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Survey on Skin Lesion Analysis towards Melanoma Detection

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***Abstract*—** Malignant melanoma is the deadliest form of skin cancer. Researches are attempting for the early automatic diagnosis of Melanoma, a lethal form of skin cancer, from dermoscopic images. The process includes different stages like pre-processing, lesion segmentation, dermoscopic feature detection within a lesion, feature extraction and disease classification. In this paper, we review the state-of-the-art computer aided diagnosis system for melanoma detection and examine recent practices in different steps of these systems. Statistics and results from the most important and recent implementations are analyzed and reported. We compared the performance of recent works based on different parameters like accuracy, sensitivity, specificity, machine learning techniques, dataset etc. Research challenges regarding the different parts of computer aided skin cancer diagnosis systems are also highlighted in this paper.

***Keywords*—**Skin cancer, Melanoma, Dermoscopy, Preprocessing, Image segmentation, Feature extraction, Classification, Ridgelet, K-Means, GLCM, SVM.

I. INTRODUCTION

Skin cancer is the most common of all human cancers. According to the studies, there are different types of skin cancers like melanoma, basal cell carcinoma (BCC) and squamous cell carcinoma (SCC). Melanoma, also known as malignant melanoma is a condition where the production of melanin is significantly reduced because of the dysfunctionality of melanocyte cells. Figure 1 shows the different skin cancers spreading in skin layers. Melanoma is the deadliest form of skin cancer and it look like moles on the skin. When diagnosed early, melanoma is easily cured by simple outpatient surgical excision [1][4].

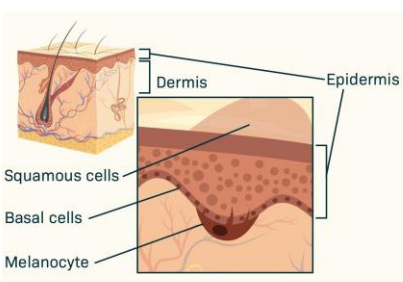

Figure 1: Different Skin cancers spreading in skin layers
[https://skincancer.net/types-signs/metastatic-melanoma-diagnosis-stages/]

We can keep an eye on the difference between normal moles and melanoma. The following characteristics are used by dermatologists to classify melanoma. It is known as **ABCDE Rule** [2].

1. Asymmetry (A) : One half of the mole does not match with the other half.
2. Border irregularity (B) : The edges of the mole are ragged or notched.
3. Color (C) : The color of the mole is not the same all over. There may be shades of tan-brown or black and sometimes patches of red, blue or white.
4. Diameter (D) : The mole is usually wider than about 1/4 inch.
5. Evolution (E) : The history of change in the lesion.

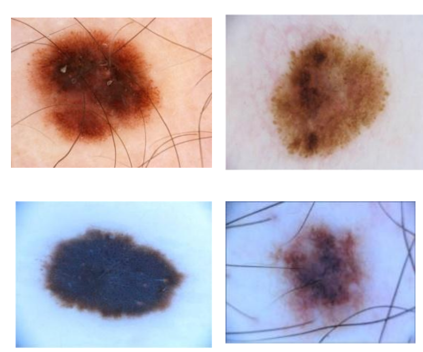

Figure 2 : Sample Skin Lesion Dermoscopy Images Taken From ISIC Archive Dataset [3]

Dermoscopic images of the infected region is analysed by dermatologist for diagnosing skin cancer. The images can be classified as either benign or malignant based on the type of melanoma. Automated image analysis tools can be useful in early detection of Melanoma, since even without consulting the doctor a preliminary suggestion about the seriousness of the illness can be given to the patient by the tool and treatment can be started in an early stage after consulting the doctor. Developing such automated melanoma detection systems will save both time and money for the patients and can be useful for the doctor for faster diagnosis.

In this paper we are conducting a study on the existing work that has been done for automating the various stages of melanoma detection from dermoscopic images. Rest of the paper is organized as follows, In Section II the steps in skin lesion analysis is discussed, Section III contain the related works, The challenges involved in the research is described in Section IV, section V contains the details of the available datasets and Section VI concludes research work with future directions.

II. STEPS IN SKIN LESION ANALYSIS

The image analysis tools enable the automated diagnosis of melanoma from dermoscopic images. Figure 3 shows the steps involved in skin lesion image analysis. It is composed of 3 parts [1] : Lesion Segmentation, Detection and Localization of Visual Dermoscopic Features/Patterns and Disease Classification. Dermoscopy is an imaging technique that eliminates the surface reflection of skin. Prior research has shown that when used by expert dermatologists, dermoscopy provides improved diagnostic accuracy, in comparison to standard photography [5].

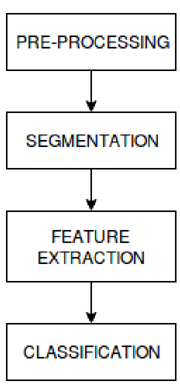

Figure 3 : Steps Involved in Skin Lesion Analysis.

The first stage of skin lesion analysis is image acquisition and this stage is essential for the rest of the system. It is achieved through the dataset of annotated lesion images or by capturing the images using a high pixel mobile phone or high quality camera. We can classify the dermoscopy images into two classes - Benign and Malignant based on the type of melanoma. Malignant melanoma has been proved to be a deadly skin cancer that is more prevalent to people between the age of 15 years and above. Malignant melanoma lesions are asymmetrical and have irregular borders with notched edges. Like that, Atypical moles are unusual-looking benign (non-cancerous) moles, also known as **dysplastic nevi.** Atypical moles may resemble melanoma, and people who have them are at increased risk of developing melanoma in a mole or elsewhere on the body. Figure 4 shows lesion classification for the benign and malignant (melanoma) skin lesion images taken from the ISIC dataset.

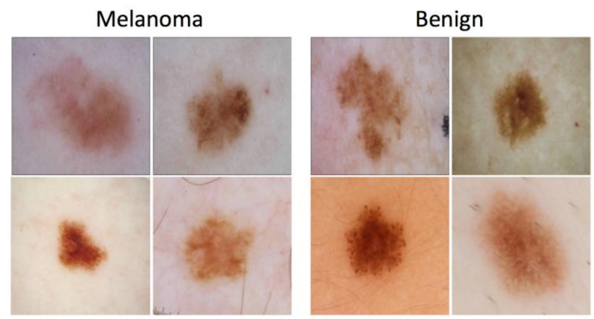

Figure 4 : Skin Lesion Classification [1][3]

The performance of the system is usually evaluated using the metrics accuracy, sensitivity, specificity, sensibility, precision, Dice coefficient, Jaccard index etc [1]. Figure 5 shows the melanoma statistics from the year 1975 to 2020. The graph shows that the rate of melanoma is gradually increasing.

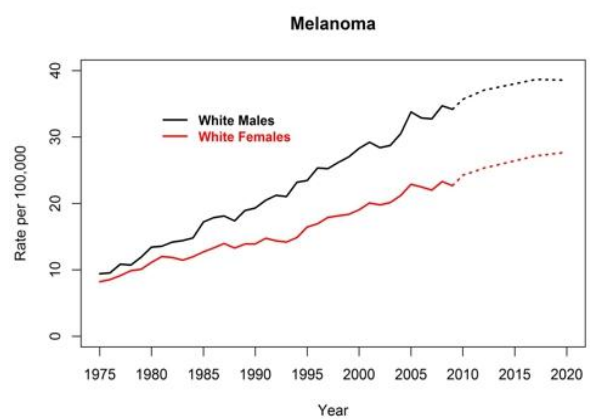

Figure 5 : Skin Cancer Statistics

[https://www.cdc.gov/cancer/dcpc/research/articles/cancer2020 incidence.htm/]

A. PRE-PROCESSING

The objective of the preprocessing stage can be achieved through image enhancement, back ground correction, hair detection, hair removal and image restoration.

a. Hair Detection and Removal

In dermoscopy images, if hair exists on the skin, it will appear clearly in the dermoscopy images. Consequently, lesions can be partially covered by body hair. Thus, hair can obstructs reliable lesion detection and feature extraction, resulting in unsatisfactory classification results. This section introduces image processing techniques to detect and exclude hairs from the dermoscopy images as an essential preprocessing step. **Image inpainting** is the technique of filling in the missing regions and removing unwanted objects from an image by diffusing the pixel information from the neighbourhood pixels. Figure 6 shows the pre-processing stages of two images.

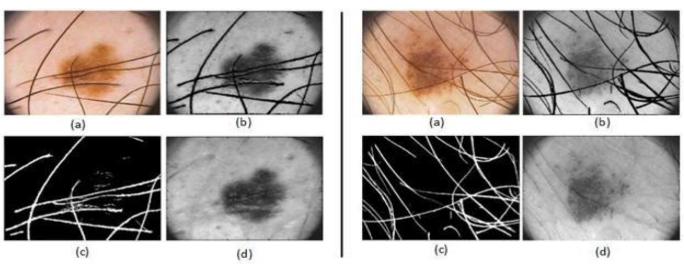

Figure 6 : Hair Detection, Hair Removal and Reconstruction of Two Images [7]

B. Lesion segmentation

This part automates the prediction of lesion boundaries from available dermoscopic images. Pigmented skin lesion segmentation to separate the lesion from the background is an essential process before starting with the feature extraction in order to classify the two different types of lesions (i.e. benign and malignant) [38][51]. Figure 7 shows the skin lesion image and its corresponding mask taken from ISIC Archive dataset and the segmented output obtained by combining the image and the mask.

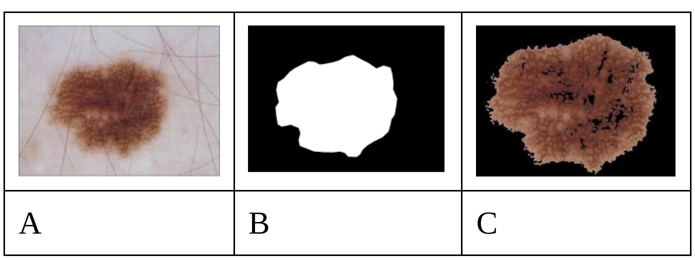

Figure 7: (a) Lesion [3] (b) Mask [3] (c) Segmented Lesion

C. Lesion Dermoscopic Feature Extraction

This part processes the automated extraction of dermoscopic features, including both localization and classification from the segmented lesion images [53]. The skin lesion classification accuracy was improved when the methods of feature extraction were extended and concatenated with the high level features. Feature extraction focuses on mainly three types of features: Texture, Shape and/or ABCDE dermoscopic features. The GLCM (Gray Level Co-occurrence Matrix) texture based second order statistical features like contrast, correlation, energy, entropy and homogeneity and LBP (Local Binary Patterns) features are mainly used for feature extraction from skin lesions.

D. Lesion classification

In the classification stage, by using the extracted features from images the segmented region is classified as either benign or malignant. Prediction scores were normalized into confidence intervals from 0.0 (benign) to 1.0 (malignant) [1][2]. Figure 8 shows all the stages of lesion classification from pre-processing to class label.

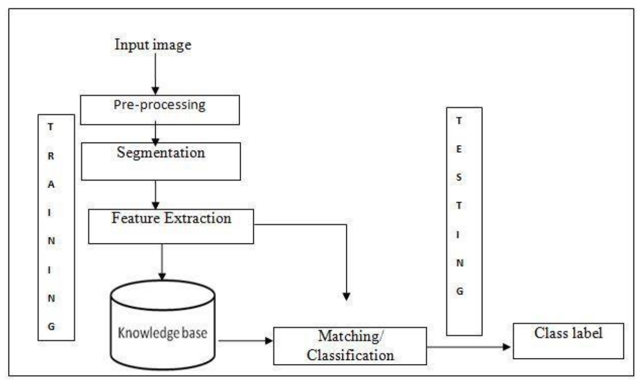

Figure 8 : Lesion Classification [55]

III. Related Work

The IEEE international symposium on biomedical imaging is a scientific conference that addresses various challenges every year in the area of biomedical imaging. David Gutman et al. [1] presented a challenge in (ISBI) 2016 hosted by the International Skin Imaging Collaboration (ISIC) aiming at getting support for research and development in Melanoma detection. After, Noel C. F. Codell et al. [44] presented a challenge in (ISBI) 2017 hosted by ISIC consisted of 3 tasks: lesion segmentation, dermoscopic feature detection with feature extraction and disease classification. Lesion segmentation training data included the original image, paired with the expert manual tracing of the lesion boundaries in the form of a binary mask. 900 images and associated ground truth data were supplied for training. Approximately 30.3% of the dataset was malignant (273 images in the training set). For evaluating the performance of the Segmentation task mainly the metrics calculation of pixel-level accuracy, pixel-level sensitivity, pixel-level specificity, Dice coefficient and Jaccard index were used as efficiency measures.

For assessing the performance of Classification task the metrics of accuracy, sensitivity and specificity were measured at the whole image level. Also the area under the receiver operating characteristic (ROC) curve (AUC) is measured. Finally, the metric of average precision, evaluated between sensitivity of 0-100%, which is a common measure of performance in the computer vision community.

Nurulhuda Firdaus MohdAzmi et al. [2] presented analysis of automated segmentation called the ABCD rules (Asymmetry, Border irregularity, Color variegation, Diameter) in image segmentation. The authors proved that the rule successfully classify the images with high value of total dermatoscopy score (TDS). The experiment was carried on malignant tumor and benign skin lesion images.

Brian D Alessandro et al. [4] presented an automatic segmentation tool for ELM (epi-illumination) and TLM (transillumination) images and interaction with adaptive learning. The authors used a combination of K-means clustering, wavelet analysis and morphological operations to segment the lesion and blood volume and presented the user with six segmentation suggestions for both ELM and TLM images. Also presented a support vector machine (SVM) classifier using the results from the interactive segmentation method along with ratio, color, texture and shape features to characterize skin lesions into three degrees of dysplasia on a set of 81 pathologically validated lesions with promising accuracy. The classification was repeated 10 times to find an average test accuracy of 81.0% and average training accuracy of 90.4%.

Thanh-Toan Do et al. [6] proposed a mobile imaging system that using smartphone-captured images for early diagnosis of melanoma. The images taken under loosely-controlled conditions introduced new challenges for melanoma detection, while subject to computation and memory constraints. To address these challenges, the authors proposed to localize the skin lesion by combining Otsu's method and Minimum Spanning Tree (MST) method to get better segmentation results. They proposed new features to capture color variation and border irregularity. They also proposed a new feature selection criterion to select a small set of good features used in the final lightweight system. They examined 80 features belonging to four categories (color, border, asymmetry and texture) to describe the lesion. Feature selection procedure used Normalize Mutual Information Feature Selection (NMIFS) to select and extract features. To overcome the draw-back of MI (Mutual Information) based criterion, the authors proposed "Average Neighborhood Margin (ANM) maximization". The database contains 81 color images provided by National Skin Center, Singapore. Number of cancerous and non-cancerous images are 29 and 52 respectively. This criterion achieved a high accuracy of 96.67% for cancer samples.

A technical survey conducted by O.Abuzaghleh et al. [7] proposed two major components. The first component is a real-time alert to help users to prevent skin burn caused by sunlight and a novel equation to compute the time for skin to burn. The second component is an automated image analysis module, which contains image acquisition, hair detection and exclusion, lesion segmentation, feature extraction and classification. The proposed system used PH2 dermoscopy image database from Pedro Hispano Hospital. The database contains 200 dermoscopy images of lesions, including benign, atypical and melanoma cases. The experimental results showed that the proposed system is efficient, achieving classification of the benign, atypical, and melanoma images with accuracy of 96.3%, 95.7% and 97.5% respectively.

Maria João M. Vasconcelos et al. [8] presented the methodology using supervised classification to independently assess the Asymmetry, Border, Color and Dermoscopic Structures score (ABCD rule) and the corresponding total dermatoscopy score of a skin lesion. A dermoscopic image dataset was used to test the proposed approach. Accuracy rates of 74.0%, 78.3% and 53.5% were achieved for the estimation of the ABCD score of the asymmetry, border and color criterion as well as accuracy rates for the presence of the five differential structures of 72.4%, 68.5%, 74.0%, 74.0% and 85.8% for dots, globules, streaks homogeneous areas and pigment network. Also sensitivity and specificity rates of 93.3% and 69.1% were achieved for the classification of the dermoscopic images as melanoma or non-melanoma.

Uzma Jamil et al. [10] presented detailed information regarding feature extraction and selection techniques for dermoscopic images. Feature extraction can be divided into texture, shape and color features. Texture feature extraction is an efficient method to find the structure, orientation and roughness of the regions in an image. Texture extraction methods include statistical, structural, model and filtering-based methods. Shape features includes shape asymmetry and fourier descriptors. Here the authors presented the knowledge of high level techniques and algorithms for pre-processing, segmentation, feature extraction and selection which needs more effort for making correct diagnosis of melanoma.

J. Premaladha et al. [11] proposed a Computer Aided Diagnosis (CAD) system which equips efficient algorithms to classify and predict melanoma. Enhancement of the images are done using Contrast Limited Adaptive Histogram Equalization technique (CLAHE) and median filtering. A new segmentation algorithm called Normalized Otsu's Segmentation (NOS) is implemented to segment the affected skin lesion from the normal skin. 15 features are derived and extracted from the segmented images and fed into the proposed classification techniques like deep learning based neural networks and Hybrid Adaboost-Support Vector Machine (SVM) algorithms. The proposed system is tested and validated with nearly 992 images (malignant & benign images) and it provides a high classification accuracy of 93%.

Teck Yan Tan et al. [12] employed pre-processing such as dull razors and median filters to remove hair and other noises. Segmentation is done by using pixel limitation technique to separate lesions from image background. Support Vector Machine (SVM) classifier performs benign and malignant lesion recognition. The method was evaluated using Dermofit dermoscopy image database with 1300 images and achieved an average accuracy of 92% and 84% for benign and malignant skin lesion classification. Genetic Algorithm (GA) is also applied to identify the most discriminative feature subsets to improve classification accuracy.

Lequan Yu et al. [15], M.H. Jafari et al. [43], Yading Yuan et al. [50] and Mohamed Attia et al. [51] proposed method for accurate extraction of lesion region and melanoma recognition that is based on deep learning approaches. Convolutional neural networks(CNN) are widely used for melanoma detection. The concept of CNN is inspired by human visual cortex.

Qurrat Yu Ain al. [16] introduced GP (Genetic programming) that has been utilized as a classifier for skin cancer detection and also analysed GP as a feature selection method. GP has given domain specific features and Local Binary Pattern (LBP) features extracted from the dermoscopic images. The domain features have high mutual information values as compared to LBP features. The GP method describes the function set, terminal set and fitness function. For combining the knowledge of dermatology and computer vision techniques, GP has been given domain specific features provided by the dermatologists. The highest accuracy achieved is 97.92%. The dataset used is PH2. SVM using GP selected features has achieved 0.0 standard deviation, which is the best result.

Sabrina Conoci et al. [17] proposed an effective pipeline which is based on an analytic innovative hand-crafted image features combined with a machine learning system for skin lesion analysis with related oncological outcomes. The database used is PH2 which consists of 200 dermoscopy images. The time performance of the proposed method is short and it is able to analyze a single nevus in about 2.5 sec, so this pipeline can be easily ported on embedded platform based on STM32. The authors proposed a system based on 32F429IDISCOVERY STM32 board for grabbing images from external wireless 8-bit camera module or by using wired camera module. The acquired images are stored in the SDRAM of the STM32 board in which the proposed method is running as firmware with neural weights stored in a specific partition of embedded FLASH memory placed in the embedded board.

The techniques and methods proposed for skin lesion analysis in previous works and the performance measures obtained are summarized in Table 1.

Table 1. *Comparison of Skin Lesion Analysis System*

Ref.	Segmentation	Feature	Classifier	No.of images	Database	Result
[4]	K-means, Wavelet	Ratio, color, texture, shape	SVM	81	Dermoscopy dataset	Test AC=81.0% Train AC=90.4%
[6]	Otsu's method, MST	Color, border, asymme-try, texture	SVM	81	National Skin Center, Singapore	AC=96.67 %
[7]	Gaussian, thresh-old	Shape,orientation, mar-gin,intensity	SVM	200	PH2	AC=96.3%(Benign), 97.5%(Melanoma)
[8]	ABCD Rule	Asymmetry, border,color	SVM, Bayes, Ib-3	200	PH2, Mobile dataset	SE=93.3%, SP=69.1%
[11]	NOS	15 features	SVM & ANN	992	N/A	AC=93%
[12]	Pixel limitation	Genetic Algorithm	SVM	1300	Dermofit	AC=92%(B), 84%(M)
[16]	N/A	LBP, Specific features	GP	200	PH2	AC=97.92 %

AC=Accuracy, SE=Sensitivity, SP=Specificity

a. Pre-processing

The survey found different approaches for image denoising like wavelet transform [21][27], curvelet transform [20][28][34], ridgelet transform [22][31] etc. The ridgelet transform is an approach for image denoising where the signature is extracted from the ***Radon*** domain and entropy coded after a ID wavelet transform and that is computationally less intensive than curvelets, but with similar denoising performance.

Image Inpainting can be performed using methods like an Adaptive Bilateral Filter (ABF) [19], wavelet based total variation inpainting [21], particle filters [23], Directional Median Filters (DMF) [26] etc. All these introduced novel algorithms for digital inpainting still images that attempts to replicate the basic techniques used by professional restorators. The wavelet based inpainting manipulates pixel domain to control and restore wavelet coefficients in the wavelet domain.

Sookpotharom Supot [25] proposed a method consists of image pre-processing and image segmentation. The first step is implemented to remove noise and undesired structures using median filtering and the fuzzy C-means (FCM) thresholding technique is used to segment and localize the lesion. The proposed method is tested on some set of dermoscopy images taken from the Interactive Atlas of Dermoscopy and gives more reliability and visually precise boundary tracing. The border detection results are visually examined by an expert dermatologist and are found to be highly accurate.

Sandeep Palakkal et al. [28] proposed a strategy to combine the variance stabilizing transform (VST), used for Poisson image denoising, with the fast discrete curvelet transform (FDCT). The VST transforms the Poisson image to approximately Gaussian distributed and the subsequent denoising can be performed in the Gaussian domain. The proposed FDCT method yields performance comparable with the first generation curvelets. The results showed that the VST combined with the FDCT is a promising candidate for Poisson denoising.

Mohammad Taghi Bahreyni Toossi et al. [29] presented a scheme that automatically detects and removes hairs from dermoscopy images. Firstly, light and dark hairs and ruler marking are segmented through adaptive canny edge detector and refinement by morphological operators. The hairs are repaired based on multi-resolution coherence transport inpainting. The proposed method was tested on a set of 50 dermoscopy RGB color images with dimensions ranging from 520X340 pixels to 1600X1200 pixels. The accuracy was performed using TDR (True Detection Rate), FPR (False Positive Rate) and DA (Diagnostic Accuracy) metrics and achieved high DA of 88.3%, TDR = 93.2% and FPR = 4%. The segmentation error is effectively reduced. Also Adam Huang et al.[30] used conventional matched filters to enhance curvilinear structures. The hair intersection patterns, which were known to generate low matched filtering responses were recovered by using region growing algorithms from nearby detected hair segments with linear discriminant analysis (LDA) based on a color similarity criterion. The preliminary results indicated that the proposed method was able to remove more fine hairs and hairs in the shade, and lower false hair detection rate by 58% (from 0.438 to 0.183) at the true detection rate of 0.81. The above two mentioned papers achieved better performance compared to the DullRazor's approach.

Azadeh Noori Hoshyar et al. [32] presented the pre-processing techniques using for skin cancer detection system. It has classified the whole process into two sections of image enhancement and image restoration. In these two processes, all the steps with its beneficial techniques to enhance the skin cancer images and also the useful filters to remove the noise and smoothing the images have been explained.

Sumit Kumar et al. [34] presented image denoising based on curvelet transform, provided a better means for removal of noises from images without losing or affecting the useful information presented in the image. It is based on the implementation of a modified window neighborhood processing that adapt itself based on the variance of neighboring pixels. The sub-band decomposition of curvelet transform is carried out by using wavelet transform. The performance evaluation parameters are MSE (Mean Square Error) and PSNR (Peak Signal-to-Noise Ratio).

Tomáš Majtner et al. [35] proposed three artefacts removal step namely the kernel-based edge detection, the second order derivatives of Gaussian, and the mathematical morphology bottom-hat filtering. It is concluded that the EM (Expectation-Maximization algorithm) method outperforms Chan-Vese segmentation and gains more from the artefacts removal in terms of increasing the segmentation accuracy. Also introduced a novel artefacts removal method in combination with the EM algorithm outperforms all the tested methods. All of these methods were tested on 103 images from ISIC Archive containing thin artefacts.

The techniques proposed along with the results obtained for pre-processing stage (hair detection on lesions, inpainting, noise removal, enhancement etc.) in related works are summarized in Table 2.

Table 2. *Comparison of Pre-Processing Step*

Ref.	**Colour Space**	**Hair Detection Tech-nique**	**Hair Repair Technique**	**No of Images**	**Results**
[20][21][22][27][28][31][34]	RGB & Gray scale	Wavelet, Ridgelet & Curvelet Transform	Wavelet Based	N/A	Highly denoised
[29]	RGB	Adaptive Canny Edge Detector	Multi Resolution Coherence Trans-Port	50	DA=88.3% TDR=93.2% FPR=4%
[35]	RGB	EM algorithm	Median Filters	103	High Segmenta-tion Accuracy

TDR=True Detection Rate, FPR=False Positive Rate, DA=Diagnostic Accuracy

b. Lesion Segmentation

Different methods were proposed for lesion segmentation by various researchers. Previous works used color segmentation [36][37][45], K-means algorithm [38][41], thresholding [40], deep learning [43][48][49][50[51] and ABCD rule [2] for segmenting lesion from background.

Ph.Schmid and S.Fischer [36] presented a colour segmentation scheme based on two-dimensional histogram analysis and the fuzzy C-means clustering technique. The method is applied to digitised epiluminescence microscopy images of pigmented skin lesions and is used for the extraction of all homogeneously coloured regions.

Heng-Da Cheng et al. [37] also proposed methods for color image segmentation techniques. It is based on monochrome segmentation approaches operating in different color spaces. The authors discussed the major segmentation approaches for segmenting monochrome images : histogram thresholding, characteristic feature clustering, edge detection, region-based methods, fuzzy techniques, neural networks etc. Also the different color features like linear transformations, non-linear transformations and hybrid colorspace are represented. The results are compared against groundtruth using Jaccard index or Dice's coefficient. Also Chiranjeev Sagar et al. [45] proposed methods for color channel based segmentation of skin lesion. The different color channel is derived by performing logical AND and OR operations on two or more individual color channels. For R, G, B, L (Lab color space), color channels RoGoB and L *RoGoB are derived by logical operations. The color space L *RoGoB shows best approximation of segmented lesion. The algorithm has been evaluated using 175 images from different online public databases and achieved 94% accuracy.

Wan-Ting Lin et al. [38] segmented objects using K-means algorithm for extracting texture features. The algorithm transforms color images into gray images. The advantages of the case where the edges of even textured objects are not prominent due to fast movement, the background color and the object color are similar and difficult to distinguish, and the edges of objects are blurry due to shadows. Also Nameirakpam Dhanachandra et al.[41] proposed unsupervised K-means clustering and subtractive clustering for image segmentation.

Xiang Li et.al. [39] conducted an analysis of manual segmentations to have a better understanding of the pattern. They proposed a level-set based approach that solves the ground truth estimation in a probabilistic formulation. Experiments on both synthetic and real lesion data reveal that LSMLP (Maximize the a posteriori probability based method incorporating the segmentation pattern information) outperforms all the other methods that do not consider the prior information, followed by LSML (Maximize the a posteriori (MAP) probability based method) and STAPLE, based on both synthetic and real lesion data.

R.Yogamangalam et al. [40] classified segmentation in different ways such as region based, edge based, threshold, feature based clustering and model based. The authors claimed that model based Markov Random Field (MRF) is the strongest method of noise cancellation in images and thresholding is the simplest and computationally fast technique for segmentation.

Fahimeh Sadat Saleh et al. [42] proposed automatic multiple regions segmentation of dermoscopy images. In the first stage, the image is segmented to regions using *Mean Shift algorithm.* In the second stage, a graph-based representation is used to demonstrate the structure of the extracted regions and their relationships. After clustering process is applied, considering the neighborhood system and analyzing the color and texture distance between regions. Experiments showed that challenging features of skin lesions are handled as might be expected when compared to five state of the art methods. The proposed segmentation method was tested on PH2 database. The disadvantages of this method is to achieve better accuracy of the segmentation algorithm, at least one of the following conditions were excluded (a) Lesions which has not fully considered in the frame (b) Lesions with the presence of excessive hair. The method has achieved the specificity of 92.45 and the sensitivity of 90.34, also the method achieved the minimum error and computation time.

M.H. Jafari et al. [43] proposed methods for skin lesion segmentation in medical images using deep learning technique. After being preprocessed the input image is applied to a deep convolutional neural network (CNN). The CNN combines local and global contextual information and outputs a label for each pixel, producing a segmentation mask that shows the lesion region. The method is evaluated using Dermquest database. Experimental results showed that the proposed method can reach a very high accuracy of 98.5% and sensitivity of 95.0% that outperforms other state-of-the-art methods.

Dao nam Anh Pre [46] proposed a method that uses advantage of specific priori knowledge of lesion region detected by moment of patch. The basis of lesion region determination is color values and surrounding pixels area moment of difference of two image patches predicts homologous changes as evaluation of similarity of the patches. The authors exercise the area moment to compose a database of skin lesion templates and a lesion region detection scheme that estimates the image patches resemblance based on moment of patches so that lesion region can be discovered. The sensitivity, specificity and accuracy are used as performance metrics. The second order moment version of the RSMP (Detection of Lesion Region in Skin Images by Moment of Patch) algorithm is the optimum solution as it reserves reasonable time and high rates of quality metrics. It didn't involve tasks including de-noising, hair removal and light condition balancing.

Neda Zamani Tajeddin et al. [47] proposed a novel method for skin lesion segmentation that could be applied to a variety of images with different properties and deficiencies is proposed. After a multi-step preprocessing phase (hair removal, illumination correction etc.), a robust histogram-based Otsu's thresholding technique is used to obtain an initial mask of the lesion. The initial mask is used to sample the lesion's color and drive a contour propagation algorithm. A color probability map of the image is calculated based on sampled pixels and Bayesian classification. Using this probability map and image gradient, a novel dual-component speed function is constructed to improve the performance of propagation model. The dataset used is ISIC dataset. Dice and Jaccard coefficient values are 0.89 and 0.79 respectively.

Behzad Bozorgtabar et al. [48] presented two fully convolutional networks with several side outputs to take advantage of discriminative capability of features learned at intermediate layers with varying resolutions and scales for the lesion segmentation. Also integrate fine and coarse prediction scores of the side-layers which allows the framework to not only output accurate probability map for the lesion, but also extract fine lesion boundary details such as the fuzzy border, which further improves the lesion segmentation. The dataset used is ISIC dataset and achieved Jaccard index of 82.90%.

Rashika Mishra et al. [49] presented the method based on deep convolutional neural networks (CNN) for extraction of lesion regions in dermoscopic images. The authors defined a simple and efficient architecture for the CNN and compared the results with traditional Otsu's thresholding method and found the CNN to give better results. Experimental results showed that the proposed method gives Jaccard index of 0.842 and has a very high accuracy of 92.8%. Also Yading Yuan et al. [50] proposed a 19-layer deep convolutional neural networks (CNNs) that is trained end to end and designed a novel loss function which is based on Jaccard distance to eliminate the need of sample re-weighting, a typical procedure when using cross entropy as the loss function for image segmentation due to the strong imbalance between the number of foreground and background pixels. The method achieved promising segmentation accuracy and evaluated using two publically available databases ISBI 2016 challenge dataset and PH2 database. The image size ranges from 542X718 to 2848X4288. The image size in PH2 is fixed as 560X768. Also Mohamed Attia et al. [51] proposed a hybrid method that utilizes two popular deep learning methods : convolutional and recurrent neural networks. The images were obtained from ISBI 2016 challenge dataset. They achieved segmentation average accuracy of 0.98 and Jaccard index of 0.93. It has the highest median and mean accuracy while maintaining the lowest variance. Recurrent layers were introduced in the proposed solution to derive the spatial neighborhood relations between patches before the decoding part of the deep architecture and it does not require any preprocessing of the input or dimension reduction by gray scale conversion. So it made the segmentation network more robust and consistent.

The different existing techniques proposed for lesion segmentation by researchers are summarized in Table 3.

Table 3. *Comparison of Segmentation*

Ref.	Colour Space	Technique	Feature	Database	Result
[42]	Gray Scale	Multiple region segmentation	Color, Texture	PH2	SP=92.45% SE=90.34%
[43]	Gray Scale	CNN	Texture	Dermquest	AC=98.5% SE=95%
[45]	RoGoB, L*RoGoB	Color Segmentation	Color	Public	AC=94%
[47]	Gray Scale	CNN	Texture	ISIC	DC=0.89 JI=0.79
[48]	RGB	Deep learning	N/A	ISIC Archive	JI=82.9%
[49]	RGB	CNN	N/A	ISIC Archive	JI=0.842 AC=92.8%
[51]	RGB	Deep learning	N/A	ISIC Archive	JI=0.93 AC=0.98

AC=Accuracy, SE=Sensitivity, SP=Specificity, JI=Jaccard index, DC=Dice coefficient

C. Lesion Dermoscopic Feature Extraction

In previous works, the different types of features are extracted from lesion images by using different methods for lesion classification. The papers [53][54] used color and texture features, [56] used color and shape features, [57] used border irregularity feature, [58][59] used texture feature. The GLCM (Gray-Level Co-Occurrence Matrix) based features are mainly used for feature extraction.

Miroslav BENCO et al. [53] presented feature extraction methods for *color*, *texture* features using GLCM and compared gray-level and color features extraction for GLCM and GF (Gabor filters) techniques. A new method called CGLCM (Color GLCM) has been developed. The advantages of the approach are the best precision score for GLCM based methods achieved in the RGB color space, and for GF based method in the HSV color space. The smaller length of feature vector makes the new method better than GF methods.

Giuseppe Di Leo et al. [54] dealt with ELM (Epiluminescence microscopy) image processing for automatic analysis of pigmented skin lesions. The “ELM 7 point checklist” defines a set of seven features, based on colour and texture parameters, which describe the malignancy of a lesion. The image processing algorithms and classification techniques involved in the automatic detection of the occurrence of two criteria (Blue-whitish Veil and Regression structures) are introduced. The main stages are image segmentation, lesion segmentation and region classification. The approach was tested using the CD-ROM Interactive Atlas of Dermoscopy image set. The sensibility and specificity values are 0.87 and 0.85 respectively.

Omar Abuzaghleh et al. [56] introduced an automated skin lesion segmentation and analysis for early detection and prevention based on *color and shape* geometry features set. Here PH2 dermoscopy image database was used. The framework compared two-level classifier and one level classifier. The two-level classifier achieved accuracy of 90.6%, 91.3% and 97.7% for normal, atypical and melanoma images.

Sinan Kockara et al. [57] focused on quantitative assessment of *shape-based irregularity* features of skin lesions in dermoscopy images. Then quantitatively measures irregularity of the extracted border by using eleven different fractal measures. Classification and feature selection analysis showed that malignancy in dermoscopy images can be detected with a high accuracy by using fractal features. Experiments are conducted on 100 dermoscopy images, analyzed with a feature selection algorithm which claimed to detect malignancy with high accuracy by using a single feature, border irregularity. Also among 11 fractal dimension methods, the four fractal features (Cumulative Intersection, Fast (Hybrid), Parallel Lines and Mass Radius (Short)) are optimum subset to achieve the best accuracy. LOO (leave one out) reaches maximum (82%) with four features and 10xCV (10-fold cross validation) achieved maximum 79% in accuracy.

M.Suryapraba et al. [58] proposed wavelet transformation for image improvement, denoising and histogram analysis, also classified the type of approach for skin cancer using Artificial Neural Network (ANN). The extraction of texture features in the detected tumor has been achieved by using Gray Level Co-occurrence Matrix (GLCM). These features are given as the input to the Artificial Neural Network, Co-occurrence Matrix and Back Propagation Network Classifier. It classifies the given data set into cancerous or non-cancerous. Achieved 100% for sensitivity, 95% for specificity, and 97.5% for accuracy.

Seema Kolkur et al. [59] presented *texture based* features derived from GLCM that is used for the detection of skin diseases. Many researchers have used additional features along with texture based features to improve accuracy of classification. Top five features used in all this work are contrast, correlation, energy, entropy and homogeneity. Texture based features are widely used in image analysis for medical diagnosis. The classifiers used are neural networks and SVM. The overall accuracy achieved in related works is around or above 90%.

The summary of the type of features extracted from the segmented lesion images in the previous works are given in Table 4.

Table 4. Comparison of Feature Extraction

Ref.	Colour Space	Features	Type	Database	Results
[53]	RGB	Color, Shape geometry	GLCM	N/A	Best precision score
[54]	RGB	Color, Texture geometry	N/A	CD-ROM Interactive Atlas of Dermoscopy	SB=0.87, SP=0.85
[56]	RGB	Color, Shape geometry	N/A	PH2	AC=90.6%, 91.3%, 97.7% for normal, atypical, melanoma
[57]	RGB	Border Irregularity	SVMRFE	100 dermoscopy images	AC=79% for 10xCV
[58]	Gray Scale	GLCM Features	ANN	N/A	SE=100%, SP=95%, AC=97.5%
[59]	Gray Scale	GLCM	Neural, SVM	N/A	AC=90%

AC=Accuracy,SE=Sensitivity, SP=Specificity, SB=Sensibility

D. Lesion Classification

Different methods were proposed for feature extraction from segmented lesions and the type of classifier used in different papers to classify the lesion inputs are melanoma or non-melanoma. The previous works used wavelet or curvelet decomposition methods [60][62], SVM (Support vector machine) classifier [62][63][64][71], ANN (Artificial neural network) classifier [60][66][67][68][69], both SVM and Neural classifier [65], k-NN (k-nearest neighbors) classifier [74][75] for disease classification.

Md.Khalad Abu Mahmoud et al. [60] proposed two segmentation methods used to identify the normal skin cancer and to extract the useful information from these images that passed to the classifier for training and testing. The features used for classification are the coefficients created by wavelet decompositions and simple wrapper curvelets. Curvelet is suitable for the image that contains oriented texture and cartoon edges. Recognition accuracy of the three layers back-propagation neural network classifier with wavelet is 51.1% and with curvelet is 75.6% in digital images database. It was found that the curvelet method has 14.5% higher accuracy than wavelet in the classification test. The classifier used neural networks to improve the predicted new image. The overall result, based on mixed type of images database, is 55.94% for back-propagation neural network using wavelet and 70.44% for using curvelet.

Maen Takruri et al. [62] proposed an automated non-invasive system for skin cancer (melanoma) detection based on Support Vector Machine (SVM) classification. The features are extracted from the wavelet or the curvelet decomposition of the grayscale skin lesion images and color features obtained from the original color images. The dataset used include both digital images and dermoscopy images for skin lesions that are either benign or malignant. The recognition accuracy obtained by the Support Vector Machine classifier used in this experiment is 87.7% for the wavelet based features and 83.6% for the curvelet based ones. The proposed system also resulted in a sensitivity of 86.4% for the case of wavelet and 76.9% for the case of curvelet. It also resulted in a specificity of 88.1% for the case of wavelet and 85.4% for the case of curvelet. The obtained sensitivity and specificity results are comparable to those obtained by dermatologists.

Diwakar Gautam et al. [63] proposed a method to classify images as malignant and benign classes using Support Vector Machine (SVM) optimized by Sequential Minimal Optimization(SMO). As a part of the preprocessing step, an illumination compensation based segmentation algorithm is deployed. Then an iterative dilation method to remove noise from a lesion. Some prominent features calculated from the segmented image based on asymmetric lesion-behavior, border irregularity, color variations and spanned diameter. Finally, these feature vectors are applied as an input to SVM classifier, which is used to distinguish malignant from benign samples of skin lesions. The dataset is divided into training and testing data to account and validate the system performance.

R.S. Shiyam Sundar et al. [64] proposed methods for the queried images are grouped and matched to classify the type of melanoma. The multi class support vector machine (MCSVM) has simulated for solving the classification problem. The algorithm is based on learning of each stage with training sample. The color and texture features such as gradient, contrast and edges are extracted. And Hiam Alquran et al. [71] also proposed classification using support vector machine.

Muhammad Ali Farooq et al. [65] focused on ALDS (Automatic Lesion Detection System) framework based on probabilistic approach that initially utilizes active contours and watershed merged mask for segmenting out the mole and later SVM and neural classifier are applied for the classification of the segmented mole. This is the extended work of Chang et al. [5]. After segmentation, the features are classified to check melanoma or non-melanoma. The ANN classifier is implemented as second level classifier to witness the results obtained from SVM and also to check the cases where SVM fails to classify. The approach is tested for varying datasets for the effectiveness of the proposed system. The SVM and ANN complement each other and help to provide better classification decisions. The accuracy of neural networks can be further enhanced by increasing the number of samples and the number of features in the training phase.

Wiem Abbes et al. [66] considered several extracted dermatoscopic features for automatic detection of melanoma in order to generate new high level features allowing semantic analysis based on shape characterization, color and texture features. A neural network classifier is used for classification, Experimental results showed good sensitivity of 92.8% and a specificity of 95.4% on a database of 206 skin lesion images.

Adria Romero Lopez et al. [67] presented a deep-learning based approach to classify a skin lesion as malignant or benign. The proposed solution is built around the VGGNet convolutional neural network architecture and used the transfer learning paradigm. Experiment supports ISIC Archive dataset and achieved a sensitivity of 78.66%, specificity of 84.00% and precision of 79.74%, which is significantly higher than the current state-of -the-art on that dataset. The 3 methods followed here are training from scratch, ConvNet as feature extractor and fine-tuning the ConvNet.

Saeid Amouzad Mahdiraji et al. [68] introduced novel boundary features based on the color variation of the skin lesion images. New sets of boundary features were proposed to describe the color variation of boundary lesion images acquired using standard cameras. To get higher performance in melanoma detection, a set of textural and morphological features are associated with proposed features. Multilayer perceptron neural network is used as classifier. Also achieved the highest mean accuracy (87.80%), sensitivity (87.92%), specificity (87.65%) and precision (90.39%) in comparison with the previous works in Dermatology Information System (IS) and DermQuest datasets.

A Rajesh [69] proposed methods for skin lesion classification by using back propagation neural network and ABCD rule.

The classifiers proposed for lesion classification as malignant or benign and accuracy achieved in related works are summarized in Table 5.

Table 5. *Comparison of Classification*

Ref.	Colour Space	Classifier	Type	Features	Database	Results
[62]	RGB	SVM	Wavelet, Curvelet	N/A	N/A	AC=87.7%(W), 83.6%(C) SE=86.4%(W), 76.9%(C) SP=88.1%(W), 85.4%(C)
[66]	RGB	Neural	N/A	Shape, Color, Texture	206 skin lesions	SE=92.8%, SP=95.4%
[67]	Gray Scale	VGGNet Convolutional Neural N/W	Transfer learning	N/A	ISIC Archive	SE=78.66%, SP=84%, PR=79.74%
[68]	RGB	Neural	Multilayer perceptron	Texture, morphological	N/A	AC=87.8%, SE=87.92%, SP=87.65%, PR=90.39%

AC=Accuracy, SE=Sensitivity, SP=Specificity, PR= Precision

Classification Techniques Used in Literature

Figure 9 graphically shown the pie chart for the percentage usage of machine learning classification techniques used by existing systems in literature and the average accuracy obtained for each classification technique.

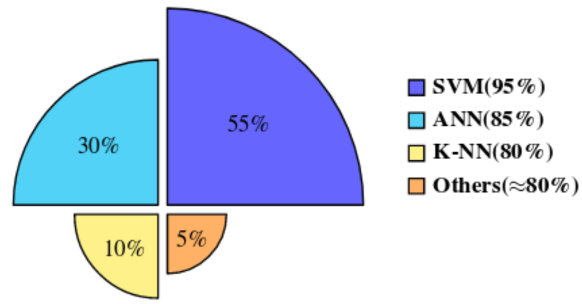

Figure 9 : Image Classification Techniques and Average Accuracy Obtained from Literature

IV. CHALLENGES

Automated melanoma recognition in dermoscopy images is a very challenging task due to the low contrast of skin lesions, the huge intraclass variation of melanomas in terms of color, texture, shape, size and location in the dermoscopy images, the high degree of visual similarity between melanoma and non melanoma lesions, and the existence of many artifacts in the images either natural (hairs, veins) or artificial (air bubbles, ruler marks, color calibration charts, etc.) may blur or occlude the skin lesions and further aggravate the situation [5][8].

V. DATASET AVAILABLE

Some datasets are publically available. The details of the dataset are as follows.

1) ISIC Archive dataset : The International Skin Imaging Collaboration (ISIC) is an international effort to improve melanoma diagnosis. The dataset is publically available. This dataset contains 900 images for the training purpose and 350 images for the testing purpose [3].

2) PH2 : PH2 is publically available dermoscopic image database acquired Dermatology Service of Hospital Pedro Hispano, Matosinhos, Portugal. The PH2 dataset has been developed to facilitate comparative studies on melanoma segmentation and classification. The dataset contains 200 images [http://www.fc.up.pt/addi/ph2%20database.html].

3) DermIS and DermQuest : Melanoma image dataset is also available on DermIS [http://www.dermis.net/dermisroot/en/home/index.htm] and DermQuest [https://www.dermquest.com/] Website. Dataset is freely available to use for educational purpose. DermIS.net is the largest dermatology information service available and DermQuest is an extensive clinical Image Library, containing images shared by the wider dermatology community.

4) Dermofit : The Dermofit Image Library is a collection of 1,300 high quality skin lesion images collected under standardised conditions with internal colour standards. Image set consist of a snapshot of the lesion surrounded by some normal skin and the binary segmentation mask. It is available under an academic licence [http://www.dermofit.org/].

VI. CONCLUSION AND FUTURE SCOPE

The aim of this survey is that we addresses the relevance of developing image analysis tools to enable the automated diagnosis of melanoma from dermoscopic images. Image analysis of skin lesions contains three stages - segmentation, feature extraction and disease classification. The different methods and algorithms were proposed for each stages of lesion analysis in the papers and the performance metrics are also compared using tables. In conclusion, there should be standard procedures and publically available datasets for the new researchers so that together we can fight against this deadliest disease.

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