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# Survey On Various Segmentation Methods For Skin Related Diseases

K. Deepasundari[1], Dr. A. Thirumurthi Raja[2]

*[1]Research Scholar, Department of computer Science, school of computing sciences, Vels institute of science technology and advanced studies (VISTAS), Chennai.*
*[2]Research Supervisor, Assistant Professor, Department of computer Science, school of computing sciences, Vels institute of science technology and advanced studies (VISTAS), Chennai.*

*Email: [2]thirumurthiraja@gmail.com*

***Abstract: In recent era, deep learning often pose serious upgrades in feature learning that helps to understand complex data patterns in precise manner. Hence, it would be essential in understanding the patterns of human skin to recognize the type of skin disease and its virulence. In this paper, we provide various machine learning and deep learning algorithm that helps in segmentation or classification of skin related disease. The machine learning and deep learning algorithm is found to be effective in maintaining the state information via its precise segmentation/classification. The study further provides the discussion on limitations associated with skin disease segmentation or classification. Further the study provides directions for future scope that possess real-time analysis.***

***Keywords: Deep learning, machine learning, Segmentation, classification***

## 1. INTRODUCTION

The skin is the delicate component of the human organ, the most impacted. Sunburn is a key feature affecting the cells of the melanocytes because of sun rays [1]. The part of the skin exposed to ultra violet rays it causes fungal, infections and viral infections, and contaminated environments are infected by different diseases. [2] [3] [4]. Symptoms of skin lesions include infections, skin sickness, allergy, coughing, blowing, fatigue, discomfort, roughness, punching, scratching, bumping, etc. Early detection of skin disorders requires a digital system [5] [6]. In the first stage, a professional dermatologist can detect skin infections. A machine learning (ML) detection method is important for detecting specific skin diseases in an early phase [7][8].
In the process of segmentation and extraction of features, an improved image of the affected part of the skin is utilised to detect whether or not there are skin diseases by the extracted features in ML algorithms. ML algorithm operates under two different phases that includes training and testing phase. The test unit is equipped with the ML/DL segmentation algorithm to segment an impacted part of the lesion from the residual filtered skin lesion. The system then turns to the extraction methods for the ML/DL features [9]. These methods are particularly useful in extracting characteristics from the sections of the dermoscopic images. The identification of skin diseases is based on ML [10] [11]. These machine learning or ANN-based ML/DL algorithms are time and space-cost-effective for classification of skin disorders. In the study unit, skin lesion conditions previously classified are maintained in the

database. The test and learning units finally detect different skin conditions. If the test and the database images are not compatible, the system is re-checked [12]. It would be very useful to patients if we could add a treatment plan [13]. The process of skin disease system is illustrated in Fig.1.

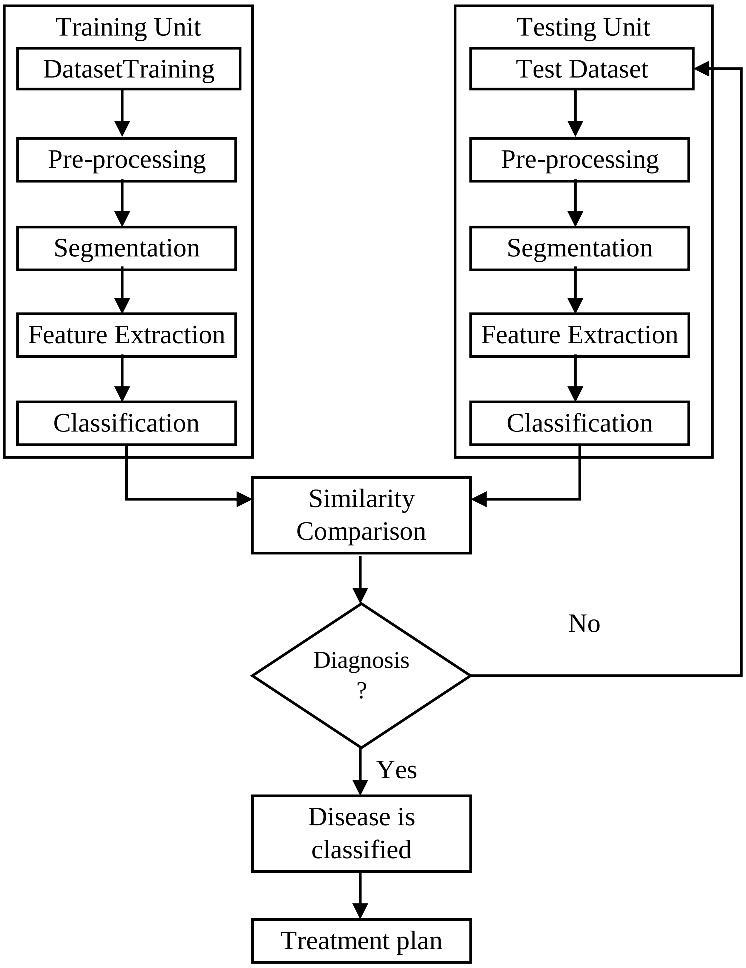


**Fig.1**. Skin disease detection system.

The ML/DL techniques for the detection of skin disorders have been analysed in this work. The strategies for segmentation, extraction, and classification include effective ML/DL methods. These ML/DL automated approaches work with computer complexity effectively.
The primary contributions to this study are:

- The latest trends in ML/DL feature extraction, segmentation, and classification approaches are presented.
- The effective method of diagnosis of skin diseases has been identified.
- The study provides the constraints associated with existing ML/DL processes and future areas for study.

**Related Literature**

Several methods on [14] – [38] for detection of skin disorders have already been conducted. Elgamal [14] presented an automated approach for the extraction of the features of a colour-based segmented image section of the skin injury by using the discrete wavelet transform (DWT). The principle component analysis is used to decrease the features or characteristics.

The system proposed is time and space-cost-effective. The k-nearest neighbor (kNN) method is employed based on its attributes, to diagnose skin conditions such as normal or abnormal with 97.5% system accuracy, 100% sensitivity and 95% specificity. However, occasionally the DWT approach cannot adequately extract features. An alternative method [15] describes an embedded real-time system which uses the grey level cooccurrence matrix (GLCM) for categorising skin diseases such as basal cell and squamous cell carcinoma, melanoma, and actinic keratosis via a neural backbone (BPNN). The segmentation process is utilised for Otsu thresholding and K-mean clustering. Here, the threshold value of the images is grouped. 95.83% precision is provided in the system. This methodology operates on with 50 images for four separate detections of skin cancer, and the algorithm process is not clear. Sumithra et al. [13] proposed a system that uses a region-widening process to segment the image regions to boost the segmentation using GLCM method. This method uses various colour spaces that extracts characteristics like standard deviation, median, skewness, variation contrast, angular moment, sum of variance, correlation, sum difference, total average, difference variance, entropy sum and difference, correlation measurements like maximum correlation, etc. In the SVM-KNN ML/DL approach, these features are used to classify skin diseases with 98% system accuracy, such asseborrhic keratoses, melanoma, squamous cells and shingles. However, the system is susceptible to complicated collection of features and sometimes displays an inappropriate data set.

A preprocessing system [17], especially a contrast, is employed to decrease data set problems by using a limited adaptive histogram equalisation technique with medium filtering. Here, a segmentation method is applied for segmenting the skin lesions from the skin, such as the normalised thresholding of Otsu. As a feature extraction method, geometric features abided with GLCM is well applied. To speed-up the classification process, the principle component analysis technique is employed to reduce features. For the classification of skin diseases, Deep Learning Neural Network (DLNN) and AdaBoost algorithms are utilised. The accuracy of the system is approximately 93%.

Another article [18] depicts a system that is able to extract features such as entropy, energy, homogeneity, contrast, using local binary pattern (LBP) algorithm. These functions are utilised to categorise skin diseases with 90.32% system precision and an 85.84% sensitivity rate. But the precise system is not integrated into the technology of smartphones. Taufiq et al. [19] discussed a smartphone system using the Grabcut algorithm for segmentation of the image. For extracting features such as the lesion perimeter, mean, eccentricity, lesion angle, standard deviation, etc. from the segmented image, the histogram basic ABCD rule is utilised. The SVM classification of skin diseases is 80% and 75%, respectively, with high rates of sensitivity and specificity. The GLCM-LBP feature extraction approach is comparatively poor. The method in [20] employs a rough-set selection algorithm to remove characteristics such as scaling, erythema, itching, edges, polygonal papules, coebner phenomenon, follicular papules, knee-elboxing, oral mucous implication and scalp implication, and various demographic variables including age, family history, etc. The accuracy of the system is approximately 97%. Minimizing the extracted features, the model in [21] produced a highly efficient PH2 data package imaging system. For image segmentation, the Otsu threshold procedure is employed with edge-based morphological processes. The pixel-based approach with erosion and dilation works efficiently here. A more segmented image component is produced. Tan et al. [22] suggested a system of intelligent decision support using the adaptive snake approach, which is based on the gradient threshold value for segmenting grayscale images. Here, Epiluminescence Microscopy (ELM) and Area, Border, Colour, and Diameter (ABCD) Rule are utilised for the extraction and classification of features and a genetic algorithm with radial base function (RBF). Since this model acquires low efficiency, ML/DL segmentation and classification algorithms are required to improve the efficiency.

Liao et al. [23] proposed a method for classification of skin diseases on the basis of the characteristics of images impacted by using the Multi-Level Convolution Network (CNN) based on the AlexNet model based on block variation associated with local correlation coefficients. It offers 70% system accuracy. In that context, Alquran et al. [24] presented a method using the Otsu segmentation threshold and the GLCM-ABCD rule for extracting features. PCA is used to detect optimal features such as total dermoscopic score, average, standard deviation, energy, contrast, etc. Here, skin conditions in the SVM of the correlation matrix are categorised with 92.10% system accuracy. The system accuracy will be increased if it uses a method of ML/DL classification such as an SVM with a kNN or a decision tree (DT) or an SVM with CNN.

Janney et al. have suggested a method [26] describing a system for extracting featureities utilising a regionally segmented image section using the ABCD rule based on the GLCM. Extracted characteristics based upon ABCD rule are entropy, energy, correlation, contrast, etc. Asymmetry, border, colour, diameter, total dermoscopic score, and GLCM-based extraction. The application of BPNN with a system precision of 90.45% is employed for classifying skin conditions into benign or malignant disorders.

The GLCM-based ABCD rule uses the [25] [26] LBP model to extract texture and ABCD characteristics. The skin is diagnosed as benign or cancerous with a system precision of 75%. That is not enough by the Backpropagation Neural Network (BPNN).

Victor et al. [27] is a technique that inputs medical photos that have been pre-processed. They employed an active contour-based watershed control marker method to categorise the skin disorders with the SVM algorithm to segment the images and statistically to GLCM. They have achieved 94% accuracy. The method is more efficient if researchers can apply an ML/DL classification algorithm. Ajith et al. [28] have developed a mobile technique that uses a feature extraction algorithm based on DWT, DCT and Singular Value Decomposition (SVD). Because of its simplicity, this strategy can be employed in rural mobile health systems, although it does not match. To enhance system performance, an effective ML/DL segmentation or grading algorithm is necessary. In order to develop a cloud-based skin disease system, [29] the Canny Edge Detection (CED) recognise sharp edges and image boundaries is proposed to create an efficient system.

Nasir et al [30] suggested an approach that employs the method of active contour fusion with a consistent distribution based segmentation. Bajaj et al. [31] discussed a system which uses an active contour approach for edge segmentation. A Bottom-hat filter, which speeds the segmentation process, is employed in other research [32]. The selected part of the skin is segmented by the Otsu threshold and morphologic procedures (dilation-erosion). Pixels are concerned with the Otsu thresholding approach. In this case, the ABCD rule applies to skin conditions such as benign, suspect, and malignant, but the correctness of the system is not indicated.

A system using Google Net-AlexNet and VGGNet is proposed in document [33] for classification of skin conditions such as nevus, melanoma, and seborrheic keratoses. The system accuracy (83.8%) and recovery rates (84.8%), which is not as good as the technique based on DWT-PCA.

The model in [34] describes a system for the automatic selection of the region of interest (ROI) on the skin lesions by the Otsu thresholding approach. For the extraction of features, the approach uses many colour models, GLCMs, and the gray-ton differential neighbourhood matrix (NGTDM). SVM is used to categorise skin diseases like eczema, acne, melanoma, psoriasis, etc. Precision is not too good.

Arasi et al. [35] have presented a technique using DWT in order to extract high precision features. The wavelet here separates the image into four sub-bands, such as a horizontal, vertical, and diagonal approximation. For reduction of characteristics, PCA is utilised with DWT. The Classification Naive Bayes is here for classifying skin diseases with 98.8% system accuracy.

The approach using Alexnet's CNN, which extracts the multi-level CNN characteristics of affected sections and classifies the skin disorders such as acne, eczema and benign or malignant using ECOC SVM, has been explained by Hameed et al. [36] The precision achieved is small. For segmentation with 93% accuracy, the ML/DL ant colony optimization with genetic algorithm (ACO-GA) technique is applied in [37]. For extraction and classification features, the GLCM and transductive SVM (TSVM) are used. The fitness function has a total system accuracy of 95%.

**LearningModels for Skin Disease Detection**

The clinical images or dermoscopy are prepared and trained for detection of skin disease by segmenting and extraction features, classification stages, then saved in the study database [14]-[17]. [14]. ML/DL segmentation, extraction of functions and classification algorithms are utilised to efficiently detect skin disorders. The corresponding algorithm validates the required features to classify skin conditions. The features of the previously stored learnt images [18] are related with extraction of features from the input test images. It works to classify diseases and, finally, the patients obtain an e-prescription if they are detected [21] – [24]. The algorithm also works so that healthy skin is defined if disease is detected. Fig.2 shows the detection framework for skin disease.

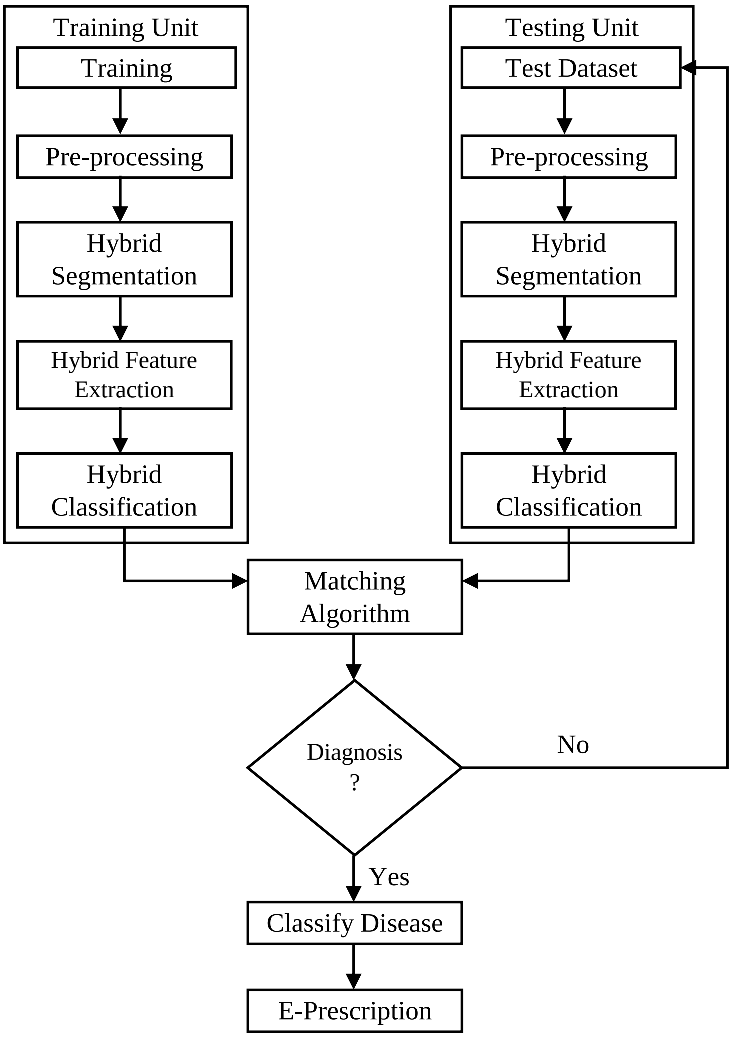


**Fig.2**. A general framework on skin disease detection

**Design Requirements for Detection System**

An automated detection system for skin diseases predicts skin diseases with great performance within a short interval of time. If skin disorders are already recognised, life is spared from chronic skin diseases, such as cancer of the skin. This section describes an ML/DL models for the detection of skin disease with specific design requirements. In real-life settings, images are not considered uniform in terms of size, size, shape, light, colour, etc. In order to anticipate skin conditions, accurate image segmentation is also needed. The exact classification of the condition can be lower if image sections are clipped for feature extraction. For the development of a powerful detection system using ML/DL, some design specifications using the optimal parametric setting must be met. Data extraction, partitioning and predictability include the four fundamental needs. Fig.3 shows these essential criteria.

Robustness is the prerequisite for the detection of the afflicted skin image after some of the common image processing procedures, including scaling, resizing, spatial filters, translation, colour mapping, rotation, compression loss and noise are affected.

Another demand for an ML/DL approach for the diagnosis of skin diseases is data division that divides the afflicted pictorial region for the prediction of skin diseases. [3] [4]. The segmentation technology divides images into a few sections or too many (under segmentation) (over-segmentation). Data extraction is intended to retrieve the features produced by the segmented image section. These collected characteristics are used for efficient classification of skin diseases [5] [6]. Predictability is main factor in the automated detection method for skin diseases. Applied to the prediction of skin diseases are ML/AI algorithms [7]-[12]. The skin diseases predicted are classed as healthy, benign, suspect and malignant.

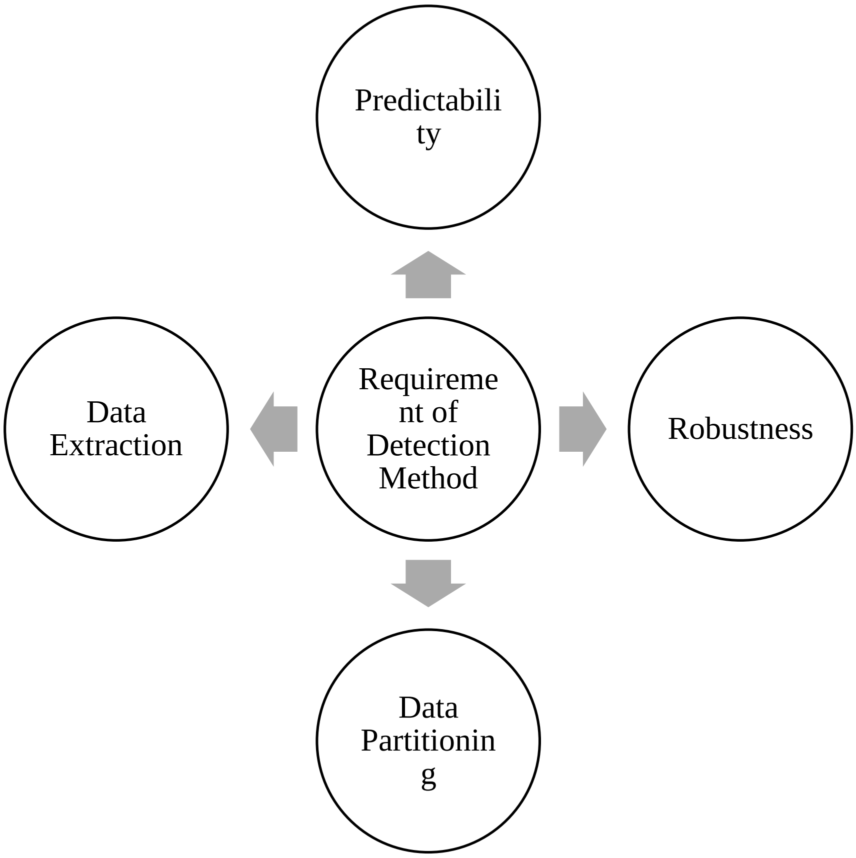


**Fig.3**. Requirements of ML/DL detection method.

## 2. SUMMARY ON HYBRID METHODS

Normally, the detection of skin disease with ML/DL method's performance and efficiency are evaluated by the use of the confusion matrix. Accuracy, sensitivity, specificity, accuracy, recall and F-measurement are the parameters used to evaluate performance, which are computed by the value of true positive (TP), real negative (TN) and false positive values of selected lesion images. [14]-[19] [31] [33]. This section explains the ML/DL segmentation approaches, feature extraction, and skin disease categorization.
For image segmentation, there are different ML/DL algorithms. The image of the key DL/ML algorithms is shown in Fig.4. Table 1 explains the present state of the art in ML/DL image dividing approaches. It provides the basis for robust distribution segments combined with an active contour approach, which yields the highest system precision of 97.5%.
ML/DL approaches are available for extracting the collected images from the skin. The image of significant ML/DL extraction methods is given in Fig.5. This table covers used data sets,

segmentation techniques, extracting methods and characteristics, classification methods, benefits and disadvantages, as well as the accuracy of the detection system for skin diseases.

Table 1. ML/DL Classifiers

| Techniques | Classification | Accuracy | Limitations |
|---|---|---|---|
| [15] | BPNN | 95.83% | Computational complexity is high due to it works in real time environment. |
| [21] | SVM | 93.50% | Well defined feature extraction algorithm is required to enhance accuracy. |
| [27] | SVM | 94% | An NN-based classification approach is needed. |
| [30] | SVM | 97.5% | Reliable and low complexity based feature extraction method is required. |
| [31] | BPNN | 90% | An efficient ML/DL feature extraction algorithm is needed. |
| [37] | Transductive SVM | 95% | ML/DL feature extraction is required. |
| [14] | kNN | 97.5% | DWT requires huge capacity and is computationally more expensive. |
| [17] | DLNN, SVM-Adaboost | 93% | ML/DL segmentation is needed to enhance system performance. |
| [18] | SVM | 90.32 | The segmentation algorithm is undefined and to boost up system performance NN based classification is required. |
| [22] | GA + SVM with RBF | 88% | An efficient and reliable segmentation algorithm is required. |
| [24] | SVM | 92.10% | ML/DL segmentation and NN-basedclassification are needed. |
| [25] | BPNN | 90.45 | A ML/DL classification algorithm is needed. |
| [26] | BPNN | 75.00% | The segmentation method is not properly maintained. |
| [34] | Quadratic Kernel SVM | 83% | Few images are produced the same features which deteriorate the system performance adversely. |
| [35] | DT, Naive Bayes | 98.8% | It is not adequate in larger datasets. |
| [38] | SVM | 96% | ML/DL classification is not defined. |

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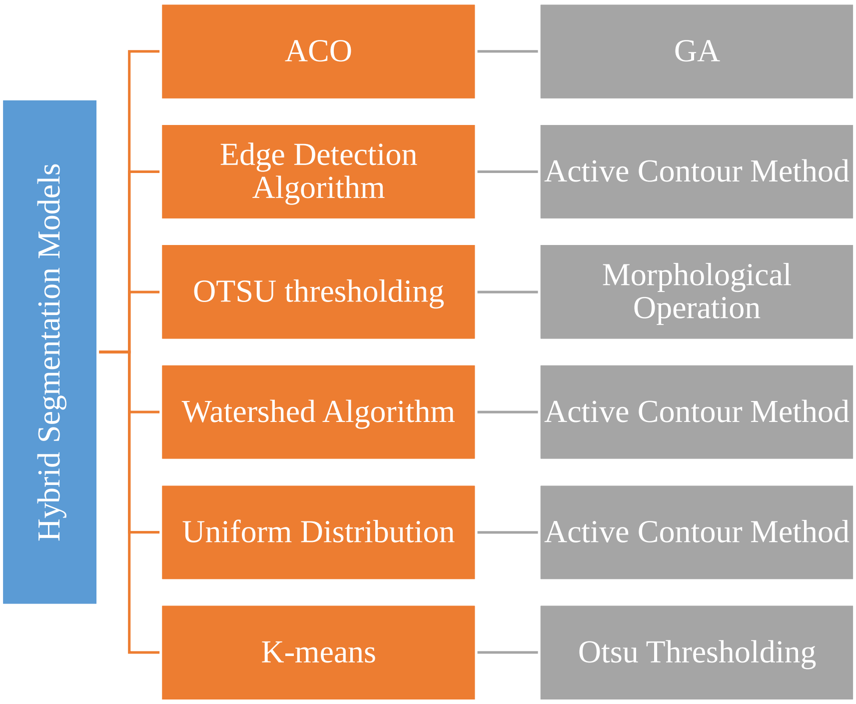


**Fig.4**. ML/DL segmentation methods.

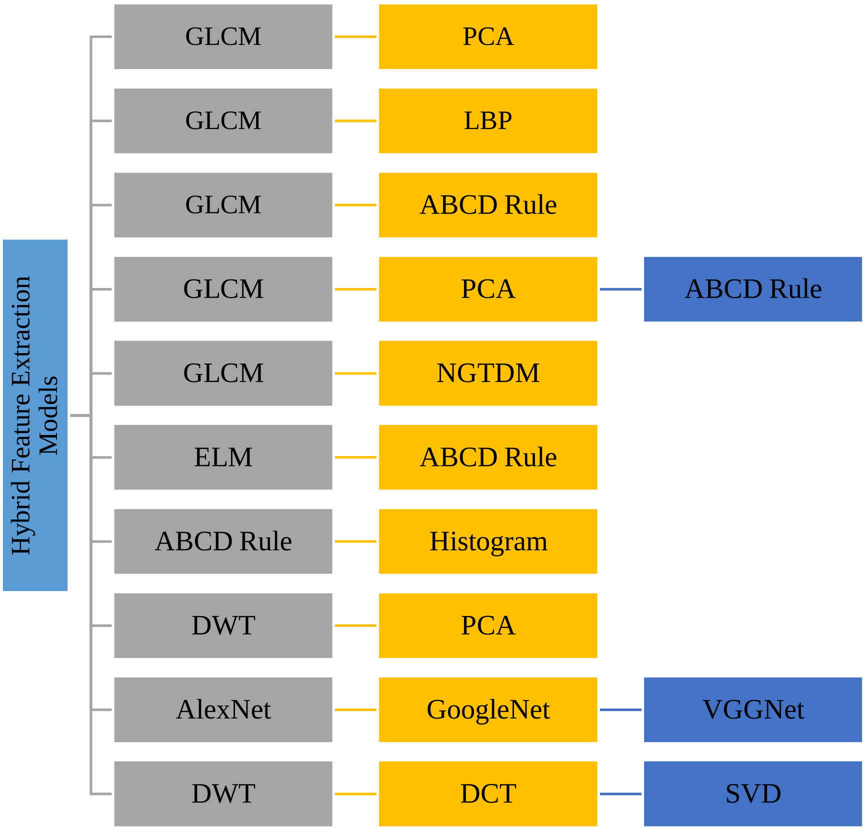


**Fig.5**. ML/DL feature extraction methods.

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Table 1 allows us to shows that the DWT-PCA is more resilient than other methods of extraction of ML/DL features. DWT wavelets have isolated the segmented regions in an image into four components that efficiently extract features with a PCA technique, reducing unnecessary characteristics and increasing the accuracy of classification. We infer, therefore, that these approaches are quite efficient at extracting characteristics. By employing the ML/DL feature extraction approach, the classification accuracy is obtained at a maximum of 98.8%.

For skin-disease classification, there are many ML/DL techniques that use recorded images. The graphic showing the key extraction methods of ML/DL is presented in Fig.6. Table 2 explains the current state-of-the-art ML/DL classification algorithms. This table describes data sets, segmentation, extraction methods and their characteristics, the method of classification, benefits and disadvantages, and the accuracy of the system for detecting skin diseases.

Table 2. ML/DL methodologies of classification.

| Techniques | Classification | Accuracy | Limitations |
|---|---|---|---|
| [16] | SVM + kNN | 98% | Dataset is not standard and the feature extraction method is not defined. |
| [20] | SVM + KNN + MLP | 97.78% | The segmentation algorithm is not defined. |
| [22] | GA + SVM with Radial Basis Function (RBF) | 88% | The segmentation method is not working properly which decreases system accuracy. |
| [23] | Multi-level CNN + BVLC Alexnet model | 70% | Poor efficiency of the system with a lower recall and precision rate.<br>The segmentation and feature extraction method is not defined. |
| [29] | GA + BPNN | - | Efficient segmentation is absent and system accuracy is also undefined. |
| [36] | Deep convolution neural network + ECOC (Error-correcting output codes) linear SVM | 86.21% | Poor system performance due to proper segmentation approach is undefined. |

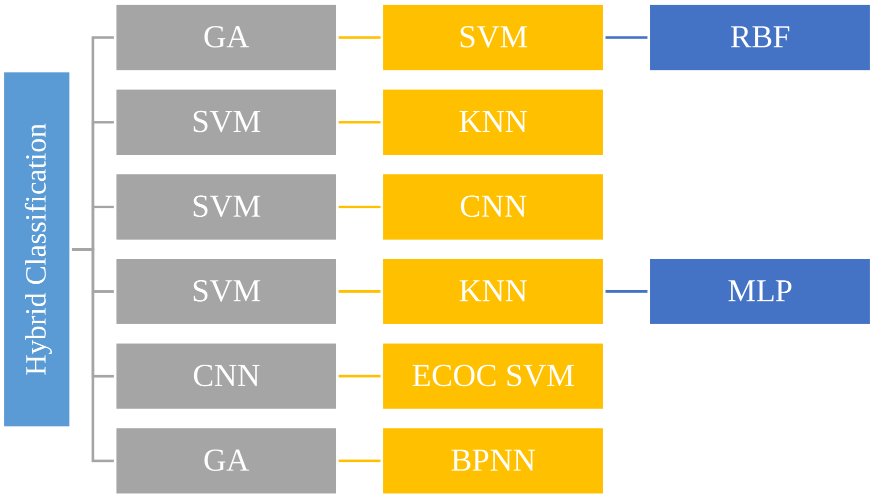


Fig.6. Several ML/DL classification methods.

In Table 2 above, we can say that the kNN SVM method is considered efficient than the conventional ML/DL methods since it ensures a very precise ML/DL classification approach. The maximum precision of the effective ML/DL skin disease categorization approach is around 98%.

**Challenges of ML/DL Skin Disease Detection Systems**

The design of a detection models consists of incurring various challenges. One prominent challenge is the availability of datasets for segmentation algorithms are insufficient. If the system is not segmented well, only a section of the skin injury image that is manually cut does not create good features. If the characteristics are not adequately removed, the particular skin diseases are not categorised properly by the classification system for ML/DL. When the test photos are not adequately preprocessed and segmented, the automated mobile detection system for skin conditions is threatened. Input photos have to utilise a denomination approach together with a good segmentation strategy to overcome this 80difficulty. The availability of optimised segmentation, extraction of features and classification techniques is a serious challenge to a successful detection system.

## 3. CONCLUSIONS

Today, many skin conditions seriously affect the vast population. Consequently, the identification of skin diseases plays a key role in precisely diagnosing these diseases at the first stage. In this research, many major state-of-the-art ML/DL methods have been examined for the precise segmentation, extraction, and categorization of skin disorders. The study summaries that the segmentation based on distribution combined with an active contour technique is robust, with a system precision maximum of around 97%. DWT also performs the PCA approach with a precision of around 98% than other feature extraction models. Moreover, the SVM-kNN is robust with a precision of nearly 98% compared to other approaches. In order to meet design criteria, ML/DL of various deep learning algorithms is crucial for identification of skin diseases.

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