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Hybrid Methodologies for Segmentation and Classification of Skin Diseases: A Study

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Abstract

Skin disorders are a serious global health problem for humans. These disorders become dangerous when they grow into the malignant stage. Hence, it is necessary to detect these diseases at their early stage. A mobile-based automated skin disease detection system is vital for detecting skin diseases. This system also offers cure or treatment plans to the affected person through the short message service (SMS) or electronic mail (e-mail). An effective skin disease detection system consists of three processes: segmentation, feature extraction, and classification. Several hybrid methodologies are already developed for the above-mentioned processes for detecting skin diseases at the initial stage. This research gives a standard hybrid framework for detecting skin diseases and highlights some design requirements for achieving high accuracy. Existing state-of-the-art hybrid methods of three processes for detecting skin diseases along with their limitations are also summarized. It also identifies the challenges for developing an effective skin disease detection system and gives future research directions.

Keywords

Segmentation, Feature Extraction, Classification, Machine Learning

1. Introduction

Skin is the most sensitive part that is more affected than any other human organ. Sunburn is one of the essential elements that affect the melanocytes cell due to the ultraviolet (UV) rays from the sun [1]. The exposer part of the skin is infected with different diseases by the UV rays, fungal or viral infections, and polluted surroundings [2] [3] [4]. The symptoms of skin lesions are aridity of the skin, infectivity, allergic signs, blaze, cough, rough skin, fever, distress, bruises, scratching, pimples, and bump, etc. A digital system is required to detect skin diseases at the earlier stage [5] [6]. An expert dermatologist can suspect skin infections at the initial stage. For detecting particular skin diseases in an early stage an automated machine learning or an artificial neural network (ANN) based detection system is essential [7] [8].

For the segmentation and feature extraction process, an enhanced image of the affected portion of skin is used, and extracted features are used in the machine learning or artificial neural network algorithm to identify whether there exist skin diseases or not. The testing and learning units are the two phases of this automated system. In the testing unit, an affected portion of the lesion from a resized filtered skin lesion image is segmented by using a hybrid segmentation algorithm. Then, the system goes to the hybrid feature extraction methods [9]. These methods are very useful in extracting features from the segmented portion of the dermoscopic images. Machine learning or ANN algorithms are used to identify skin diseases by extracting features [10] [11]. These hybrid algorithms based on machine learning or ANN are cost-effective in terms of time and space for classifying skin diseases. In the learning unit, the previously classified skin lesion diseases are stored in the database. Finally, the testing and learning units identify the various skin diseases. If there exist no matches between the test and stored database images, the system will be rechecked [12]. If we can add a treatment plan, it would be very helpful for the patients [13]. **Figure 1** illustrates the flow diagram of an automated skin disease detection system.

In this paper, we have analyzed hybrid methodologies of three processes for detecting skin diseases. Among the methodologies, we have found efficient hybrid methods of segmentation, feature extraction, and classification of skin diseases. These automated hybrid methods are functioning effectively with low computational complexity.

The main contributions of this research are as follows:

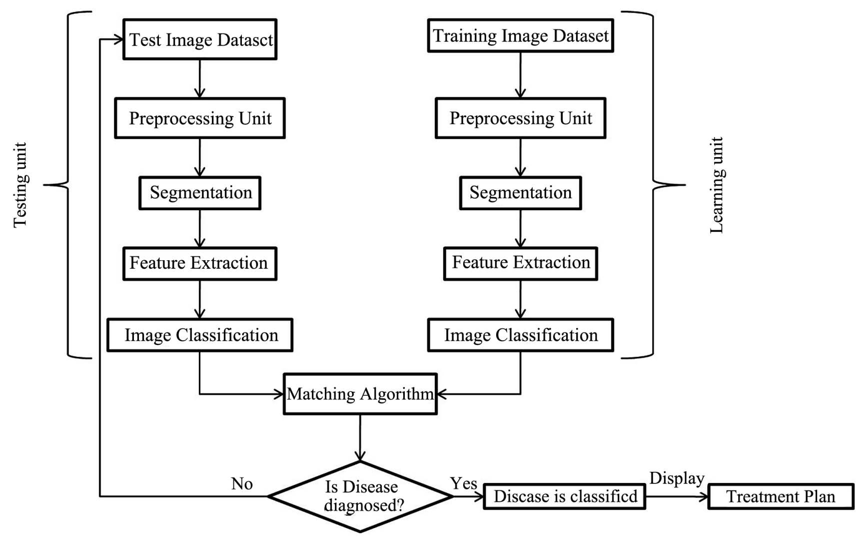

Figure 1. A general framework of the skin disease detection system [12].

- We present the current trends of hybrid methodologies for segmentation, feature extraction, and classification.
- We identify the efficient method for diagnosing skin diseases.
- We highlight the limitations and challenges of existing state-of-the-art hybrid methods along with future research directions.

The paper is organized as follows: part II describes the related literature. The general hybrid framework for skin disease detection system is explained by part III. Part IV illustrates the basic design requirements for this hybrid method. The existing state-of-the-art hybrid methods of three processes, such as segmentation, feature extraction, and classification for detecting skin diseases are summarized in part V. Part VI highlights the challenges of hybrid methodologies. Finally, the last section concludes the study along with future research guidelines.

2. Related Literature

Several studies [14]-[38] have already been performed for detecting skin diseases. Mahmoud Elgamal [14] proposed an automated system that uses discrete wavelet transform (DWT) for extracting the features of a color-based segmented image portion of the skin lesion. Here, the principal component analysis (PCA) algorithm is used to reduce the features. The proposed system is cost-effective in terms of time and space. Based on the features, the kNN (k-nearest neighbor) algorithm is used to classify the skin diseases like normal or abnormal with a system accuracy of 97.5%, sensitivity of 100%, and specificity of 95%. But DWT method sometimes could not extract features properly. Another method [15] describes a real-time embedded system that uses the gray-level co-occurrence matrix (GLCM) features are used to classify the skin diseases like melanoma, basal cell carcinoma, actinic keratosis, squamous cell carcinoma through a backpropagation neural network (BPNN). K-means clustering and the Otsu thresholding segmentation method are used for segmentation. Here, the images are clustered with a threshold value. The system provides 95.83% accuracy. This methodology works only 50 images for four different skin cancer detections and the mechanism of the classification algorithm is not clear. To enhance the system performance of the GLCM color feature-based method, Sumithra *et al.* [16] proposed a system that uses a region growing method for segmenting the regions of the image. They used various color spaces to extract features like mean, standard deviation, variation, and skewness, angular second moment, contrast, correlation, a sum of variance, inverse difference moment, sum average, sum variance, sum entropy, entropy, difference variance, difference entropy, information measures of correlation, and maximal correlation coefficient, etc. These features are used in the SVM-KNN hybrid method to classify skin diseases as melanoma, bullae, seborrheic keratosis, shingles, and squamous cells with a system accuracy of 98%. But the system will be vulnerable to complex feature sets and sometimes shows mismatch due to dataset.

To minimize dataset problem a preprocessing system [17] namely contrast limited adaptive histogram equalization technique (CLAHE) with median filtering is used. Here, a segmentation algorithm like normalized Otsu thresholding is used to segment the affected skin lesion portion from the skin. GLCM with geometric features is used as a feature extraction method. PCA algorithm is used to reduce the features to speed up the classification process. DLNN (deep learning neural network) and hybrid-AdaBoost algorithms are used to classify skin diseases. The system gives an accuracy of about 93%.

Another paper [18] describes a system that uses the feature extraction algorithm GLCM with LBP for extracting the features like energy, entropy, contrast, homogeneity, and LBP array. These features are used to classify skin diseases with a system accuracy of 90.32% and a sensitivity rate of 85.84%. But system accuracy is not somehow low and the system is not embedded in smart-phone-based technology. Taufiq *et al.* [19] explained a smart-phone based system that uses the Grabcut algorithm for segmenting the image in real-time. The histogram-based ABCD rule is used for extracting the features like lesion perimeter, eccentricity, mean, standard deviation, L1 norm, L2 norm, angle of the lesion, a major-minor axis of the lesion from the segmented image. Skin diseases are classified by SVM with the sensitivity rate and specificity rate of 80% and 75%, respectively. This method is relatively poor than the previous GLCM-LBP feature extraction method. Method [20] uses a rough-set based feature selection algorithm to extract the features like erythema, scaling, borders, itching, koebner phenomenon, polygonal and follicular papules, oral mucosal involvement, knee-elbow, and scalp involvement, family history, age, etc. These features are used to classify the skin diseases like psoriasis, seborrheic dermatitis, lichen planus, pityriasis rosea, chronic dermatitis, and pityriasis rubra pilaris through SVM-kNN with multilayer perceptron. The obtained system accuracy is about 97%. To minimize extracted features Joseph *et al.* [21] described a system that works with highly efficient preprocessed PH_2 dataset images. The Otsu thresholding method with edge-based morphological operations is used for image segmentation. Here, the edge-based method with pixel values works efficiently with dilation and erosion operations. The method produces a better-segmented image portion. Tan *et al.* [22] proposed an intelligent decision support system that uses the adaptive snake method which works with the gradient threshold value of grayscale images for segmentation. Here, ABCD rule and Epiluminescence microscopy (ELM) criteria and genetic algorithm (GA) with radial basis function (RBF) based support vector machine (SVM) are used for feature extraction and classification. As the efficiency of this method is somehow low, hence, to enhance the efficiency it requires hybrid segmentation and classification algorithm.

Liao *et al.* [23] suggested a method that classifies skin diseases based on the characteristics of affected images by using a multi-level convolution neural network (CNN) with block variation of local correlation coefficients (BVLC) based AlexNet model. It provides a poor system accuracy of 70%. This method does not use specific segmentation and feature extraction algorithms. In this backdrop, Alquran *et al.* [24] proposed a method that uses the Otsu thresholding method for segmentation and GLCM-ABCD (area, border, color, and diameter) rule for feature extraction. PCA algorithm is used to find out the optimum features like total dermoscopy score (TDS), mean, standard deviation, energy, contrast, etc. Here, skin diseases are classified through the SVM from the correlation matrix with a system accuracy of 92.10%. If the system uses a hybrid classification algorithm like SVM with kNN or SVM with a decision tree (DT) or SVM with CNN, the system accuracy will be enhanced.

Janney *et al.* proposed a method [25] that describes a system that uses a region-based segmented image portion for extracting features by using the GLCM-based ABCD rule. The extracted features based on ABCD rule are asymmetry, border, color, diameter, total dermoscopy score, and GLCM-based extracting features are energy, entropy, contrast, correlation, etc. Here, the homogeneity is used to classify the skin diseases as benign or malignant by using BPNN with a system accuracy of 90.45%.

In [26] local binary pattern (LBP) method is used for extracting the textural and ABCD features through the GLCM-based ABCD rule. Through backpropagation neural network (BPNN), the skin is classified as benign or malignant with a system accuracy of 75% which is also not high enough.

Victor *et al.* represent a technique [27] that takes preprocessed medical images as input. They used an active contour-based marker control watershed algorithm for image segmentation and statistical GLCM features to classify skin diseases through the SVM algorithm. They obtained an accuracy of 94%. If researchers can use a hybrid classification algorithm, then the system will be more efficient. Ajith *et al.* [28] described a mobile-based method that uses DCT, DWT, and singular value decomposition (SVD) based feature extraction algorithm. This method can be used in rural area-based mobile health care systems due to its simplicity, but its performance is not up to the mark. Efficient hybrid segmentation or classification algorithm is required to boost up the system performance. To make an efficient system a cloud computing-based skin disease detection system is proposed in [29] that uses the Canny edge detection (CED) algorithm to detect the sharp edges with image boundaries. These boundaries are used to classify different eczema-like: allergic contact eczema, contact eczema, dyshidrotic eczema, neurodermatitis, nummular eczema, seborrhoeic eczema, and stasis dermatitis through the genetic algorithm with BPNN.

Nasir *et al.* [30] proposed a technique that uses uniform distribution-based segmentation fused with the active contour method. Bajaj *et al.* [31] also discussed a system that uses edge-based segmentation with an active contour method. In another research [32], a bottom-hat filter is used that speeds up the segmentation process. Otsu thresholding method and morphological operations (dilation-erosion) segment the selected portion from the skin. The Otsu thresholding method concerns with pixels. Here, the skin diseases are classified as benign, suspicious, and malignant melanoma by using the ABCD rule, but system accuracy is not mentioned.

In paper [33], a system is proposed that uses GoogleNet-AlexNet, and VGGNet to classify the skin diseases like nevus, melanoma, and seborrheic keratosis. Here, the system accuracy and recall rates are 83.8% and 84.8%, respectively which is not well enough like DWT-PCA based method.

Paper [34] describes an automated system that uses the Otsu thresholding method for selecting the region of interest (ROI) of the skin lesion portion. The method uses various color models, GLCM, and neighborhood gray-tone difference matrix (NGTDM) for extracting features. The SVM (quadratic kernel) is used to classify skin diseases as acne, eczema, psoriasis, benign, and malignant melanoma, etc. The accuracy (around 83%) is not so good.

Arasi *et al.* [35] proposed a system that uses DWT for extracting features for ensuring high accuracy. Here, the wavelet divides an image into four sub-bands like approximation, horizontal, vertical, and diagonal. PCA is used with DWT for reducing the features. Here, the Naive Bayes classifier is used to classify the skin diseases with a system accuracy of 98.8%.

Hameed *et al.* [36] explained a system that uses Alexnet-pertained CNN to extract the multi-level CNN features of affected portions and to classify the skin diseases like acne, eczema, benign, and malignant through ECOC SVM. The obtained accuracy is low. In [37], the hybrid genetic algorithm with ant colony optimization (ACO-GA) algorithm is used for segmentation with 94% accuracy. The GLCM and transductive SVM (TSVM) algorithms are used for feature extraction and classification. The overall system accuracy from the fitness function is 95%. If any method is fused with GLCM then the system would more efficient. In another paper [38], the K-means clustering algorithm is used for segmenting the lesion images and LBP-based GLCM is used for extracting features. SVM is used for classification.

3. Hybrid Method Framework for Skin Disease Detection

In an automated skin disease detection system, dermoscopy or clinical images are preprocessed and learned through the image segmentation, feature extraction, classification steps, and then they are stored in the learning database [14] [15] [16] [17]. Hybrid segmentation, feature extraction, and classification algorithm are used for detecting skin diseases efficiently. The matching algorithm unit tests the features that are used to classify skin diseases. Extracting features from testing images is associated with the features of previously-stored learned images [18]. The matching algorithm works in such a way that if diseases are detected, they will be classified, and finally, the patients will get an e-prescription, otherwise, the system identifies it as healthy skin [21] [22] [23] [24]. The patients get associated information like e-prescription through the treatment plan. The above framework for the skin disease detection system is depicted in the following **Figure 2**.

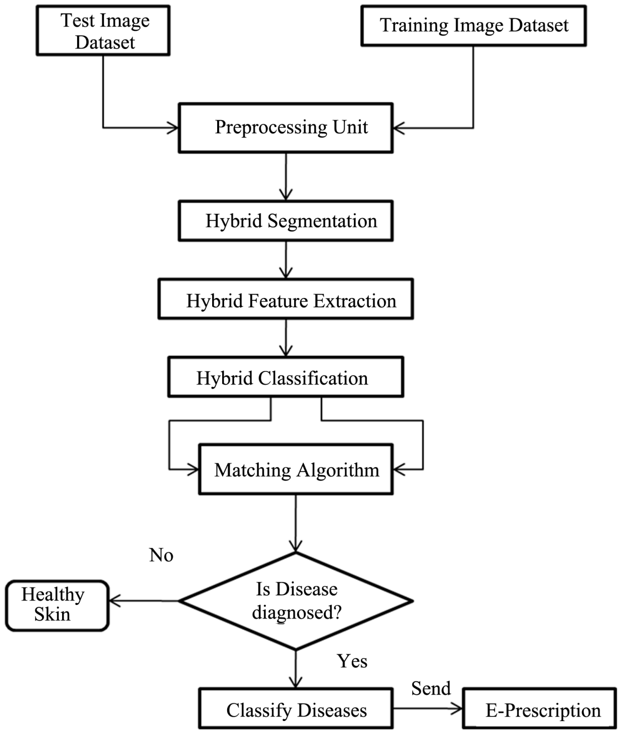

Figure 2. A general framework for a hybrid skin disease detection system.

4. Design Requirements for Hybrid Skin Disease Detection System

An automated skin disease detection system predicts the skin diseases within a short period with high throughput. If skin diseases are detected earlier, then life is saved from chronic skin diseases like skin cancer. This section discusses the design requirements of a hybrid skin disease detection system. In real situations, input images are not homogeneous in size, shape, dimension, color, and brightness, etc. Also, effective image segmentation is necessary for predicting skin diseases. If image portions are cropped for feature extractions, the disease classification accuracy may be lower. Some requirements must be satisfied for designing an efficient hybrid digital skin disease detection system. Among other requirements, the four basic requirements are robustness, data partitioning, data extraction, and predictability. These basic requirements are depicted in **Figure 3**.

Robustness is the requirement where the affected skin image can still be detected after this image has been affected by some common image processing operations include resizing, scaling, translation, spatial filtering, rotation, color mapping, noise, and lossy compression.

Data partitioning is another requirement of a hybrid skin disease detection method that segments the affected image portion for skin disease prediction [3] [4]. The segmentation technique partitions images into few (under-segmentation) or too many regions (over-segmentation). Data extraction is to extract the features that are generated from the segmented image portion. These extracted features are used to classify skin diseases efficiently [5] [6]. Predictability is also an

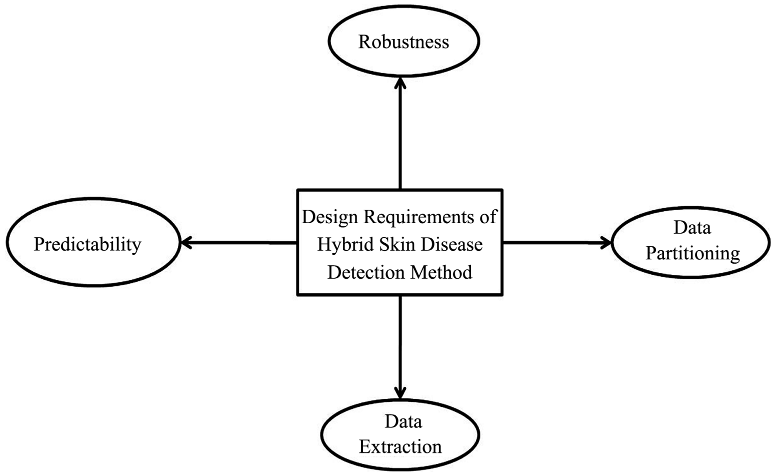

Figure 3. Basic requirements of hybrid skin disease detection method.

important criterion for an automated skin disease detection system. Machine learning and artificial intelligence algorithms are used to predict skin diseases [7]-[12]. The predicted skin diseases are classified as healthy, benign, suspicious, and malignant.

5. Summary of the State-of-the-Art Hybid Methods

A hybrid method means the two algorithms work simultaneously in a skin disease detection system. Usually, the performance and efficiency of the skin disease detection system are estimated by using the confusion matrix. The parameters for evaluating the performance are accuracy, sensitivity, specificity, precision, recall, and F-measure, which are calculated by using the values of true positive (TP), true negative (TN), false positive (FP), and false-negative (FN) values of selected lesion images [14] [16] [17] [19] [31] [33]. This section describes the hybrid methodologies of segmentation, feature extraction, and classification for detecting skin diseases.

1) Hybrid Methodologies of Image Segmentation

There are various hybrid methods for image segmentation. **Figure 4** shows the picture of important hybrid-based methods.

The current state-of-the-art hybrid methodologies of image segmentation are explained in **Table 1**. This table contains used datasets, preprocessing, segmentation and its characteristics, feature extraction, classification method, advantages or disadvantages of hybrid techniques, and accuracy of skin disease detection system.

Based on **Table 1**, we can say that uniform distribution-based segmentation fused with the active contour method is robust among hybrid segmentation methods as it gives the highest system accuracy of 97.5%.

2) Hybrid Methodologies of Feature Extraction

There are various hybrid methods for feature extraction from the captured skin images. **Figure 5** shows the picture of important hybrid-based feature extraction methods.

Table 1. Hybrid methodologies of image segmentation.

Techniques (Reference number is mentioned)	Segmentation	Characteristics	Feature extraction	Classification	Advantages	Limitations	Accuracy
[15]	K-means clustering + Otsu method	Images are clustered with the threshold value.	GLCM	BPNN	An NN-based system that is in a real-time embedded manner.	Computational complexity is high due to it works in real time environment.	95.83%
[21]	Otsu Thresholding method + Edge-based Morphological operations	Edge-based segmentation with threshold values.	2-D Fast Fourier Transform, 2-D Discrete Cosine Transform, Complexity Feature Set, and Color Feature Set	SVM	An enriched filtering algorithm helps all other stages to perform efficiently.	Well defined feature extraction algorithm is required to enhance accuracy.	93.50%
[27]	The active contour method + Marker control watershed algorithm.	The output of the active contour is used as an input to the marker control watershed algorithm	GLCM	SVM	A CAD system enhances the detection and classification and reduces the time latency.	An NN-based classification approach is needed.	94%
[30]	Uniform distribution based segmentation + Active contour method	Four metrics: DICE, Jaccard Index, Jaccard Difference, and Diameter are calculated for each segmented image.	Color features	SVM	It is a robust skin disease detection system with value.	Reliable and low complexity based feature extraction method is required.	97.5%
[31]	Edge-based segmentation + ACM	The active contours method works with sharp edges.	Sobel Operator	BPNN	An NN-based method that successfully detects several diseases.	An efficient hybrid feature extraction algorithm is needed.	90%
[32]	Otsu thresholding method + Morphological operations: dilation, erosion	A morphological operation performs on pixels.	ABCD rule	-	Almost all of the melanoma images are correctly identified using morphological operations.	Without a trained neural network, diseases are not classified properly.	-
[37]	ACO + GA algorithm	Initialize GA and ACO parameters. Segmentation accuracy is 94%.	GLCM	Transductive Support Vector Machine (TSVM)	Better segmentation accuracy gives high performance. At first, this system is predicted as 24 diseases with fitness function.	Hybrid feature extraction is required.	95%

The hybrid methodologies for feature extraction are described in the following Table 2. This table contains used datasets, segmentation method, feature extraction method and its features, classification method, advantages or disadvantages of methods, and accuracy of skin disease detection system.

Table 2. Hybrid methodologies for feature extraction.

Techniques (Reference number is mentioned)	Segmentation	Feature extraction	Features	Classification	Advantages	Limitations	Accuracy
[14]	Color segmentations	DWT + PCA	Features are extracted from DWT which are reduced for better accuracy.	kNN	It requires less computational time and memory.	DWT requires huge capacity and is computationally more expensive.	97.5%
[17]	Normalized Otsu thresholding	GLCM+ PCA	Mean, standard deviation, variance, entropy, contrast/inertia, homogeneity, energy, correlation, area, perimeter, diameter, asymmetry index, circularity index, fractal dimension, compactness index	DLNN (Deep learning NN), SVM-Adaboost	This is a CAD system that runs with lower computational time with higher accuracy.	Hybrid segmentation is needed to enhance system performance.	93%
[18]	-	GLCM + LBP	Energy, entropy, contrast, homogeneity, and LBP array features.	SVM	System performances are computed both qualitatively and quantitatively.	The segmentation algorithm is undefined and to boost up system performance NN based classification is required.	90.32
[19]	Grab Cut algorithm	Histogram + ABCD rule	Features are the area of the lesion, perimeter of a lesion, eccentricity, mean, standard deviation, L1 norm, L2 norm angle of lesion, major and minor axis of the lesion from the segmented image.	SVM	It is easy to access and use due to its Smartphone embedded applications.	An improper segmentation algorithm is used which degrades system performance.	-
[22]	Threshold-based Adaptive Snake (AS) approach	ABCD rule + Epiluminescence microscopy (ELM) criteria algorithm	Features extracted in ABCD rule with ELM criteria.	GA + SVM with Radial Basis Function (RBF)	GA reduces the dimensions and also defines the most discriminating subsets of features to boost system performance.	An efficient and reliable segmentation algorithm is required.	88%
[24]	Otsu thresholding	GLCM + ABCD rule + PCA	GLCM features are Energy, correlation, homogeneity, and contrast features. The best 5 features with maximum efficiency as follows: TDS, mean, standard deviation, energy, and contrast respectively.	SVM	The computational complexity is relatively lower than others.	Hybrid segmentation and NN-based classification are needed.	92.10%

Continued

[25]	Region-based Segmentation	ABCD rule +GLCM	Asymmetry, border, color, and differential structure. TDS = [(A × 1.3) + (B × 0.1) + (C × 0.5) + (D × 0.5)], Energy, Entropy, Contrast, Correlation, and Homogeneity.	BPNN	Due to NN based system, speed up the system performance.	A hybrid classification algorithm is needed.	90.45
[26]	-	GLCM + ABCD rule	ABCD and textural features are extracted.	BPNN	Due to the based system, it is secure and reliable.	The segmentation method is not properly maintained.	75.00%
[28]	-	DCT + DWT + SVD (Singular value decomposition)	Different coefficients are extracted which classify through SVD.	-	Due to mobile-based apps, it is used in mobile hospitals in rural remote areas with a lower computational time of 2.066 s.	Lack of segmentation and classification method, system performance is relatively poor.	80%
[33]	-	GoogleNet + AlexNet + VGGNet	The convolution layer-based approach generates features for classification.	-	Skin diseases are classified as Nevus, melanoma, Seborrheic Keratosis with lower computational time efficiency with the recall rate is 84.8%.	Segmentation and classification algorithm is not defined.	83.8
[34]	Otsu thresholding	GLCM + NGTDM	23 color and texture features are as Rmin, Gmin, Bmin, Rmax, Gmax, Bmax, Rmean, Gmean, Bmean, Hmean, Vmean, Cbmean, Crmean, Graymean, contrast, correlation, energy, and homogeneity whereas the coarseness, busyness, complexity, contrast and texture length.	SVM with quadratic kernel	Though images are taken from diverse sources system accuracy is satisfactory.	Few images are produced the same features which deteriorate the system performance adversely.	83%
[35]	-	DWT + PCA	Wavelets divide an image into 4 sub-band components which correspond to approximation, horizontal, vertical, and diagonal respectively.	DT, Naive Bayes	This system is efficient on a small dataset and easy to use.	It is not adequate in larger datasets.	98.8%

Continued

[38]	K-Means Clustering	GLCM + LBP	Mean, standard deviation, variance, skewness, LBP, and GLCM features.	SVM	K-means algorithm clustering enhances the consistency of	Hybrid classification is not defined.	96%

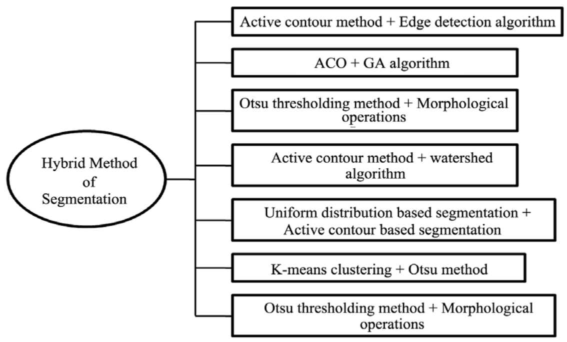

Figure 4. Several hybrid segmentation methods.

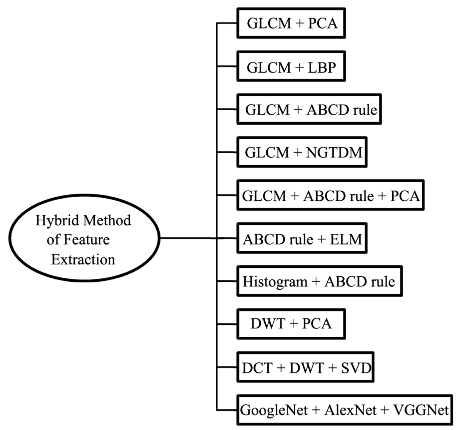

Figure 5. Several hybrid feature extraction methods.

Based on Table 2, we can say that the DWT with PCA method is robust than other hybrid feature extraction methods. DWT wavelets distributed the segmented image into the four sub-band components that extract the features efficiently with the PCA algorithm which reduces the extra features and enhances the classification accuracy. So, we conclude that these methods extract the features very efficiently. The highest classification accuracy of skin disease by using the hybrid feature extraction method is about 98.8%.

3) Hybrid Methodologies for Skin Disease Classification

There are various hybrid methods for skin-disease classification using the captured skin images. Figure 6 presents the picture of important hybrid-based feature extraction methods.

The existing state-of-the-art hybrid classification methods are explained in the following Table 3. This table describes used datasets, segmentation, feature extraction method, and its features, classification method, advantages or disadvantages, and accuracy of skin disease detection system.

Table 3. Hybrid methodologies of classification.

Techniques (Reference number is mentioned)	Segmentation	Feature extraction	Features	Classification	Advantages	Limitations	Accuracy
[16]	Pixel based-Region growing	color and textural features	Extracted features are mean, standard deviation, variation, skewness, angular second moment, contrast, correlation, the sum of variance, inverse difference moment, sum average, sum variance, sum entropy, entropy, difference variance, difference entropy, information measures of correlation, and maximal correlation coefficient	SVM + kNN	The performance is high with the fusion of the SVM-kNN classifier.	Dataset is not standard and the feature extraction method is not defined.	98%
[20]	-	Rough Set-Based Feature Selection	Features are erythema, scaling, borders, itching, koebner phenomenon, polygonal and follicular papules, oral mucosal involvement, knee-elbow, and scalp involvement, family history, age, etc.	SVM + KNN + MLP	System accuracy is robust with a faster response time.	The segmentation algorithm is not defined.	97.78%
[22]	Threshold-based Adaptive Snake (AS) approach	ABCD rule + Epiluminescence microscopy (ELM) criteria algorithm	Features extracted in ABCD rule with ELM criteria.	GA + SVM with Radial Basis Function (RBF)	GA lessens the element measurements to improve framework execution.	The segmentation method is not working properly which decreases system accuracy.	88%
[23]	-	-	-	Multi-level CNN + BVLC Alexnet model	Easy to understand and low complexity system.	Poor efficiency of the system with a lower recall and precision rate. The segmentation and feature extraction method is not defined.	70%
[29]	-	Canny edge detection	The CED method detects sharp edges with image boundaries.	GA + BPNN	Cloud computing-based skin disease diagnosis system deals with enormous amounts of datasets.	Efficient segmentation is absent and system accuracy is also undefined.	-
[36]	-	Pretrained convolutional neural network (AlexNet)	Max pooling criteria evolve with 5-layer convolutional architecture.	Deep convolution neural network + ECOC (Error-correcting output codes) linear SVM	The smart master system enhances existing work with an expansion inexactness of 3.21% in the confusion matrix.	Poor system performance due to proper segmentation approach is undefined.	86.21%

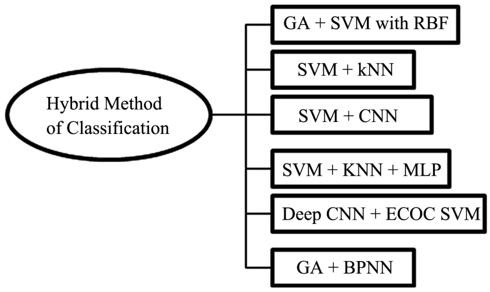

Figure 6. Several hybrid classification methods.

From the above **Table 3**, we can say that the method SVM with kNN is efficient than other hybrid classification methods, as this hybrid classification method ensures high accuracy. The highest accuracy of the efficient hybrid classification method of skin disease is about 98%.

6. Challenges of Hybrid Skin Disease Detection Systems

There are many challenges in designing an automated skin disease detection system. There is an insufficiency of datasets for hybrid segmentation methods. If the system uses no efficient segmentation technique, then only a manually cropped portion of the skin lesion image does not produce good features. When the features are not properly extracted, the exact skin disease will not be properly classified by the hybrid skin disease classification system. If the test images are not preprocessed and segmented properly, the mobile-based automated skin disease detection system will be threatening. For overcoming this challenge, the input images must use a denoising technique along with a proper segmentation technique. For a good detection system, the availability of optimized segmentation, feature extraction, and classification techniques are really challenging issues.

7. Conclusions and Future Research Directions

Nowadays the huge population is seriously affected by various skin diseases. Therefore, the skin disease detection system plays a vital role in identifying these diseases accurately at the initial stage. In this research, we have reviewed several dominant state-of-the-art hybrid methodologies for segmentation, feature extraction, and classification for detecting skin diseases accurately. This review study concludes that the uniform distribution-based segmentation fused with an active contour approach is robust with a maximum system accuracy of about 97%. Also, DWT with the PCA method is efficient than other methods for feature extraction with an accuracy of about 98%. Besides, for classification, the SVM with kNN method is robust than other methods with an accuracy of about 98%. Hybridization of various deep learning algorithms is important to use in skin disease detection to fulfill the design requirements. In addition, researchers should consider the computational complexity of the system in terms of time and space. Also, they should concentrate on developing more extensive label datasets as well as cloud and IoT-based skin disease monitoring systems.

Conflicts of Interest

The authors declare no conflicts of interest.

Authors' Contributions

M.A.M. studied and drafted the whole paper; M.S.U. initiated the concept, supervised the study, and fine-tuned the manuscript.

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