kernel to classify the images accordingly.

In a similar manner, (Scholar, 2007) presented a system to automatically detect melanoma using LBP and SVM classifier. LBP textural features and local features were considered for classification. A method to measure irregularity was also implemented. Features such as area, perimeter and standard deviation were extracted to ensure they remained same at different orientations.

A Windows Subsystem for Linux (WSL) framework was presented in (Choudhury et al., 2015) to classify skin cancer using Multi-Class SVM (MSVM) and Extreme Learning Machine (ELM). Four types of skin cancer were considered – squamous cell carcinoma, basal cell carcinoma, melanoma, and actinic keratosis. Texture features were extracted using GLCM and Histogram of Oriented Gradients (HOG) and colour features were extracted using colour histograms. The MSVM classifier performed better than the ELM.

A system to automatically detect eczema and measure the severity using image processing was proposed in (Alam et al., 2016). Image features of colour, border and texture were extracted using the 'ABCDE' technique. GLCM was used to extract the texture features. A binary SVM was used to classify the extracted features. The system was developed for the detection of eczema.

An SVM framework to detect malignant melanoma based on optimized HOG features was proposed in (Bakheet, 2017). For classification, colour and low-dimensional HOG-based texture features were considered. The evaluation of the system indicated that superior performance was achieved over two recent alternatives.

A system to classify melanoma, basal cell carcinoma and squamous cell carcinoma using an LBP based hybrid classifier was presented in (Sharma and Lal, 2017). LBP based hybrid features were extracted using a hybrid descriptor. The extracted features were input into an SVM to classify the skin cancers. The proposed system achieved rotation invariance and was able to capture microstructure and macrostructure information.

A system to recognize herpes, dermatitis, and psoriasis based on colour and texture features of an image was presented in (Wei et al., 2018). The colour features were extracted using a pixel-based skin colour detection technique and the texture features were extracted using GLCM. An SVM classifier was used for classification.

2) Artificial Neural Networks (ANN): A system to detect skin diseases namely eczema, acne, leprosy, psoriasis, scabies, foot ulcer, vitiligo, tinea, corporis, and pityriasis rosea was presented in (Yasir et al., 2014). Image features namely colour, area and edge were extracted and used for classification, as well as user's information such as liquid type, liquid colour, elevation, duration, feeling, gender and age. Image features were extracted using YCbCr algorithm, histogram and sobel operator respectively. Feed forward back propagation ANN was used for classification.

An expert system to diagnose eczema, urticaria, and impetigo was presented in (Amarathunga et al., 2015). Colour and shape features of the images were used for classification, as well as results from the questionnaire. MLP was then used to classify by identifying patterns.

A system to detect skin diseases namely psoriasis, seborrheic dermatitis, lichen planus, pityriasis rosea, chronic dermatitis, and pityriasis rubra and pilaris using image processing and machine learning was presented in (Kumar et al., 2016). Colour features were extracted using colour histogram, edges using sobel operator and segmentation algorithms – Otsu's method, Gradient Vector Flow and colour-based segmentation. ANN was used with Maximum Entropy Model (MEM) to classify.

An automated system to predict skin diseases namely eczema, psoriasis, impetigo, melanoma, and scleroderma using image processing and machine learning was proposed by researchers in (Bajaj et al., 2018). Image processing was used to optimize the images. The ANN used for prediction considered the pixels as features – the diseased region was converted to a feature vector.

3) Convolutional Neural Network (CNN): In (Patnaik et al., 2018), a system to automatically identify several diseases using Deep Learning (DL) was proposed. Three DL algorithms were used for feature extraction namely Inception_ v3, MobileNet, Resnet, and xception. Random forest / logistic regression was used as the learning algorithm for training and testing. A Convolutional Neural Network (CNN) was used to classify the images accordingly.

4) Ensemble: In (Kundu et al., 2010), a system to automatically detect ringworm using Local Binary Pattern (LBP) was presented. LBP based texture features were considered for classification. The system compared three classifiers – Artificial Neural Network (ANN), SVM and Bayesian classifier. For the Multi-Layer Perceptron (MLP) – a type of ANN, the Back Propagation (BP) learning algorithm was used to train the MLP. The major voting scheme was used to identify the optimum solution.

Researchers proposed a primary morphological classifier for macule, papule and plaque in (Macatangay et al., 2017). Contrary to the above literatures, this study was to classify morphologies rather than skin diseases. Colour features namely mean, standard deviation, uniformity/energy and entropy for each colour channels (RGB, HSV, CIELab) were extracted as well as GLCM textural features. Additional features including area, shape and colour symmetry were extracted. Four classifiers were used - K-Nearest Neighbors (KNN), Decision Tree (DT), MLP and SVM.

Table 1. summarizes the training requirements of the four main machine learning approaches for classification.

Table 1. Comparison of Training Requirements for Skin Disease Classification Approaches

	Training Requirements		
	Processing Power (High/ Low)	***Processing Time (High/ Low)***	***Dataset (Large/ Small)***
SVM	Low	Low	Small
ANN	Low	High	Large
CNN	Very High	Very High	Very Large
Ensemble	High	High	Small

Source: Author 2019

III. DISCUSSION

In the reviewed research works, it was evident that the initial application of image pre-processing techniques played a critical role in ensuring satisfactory results by the systems. Smoothing was generally used by researchers to reduce noise and contrast enhancement which tends to accentuate the affected region for further processing. These techniques greatly improved the performance during segmentation. Researchers who failed to segment the affected region generally achieved lower accuracies with their system as the healthy skin skewed the extracted features. The success of the segmentation methods used were subjective. However, watershed algorithm was used by many. Texture, colour and shape features were commonly used for classification. The features extracted depended on the type of skin disease. For example, for skin cancer, the ABCD rule of dermatoscopy was commonly used by researchers. The rule referred to asymmetry, border, colour and differential structures. However, these features may not be suitable for certain skin diseases such as eczema. Researchers have recently taken interest in utilizing feature selection methods, and the results have been impressive. For classification, factors such as expense in terms of computation power and speed need to be considered. The SVM based approaches presented required less computational power and relatively smaller datasets, however the performance could be improved with feature optimization, also referred to as feature reduction which can be achieved via statistical methods or nature inspired algorithms. The ANN based approaches presented showed promising results however, they required comparatively high computation power and larger datasets. The CNN approach produced promising results, however very high computation power and a very large dataset was required. Ensemble performed better in general, however the previously mentioned of the classification approaches drawbacks were accumulated.

IV. CONCLUSION

This paper presented a review of the image pre-processing, segmentation, feature extraction, feature selection and classification techniques used by researchers thus far to automate the identification of skin diseases. Despite the many published research works, there is yet to be a reliable system available to assist the public in identifying skin diseases. Thus, there is still room and a need for improvement to eventually make such system available to those who will benefit from it.

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