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A Survey on a Skin Disease Detection System

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ABSTRACT

Skin diseases are frequent and quite perennial in the world, and in some cases, these lead to cancer. These are curable if detected earlier and treated appropriately. An automated image-based detection system consisting of four main modules—image enhancement, region of interest segmentation, feature extraction, and detection—can facilitate early identification of these diseases. Diverse image-based methods incorporating machine learning techniques are developed to diagnose different types of skin diseases. This article focuses on the review of the tools and techniques used in the diagnosis of 28 common skin diseases. Furthermore, it has discussed the available image databases and the evaluation metrics for the performance analysis of various diagnosis systems. This is vital for figuring out the implementation framework as well as the efficacy of the diagnosis methods for the neophyte. Based on the performance accuracy, the state-of-the-art method for the diagnosis of a particular disease is figured out. It also highlights challenges and shows future research directions.

KEYWORDS

Feature Extraction, Melanoma, Segmentation, Skin-Disease Diagnosis

1. INTRODUCTION

The skin is the largest organ of the human body. For an adult, the skin surface measures approximately 16,000 cm and represents about 8% of the body weight. Skin is normally affected by sunscreen, UV rays, heat rash, itching, lesions, dark spots, and other infections. Skin diseases are a general disease like other serious diseases (Roy, 2019; Trabelsi, 2013). According to the WHO, more than 2 million people are affected by non-melanoma and around 132,000 people are affected by melanoma (a type of cancer) through the skin each year worldwide. Therefore, all skin diseases are not cancerous (melanomas) (Chowdhury, 2016; George, 2016), but, some skin diseases are also developing as side effects of other chronic diseases. The skin has mainly two layers. The outer layer is known as the epidermis consisting of three cells, such as squamous, basal, and melanocytes, and the inner layer

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is known as the dermis. Usually, skin cancer starts from the epidermis (Cheng, 2012; Dos, 2008; Hasija, 2017; Manoorkar, 2016; Oselame, 2015; Patil, 2015; Zaidan, 2010).

There are several types of skin diseases with their particular characteristics, such as dermatitis eksfoliatif generalisata, impetigo, pityriasis rosea, erisipelas, nekrolisis toksika epidermal, eczema, psoriasis, acne, warts, vitiligo, tinea corporis, scabies, hives, rosacea, and shingles, boiling, cell, cold sores, corns, calluses, dyshidrotic, malluscum contagiosum, neurofibromatosis, skin tags, melanoma, rash, malignant melanoma - squamous cell carcinoma (SCC), basal cell carcinoma (BCC), genetic diseases - genetic skin disorders, sickle cell disease anemia, leprosy, viral infection, seborrhoeic dermatitis, lichen planus, pink pityriasis, chronic dermatitis, pityriasisrubrapilaris, herpes, seborrheic kurtosis (SK), nevus, bullae, splitz, venous malformations, and scleroderma, etc. Automatic skin disease detection systems use skin images or dermoscopy images. There are some bench-mark skin disease image databases, such as DermNet [DermNet, 2020], Dermweb [Dermweb, 2010], International Skin Imaging Collaboration (ISIC, 1979) and The HAM10000 [HAM10000, 2020], etc. Usually, dermoscopy images contain hair or other noises; hence, noise reduction using different filtering methods are used as image preprocessing (Carrera, 2018; Dhanachandra, 2015; Hegde, 2018; Mahecha, 2018; RB, 2013; Sun, 2016; Wagstaff, 2001). Different segmentation algorithms are used to isolate the affected portion i.e. the region of interest (ROI) from the dermoscopic images (Ajith, 2017; Alfed, 2015; Arifin, 2012; Joseph, 2016; Mane, 2018; Maseleno, 2012; Nezhadian, 2017). In the feature extraction stage, several features, such as color feature, edge, shape, texture, diameter, asymmetrical feature, image border, image boundary, etc. are used for the identification of skin lesions (Alquran, 2017; Anitha, 2018; Haddad, 2018; Ichim, 2018; Kumar, 2016; Rathod, 2018; Suganya, 2016). The classification of skin diseases is done by classical feature-based techniques or some machine learning-based methods including artificial neural networks (ANN) (Ambad, 2016; Amarathunga, 2015; Ansari, 2017; Arivazhagan, 2012; Bajaj, 2018; Goel, 2015; Jain, 2012; Kumar, 2016; Okuboyejo, 2013; Sumithra, 2015; Zingade, 2017).

About 75% of skin cancer patients die worldwide each year. Early detection of skin cancer helps to take remedial measures for the complete elimination of the disease from the body; otherwise, the skin will be severely affected by cancer and will not be curable.

The main contributions of this research are as follows:

- We study the different methodologies of skin disease thoroughly and identify the state-of-the-art systems to diagnose a specific type of skin disease;
- We identify the limitations of the existing automated skin disease type-oriented detection techniques;
- We point out the challenges that must be addressed by future researchers.

The remainder of this paper is structured as follows: Section 2 describes the theoretical background and Section 3 explains the classification of the skin disease detection system. The summary of state-of-the-art skin disease detection systems is explained in Section 4. Section 5 focuses on challenges and recent threats in the skin disease detection system, and finally, section 6 concludes the study.

2. THEORETICAL BACKGROUND

The generic skin disease detection system and dermoscopy sample images are shown in Figure 1 and Figure 2, respectively.

The skin disease detection system (Figure 1) consists of two main stages, such as the image processing stage and the machine learning stage (Roy, 2019; Trabelsi, 2013). In the image processing stage, the dermoscopy or sample images (Figure 2) are first taken into the system as input. Then, image preprocessing operation is done for removing noise, contrast enhancement, ROI segmentation, and feature extraction. Lightweight segmentation algorithms are used to extract skin lesion portions

Figure 1. Generic skin disease detection system

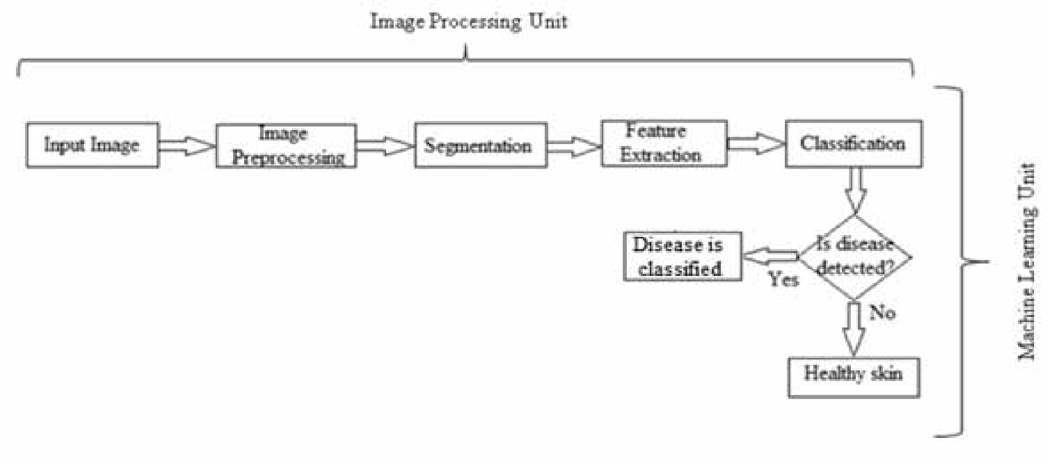


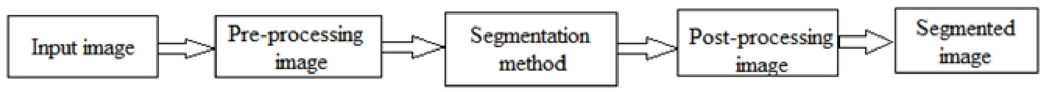
Figure 2. Sample input images of skin cancer (Arifin, 2012)

(Chowdhury, 2016; George, 2016; Manoorkar, 2016; Trabelsi, 2013). Then, the feature extraction operation is done to extract the features that are used as an input to the machine learning unit for detection and classification of the skin diseases as benign, malignant, or healthy skin (Chowdhury, 2016; George, 2016; Hasija, 2017; Manoorkar, 2016; Zaidan, 2010).

2.1 Image Preprocessing

It is an image enhancement stage. Usually, a dermoscopy image contains hairs or noises. Various filtering techniques, such as median filtering, Gaussian filtering, fast-marching painting algorithm, etc. are also used to remove these hairs and noises.

Figure 3. Block diagram of image segmentation



2.2 Image Segmentation

This stage tries to segment out the region of interest (ROI) in dermoscopy images (Chowdhury, 2016; George, 2016; Manoorkar, 2016; Trabelsi, 2013; Roy, 2019). There are diverse segmentation techniques, such as color-based segmentation, texture-based segmentation, Otsu thresholding, fuzzy C-means clustering, K-means clustering, morphological operations, background subtraction, region growing, edge-based segmentation, gradient vector-based segmentation, active contour model (ACM), Bi-level thresholding, and HED (holistically-nested edge detection) used in dermoscopy images for extraction of ROI. The color-based method segment out the selected portion concerning colors, the pixel-based method works with the pixels on a cluster basis, edge-based method segments out the selected portion concerning edges, the threshold-based method create binary images from the color images, the morphological method works using dilation, erosion, opening, and closing operations, and texture-based method performs based on texture region of images. Figure 3 shows a flow diagram of the image segmentation operation.

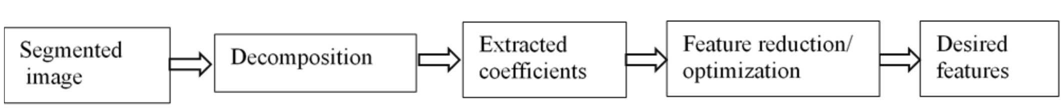
2.3 Feature Extraction

Feature extraction identifies the key features and contains the most relevant information of the input image (Dos, 2008; Hasija, 2017; Manoorkar, 2016; Patil, 2015; Zaidan, 2010). For extracting features, different tools and techniques are used, such as a) wavelet transforms, b) Gabor wavelet, c) DCT (discrete cosine transform), d) FFT (fast Fourier transform), e) edge operators, f) blob detector, g) ABCD (asymmetry, border, color, diameter) rule, h) ABCDE (asymmetry, border, color, diameter, evolution) rule, i) GLCM (gray level co-occurrence matrix), j) watershed algorithm, k) run-length method, l) DBC (differential box-counting) method, m) HOG (histogram 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 sub-sampling, s) SVD (singular value decomposition), etc. Sometimes, the principal component analysis (PCA) algorithm is used to reduce the feature sets for faster execution of classifications and an optimization technique is used to select important features. The feature extraction process takes the segmented image as input, decomposes it to extract the feature coefficients. Figure 4 shows a flow diagram of the feature extraction method.

2.4 Disease Classification

According to the characteristics or features of a segmented ROI, skin diseases are classified or identified usually through conventional as well as machine learning techniques (Cheng, 2012; DermNet, 2020; Dermweb, 2010; Dos, 2008; ISIC, 1979; Oselame, 2017; Patil, 2015; Zaidan, 2010). However, most of the machine learning techniques outperform conventional counterparts. The classification of skin diseases uses different algorithms such as a) feedforward and backpropagation artificial neural network (ANN), b) support vector machine (SVM), c) deep convolutional neural

Figure 4. Block diagram of image feature extraction



network (CNN), d) CaffeNet (convolutional architecture for fast feature embedding neural network), e) VGGNet (Visual geometry group neural network, a deep CNN model), f) k-nearest neighbor (kNN), g) decision tree (DT), h) linear discriminant analysis (LDA), i) Naive Bayes (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. The functional block diagram of the skin disease classification/ detection is shown in Figure 5.

2.5 System Performance Metric

The performance of any test system is usually measured using the confusion matrix through accuracy, sensitivity, specificity (Anitha, 2018; Ansari, 2017; Ichim, 2018; Jain, 2012; Suganya, 2016; Sumithra, 2015). Test accuracy gives the measurement of the overall correctness of the proposed work, which is calculated as the ratio of the sum of correct clusters to the total clusters and is shown in Equation (1):

$$Accuracy\left(\%\right) = \frac{TP + TN}{TP + TN + FP + FN} \times 100$$

$$= \frac{Correctly\ \ classied\ \ number\ \ of\ \ images}{Total\ \ number\ \ of\ \ images} \times 100 \qquad (1)$$

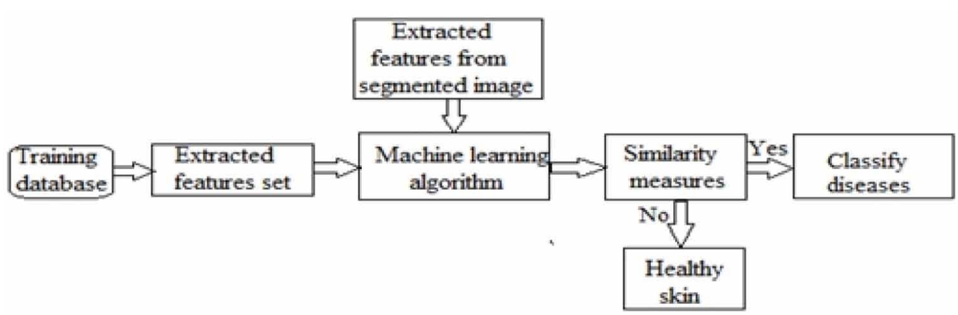
where:

True Positive (TP) - Lesion person identified as a lesion
True Negative (TN) - Healthy person identified as healthy
False Positive (FP) - Healthy person identified as a lesion
True Positive (FN) - Lesion person identified as healthy

Test Sensitivity gives the percentage of sick people who are correctly identified as sick, which means it is the ratio of the correctly identified sick people and the estimated total sick people:

$$Sensitivity\left(\%\right) = \frac{TP}{TP + FN} \times 100 \qquad (2)$$

Figure 5. Block diagram of skin disease classification



Test Specificity gives the percentage of healthy people who are correctly identified as healthy, which means it is the ratio of the correctly identified healthy people and the estimated total healthy people:

$$Specificity\left(\%\right) = \frac{TN}{TN + FP} \times 100 \quad (3)$$

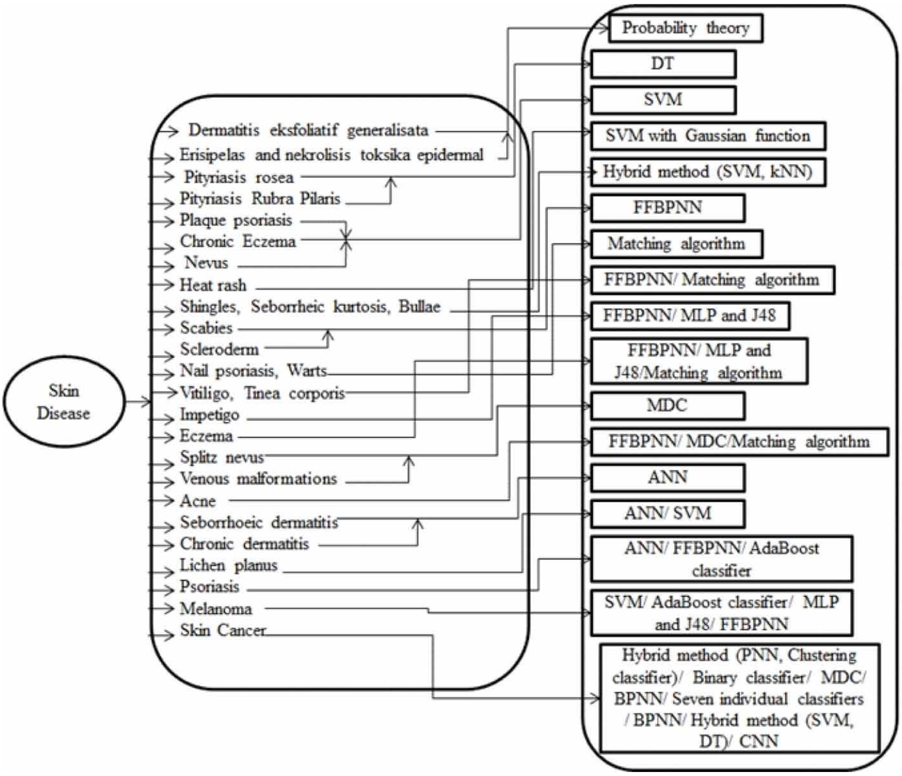
In this review, we showed only the accuracy for comparative purposes, as most of the works reported the accuracy scores.

3. CLASSIFICATION OF SKIN DISEASE DETECTION SYSTEM

Generally, human skin is affected by various skin diseases. Different researchers used various methodologies to detect skin diseases. Different types of skin diseases are shown in Figure 6, which is briefly described below:

1. **Dermatitis eksfoliatif generalisata:** The skin disease dermatitis eksfoliatif generalisata (generalized exfoliative dermatitis) causing severe inflammation of the entire skin surface is identified by the score generation and probability theory method (Maseleno, 2012). In this method, features generate the scores, and probability theory classifies the skin disease with scores.
2. **Impetigo:** Impetigo is a common contagious skin infection and it mainly affects infants and children. This skin disease is identified by three different methods. The first method uses edge-based segmentation with an active contour model, Sobel operator, and feedforward backpropagation neural network (FFBPNN) (Bajaj, 2018). The second method uses a hybrid segmentation along with feature extractions (thresholding, morphological operations, watershed algorithm) and classification algorithm (multilayer perceptron, J48) (Amarathunga, 2015). The third method generates a score from the probability theory in which skin disease is classified from a score (Maseleno, 2012). The first two methods are neural network-based and well-suited with a higher disease detection rate than the third method.
3. **Pityriasis rosea:** Pityriasis rosea is a rash that looks like a large circular or oval spot on the chest, abdomen, or back of the body. There exist two methods for identifying pityriasis rosea. The first method uses Otsu thresholding for segmentation. Then, the Sobel operator is used for extracting features. Finally, the k-nearest neighboring algorithm classifies skin disease from the extracted features (Kumar, 2016). Another method which creates score from the features using the probability distribution and classifies the skin disease by the scores(Maseleno, 2012).
4. **Erisipelas and nekrolisis toksika:** These two skin diseases are creating discomforts like itching, rash, and pain. The method used for detecting skin disease Erisipelas and nekrolisis toksika epidermal through score generation and probability distribution theory(Maseleno, 2012).
5. **Plaque psoriasis and chronic eczema:** Skin disease plaque psoriasis causing milder itching and burning. On the other hand, chronic eczema is creating prolong itching and burning. These skin diseases plaque psoriasis and chronic eczema are identified through the methods HED, GLCM, and SVM. In this method, the holistically nested edge detection (HED) algorithm segments the lesion portion, and then gray level co-occurrence matrix (GLCM) features are extracted to do the classification task by the support vector machine (SVM) (Mahecha, 2018).
6. **Nail psoriasis and warts:** Nail psoriasis alters the toenails and fingernails getting thick, developing pinprick holes, and changing color or shape. On the other hand, warts are rough and tiny dots of clotted blood vessels often on fingers or hands. In the detection of skin diseases like nail psoriasis and warts, various feature extraction algorithms, such as DCT, DWT, and SVD

Figure 6. Different types of skin diseases along with their diagnosis systems



are used. The matching algorithm matches the extracted features with the database features to detect skin diseases (Ajith, 2017).

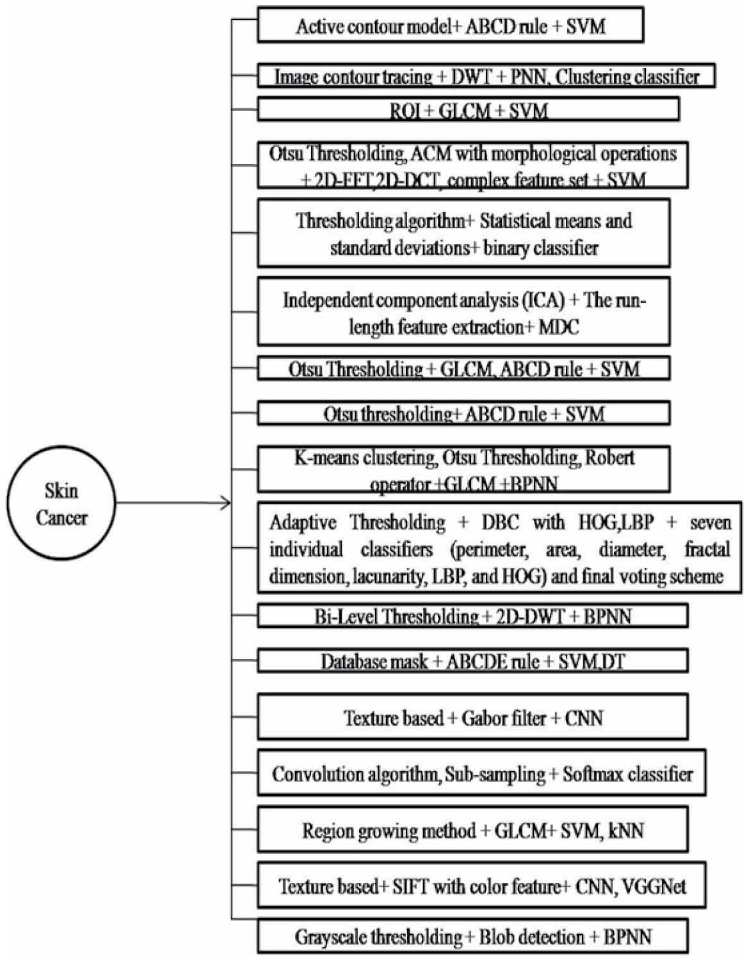
7. **Eczema:** Eczema is very common as well as a severe skin disease causing itching, dryness, swelling, and discoloring of the skin surface. Four different methodologies detect skin disease eczema. The first method uses the K-means clustering algorithm for segmentation and the GLCM method for feature extraction. Then, the extracted features are fed into FFBPNN to classify the skin disease (Arifin, 2012). The second method uses the Sobel operator for edge feature extraction. These features are fed into the FFBPNN to classify skin disease (Bajaj, 2018). The third method uses a watershed algorithm for segmentation and then uses a hybrid algorithm (thresholding, morphological operations) for feature extraction. These features are used by a classifier (multilayer perceptron, J48) to classify the disease (Amarathunga, 2015). The fourth method does not use any segmentation algorithm. In this case, disease detection accuracy is relatively low. It uses the features extracted by a hybrid algorithm (DCT, DWT, and SVD) to match with the database features (Ajith, 2017). The first method is very much efficient between these four methods in classifying the disease due to its robustness.
8. **Psoriasis:** One of the critical skin diseases is psoriasis that is identified by the six methodologies. The first method uses Otsu's thresholding and Sobel operator along with k-nearest neighbor (kNN) to classify the disease (Kumar, 2016). The second method uses the K-means clustering algorithm along with GLCM to extract features and the then neural network classifier to classify the skin disease (Arifin, 2012). The third method uses the thresholding-based segmentation algorithm followed by the DWT feature extraction algorithm and then the AdaBoost classifier to classify the disease (Ambad, 2016). The fourth method uses active contour-based edge segmentation and FFBPNN to detect the disease (Bajaj, 2018). The fifth method uses a fuzzy C-means clustering

algorithm along with a color-based hybrid GLCM for feature extraction, and finally, an SVM classifier to classify the skin disease from the extracted features (Haddad, 2018). The final method uses a thresholding-based segmentation algorithm followed by an ABCD feature extraction rule to feed into KNN to classify the skin disease (Kumar, 2016). Among these methods, the first method is suitable for Psoriasis disease detection due to efficient segmentation, feature extraction, and neural network-based classification algorithm.

9. **Acne:** Acne is the most affected and harmful skin disease of humans. Five methodologies are used for the detection of this disease. The first method uses the K-means clustering and GLCM algorithm for segmentation and feature extraction, respectively. Then, extracted features are fed into the neural network classifier to classify the disease (Arifin, 2012). The second method uses independent component analysis (ICA) for identifying the lesion component, which is followed by the run-length feature extraction. A minimum distance classifier is used to classify skin disease (Arivazhagan, 2012). In the third method, a hybrid feature extraction algorithm (DCT, DWT, and SVD) is used to extract features and match the features with database features to classify the disease based on the matching score (Ajith, 2017). The fourth method uses the fuzzy C-means segmentation algorithm, which is followed by a color-based hybrid GLCM algorithm, and then the SVM classifier is used to classify the disease (Haddad, 2018). The fifth method uses thresholding-based segmentation followed by an ABCD feature extraction rule and the extracted features are fed into the KNN to classify the skin disease (Kumar, 2016). Due to the cluster-based segmentation, GLCM features along with neural network-based classifier are more efficient and reliable than the other four methods.
10. **Vitiligo and Tinea corporis:** Two methodologies are used to identify skin diseases vitiligo and tinea corporis. One method classifies the skin diseases using FFBPNN through GLCM features obtained from the region of K-means clustering (Arifin, 2012). Another method uses the matching algorithm for the detection of diseases from the extracted features obtained by a hybrid feature extraction algorithm (DCT, DWT, and SVD) (Ajith, 2017).
11. **Scabies:** The severe itching skin disease scabies is identified by the methodology that uses the K-means clustering algorithm for segmentation. Then the GLCM feature extraction method is used to extract features that are fed into FFBPNN to classify the disease (Arifin, 2012).
12. **Shingles, Seborrheic kurtosis, and Bullae:** To detect these diseases, region growing segmentation methods followed by the GLCM feature extraction algorithm are used. Then the features are applied to the fusion of SVM-kNN to classify the skin diseases efficiently (Sumithra, 2015). In this case, the hybrid classification algorithm speedup the disease detection performance with reduced computational time.
13. **Chronic dermatitis, Pityriasis rubra pilaris, and Seborrhoeic dermatitis:** These three severe skin diseases chronic dermatitis, pityriasis rubra pilaris, and seborrhoeic dermatitis are detected by Otsu thresholding followed by the Sobel operator and k-nearest neighbor classification algorithm (Kumar, 2016).
14. **Nevus:** For detecting this skin disease, the K-means clustering algorithm followed by the probability distribution based statistical Wilks' Lambda and SVM classifier are used (Suganya, 2016). The cluster-based segmentation and the supervised classifier speed up the system performance.
15. **Splitz nevus and Venous malformations:** The skin diseases splitz nevus and venous malformations are identified by Euclidian distance-based classification methodology, which uses run-length feature extraction from the ICA-based lesion component (Arivazhagan, 2012).
16. **Heat rash:** This disease is detected by fuzzy C-means clustering along with the GLCM features and the SVM classifier (Haddad, 2018).
17. **Lichen planus:** Two different methodologies are used to classify the lichen planus skin disease. One of them uses Otsu thresholding along with the Sobel edge detector and kNN classifier (Kumar, 2016). Another method utilizes an SVM classifier using the GLCM features (Mahecha, 2018).

18. **Scleroderm:** Feedforward backpropagation neural network (FFBPNN) classifies the skin disease scleroderm using the edge-based extracted features through the Sobel operator (Bajaj, 2018).
19. **Melanoma:** Melanoma is a severe case of skin diseases. There are eight different methodologies for the detection of melanoma. The first method uses the K-means clustering algorithm followed by Wilks' Lambda for segmentation and feature extraction, respectively. By using extracted features, the SVM classifier classifies the disease (Suganya, 2016). The next methodology uses a hybrid segmentation and a feature extraction algorithm for a robust skin disease detection system. Then, the SVM classifier is used to classify the disease (Joseph, 2016). The third method works with the AdaBoost classifier, which classifies the disease. Thresholding based segmentation algorithm is used for the extraction of a better-segmented portion of the lesion (Ambad, 2016). The fourth method is used for identifying skin disease through a neural network-based classifier. The edge-based features are extracted using the Sobel operator (Bajaj, 2018). The fifth melanoma detection method uses a watershed algorithm and morphological operations for segmentation and feature extraction. Finally, a multilayer perceptron along with a decision tree-based hybrid classification algorithm classifies melanoma (Amarathunga, 2015). The sixth method uses a region growing segmentation followed by the GLCM feature extraction algorithm, and then a hybrid classification algorithm (SVM and KNN) is used to classify the melanoma (Sumithra, 2015). The seventh method uses the ABCD feature extraction rule followed by the Otsu thresholding and morphological operations. Then, a TDS (total dermoscopy score) is generated to classify melanoma (Anitha, 2018). This methodology does not use any machine learning method. The final methodology uses the fuzzy C-means segmentation followed by a hybrid GLCM feature extraction. Then, an SVM classifier classifies the melanoma concerning features (Haddad, 2018). Among the methodologies, the first method that uses K-Means clustering, Wilks' Lambda and SVM classifier are the best due to its highest classification rate.
20. **Skin cancer:** Skin cancer is the most critical and severe case among skin diseases. Seventeen different methodologies are proposed for the detection of skin cancer, which is depicted in Figure 7. In the first method, after image enhancement, the active contour model-based segmentation algorithm is used for the extraction of the lesion region. Then the ABCD feature extraction rule is used for feature extraction, and finally, the support vector machine is applied to classify the skin disease (Anitha, 2018). The second method uses the image contour tracing algorithm for segmentation that is followed by the DWT feature extraction algorithm and then a hybrid PNN (probabilistic neural network) classifier classifies the skin cancer (Jain, 2012). The third method uses the GLCM algorithm for feature extraction from the ROI of the lesion, and then the SVM classifier is used to classify skin cancer (Ansari, 2017). The fourth methodology uses the Otsu thresholding for segmentation and DCT for feature extraction. In this case, the SVM classifier is used to classify skin cancer from the complex feature sets (Joseph, 2016). In the fifth methodology, the thresholding algorithm segments the affected portion of skin, and the statistical features are used as input to the binary classifier to classify skin cancer (Alfed, 2015). The sixth methodology uses the Euclidian distance-based classifier, which takes features from the run-length feature extraction procedure on ICA-based lesion components (Arivazhagan, 2012). The seventh methodology classifies skin cancer that uses probability theory concerning TDS (Maseleno, 2012). The eighth methodology uses the Otsu thresholding algorithm that segments the skin lesion portion, which is followed by ABCD feature extraction rules, and then the SVM classifier classifies the skin cancer concerning features (Mane, 2018). The ninth methodology uses K-means clustering to isolate the lesion portion, and GLCM is used to extract features of that portion. Finally, a neural network-based classifier BPNN classifies skin cancer (Goel, 2015). The tenth methodology uses a hybrid segmentation algorithm to segment out the affected portion of the dermoscopy image and then seven attributes, such as perimeter, area, diameter, fractal dimension, lacunar stroke, HOG feature are used to classify skin cancer through a voting scheme (Ichim, 2016). The eleventh methodology uses bi-level thresholding as image segmentation,

Figure 7. Methodology used in the detection of skin cancer



which is followed by the DWT feature extraction algorithm. Finally, BPNN classifies skin cancer (RB, 2013). The next methodology uses a mask-based segmentation followed by the ABCDE rules for extracting features. Then, a decision tree-based SVM classifier classifies the skin cancer based on features (Carrera, 2018). Texture-based segmentation and Gabor filter-based feature extraction algorithm are used in the thirteenth skin cancer detection methodology. In this methodology, the convolution neural network (CNN) classifies skin cancer (Sun, 2016). In the fourteenth methodology, the sub-sampling-based hybrid convolution algorithm extracts features for classifying skin cancer by a softmax activation function (Rathod, 2018). In the fifteenth methodology, a hybrid SVM-kNN classifier is used to classify skin cancer. For robust detection, region growing segmentation and GLCM feature extraction algorithm are applied here (Sumithra, 2015). Texture-based segmentation and SIFT-based color feature extraction algorithms are used in the sixteenth methodology. A VGGNet-based deep CNN classifier algorithm is used to detect skin cancer (Sun, 2016). In the last methodology, a blob detection algorithm extracts features of the segmented portion. Finally, the feedforward backpropagation neural network (FFBPNN) classifies skin cancer (Zingade, 2017).

Among these methodologies, the best-fitted methodology is the active contour model with ABCD rule and SVM. The active contour model signifies the image boundary detection (Jain, 2012; Joseph, 2016; Nezhadian, 2017). This model includes the snake model, gradient vector flow, balloon model, and geometric contour. This segmentation algorithm is robust than any other algorithm due to its active model feature. The ABCD rule is the best fit in this context due to its asymmetry, border, color, and diameter detection features. Firstly, the lesion image is converted into a grayscale image. After that ABCD rule is applied (Alquran, 2017; Anitha, 2018; Kumar, 2016; Mane, 2018; Nezhadian, 2017; Okuboyejo, 2013). GLCM, DWT, DCT, and various hybrid algorithms are also significant in other cases of skin diseases. According to disease classification, accuracy SVM is the best-fitted classifier to classify skin cancers. It finds an optimal boundary between the possible outputs by using the kernel trick to transform the feature data. It fits the decision line perfectly since it is a linear classifier (Alquran, 2017; Ansari, 2017; Carrera, 2018; Haddad, 2018; Hegde, 2018; Joseph, 2016; Mane, 2018; Nezhadian, 2017; Suganya, 2016; Sumithra, 2015) PNN and FFBPNN are also used to classify cancers instead of SVM. Recently the deep CNN is showing promising performance and it is expected that the deep CNN will become the ultimate classifier in skin disease detection shortly.

4. SUMMARY OF THE STATE-OF-THE-ART SKIN DISEASE DETECTION SYSTEM

The outline of various skin disease detection techniques as explained in Table 1. It consists of the type of diseases, methodology (segmentation, feature extraction, classification), accuracy, advantages, limitations, and the best-fitted methodology to become state-of-the-art for a specific skin disease.

From the above table, we observed that there are many methods for the detection of skin diseases. However, some techniques (such as the active contour model + ABCD rule + SVM) work for a couple of skin diseases. But, for some automated systems, the methodologies were not properly described, and some systems did not quantify the accuracy. We have ranked the best-fitted methodology according to their detection accuracy.

5. CHALLENGES AND RECENT THREATS IN SKIN DISEASE DETECTION

Dermatological images face certain challenges that make it difficult for computers to identify lesions of the skin. The most common artifacts found in images like hair, changes in lighting, different skin types, reflections, and oil bubbles, etc. Some diseases with low color contrast in the foreground (lesion) and background (healthy skin), which are difficult to identify due to the diversity in the appearances and attributes. If the data sets are not good enough, the accuracy of the system will be lower. Moreover, if the segmentation is not good enough then the machine learning algorithms along will not be able to detect the disease correctly. Moreover, it is noted that for skin diseases, clinical test data are also required in addition to image data. So, the machine learning techniques should be designed in such a way as to work with clinical and image data together.

6. CONCLUSION AND FUTURE RESEARCH DIRECTIONS

A thorough review of the implementation and effectiveness analysis of the different image-based skin disease diagnosis systems was presented in this paper. We extracted the state-of-the-art technique for every specific skin disease based on comparing the performance accuracy of different techniques used in the diagnosis of that disease. We also discussed the various challenges and difficulties of the current diagnosis methods. At present, the researchers should focus on improving the detection of specific diseases with the highest accuracy rate as well as robustness. Although some databases have been developed, more versatile as well as larger databases are inevitably required for the detailed effectiveness analysis of an implemented diagnosis system. Instead of conventional machine learning-

Table 1. State-of-the-art skin disease detection system

Disease Type	Methodology (Segmentation + Feature Extraction + Classification)	Accuracy	Advantages	Limitations	Best –Fitted methodology
Dermatitis eksfoliatif generalisata	Score generation+ Probability theory (Maseleno, 2012)	-	Simple implementation and easy to use.	The image segmentation algorithm is not discussed, and the image dataset is unknown.	Score generation+ Probability theory
Impetigo	Edge-based segmentation with ACM + Sobel Operator + FFBPNN (Bajaj, 2018)	90%	Accuracy is good.	The computation cost is high.	Edge-based segmentation with ACM + Sobel Operator + FFBPNN
	Morphological operations + Watershed algorithm + MLP and J48 (Amarathunga, 2015)	85% to 95%	Questionnaire-based system and user friendly.	The sample size is not specified.	
	Score generation+ Probability theory (Maseleno, 2012)	-	Implementation format is simple and accessible.	Image datasets and image segmentation algorithms are unknown.	
Pityriasis rosea	Otsu's method, gradient vector flow + Sobel operator + kNN, DT, BPNN (Kumar, 2016)	95%	User-friendly mobile-based apps and their accuracies are high.	The feature extraction algorithm is not satisfactory.	Otsu method, gradient vector flow + Sobel operator + kNN, DT, BPNN
	Score generation+ Probability theory (Maseleno, 2012)	-	Simple implementation and easy to use.	Image datasets are not mentioned and the segmentation algorithm is not used.	
Erisipelas and nekrolisis toksika epidermal	Score generation+ Probability theory (Maseleno, 2012)	-	Simple implementation and easy to use.	The image segmentation algorithm is unknown.	Score generation+ Probability theory
Plaque psoriasis, Chronic Eczema	HED+GLCM+SVM (Mahecha, 2018)	82.58%	A supervised machine learning algorithm is used for classification.	Large feature dimension.	HED+GLCM+SVM
Nail psoriasis, Warts	2D-DCT, DWT, SVD + Matching algorithm (Ajith, 2017)	80%	The system is usable in rural areas due to offline.	Unspecified dataset.	2D-DCT, DWT, SVD + Matching algorithm
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)	85% to 95%	User-friendly questionnaire-based system with dashboard.	The sample size is unknown and the J48 decision tree is not sufficient.	
	2D-DCT, DWT, SVD + Matching algorithm (Ajith, 2017)	80%	The system is used in rural areas.	Offline based systems and data sources are challengeable.	
Psoriasis	Otsu method, gradient vector flow + Sobel operator + kNN, DT, BPNN (Kumar, 2016)	95%	User-friendly mobile-based 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.	
	K-means, Fuzzy C-means+ GLCM, color feature +SVM with Gaussian function (Haddad, 2018)	-	The system is mobile-based and easy to use.	A small dataset is used and the system accuracy is not specified.	
	Thresholding + ABCD rule + kNN (Kumar, 2016)	-	It provides a cost-effective, easier and faster result.	Sample sizes are unknown and system accuracy is not identified.	
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
	Independent component analysis (ICA) + Run-length feature extraction+ MDC (Arivazhagan, 2012)	92.72%	Performance is accurate due to Euclidian distance-based classifier	Computational time is high.	
	2D DCT, DWT, SVD + Matching algorithm (Ajith, 2017)	80%	The system is easily accessible to users in rural areas.	Dataset is not specified.	
	K-means, Fuzzy C-means + GLCM, color feature +SVM (Haddad, 2018)	-	The system is mobile-based and easy to use.	A small dataset is used and the system accuracy is not specified.	
	Thresholding + ABCD rule + kNN (Kumar, 2016)	-	It provides a cost-effective, easier and faster result.	Sample sizes and system accuracy are unknown.	

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Table 1. Continued

Disease Type	Methodology (Segmentation + Feature Extraction + Classification)	Accuracy	Advantages	Limitations	Best –Fitted methodology
Vitiligo, Tinea corporis	K-means clustering with color gradient + GLCM+ FFBPNN (Arifin, 2012)	94.016%	Disease classification accuracy is satisfactory.	A low configuration camera produces poor image datasets.	K-means clustering with color gradient + GLCM+ FFBPNN
	2D DCT, DWT, SVD + Matching algorithm (Ajith, 2017)	80%	Due to the simplified system, it is used in rural areas.	Unknown datasets.	
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
Shingles, Seborrheic kurtosis (SK), Bullae	Region growing method + GLCM+ SVM, kNN (Sumithra, 2015)	61.03%	Disease classification accuracy is satisfactory.	System accuracy is low.	Region growing method + GLCM+ SVM, kNN
Chronic dermatitis, Pityriasis rubra pilaris, and Seborrhoeic dermatitis	Otsu method, gradient vector flow + Sobel operator + kNN, DT, BPNN (Kumar, 2016)	95%	The system is easy due to mobile-based applications.	A well-suited feature extraction algorithm is preferable.	Otsu method, gradient vector flow + Sobel operator + kNN, DT, BPNN
Nevus	K-Means clustering + Wilks' Lambda + SVM (Suganya, 2016)	96.8%	The sample size is enough than the others. The system accuracy formula is well defined.	Disease classification is not sufficient.	K-Means clustering + Wilks' Lambda + SVM
Splitz nevus, Venous malformations	Independent component analysis (ICA) + Run-length+ MDC (Arivazhagan, 2012)	92.72%	Satisfactory sample size and Euclidean distance-based classifier is used.	Computational time is high.	Independent component analysis (ICA) + Run-length+ MDC
Heat rash	K-means, Fuzzy C-means+ GLCM, color feature +SVM with Gaussian function (Haddad, 2018)	-	The system is mobile-based and easy to use.	A small dataset is used and the system accuracy is not specified.	K-means, Fuzzy C-means+ GLCM, color feature +SVM with Gaussian function
Lichen planus	Otsu method, gradient vector flow + Sobel operator + kNN, DT, BPNN (Kumar, 2016)	95%	The system is easy to use due to its mobile-oriented implementation.	Features are not extracted properly due to poor algorithms.	Otsu method, Gradient Vector Flow and color-based + Sobel operator + kNN, DT, BPNN
	HED+GLCM+SVM (Mahecha, 2018)	82.58%	The SVM classification algorithm enhances system accuracy.	A large feature dimension is problematic.	
Scleroderm	Edge-based with ACM + Sobel Operator + FFBPNN (Bajaj, 2018)	90%	Edge-based segmentation performs better.	Sobel operator deteriorates disease classification accuracy.	Edge-based with ACM + Sobel Operator + 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 + 2D-DWT + AdaBoost classifier (Ambad, 2016)	90% or more	Statistical analysis enriched the system.	Computational time is high.	
	Edge-based segmentation with ACM + Sobel Operator + FFBPNN (Bajaj, 2018)	90%	Neural network-based classification speed up the system.	Hybrid feature extraction is needed.	
	Thresholding, Morphological operations + Watershed algorithm + MLP and J48 (Amarathunga, 2015)	85% to 95%	Easy and simple questionnaire-based implementation.	The image dataset is small and the image size is not mentioned.	
	Region growing method + GLCM+ SVM, kNN (Sumithra, 2015)	61.03%	Disease classification accuracy is satisfactory.	Disease detection accuracy is too low.	
	Otsu Thresholding and Morphological operations + ABCD rule + Total Dermatascopy Score (Anitha, 2018)	-	The score generation-based classification system is a simpler technique.	A machine learning algorithm is not used and system accuracy is not mentioned.	
	K-means, Fuzzy C-means+ GLCM, color feature +SVM with Gaussian function (Haddad, 2018)	-	Mobile application-based system and easy to use.	A small image dataset is used and the system accuracy is not defined.	

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Table 1. Continued

Disease Type	Methodology (Segmentation + Feature Extraction + Classification)	Accuracy	Advantages	Limitations	Best –Fitted methodology
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.	Active contour model+ ABCD rule + SVM
	Image contour tracing + DWT + PNN, clustering classifier (Jain, 2012)	97.5% - PNN, 93.5% -clustering classifier	Image features are extracted properly and high system accuracy.	The sample size and image segmentation algorithms are not efficient.	
	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, ACM with morphological operations + 2D-FFT, 2D DCT, complex feature set + SVM (Joseph, 2016)	93.5%	Due to robust image enhancement techniques, segmentation works efficiently.	Accuracy is not so high.	
	Thresholding algorithm + Statistical means and standard deviations + binary classifier (Alfed, 2015)	93%	Easy implementation and easy to use.	The statistical feature extraction algorithm is not efficient.	
	Independent component analysis (ICA) + The run-length feature extraction+ MDC (Arivazhagan, 2012).	92.72%	The system performs well with large amounts of images.	High computational time.	
	Otsu Thresholding + GLCM,ABCD rule + SVM (Maseleno, 2012)	92.1%	Lower computational complexity.	Dataset is not specified.	
	Otsu thresholding+ ABCD rule + SVM (Mane, 2018)	90.47%	Less time consuming and less costly.	Dataset is not specified.	
	K-means clustering, Otsu Thresholding, Robert operator + GLCM + BPNN (Goel, 2015)	85-100%	Real-time embedded system.	It has a low sample size.	
	Adaptive Thresholding + DBC with HOG, LBP + seven individual classifiers (perimeter, area, diameter, fractal dimension, lacunarity, LBP, and HOG) and final voting scheme (Ichim, 2016)	85%	The feature extraction algorithm works efficiently with a small sample size.	The system accuracy is low.	
	Bi-Level Thresholding + 2D DWT + BPNN (RB, 2013)	84%	Cost-effective and efficient decision making.	But no detection of overall diseases.	
	Database mask + ABCDE rule + SVM, DT (Carrera, 2018)	75-84%	Relatively cheap, easy to use the system.	It has a feature extraction problem.	
	Texture based + Gabor filter + CNN (Sun, 2016)	77.50%	Telemedicine services are used.	Low illumination images show low accuracy.	
	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.	
	Region growing method + GLCM+ SVM, kNN (Sumithra, 2015)	61.03%	Region-based segmentation performs satisfactorily. .	System accuracy is too low.	
	Texture based+ SIFT with color feature+ CNN, VGGNet (Sun, 2016)	52.19%	16-layers CNN architecture is used.	Due to low color contrast and low illumination problems, the accuracy is too low.	
	Grayscale thresholding + Blob detection + BPNN (Zingade, 2017)	-	Disease detection capability is higher than others.	Sample sizes and system accuracy are unknown.	

based diagnosis systems, researchers should emphasize the investigation on deep learning strategies, as these confirmed better accuracy in diverse domains. Furthermore, the researchers should focus on the implementation of hybrid models for the detection and classification of skin diseases in more efficient, reliable, and precise ways. Finally, the development of a more general detection methodology needs specific attention.

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