# Skin Cancer Detection using Image Processing: A Review

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**Abstract** This review paper focuses on different algorithms used for detection and classification of skin cancer which include steps such as Image Pre-Processing, Image segmentation, Feature Extraction and Classification. The Image Preprocessing techniques discussed are Median Filter, Gaussian Filter and Contrast Enhancement technique. The techniques reviewed in the paper for Image Segmentation are K-means algorithm, Otsu thresholding, Edge Detection. Feature Extraction is based on ABCD Rule of Dermatoscopy, Texture, etc. The classifiers which we will discuss are Support Vector Machine (SVM), Neural Network, K-NN Algorithm and Random Forest. There are several proposed algorithms and there is comparison among all of them based on various performance metrics such as Accuracy, Sensitivity and Specificity.

**Keywords** Melanoma · SVM Classifier · Neural Network Classifier · ABCD Rule · K-Means · Random Forest · GLCM

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# 1 Introduction

Skin cancer detection using computer vision can play an important role in skin cancer detection. Early detection and treatment of cancer can save many lives. It is crucial to have an efficient and enhanced image processing techniques to classify the skin lesions as skin cancer accurately. The paper will be discussing about detecting melanoma skin cancer, which is the deadliest among the other types of skin cancer with 75% of all skin cancer death. The other types of skin cancers are Basal Cell Carcinoma(BCC) and Squamous Cell Carcinoma(SCC). However, melanoma is the rarest of all with only 4% cases of all skin cancer cases [16]. Melanoma developed in the melanocytes, cells that develop skin pigments. While the exact cause is not yet clear, exposure to ultraviolet radiation can increase the chances of developing melanoma. In men, chest and back are the areas that are most likely to be affected whereas in women, legs are most likely to be affected. Neck and face are other most common areas. Pigmented patches and unusual growth on skin are symptoms of Melanoma.

There are five stages of Melanoma as shown in Fig. 1:

- **Stage 0:** Cancer starts to develop in the outer most part of the skin.
- **Stage 1:** The lesion is not more than 2mm thick. There is no indication that the cancer has reached lymph nodes or body organs and no signs of ulceration.
- **Stage 2:** The lesion size is might be greater than 4 millimetre and usually more than 1.0001 millimetre. It may or may not have broken skin (ulceration) and no signs of infection in lymph nodes or other sites. There are 3 subgroups of this stage: IIA, IIB, IIC.
- **Stage 3:** The lesions show signs of spreading to nearby lymph channels or nodes and not distant sites. It is visible, if it is size greater than 4 millimetre, and it may contain ulcer. The 4 subgroups of this stage are: IIIA, IIIB, IIIC, IIID.
- **Stage 4:** The cancer has shown signs of much deeper spreading. The cancer spreads to distant organs and leaf nodes. Brain, lungs or lever may be affected.

The severity of the cancer increases with the increase in stages. Thus, the stage of cancer defines the kind of treatment required.

# 2 Overview

Fig. 2 describes the approach for detection of skin cancer. Skin Cancer Detection can be broadly classified into 5 different steps. These steps are further explained in the following sections. Throughout the paper, we will discuss each step within which we will analyse different techniques that can be applied. Section 3 talks about Image Pre-Processing, Section 4 about Image Segmentation, Section 5 mentions Feature Extraction, Section 6 is about Classification of skin lesion and Section 7 gives an

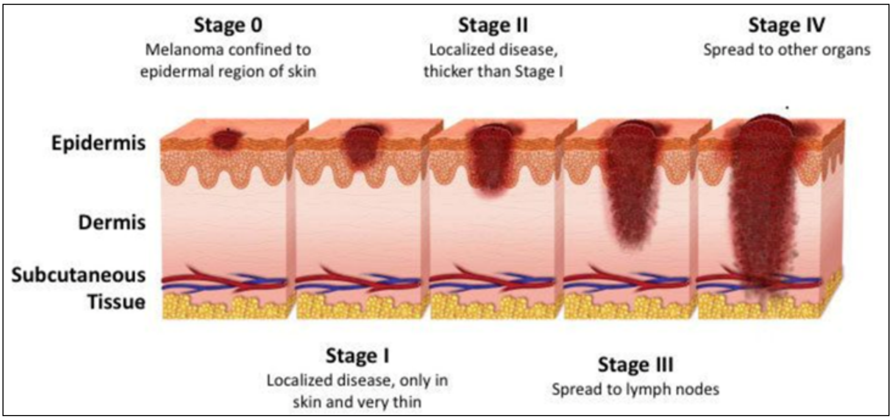


**Fig. 1** Stages of Melanoma

insight on the Performance Evaluation Metrics. We finally end the paper with result and conclusion.

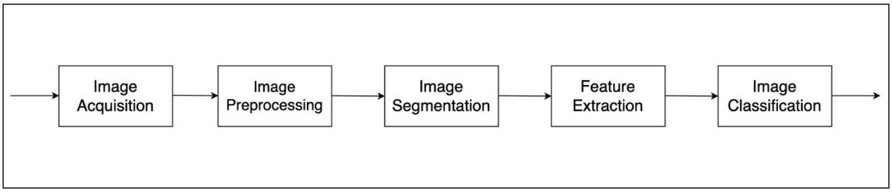


**Fig. 2** Skin Cancer Detection Technology Pipeline

## 3 Image Pre-Processing

The images which are available may contain unwanted distortions such as noise, hairs, air bubbles, etc. Such images are not suitable as inputs for direct usage. Thus, we use different filters to de-noise them. Preprocessing can be seen broadly as a three step process which includes colour to pray scale conversion, de-noising the image, and, lastly, image enhancement [6]. The first step grab scale conversion is important for better processing of the image when working on it later. Colour images are more time consuming and more complex. Dermatoscopic images can be preprocessed using various techniques in image processing. Some of them include equalising illumination, normalizing colour range and image resolution [17]. These images also contain noises in the form of body hair, air bubbles. These have to be removed using gaussian and median filters. In the end, image is enhanced with the help of histogram equalization for colour enhancement in the image.

## *3.1 Median Filter and Gaussian Filter*

Median Filter is used to eliminate noise and bubble that may distort image. It is a non-linear filter used for evening of the image and effectively removes salt and pepper noise. In median filter we analyze each and every pixel and we replace each pixel by the mean of its neighboring pixels [20]. Median filter is very helpful as it preserves the edge of the image which is to be used for segmentation. A Gaussian filter reduces noise by blurring the image and reducing its contrast. [23].

## *3.2 Dull Razor Software*

Dull Razor Software, Fig. 3 [13], is useful for removing hairs from the image. In this process, gray scale morphological closing operation determines the hair location and confirmation of hair is done by determining the thickness and intensity of hair and comparing with some threshold value and if found it replaces the hair pixel by adaptive median filter [19].

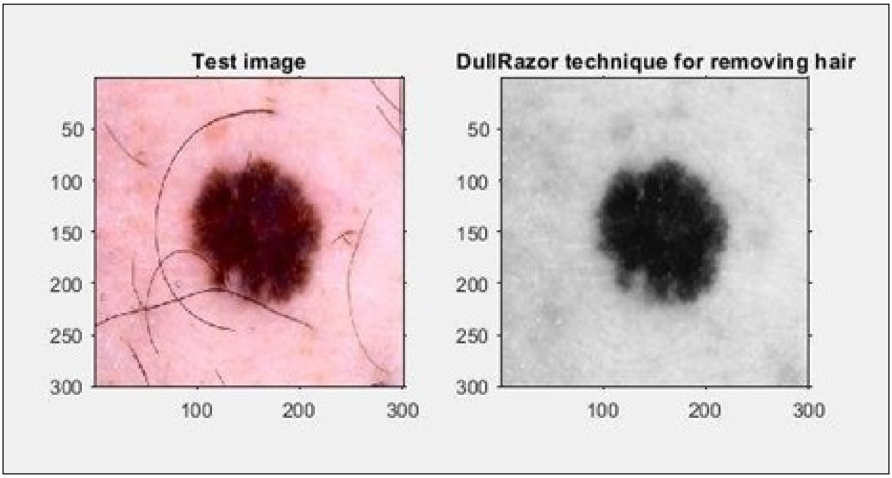


**Fig. 3** Dull Razor Technique for Removing Hair

### 3.3 Contrast Enhancement

Contrast Enhancement Technique,Fig. 4 [14], is useful for improving the visibility of the image. In this method we convert the image into the gray scale and we replace each pixel by increasing its contrast by one unit. This allows better visibility of image as this technique increases the intensity of each pixel. Contrast Enhancement is usually used with Adaptive Histogram [20]. An image's intensity distribution is defined as histogram by providing graphical impression. Histograms have 2 axis. X-axis determines whose frequency we are about to calculate and Y-axis determines frequency of pixel. Histogram equalization is a used to give a contrast in images with varying colour distribution. On applying histogram equalization to an image the brightest spot will be given a colour and other dark spots will be assigned a black colour [17].'a' is adaptive histogram and 'b' is histogram equalization.

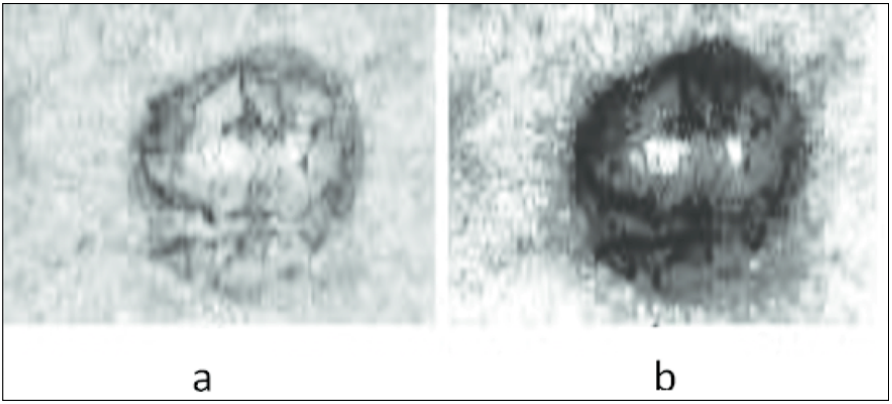


**Fig. 4** Implementation of Contrast Enhancement Technique

## 4 Image Segmentation

Image segmentation is process of dividing an image into several parts according to the characteristics of each pixel in image. After the process of image segmentation, it becomes easy to study the image as the foreground and background are separated in the image and the borders of the region of interest are highlighted. Basically, image segmentation classifies each pixel into categories such that the pixels in the same category share the same characteristics.

## 4.1 K-Means Clustering Algorithm

K-Means Clustering Algorithm, Fig. 5 [1], is an unsupervised and iterative algorithm which is used to separate the region of interest from the background. It randomly selects K points as centroids and creates K-clusters. Before using this algorithm, the image is enhanced so that there is no unwanted noise or impurity in the image. This algorithm is used when there is uncategorized pixel data in the image. It creates the clusters based in the data similarity.

**Fig. 5** Implementation of K-Means Clustering Algorithm

Advantages:

- Relatively easy to implement.
- Scales to large sets of data.
- Ensures convergence.
- The locations of centroids could warm-start.
- It adapts easily to new samples.
- Generalizes according to clusters of various sizes and shapes, like an elliptical cluster.

Disadvantages:

- Manual selection of k.
- Being reliant on initial values.
- Clustering data of different sizes and density.
- Clustering outliers.
- Scaling with various dimensions.

## 4.2 Otsu Thresholding

Otsu Thresholding Technique, Fig. 6 [5], separated the foreground from the background by comparing each pixel with the threshold value. If the intensity of a pixel is less than the threshold value, that pixel is replaced with a black pixel and if the intensity of a pixel is greater than the threshold value, it is replaced with a white pixel. This is how foreground and background can be separated. The threshold value is calculated by obtaining the histogram of the input image and selecting the value whose sum of background and foreground spreads is least.

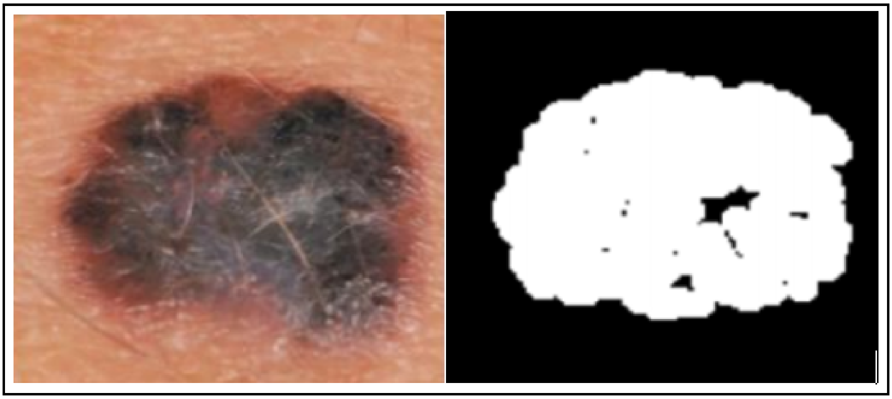

**Fig. 6** Implementation of Otsu Thresholding

Advantages:

- Since Otsu Thresholding works on histograms, it is very fast.
- Easy to implement.

Disadvantages:

- Assumption of standard illumination.
- The histogram should be bimodal and so the image.
- It avoids the usage of any object structure or spatial coherence.
- Uniform statistics are assumed by the non-local version.

## 4.3 Canny Edge Detection

Canny Edge Detection, Fig. 7 [27], is a multi-stage technique which detects the edges of the region of interest in the image. It used a Gaussian Filter to remove the unwanted noise from the image so that the edges are detected without and flaw.

After smoothening the image using Gaussian Filter, the image is filtered with a Sobel Kernel to obtain the horizontal and vertical derivative of the image. These two images are used to find the edge gradient and the direction of each pixel. Then by removing the non-maximum pixels of the gradient magnitude, hysteresis thresholding is used to detect the final edges of the region of interest in the image.

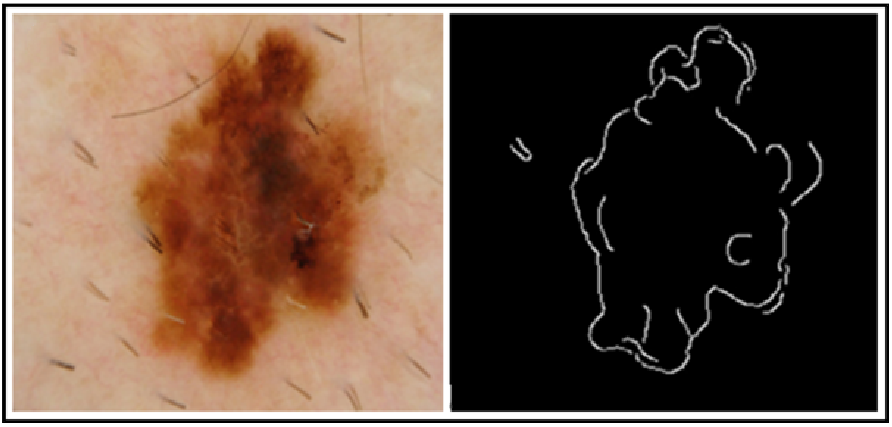

**Fig. 7** Implementation of Canny Edge Detection

Advantages:

- The presence of a Gaussian filter helps any noise in an image to be eliminated.
- With respect to the noise ratio, the signal can be improved by a non-maximum suppression method that results in ridges of one pixel wide as the output.
- Applying thresholding method identifies the edges in a noisy state.
- By using parameters, the effectiveness can be modified.
- It provides strong localization, reaction and is resistant to a noisy environment.

Disadvantages:

- The biggest drawback of using the Canny edge detector is that, due to its complicated calculation, it takes a lot of time.
- Implementation of reaching a real-time response is difficult.

## 5 Feature Extraction

Feature Extraction is the process of gathering unique features from an image. Thus, peculiar features of image will help in characterizing where the segment belongs to. Benign lesions have uniform color whereas melanoma skin lesion have color variations. Melanoma skin lesions are irregular in shape while circular shape is characteristic of benign lesion. Thus, we extract different features from images of skin lesion.

## 5.1 ABCD Rule of Dermatoscopy

ABCD Rule tests the lesions according to different parameters to generate TDS (Total Dermatoscopy Score). TDS evaluates the lesion according to A-Asymmetry, B-Border, C-Color, D-Diameter [30].
Formula for TDS:

$$TDS = wA + xB + yC + zD \tag{1}$$

w, x, y, z are weight factors for Asymmetry, Border, Color and Diameter respectively.

**Table 1** Criterion for Stolz Algorithm

| Criterion | Score | Weight Factor |
|---|---|---|
| Asymmetry | 0-2 | 1.3 |
| Border | 0-8 | 0.1 |
| Color | 1-6 | 0.5 |
| Diameter | 1-5 | 0.5 |

Table 1 displays the value of weight factor for each criterion and the possible final score for them.

**Table 2** Total Dermascopic Score and its Interpretation (Reference TDS Value)

| Total Dermatoscopy Score | Interpretation |
|---|---|
| $< 4.75$ | Benign Lesion |
| 4.75 - 5.45 | Suspicious Lesion |
| $> 5.45$ | Highly Suspicious Lesion |

As mentioned in Table 2 [9], if TDS $< 4.75$, then lesion is determined to be benign. If TDS $> 5.45$, then the lesion is highly suspicious of being malignant. A lesion is suspicious in nature if TDS is between 4.75 and 5.45.
**Asymmetry:** Asymmetry of structures, color and contours determine the Asymmetry Score. The asymmetry is evaluated on both sides of axis for all parameters. The asymmetry score is 0 if there is no symmetry along any axes. Asymmetry Score is 1 and 2 if symmetry is along 1 axis or both axes respectively. w is weight factor of Asymmetry Score is 1.3.

**Border:** To determine border score, lesion is divided into 8 parts and parts having gradual cut-off/sharp cut-off are identified. The border score is equal to the number of parts where there is a sharp or gradual cut-off. Weight factor of y in TDS score is 0.1. Minimum and Maximum values of Border Score are 0 and 8 respectively.
**Color:** Red, dark brown, light brown, bluish-gray, black and white are colors considered for determining Color Score. The score will increment by 1 if there is presence of 1 color from the above-mentioned colors. Minimum score is 1 and Maximum score is 6 for color parameter. Y has weight factor of 0.5 in TDS.
**Diameter:** To evaluate diameter, image resolution of the image is determined. Then, maximum distance between 2 pixels of lesion represents the diameter and diameter score is incremented by 1 for every 1 mm of diameter. Skin lesions having diameter more than 6 mm indicate that it might be malignant in nature. Weight factor of z is 0.5 in Total Dermatoscopy Score [30].

### *5.2 2D Wavelet Transform*

2D wavelet transform is used for the feature extraction. Grayscale image is given as in input and 2D wavelet packet is used. Decomposition occurs in two steps using Biorthogonal wavelets [18]. At each step of decomposition, primary image wavelet divides detailed images which reveal required information and vertical, horizontal and diagonal details. Mean, Mean Absolute Deviation, Standard deviation, L1 Norm and L2 Norm are features extracted using this method which can be passed on to Neural Network Model as input for accurate classification.

### *5.3 Geometry Feature Extraction*

Geometric feature extraction is based on location and structural graphics. In this method we try to find the area and other texture characteristic such as their shape, etc. These can be useful for determining malignant skin lesion in classification stage [16]. Geometry Features include:
**Perimeter (P):** No. of edge pixels.
**Area (A):** No. of pixels in the lesion.
**Greatest Diameter (GD):** The length of the line connecting the most distant boundary points and also passing through centroid of the lesion.
**Shortest Diameter (SD):** The length of the line linking two closest boundary points and also passes through centroid.
**Circularity Index (CRC):** It gives regularity of shape.

$$CRC = \frac{4A\pi}{P^2} \tag{2}$$

**Irregularity Index A (IrA):**

$$IrA = \frac{P}{A} \quad (3)$$

**Irregularity Index B (IrB):**

$$IrB = \frac{P}{GD} \quad (4)$$

**Irregularity Index C (IrC):**

$$IrC = P(\frac{1}{SD} - \frac{1}{GD}) \quad (5)$$

**Irregularity Index D (IrD):**

$$IrD = GD - SD \quad (6)$$

### *5.4 Gray Level Co-occurrence Matrix (GLCM)*

GLCM is a texture feature calculation technique. Gray level intensities in the image are represented in tabulated for in GLCM. First step is to convert the given image into gray scale image. Then we create a GLCM which specifies the number of times a pixel having an intensity in given intensity range occurs in the image. This helps us to find how many times a pixel having intensity i is there in the image having spatial relationship with pixel having intensity j. By this, whole image is converted into a gray level matrix and the scaling is done which reduces the no. of intensity values in the matrix from 256 to 8. Number of gray levels determine GLCM size [19]. We can cluster out the required color features from the image and can carry out the extraction from the image having specified or required color using this algorithm. The feature extracted based on GLCM are: Entropy, Contrast, Cluster Prominence, Homogeneity, Correlation, Dissimilarity, Energy [3].

## 6 Classification

Image classification is the last and final step in detection technique. It is important as all the features are extracted accordingly and whether we are able to find or differentiate from all the above processes carried out. All the processes such as features extraction, segmentation, pre-processing is carried out keeping in mind the classification step. There can be many features based on which the decision of presence of cancer depends on and so we need to carry out prominent features, features on which we want to classify. Classification is just not only a result giving step it also involves learning. It involves finding the characteristics, finding pattern, finding the differentiation line, etc. Classification is based on machine learning techniques and for machine learning techniques we need training data and the testing data [11]. To make the system robust, in order to incorporate various changes, to make system to adapt with different types of errors, with different types of parameters, the system is made to be trained on the training dataset to make it familiar and it is tested with testing dataset to make it learn variations and errors. Then the model is given for applications, all this in order to make it more and more accurate bit by bit.

### *6.1 Support Vector Machine*

Support Vector Machine (SVM) is a multi-classifier [3] which here classifies the image into melanocytic cells and benign cells by being a binary classifier. Support Vector Machine (SVM) is a supervised classifier which separates the image into binary datapoints by using n-dimensional hyperplane where n depends on the number of classes for classification. For understanding SVM we need to understand hyperplane [3]. Hyperplane is a vector plane which differentiates the classes and acts as a boundary plane between the classes. If the data-points can be separated into n different classes the we need to create a total of n-1 dimensional hyperplane for classification. SVM creates a 1-dimensional hyperplane classifying it into 2 datapoint classes. SVM nonlinear classification is based on the kernel function used for classification [4]. The kernel is like a mathematical function which performs the acquisition of given set of inputs and the features for classification and transform it into required form. SVM is a supervised classifier which means it can only act upon labelled data. Accuracy, specificity, sensitivity and various other parameters can be calculated [4] [21]. By being a supervised classifier, its accuracy is very high and it is one of the best algorithms for classification.

### *6.2 Neural Network Classifier*

Recently the deep learning models are highly preferred for any kind of complex problems. Deep learning models are highly flexible and counts for even slightest of errors. Deep learning is developed to make complex tasks easy and to make the models learn and incorporate the variations [11]. Deep learning incorporates neural network for problem solving. Neural network is a structure just like human brain and is used to solve the purpose [10]. Neural network is made of combinations of layers, layers that have different function, have different output patterns. Every neural network consists for 3 layers: the input layer, the hidden layer, the output layer [10]. Every neural network architecture has combinations of layers connected one after the other forming specific architecture. This architecture is capable of extracting features from the image and classifying them into the output. Combination of layers determine the accuracy of the model. Whole classification depends on the architecture and architecture depend on the layers selected.

## *6.3 Artificial Neural Network(ANN)*

ANN is just like the structure in the brain. It has 3 layers: the input, hidden layers, output layer [10]. The computation and transformation of data takes place in the hidden layers. Hidden layers are used for calculating resulting values, feature extraction and also for correcting the errors and incorporating adaptations. In ANN there can be many hidden layers based on the fact that each layer makes classification taking it closer to becoming precise. The model is able to learn because of the hidden layers. There can also be different kinds of layers for extracting particular features. In ANN each layer interacts with each other and due to this reason, it can learn itself. Network neurons communicate [10] with the next layer of neurons, with each output serving as an input for a next layer. Weights are the functions associated with each layer which transform the input and generates the output. This output is transformed and is given as an input to the next layer for further transformation. At the output layer we get the output which is based on the type of neural network used. Different types of neural network are Feed Forward Neural Network, Back Propagation Neural Network, Convolutional Neural Network, etc. All this have different kind of characteristic for calculation and functioning.

## *6.4 Back Propagation Network*

Back Propagation Neural Network (BPN) is a cyclic neural network model. In BPN the input is transformed by the hidden layer and the output of the hidden layer is analysed with the desired output and the difference considering as a loss is given back to previous layers in order to make it more precise and reduce the error [19]. Which can be considered as after the transformation of the input to the present layer and gradient of loss function is calculated at each layer and this loss is transmitted back to the previous layers for error correction and also the weights of the hidden layers are changed accordingly for backpropagation. Hence this method forms looping with previous layers in which present output goes to previous layers for error correction. By this method accuracy of the output value increases as compared to Feed Forward Neural Network.

### 6.5 Feed Forward Neural Network

Feed Forward Neural Network is the most basic neural network model available and is linear in nature. In Feed Forward Neural Network the output of present layer does not go backward to the previous layer forming no loops. It is a very straight forward model where data we can consider that the loss can be accounted in further calculations, which is different than BPN and CNN [21]. Inputs given goes only to higher level hidden layers from present layer and finally output is produced. The processing speed of this algorithm is fairly faster than other neural network algorithms which have interactions with previous layers.

### 6.6 Convolutional Neural Network(CNN)

Convolutional Neural Network is the most detail oriented deep learning algorithm. Convolutional Layers are a combination of various kinds of layers. There are two major kind of constituents of CNN, which are: Fully Convoluted Layers and pooling layers [24]. The function of convoluted layer is to generate the feature maps of the given input which depends on the convolutional filters present in the layer. These feature maps are to be normalized and the usual procedure is to use batch normalization for this purpose which normalized he input given to it by the preceding layers [24]. This normalized image is given to activation function for determining the result are obtained correctly or not. These all rely on pooling layers which does the job of lowering the size of the feature maps generated. There are many pooling layers and activation functions available which can be opted according to the application. Convoluted layers extract high level features from the image and pooling layer reduces the dimensional size of the convolved feature so that the computation power taken should be less. Due to high number of layers and functionality involved the computation time for CNN is usually high [24] especially for training, but the suitable thing to overcome this is to run the model on GPU which gives it the kind of resources it requires. CNN is one of the most accurate algorithms and it is widely used currently not only it gives classification but it is impressive while reducing loss.

### 6.7 k Nearest Neighbour(KNN)

K Nearest Neighbour is a supervised algorithm used to classify the features that are at resemblance or the features that belonging to one class and the another. The algorithm works on the fact that closest neighbouring element belongs to same. It works on majority voting and K-Nearest Neighbours (KNN) Classifier finds the closest K neighbours of the element having the specific properties and based on this

I classifies the belonging of the element. Vote is casted by each data point among the K nearest samples. The class with most votes is chosen.

### *6.8 Random Forest(RF)*

Random Forest classification uses combination of decision trees. The Trees are have leaf nodes which contain labels, while the connecting branches are features that lead to labels [26]. This collection of decision trees can be formed to give different individual predictions and thus, the ensemble of trees can produce more accurate predictions. There are five steps involved in this classifier. The first is development of the training set to grow the tree. Then, bootstrap sample of data is used to increase each tree. The second step is the creation of the secondary training set where numeral n trees are drawn using bootstrap technique. Next, the features are are chosen randomly to divide for existing decision tree, this is the third step. The optimal is selected for splitting. The fourth step average is chosen among the n trees for the prediction, a mass voting is used. Finally, the error rate is computed using the data other than the bootstrap sample [25]. The error rate is used to calculate the importance of the variable importance. To calculate the variable importance we need variables, of which two are based on Gini index [7].
Gini Index is defined as:

$$G(t) = 1 - \sum_{k=1}^{Q} p^2(k|t) \tag{7}$$

Given a node t and estimated class probabilities p (k—t) k = 1,...,Q and Q is total number of classes.

The decrease in the GINI index is calculated for a variable which is then used to make the required split.

## 7 Performance Evaluation Metrics

Performance of the system can be determined by following metrics: Accuracy, Sensitivity, Specificity.

**Sensitivity:** Sensitivity is used to calculate the positive ratio that is correctly identified; the outcome positively denotes (disease). It is calculated using the following equation:

$$Sensitivity = \frac{TP}{TP+FN} * 100\% \tag{8}$$

**Specificity:** Specificity is used to calculate the correctly identified negative ratio; the outcome denotes negative (non-disease). It is calculated using the following equation:

$$Specificity = \frac{TN}{TN + FP} * 100\% \tag{9}$$

**Accuracy:** Accuracy is the degree to which the results align with the expected and desired outcome. It is calculated using the following equation:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} * 100\% \tag{10}$$

Where,
TN is True Negative that is correctly determined negative case.
TP is True Positives that is correctly diagnosed positive case.
FN is False Negatives that is incorrectly diagnosed positive case.
FP is False Positive that is incorrectly determined negative case.

## 8 Result and Comparison

**Table 3** Comparison of different Classifiers for GLCM Feature

| **Parameters** | **Classifiers** | | |
|---|---|---|---|
| | **SVM** | **RF** | **KNN** |
| Accuracy (%) | 85.72 | 74.32 | 65.39 |
| Sensitivity (%) | 87.68 | 76.85 | 71.79 |
| Specificity (%) | 83.76 | 71.79 | 62.51 |

**Table 4** Comparison of different Classifiers for ABCD Rule

| **Parameters** | **Classifiers** | | |
|---|---|---|---|
| | **SVM** | **RF** | **KNN** |
| Accuracy (%) | 89.43 | 76.87 | 69.54 |
| Sensitivity (%) | 91.15 | 78.43 | 71.32 |
| Specificity (%) | 87.71 | 75.31 | 67.76 |

In Table 3, Table 4 and Table 5 [25], different classifiers with different feature extraction techniques are compared considering the performance metrics, Accuracy,

**Table 5** Comparison of different Classifiers for Shape Feature

| Parameters | Classifiers | | |
|---|---|---|---|
| | **SVM** | **RF** | **KNN** |
| Accuracy (%) | 82.31 | 71.97 | 62.19 |
| Sensitivity (%) | 87.76 | 74.75 | 65.72 |
| Specificity (%) | 78.86 | 69.19 | 58.66 |

Sensitivity and Specificity. The Accuracy of all the classifier techniques is optimal when used with ABCD Rule of Dermatoscopy. In the three tables above, SVM is the most accurate and has higher Sensitivity and Specificity. Following SVM, Random Forest Technique is seen to produce better results.

**Table 6** Comparision of Mobile Based Melanoma Detection

| Method | Training Set | Performance Metrics |
|---|---|---|
| SVM [31] | 1300 | Sensitivity: 80.76%<br>Specificity: 85.57% |
| SVM [32] | 347 | Sensitivity: 87.27%<br>Specificity: 71.21% |
| KNN [29] | 83 | Accuracy: 66.70%<br>Sensitivity: 80.76%<br>Specificity: 85.57% |
| CNN [15] | 140000 | Sensitivity: 98.50%<br>Specificity: 95.00% |
| CNN + Novel Regularizer [2] | 8000 | Accuracy: 97.49%<br>Sensitivity: 94.30%<br>Specificity: 93.60% |

Table 6 shows the comparision between CNN, SVM and KNN based on performance metrics such as Accuracy, Sensitivity and Specificity. As shown in the table, CNN is comparable to SVM in terms of performance metrics, given the training dataset for CNN is much larger. CNN being an unsupervised learning algorithm, fetching labled data is not a mandatory requirement which is not the case in SVM. CNN can make classification based on more parameters as compared to SVM. But, CNN requires high computational.

Table 7 shows the performance of CNN algorithm with regards to different types of application in detection of skin cancer.

**Table 7** Classification Based on CNN and its Applications

| Method | Application | Accuracy(%) |
|---|---|---|
| CNN [28] | Skin Mole Lesion Classification | 93.0 |
| CNN [8] | Skin Cancer Classification | 91.0 |
| CNN [22] | Skin Lesion Classification | 84.7 |
| An ensemble based CNN Framework [12] | Dermatoscopy Image Classification | 86.6 |

## 9 Conclusion

Melanoma has the highest fatality rate considering all types of skin cancers. Chances of survival can increase greatly if Melanoma is detected early. This paper focuses on germane methods for each process used in detection of skin cancer. The accuracy of traditional biopsy for detection of skin cancer is very high but it is also very time-consuming, instead of this image processing can be used in order to make fast detection at earlier stages to be assured against any kind of risk. The computer aided program uses various pre-processing techniques making the image suitable for getting features from the image and after extraction of specific features classification is carried out. The paper reviews the most recent methods for each process required in each step of detection. Combination of various methods from different domain can be used for getting desired results. These methods are time efficient as compared to biopsy these methods can be used for stage 1 detection of skin cancer. Various improvements in accuracy have been made such that these things can be widespread as with requirements being a photo camera, it also becomes cost effective. However, with the knowledge, more the accuracy and less the time, better the output, we can aim on improving the accuracy thereby generating desired results.

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