SUMMARY OF DIFFERENT COMPUTER VISION METHODS FOR DIAGNOSING SKIN CANCER

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Abstract

Skin cancer is caused by many reasons, such as ultraviolet waves in the sunshine. Detection of cancer in the early steps of cancer can help a lot to cure it and prevent it from being bad and makes people suffer from that and pay a lot of time and money to cure it. Melanoma is a deadly skin cancer. Although it has a low percentage of patients worldwide, it is the cause of most skin cancer kills.

To predict this cancer in its early stages, we can use computer vision to achieve a high level of accuracy.
Keywords: computer vision, diagnosing skin cancer, machine learning, deep learning.

1. Introduction

The rate of skin cancer has been rising these years because of different circumstances. Among all of these types, Melanoma is the most dangerous. It accounts for only 4 percent of all skin cancers; it is responsible for 75 percent of all skin cancer deaths.
In the initial stage of detection, Melanoma could save millions instead of treatment procedures for that deadly disease. Compared to other kinds of cancers worldwide, the ratio of Melanoma is rapidly increasing.

We can use computer vision and image processing for the initial detecting stage. For detection, we can measure different parameters in the image of the skin, and by these measurements and machine learning, we can guess whether the image is cancer or not.
These clinical features of skin cancer-related pigmented lesions are known as skin cancer ABCDs.

It has to pass through different steps to detect cancer by measuring different features in the image. The main processing steps are image acquisition of the skin lesion image, segmentation of the skin lesion from the Image Preprocessing, Image Segmentation, Feature Extraction, and Classification.

Image Preprocessing is a step in which we change different aspects of the image, like lighting, to be ready for the process.

Segmentation refers to separating the lesion from the surrounding skin because we do not want any part of regular skin in our image.

In feature extraction, we extract features similar to those visually detected by dermatologists.

In the last step, we classify the image to find if there is any problem or not.

2. Related Work

Because of the importance of skin cancer detection to save the lives of many people, many researchers have been working on it to achieve efficient methods to detect skin cancer with high accuracy. Scientists have invented Many different approaches for different steps of detecting skin cancer.

We can use filters like the Gaussian filter, median filter, and adapt media filter for preprocessing the input image [2]. Sometimes images have terrible lighting conditions, or skin has bubbles in it.

You can use manual, semi-automatic, or fully automatic border detection methods to segment skin lesions in the input image.

For extracting features, there is a wide range of methods. We can divide these methods the handcrafted and non-handcrafted methods. The first category uses traditional machine learning, and the second uses deep learning [2]. In classification, we can use deep learning implementations or other methods; you can see a few implemented and compared methods in [3].

3. Proposed Method

The process of detecting skin cancer is illustrated in Figure 1 [1]. In the initial steps, we preprocess the image to enhance its quality for subsequent steps, as preprocessing significantly influences the model's accuracy. Next, we use image segmentation to isolate the specific part of the image we want to process. In this step, we ensure that both the lesion and the normal skin areas are preserved. After segmentation, we extract features from the image, such as ABCD features.

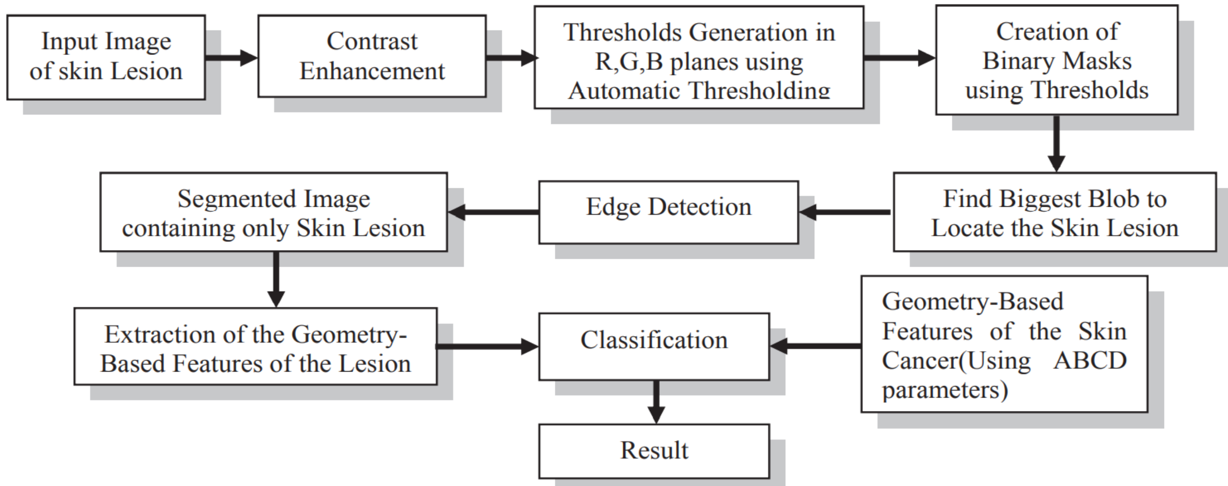

Figure 1. System Flow Diagram

Feature Extraction is a crucial step because we detect skin cancer based on extracted features from the image, so we have to be accurate. By classifying by extracting features, we can decide if skin cancer exists.

In the following chapters, we will discuss the different steps mentioned above. Also, we will introduce proposed methods for each step, show their usage, and compare their performance of different datasets.

3.1. Preprocessing

The input image may have different disorderings. It may have air bubbles, hair, poor lighting conditions, poor contrast, and specular reflections. These disorders can decrease the quality of the image.

Poor image preprocessing greatly influences image segmentation and decreases accuracy in detecting cancer. Different methods exist to omit these unwanted features, like DullRazor or gamma correction. Other methods include edge and contrast enhancement or illumination correction [2].

3.2. Segmentation

The main purpose of separating the lesion from the surrounding normal skin is to help feature extraction [1]. If we do not separate normal skin, the model will process the normal skin. Not separating normal skin decreases accuracy in cancer detection. We can use different types of Image segmentation techniques like the 3-plane masking procedure and edge detection [1].

Edge detection is a method to identify edges and curves on an image. By identifying edges, the model can learn the shape of skin cancer. In the simplest change in the gradient of the pixels within this 3x3 kernel. When the change in pixel intensity becomes more, the edge becomes more significant.

Threshold-based segmentation is another segmentation method. In this method, we define a threshold and all the pixels with a value less than that threshold will turn black.

3.3. Feature Extraction

To detect skin cancer, we have to classify different skin types from each other so that one has or does not have cancer. The most important thing for classifying images is extracting features from the image. We can say feature extraction is the backbone of image classification [2].

In the feature extraction process, we must consider many features. Too many features will confuse the model, and not enough features decrease the model's accuracy in detecting skin cancer.

We can find different image features and algorithms for detecting them [2]. There are two crucial types of feature extraction methods for detecting skin cancer: handcrafted and non-handcrafted. The first category works with traditional machine learning, but the base of the second method is deep learning [2]. In the following chapters, we will discuss different features and determine whether they are handcrafted or non-handcrafted.

3.4. Handcrafted Feature Extraction

Handcrafted refers to manually designed and extracted features for traditional machine learning techniques, training, and testing. It contains histogram

Table 1. Seven-point checklist method

S. no	Major criteria	Score	S. no	Minor criteria	Score
1	Atypical pigmented network	2	4	Irregular streaks	1
2	Blue-white veil	2	5	Irregular pigmentation	1
3	Atypical vascular pattern	2	6	Irregular dots/globules	1

orientation gradient, shape-based features [4], and texture-based Gabor wavelet transformation [5, 6].

3.4.1. Color features. Also known as chromatic features, in biomedical image analysis, we use these features because healthy skin color is different from cancerous skin [7]. We have different methods to discuss color features, like color-swift features. A comparison between color-SIFT and SIFT features also concluded that the color-SIFT features work better relative to SIFT [8].

3.4.2. Clinical features. There exist different types of clinical features. Seven-point checklist and the ABCD rule are two of the best methods. The ABCD rule offers higher consistency and less computation than other methods. The seven-point checklist has two types of criteria for detecting features, the first one is major criteria, and the second one is minor criteria. Each major criterion has a score of 2 points, and every minor criterion has a score of 1point [9].
In Table 1, you can see each criterion and its score [2].

ABCD rule is another clinical feature, conducting 31 dermoscopic parameters. It is a commonly used clinical feature because of its low computation expense and providing high consistency for clinical diagnosis. Table 2. presents ABCD rules and results [2].

3.5. Traditional machine learning for handcrafted feature extraction

Because of the importance of detecting cancer and saving people's lives, scientists have developed many approaches over the decades.
By using traditional machine learning on handcrafted features, researchers tried to classify cancerous skin from normal skin. Here we discuss a few attempts.

Ramya, Navrajan, Prathipa, and Kumar used the system flow mentioned in Figure 1. They used an adaptive histogram equalization technique and a wiener filter for preprocessing. They used GLCM-based features and an SVM binary classifier for feature extraction to classify images as malignant or benign [10].

In another approach, Barerio Paniagua used the ABCD rule for feature extraction and the SVM classifier for the classification step [11].

Because of the high rate of skin disease, it is a good idea to have real-time mobile applications that can determine if a person has skin cancer. Taufiq, Hamed, Anjum, and Hameed [12] proposed an application with that idea. They wanted to remove noise from the input picture for preprocessing, so they used the Gaussian filter and Grabbed Cut method for segmentation. After that, this app uses features like eccentricity, perimeter, and area for feature extraction and feeds them to an SVM classifier to find if there is skin cancer or not.

Dalila, Zohra, Reda, and Hocine suggested an approach that uses two K nearest neighbors (KNN) and an Artificial Neural Network (ANN) instead of an SVM classifier [13].

You can see a summary of different approaches in Figure 2. This Figure mentions different methods for every step [2].

Table 2. Asymmetry, border color, and diameter (ABCD) rules and results.

Property	Description	Factor	Scoring
Asymmetry	Structure, colors and contour	1.3	0–2
Border	Eight segments	0.1	0–8
Color	Light-brown/tan, blue-grey, black-red, white and dark-brown	0.5	1–6
Diameter	Larger than 6 mm	0.5	1–5

Categories	TDS (Total dermoscopy score)
Benign	Below from 4.76
Suspicious	Between 4.76 and 5.45
Malignant	Larger than 5

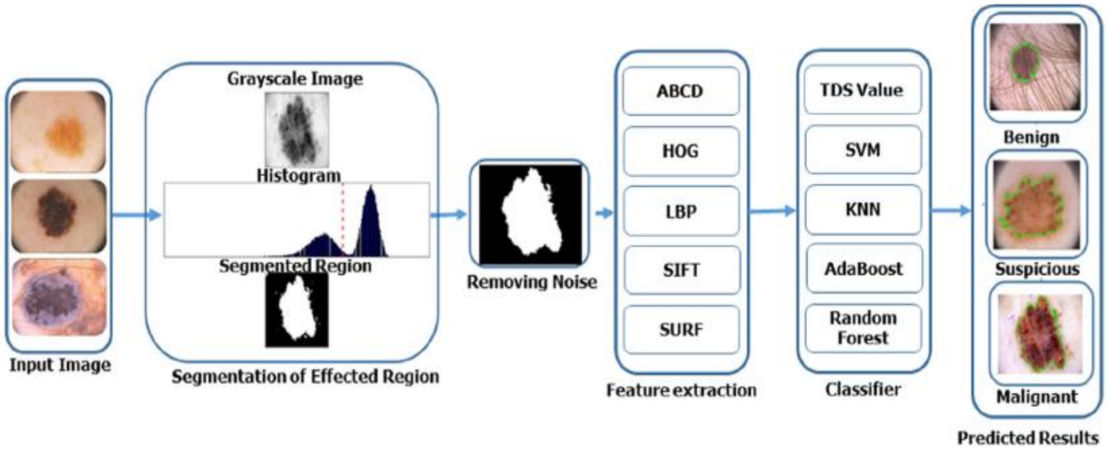

Figure 2. Summary of machine learning methods.

3.6. Non-Handcrafted Features for deep learning-based classification

Recently, scientists have been working on new AI methods for classification. There has been much work on convolutional neural networks (CNN). Researchers use these networks in bioinformatics, medical imaging, and cancer detection. In CNN, you do not need to separate feature extraction and classification steps; they will be done together by automatic feedback. CNN gets the feedback by using a loss function which shows how accurately the model detects skin cancer. By getting that feedback model will learn different features of skin cancer pictures and then can classify them. To train CNN, we need labeled datasets. However, in medical and biomedical imaging, an excellent labeled dataset is very expensive; it takes much time to diagnose cancer by doctors and label all the photos, so we can use transfer learning instead. In transfer learning, we can train a CNN on a pretext task and then transfer that trained convolutional neural network to the main task and train it with a smaller dataset. The pretext task helps the initial convolutional neural network learn different features of the image. The jigsaw puzzle is a very efficient pretext task that helps the model extract different features of the input image as much as possible [13]. Figure 3. shows the overview of a CNN model [2].

6. Experiments

We need biomedical datasets for skin cancer to test and experiment with the proposed methods. Scientists can use different data sets for testing, like the ISIC dataset, Asan data set, ISBI 2016 and 2017 data set, and UMCG dataset. These data sets contain thousands of images we can use to train our models or test them and find model performance.

We need different metrics for analysis and comparing the results of experimenting with different models. Here are some examples from metrics we use to compare results [2]:

$$Sensitivity\ SE = \frac{TP}{TP + FN} \quad (1)$$

$$Specificity\ SP = \frac{TN}{TN + FP} \quad (2)$$

$$Accuracy\ ACC = \frac{TP + TN}{TP + FP + FN + TN} \quad (3)$$

$$Precision\ PREC = \frac{TP}{TP + FP} \quad (4)$$

$$Positive\ Predictive\ Value = \frac{TP}{TP + FP} \quad (5)$$

$$Negative\ Predictive\ Value = \frac{TN}{TN + FN} \quad (6)$$

$$Dice\ coefficient\ DC = \frac{2.TP}{2.TP + FN + FP} \quad (7)$$

$$Jaccard\ Index\ JA = \frac{TP}{TP + FN + FP} \quad (8)$$

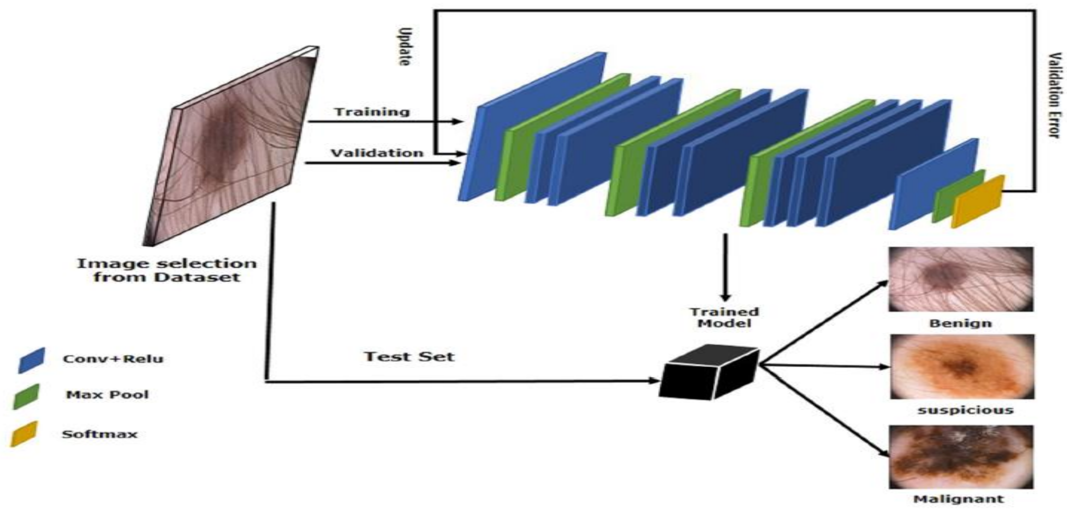

Figure 3. CNN architecture

You can see result of testing different algorithms on different data sets in the Table 3. and Table 4.
Table 3. is for machine learning using handcrafted features and Table 4. is for using deep learning for non-handcrafted features [2].

5. Conclusion

Because of the importance of diagnosing skin cancer, researchers developed advanced methods for cancer detection. This article introduced and comprehended different methods for diagnosing skin cancer using image processing.

Table 3. Machine learning using handcrafted features

Reference	Approach	Data sets	Results (%)
(Murugan et al., 2019)	Features are extracted using shape, GLCM and ABCD rule. For classification KNN, random Forest and SVM classifiers are used.	ISIC	89.43 (accuracy) 91.15 (sensitivity) 87.71(specificity)
(Afifi, Gholamhosseini, & Sinha, 2018)	FPGA platform, monolithic SVM HLS IP and dynamic cascade SVM	Clinical data set	97.9 (accuracy)
(Hamzah et al., 2018)	Watershed marker control canny edge detection methods and the features are extracted using ABCD rules	PH2	With melanoma 9/10 accuracy And with non-melanoma 8/10 accuracy
(Akram et al., 2018)	From a segmented image, different features are extracted that is, color, shape, and clinical. The extracted features are combined to employ serial methods and further reduce it by using NCA method. Finally, for classification M-SVM is used.	ISBI 2016	99.2 (accuracy) 99.2 (sensitivity) 99.4 (specificity) 99.4 (precision) 0.6 (NPV) 0.8 (FNR) 0.005 (FPR) is achieved on M-SVM
(Bakheet, 2017)	Features are extracted by using HoG feature descriptor and SVM is used for classification	Atlas	97.32 (accuracy) 98.21(sensitivity) 96.43(specificity)
(Wahba, Ashour, Napoleon, Elnaby, & Guo, 2017)	The fusion of gray-level-difference and bi-dimensional-empirical-mode-decomposition methods are used for features extraction and quadratic-SVM	ISIC	100 (accuracy) 100 (sensitivity) 100 (specificity) 1 (F-measure)
(Taufiq et al., 2017)	Hair removing is performed by Gaussian filter, for region-of-interest grab cut segmentation method is used, features like eccentricity, area and perimeter are extracted and SVM is used for classification	ISIC	With melanoma 80 (accuracy) And with non-melanoma 75 (accuracy)
(Dalila et al., 2017)	Relative colors, texture and geometrical features are extracted and used two classifiers KNN and ANN	ISIC	85.22 (accuracy) using KNN And 93.60 (accuracy) using ANN

Table 4. Deep learning using non-handcrafted features

Reference	Methodology	Data set	Results (%)
Kadampur and Al Riyaee (2020)	Convolutional Neural Network (CNN)	HAM10000	99.77 (AUC)
Brinker et al., 2019	Convolutional Neural Network (CNN)	ISIC	92.8 (sensitivity) 61.1 (specificity)
Saba et al., 2019	HSV color transformation and FILpF for image enhancement, the boundary is extracted using XOR and color CNN method, transfer learning using inception V3 and fusion using hamming distance (HD) approach	ISBI 2016 ISBI 2017 PH2	95.1 (accuracy) 94.8 (accuracy) 98.4 (accuracy)
Rodrigo-Nicolás et al., 2018	Deep convolution neural network (DCNN)	Clinical images from University of Tsukuba Hospital from 2003 to 2016	76.5 (accuracy) 96.3 (sensitivity) 89.5 (specificity
Brinker et al., 2018	Artificial intelligence-based skin cancer detection	ISIC	76.9 (ROC) 89.4 (sensitivity) 64.4 (specificity
Navarrete-Dechent et al., 2018	Deep Convolution Neural Network (DCNN)	ISIC	82 (melanoma) 68 (basal cell carcinoma) 83(intraepithelial carcinoma) 30 (squamous cell carcinoma) 65.7 (overall accuracy)
Han et al., 2018	Finetuned ResNet-152 model	Asan data set, MED-NODE data set, and atlas site images	86.4 ± 3.5 (sensitivity) 85.5 ± 3.2 (specificity) 91 ± 0.01 (AUC)
Rundo et al., 2018	SC-Cellular Neural Networks are used for segmentation, ABCDE features are extracted and Stacked Deep Autoencoder as classifiers	PH2	98 (sensibility) 98 (specificity)
Ayan & Ünver, 2018	Data augmentation and CNN model are used for feature extraction and classification	ISIC	81 (accuracy) 0.41 (loss)
	Convolution Neural Network (CNN)	Clinical images	72.1 (accuracy) 91 (AUROC)
Rundo, Conoci, Banna, Stanco, & Battiato, 2017	SC-Cellular Neural Networks are used for segmentation and preprocessing, ABCDE features are extracted and pre-trained Levenberg Marquardt Neural Network are used for decision	PH2	97 (sensibility) 95 (specificity)
Nasr-Esfahani et al., 2016	Pre-trained Convolutional neural network (CNN)	UMCG	81 (accuracy) 81 (sensitivity) 80 (specificity) 75 (PPV) 86 (NPV)
(Xie et al., 2016)	A neural network ensemble model employed using lesion extraction, color, texture, border features.	ISIC	94.17 (accuracy) 95.00 (sensitivity) 93.75(specificity)
Majtner et al., 2016	Deep learning method combined with handcrafted RSurf features and local binary patterns.	ISIC	82.6 (accuracy) 53.3 (sensitivity) 89.8(specificity) 78.0(AUC)

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