A Systematic Study And Approach On Detection Of Classification Of Skin Cancer Using Back Propagated Artificial Neural Networks

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Abstract: Skin cancer is the leading type of cancer that causes millions of deaths of human beings. Early identification and appropriate medications for new harmful skin malignancy cases are fundamental to guarantee a low death rate as the survival rate. Most of the related works are focusing on machine learning-based algorithms, but they provide the maximum accuracy and specificity. In the preprocessing stage, sharpening filter and smoothening filters are used to remove the noise along with enhancement operations. Then segmentation is used for efficient detection of the region of skin cancer. Finally, to achieve the maximum accuracy for classification back-propagated based artificial neural network (BP-ANN) developed for the classification of skin cancer with the spatially gray level dependency matrix (SGLD) features. The suggested research work can be effectively used for the classification of Benign and Melanoma skin cancers.

Keywords: Back Propagation-Artificial Neural Network (BP-ANN), Spatially Gray Level Dependency Matrix (SGLD), Support Vector Machine (SVM)

1. Introduction

In recent days, skin cancer becomes the most affected disease among different types of cancers, and it is divided as benign and malignant. In these two types, melanoma is recognized as deadliest one while comparing with the non-melanoma skin cancers. It is a known fact that melanoma affects more people year by year and early treatment is important for the survival of the patients. Inspection of malignant melanoma needs well-experienced dermatologists. These people use a computer-assisted system early detection of melanoma. More algorithms in deep learning models were used for the diagnosis of a skin cancer diagnosis. Achieving a high accuracy rate has become a challenging task and facing many problems in classification. Many research papers have utilized image preprocessing for the identification of melanoma at the initial times, which leads to effective treatment. In this way, it is necessary to broaden the span of such essential diagnostic care by arranging efficient frameworks for skin disease classification. In [3-4] authors have utilized image preprocessing for the identification of melanoma at the initial times, which leads to effective treatment. Proficient dermatologists have set up the ABCDEs (Asymmetrical shape, Border irregularities, Color, Diameter, and Evolution) as the standardized descriptions to help with visualizing standard features of severe melanoma cases. One of the main challenges of classifying harmful skin injuries is due to sheer proportions of varieties over the different skin tones from people of different ethnic backgrounds. Recently new accomplishments in the improvement of convolutional neural networks (CNN) have permitted computers to beat dermatologists in skin cancer classification tasks. The following phase is to improve the accuracy of melanoma location further.
The remainder of the paper is structured as a Literature survey conducted for the paper is covered in Section II and Section III covers the suggested melanoma detection method while Section IV describes the environment in which experiments were conducted. Finally, Section V has remarks that conclude the outcomes and draw inferences from the presented research work.

2. Literature Survey

Related work about skin image processing and their multiple applications using different kinds of methods and approaches. It also describes various methods and techniques used in the skin cancer detection process which is used to detect tuberculosis utilizing technical and medical approaches.

2.1 Filter and Adaptive Histogram Technique

The adaptive histogram equalization technique used for preprocessing operation. In this work novel classification and segmentation of skin lesions [1]. The main aim of is to identify a skin cancer detection system with a minimum error by selecting the proper approach in every stage. The standard digital camera is used for capturing the skin lesion image that shows the high screening process of lesion images. The combination of analytical method and segmentation method aims to enhance these two approaches to create an interface for assist dermatologists in the diagnostic process

[2]. The initial step in this work, a series of preprocessing is executed to unwanted structures and removes noise from the given image. Then, an automatic segmentation method traces the skin lesion. Second step is feature extraction is done by using ABCD rule which used to calculate the Total Dermoscopy Score.
In this work, three diagnosis methods are utilized such as benign skin lesion, suspicion, and melanoma. The experimental work uses 40 images comprising suspicious melanoma skin cancer. From the experimental results in this work obtain 92% classification accuracy reflects its viability. The preprocessing technique, morphological operations for removing the hair was used [3]. The edge detection techniques such as Prewitt and Sobel filter are to detect the affected area. These methods have been tested on online skin disease datasets. It has implemented the morphological operations for the removal of hair. The foreground is removed in the first phase using Opening operation whereas, in the second phase, the closing operation removes the background. The morphological operation has given the hair removed image that helped in further processing. Finally, Edges are detected by using Prewitt edge detection and Sobel edge detection techniques. The morphological operation gives better Peak Signal to Noise Ratio and Mean Square Error values, Prewitt edge detection is better than Sobel edge detection based on the PSNR value.

2.2 Gaussian Method

The segmentation processing of Magnetic Resonance Images (MRI) by utilizing the Unsupervised Neural Network Algorithm (UNNA)[4]. Here we are considering two different kinds of problems: such as the trained network takes a long time to obtain the Desired Output. Another one that has obtained results from the training process is not correct which contains a lot of noise as a result of the training process. Thus, in this work we employed the2D Discrete Wavelet Transform (DWT) learned Patterns for denoise operation (noise removal or reduction) by processing entire outcomes from the activity of the segmentation of MRI. The UNNA like Kohonen Network considering the outcome image and the trained process is findings of the given original images. There was a reduction in training time as well as a better performance of the skin cancer patient’s diagnosis system. The quality of the image by utilizing the de-noising and resolution concepts such as wiener filter, median filter, average filter, discrete wavelet transform, and the dual tree-based complex wavelet transform approach. This approach eliminates the noise present in the image and improving the quality of the image which is used to identify cancer inefficient manner. Then the performance is evaluated using the PSNR metrics.
The different preprocessing methods for detecting the lesions and micro-calcification from the mammogram image [5]. These preprocessing methods eliminate the unwanted noise present in the input image which is implemented in the MATLAB tool. Then the performance of the preprocessing techniques has been evaluated using the 30 different mammogram image and the efficiency is analyzed using the peak signal to noise ratio. From the discussions, the anisotropic techniques and median filtering eliminate the noise efficiently when compared to the other preprocessing techniques such as unsharp masking, morphological processing, and so on.
Enhancing the quality of the images by applying the filtering and resolution methods such as median, average, and wavelet filters [6]. These filters estimate the neighboring pixel value for efficiently estimating the new brightness values. Also, these filters maintain the quality of the edge and contour information. Then the performance of the system is analyzed using the peak to signal ratio metrics. These resolution based preprocessing methods improves the quality and also enhance the classification accuracy efficiently.

2.3. Segmentation Techniques

Melanoma is a sort of dangerous skin disease; it can be diagnosed only in its early stage but using the normal conventional dermatological approach is a difficult one. Image processing approach by using an efficient segmentation algorithm named a radial search method to obtain the truth of the lesion region in dermoscopy skin images [7]. The thresholding method is applied in the segmentation process and finds the edge using the radial search process. The radial search approach is called a semi-automatic method and it requires manual initialization to start the process.
To accomplish an efficient way to identify skin cancer at an early stage without performing any unnecessary skin biopsies, digital images of skin lesions have been investigated. To complete this goal, feature extraction is considered as an essential-weapon to analyze an image properly. Then, a graphical user interface is designed for the lesion probability detection and after this work comprehensive discussion is explored based on the obtained results.
The melanoma skin cancer can be recognized through Otsu thresholding which segments the lesion from the whole image [8]. Further segmentation is done by using a Boundary tracing algorithm. After removing the features from the lesion, the classification process is done by using the Stolz algorithm stage.
With the help of edge detection and color spaces in green red channels the skin-tone regions can be identified [6]. The prominent feature of the face is extracted by using wavelet approximations. The experimental results obtained the enhanced False Acceptance Rates (FAR) over either utilizing a grayscale image for segmentation and which algorithm is not using any kinds of edge detection.

2.4. Artificial Neural Network Based Techniques

The ANN-based Classification methodology utilizing Artificial Intelligence and Image processing approach for early diagnosis[9]. In this work dermoscopy image of skin cancer is taken for analysis using Computer-Aided Classification, and it is considered with different kinds of image enhancement and pre-processing. Cancer affected area is detached from the healthy skin utilizing the segmentation process. To minimize the classification complexity, some unique features of benign melanoma and malignant are obtained. The 2D Wavelet transform is a well-known Feature Extraction approach used in this work. These features are feed into as input as in ANN Classifier. It classifies the given data set into non-cancerous or cancerous.

The automatic cancer detection process is used by utilizing the effective image segmentation process [10]. Before segmenting the image, the noise present in the image should be eliminated by converting the RGB images into the Grayscale image. Then the region growing method has been applied to the noise removed image which combining a similar gradient value based on the image intensity constraints. From the segmented image the affected region related features are calculated which is fed into the supervisor classifier to analyze cancer effectively.

The tumor region by utilizing the fuzzy c means based support vector machine [11]. Initially, the MRI image neighboring pixel value has been analyzed and the input is labeled by using the Fuzzy C - Means method. From the input vectors, the membership function is applied and the affected region is efficiently segmented by using the support vector machine. Then the suggested FCM with Support Vector Machine based segmentation methods has been analyzed using the quadratic kernel function and the non-linearity approach. Thus the suggested method enhances the segmentation process which is used to achieve the enhanced results while classifying the segmented region. Finally, the performance of the system is compared with the silhouette method, fuzzy entropy, fuzzy partition coefficient methods.

2.5. Feature Extraction Techniques

The various feature extraction process for recognizing cancer [12]. The author examined skin cancer detection using the computer-aided diagnosis process. The biopsy method is known as the Conventional diagnosis method which is used for the skin cancer detection process. It is done by scraping or removing off the skin and these samples fed into a series of laboratory testing. In this work we utilize a neural network (NN) system as promising modalities for the skin cancer detection process. This work involves different stages of detection which contain a collection of Dermoscopic images, feature extraction utilizing GLCM and classification utilizing ANN, segmenting the images utilizing Maximum Entropy Threshold, filtering the images for removing noises and hairs, It classifies the given data set into the non-cancerous or cancerous image. Cancerous images are classified as non-melanoma and melanoma skin cancer.The diagnosing methodology uses Artificial Intelligence and Image processing techniques [13]. The dermoscopy image is taken and then the different pre-processing operation is done for image enhancement and noise removal. After that, the image is fed into the segmentation process utilizing Thresholding.

In this working diagnosis of the psoriasis skin disease[14]. This work process with both skin texture and color features (GLCM) to give more efficient and better recognition results. Feed Forward Neural Networks are used to classify the image as non-psoriasis infected or psoriases infected. This suggested system gives promising results in terms of finding the generalization face. Extracting the shearlet features from the ultrasound cancer image for detecting the normal and abnormal tissues in the affected part. The shearlet transform analyzes the image and the texture metrics are analyzed in the high dimensional way. The extracted features are classified by applying the different classifiers such as the support vector machine, ad boost technique. The extracted features are compared with the different feature extraction techniques such as the contourlet, curvelet, and GLCM approach. The performance of the suggested system is analyzed using the experimental results in terms of accuracy, sensitivity, specificity, predictive values.

2.6. Feature Selection Techniques.

Automatic detection of cancer by selecting the optimal feature set from the various features[15]. The different intensity, texture-based features are extracted from the segmented image then the haralick and features are selected from the set of features. During the feature selection process, the features are ranked and the best features are selected using the wrapper approach. Then the selected features are fed into the nearest neighbor classifiers which classify cancer into the benign and malignant. Thus the suggested system efficiently classifies the tumors.

Analyzing the various feature selection methods such as information gain, gain ratio, best-first search algorithm, chi-square test, recursive feature elimination processes, and the random forest approach [16]. These features select the optimal features from the set features such as the texture, shape, color, and other spectral features. The selected features reduce the dimensionality of the feature set which is fed into the different machine classifiers for identifying the normal and abnormal tissues. Thus the optimal features ensure efficient results with minimum time complexity.

2.7. Machine Learning Techniques

In this work use of soft computing techniques for analyzing the skin lesion image[17]. Here differentiate the melanoma skin lesions is done by using ABCD and this approach is also done the preprocessing operation and finally, the optimization is done by soft computing operation. The author shows better accuracy in terms of diagnosing melanoma. An intelligent automated approach for identifying the different sorts of skin lesions utilizing machine learning procedures. Two sorts of texture features have been utilized to perform the classification of non-melanoma and melanoma.

Initially, local information is getting over the Local Binary Pattern (LBP) on various kinds of scales, and GLCM at different angles has been mined as a kind of texture feature. Typically, these features are robust because of scale rotation invariant property of GLCM features and invariant property of LBP. The Global information of altered color channels has been integrated through four various moments mined in six different color spaces. Thus a merged hybrid texture color and local as global features have been recommended to categorize the non melanoma and melanoma. The SVM has been utilized as a classifier to classify non-melanoma and melanoma.

The Livewire segmentation is done for evaluation of this work. The segmentation results are quantitatively evaluated in terms of a comparative experiment on a given set of skin cancer images. The results designate that this suggested work shows efficient and effective for the skin cancer image segmentation process. Different kinds of methods such as log filtering, k-means, k-nearest neighbor, fuzzy-based split and-merge algorithm (FBSM) Region refinement, Adaptive Snake (AS), Gradient Vector Flow (GVF) and Adaptive thresholding(AT) has been utilized for melanoma segmentation images. Additionally, this work collected dataset and discusses different kinds of segmentation methods. The mined feature parameters are utilized to categorize the image as Melanoma cancer lesion and Normal skin. The automatic skin detection process after an initial camera calibration and basically, the test individuals are taken from the human sampling [18]. A scaling is implemented on the work data, before employing the distance that confirms better results than preceding works. In this work use of TSL color space and also successfully utilized, where undesired effects are minimized and the Gaussian model shows the better skin distribution process considering other color spaces. Additionally, utilizing an initial filter, generally, huge parts of effortlessly distinct non-skin pixels, are eradicated from further processing. Grouping and analyzing the resulting features from the discriminator progresses the ratio of precise detection and minimize the small nonskin region existent in a common complex image including interracial descent persons, Caucasian, background, African, and Asiatic. Also, this approach is not limited to grouping, size, or orientation candidates.

The skin disease utilizing skin image texture analysis and by comparing the test image to reference images or defined images [19]. The matching of reference and test images compared that get the skin diseases percentage in the obtained skin texture image. The classification detection process by extracting only the specified features such as shape, intensity, and histogram values.The captured images are processed by applying the gamma correction process and the light intensity based features are extracted. The extracted features are classified as the support vector machine which classifies into the malignant and benign. The performance of the system is analyzed using the different feature extraction methods.

2.8 Digital Image Utilizing Technique

The image processing approaches such as a fuzzy inference system and a Neural Network (NN) system were utilized in this work as promising modalities for the detection of various sorts of skin cancer [20]. Extracting the shearlet features from the ultrasound cancer image for detecting the normal and abnormal tissues in the affected part. The shearlet transform analyzes the image and the texture metrics are analyzed in the high dimensional way. The extracted features are classified by applying the different classifiers such as the support vector machine technique. The extracted features are compared with the different feature extraction techniques such as the contourlet, curvelet, and GLCM approach. The performance of the suggested system is analyzed using the experimental results in terms of accuracy, sensitivity, specificity, predictive values. Hierarchal Neural Network gets 90.67% while utilizing the neuro-fuzzy system is 91.26% and NN sensitivity is 95% and specificity is 88%. At the same time, the skin diagnosis system using the neuro-fuzzy system is getting 89% of specificity and 98% sensitivity.

The optical spectroscopy and a multi-spectral classification scheme utilizing SVM to assistance dermatologists in the diagnosis of malign, benign, and normal skin lesions[21-22]. Initially, in this works show effective classification with 94.9% of skin 45 lesions from normal skin in 48 patients depends on the 436 features. The various classifiers involved in the cancer recognition process which is explained as follows. There are several classification techniques like Bayesian Classifiers, Hidden Markov Model, Support Vector Machine, Self-Organization Map, Fuzzy based Approach, and Neural Networks are used to analyze the different type of cancer. The traditional telemedicine across the world and this study focus on modeling and designing a system initially collate past Pigmented Skin Lesion (ELM) in aiding diagnosis. In this work use of Pigmented Skin Lesion (PSL) and analysis of the images related to skin cancer.

In this work also use of computational intelligence methods to examine, classify, and process the given image library. Here texture and morphological features from the given image are extracted. These results are shown in mobile data acquisition devices which in turn specify the benign (non-threatening) or malignancy (life-threatening) status of the imaged PSL. This forms the fundamental for upcoming automated classification process in term of skin lesions in skin cancer patients.

2.9 Data Mining Techniques

The data mining concepts and their different methods are available in the literature on medical data mining [23-24]. In this work we mainly emphasize on the data mining application on skin diseases. A classification has been offered depends on the various kinds of data mining approaches. The effectiveness of the numerous data mining procedures is highlighted. Usually, association mining is suitable for mining rules. It has been utilized particularly in cancer diagnosis. A classification is a robust approach to medical mining. This work summarized the various kinds of classification using process in dermatology. It is one of the most significant approaches for the diagnosis of erythematous-squamous diseases. There are different kinds of methods available for examples like fuzzy classification, Genetic Algorithms, and Neural Networks in this topic. Clustering is a suitable technique in medical image mining. Thus, this work investigated some experiments which exist in mining skin data. The computer vision-based diagnosis system which discussed some clinical diagnosis approach which is being combined with the tool for detecting a different type of lesion process.

In the epidermis area, finding the Melanocytes in the epidermis is a significant process and a difficult process also. Thus, the author proposes a novel technique for the detection of Melanocytes in the epidermis area [25]. The suggested technique based on radial line scanning, this process used for estimating the halo region and from all the keratinocytes has to detect Melanocytes is this process by using the nuclei approach. Experimental evaluation based on 40 different histopathological images it comprises 341 is Melanocytes. Useful information can be extracted from these medical images and pass to the classification system for training and testing using MATLAB image processing toolbox for the detection of dead skin.

A novel approach for skin cancer analysis and detection from cancer effected images [26-27]. The image enhancement and de-noising process by using Wavelet Transformation and the Asymmetry, Border irregularity, Color, Diameter (ACBD) rules are used for histogram analysis. Finally, the classification process is done by using the Fuzzy inference system. The pixel color is used for determining the final decision of 48 skin cancer type, the decision may be two stages like a malignant stage and beginstage of skin cancer. A computer vision-based skin image Diagnosis system and initially, in this work, the skin lesion segmentation process is done. After those vital steps are to mine the pattern and feature analysis processes to create a diagnosis of the skin cancer affected area. This work provides an idea to process the classification, detection, and segmentation of skin cancer and the skin cancer affected area utilizing a hybrid image processing approach.

The k-means algorithm, watershed method, and the difference in strength methods[28-29]. Initially, the image has been segmented into the different regions by using the k-means clustering approach. From the segmented regions, the intensity value is calculated for each region, and the effective boundary and edge information is obtained by the difference strength method. Finally, the watershed algorithm is applied to each edge to analyze the broken lines in the entire image. From the region, the tumors have been segmented efficiently. Then the performance of the suggested system is analyzed using the experimental results and discussions.

An intelligent automated approach for identifying the different sorts of skin lesions utilizing machine learning procedures[30]. Two sorts of texture features have been utilized to perform the classification of non-melanoma and melanoma. Initially, local information is getting over the Local Binary Pattern (LBP) on various kinds of scales, and GLCM at different angles has been mined as a kind of texture feature. Typically, these features are robust because of scale rotation invariant property of GLCM features and invariant property of LBP. The Global information of altered color channels has been integrated through four various moments mined in six different color spaces. Thus a merged hybrid texture color and local as global features have been recommended to categorize the non-melanoma and melanoma. The SVM has been utilized as a classifier to classify non-melanoma and melanoma. Experiments outcome shows that the promising results when compared with other existing methods.

Table 1: comparison of various works of literature

Author	**Skin Cancer type**	**Feature extraction**	**Method Applied**	**Advantages**	**Challenges**
Nasiri, Sara, et al[1]	Melanoma	Texture	K-NN	This method has effectively segmented the image with high accuracy	Due to texture features Asymmetry property was not fulfilled and results in inaccurate classification.
Mohammad Ali Kadampur, Sulaiman Al Riyaee[3]	Dermal cell images	Global	CNN	This method was effectively utilized to classify the dermal cells but not useful for radiologists	The Global features are majorly focused on entire image properties, thus the background image properties affect the classification accuracy.
Akram, Tallha, et al.[4]	Melanoma	Entropy-controlled NCA	CNN	The multi-layer deep learning CNN architecture gives the maximum specificity.	Due to neighborhood component analysis, the homogeneity and color properties will not be covered for classification.
Gaonkar, Rohan, et al. [6]	Benign, Malignant	Entropy, Contrast, Homogeneity correlation	RBFN	This method used to classify the different types of skin cancers using radial basis function	The features are majorly depending on the gray level components but not depending on the color and size features.
Roslin, S. Emalda. [10]	Benign, Malignant	GLCM	Random Forest	The fuzzy c means clustering approach effectively used for the detection of skin cancer.	The GLCM features more depending on the distance metrics instead of orientations, thus random forest was not synchronized.
Hosny, Khalid M, et al. [12]	Melanoma, common nevus, Atypical nevus	Local	DCNN	This method used to classify the different types of skin cancers using Deep learning models.	The deep learning model does not contain backpropagation properly to improvise the qualitative evaluation.
Khamparia, Aditya, et al.[15]	Benign, Malignant	COLOUR	CNN	The hybrid multilayer neural network model can effectively improve the quantitative metrics	Only the color based features are not enough to classify cancer, it also needs the asymmetry,border and texture features
Rehman, Amjad, et al. [16]	melanoma	HOG, SURF, COLOUR	Cubic SVM	The detection of cancer region extracted effectively and multiple features are extracted.	The cubic SVM is failed to classify the benign type of skin cancers and sensitivity related issues are raised.
Amin, Javeria, et al. [18]	Benign, Malignant	Deep learning Features	DCNN	The multi-layer deep learning CNN architecture gives the maximum specificity.	The computational complexity is much high and takes more time to extract deep learning features.

3. Suggested Method

The suggested research work majorly focusing on the detection of following skin cancers such as Malignant – Melanoma, Malignant - Basal Cell Carcinoma, Malignant - Basal Cell Carcinoma, Benign - Melanocytic Nevi,Benign - Melanocytic Nevi,Benign – Seborrheic Keratoses and Benign –Acrochordon. The detailed operation of skin cancer detection and classification approach is presented in Figure1.

3.1 Database Training and Testing

The database is trained from the collected images of "International Skin Imaging Collaboration (ISIC)" Archive. ISIC is one of the biggest available collections of quality-controlled dermoscopic images. The dataset consisted of 1000 benign and 1000 malignant images of melanoma. All the images are trained using the BP-ANN network model with SGLD features. And random unknowntest sample is applied to the system for detection and classification respectively.

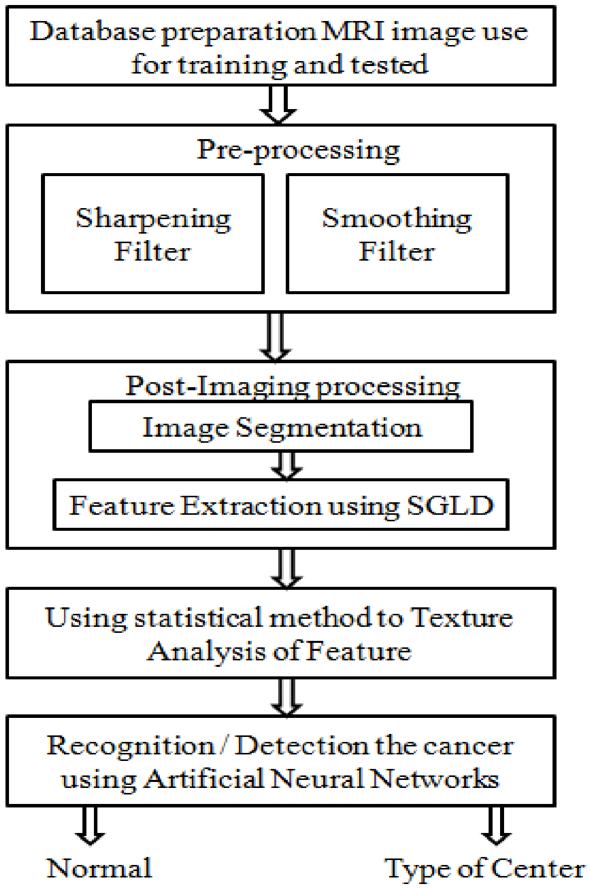

Fig 1: Skin cancer detection and classification

3.2 Preprocessing:

The query image is acquired from the image acquisition step, which includes background information and noise. Pre-processing is required and necessary to remove the above-mentioned unwanted portions. The pre-processing stage is mainly used for eliminating irrelevant information such as unwanted background parts, which includes noises, labels, tape and artifacts, and the pectoral muscle from the skin image. The different types of noise that occurred in the mammogram images are salt and pepper, Gaussian, and speckle and Poisson noise. When noise occurs in an image, the pixels in the image show different intensity values instead of true pixel values. So by choosing the perfect method in the first stage of pre-processing, this noise removal operation will perform effectively. Reduction of the noise to a great extent and avoiding the introduction visual artifacts by the analysis of pixels at various scales, sharpening and smoothing filter de-noising efforts to eradicate the noise presented in the pixel, as it conserves the image uniqueness, despite its pixel satisfied. These filterscan effectively detect and remove noise and thin hairs from the image; then we perform top-hat transform for removing the thick hairs.Contrast limited adaptive histogram equalization CLAHE is also performed on the skin lesion to get the enhanced image in the spatial domain. Histogram equalization works on the whole image and enhances the contrast of the image, whereas adaptive histogram equalization divides the whole image and works on the small regions called tiles. Each tile is typically 8*8 pixels, and within each tile histogram is equalized, thus enhancing the edges of the lesion. Contrast limiting is applied to limit the contrast below the specific limit to limit the noise.

3.3 Image Segmentation: After the preprocessing stage, segmentation of lesion was done to get the transparent portion of the affected area of skin. The Otsu's method is applied to the image to segment the skin lesion area based on thresholding. In the Otsu's algorithm, Segmentation is the initial process of this work, at the cluster centers, cost junction must be minimized which varies concerning memberships of inputs.

3.3 Feature Extraction: Several features can be extracted from the skin lesion to classify the given lesions. We extracted some of the prominent features which help us in distinguishing the skin lesions, those are statistical and texture features. SGLD is a statistical technique of scrutinizing textures considering the spatial connection of image pixels. The texture of mage gets characterized by SGLD functions through computations of how often pairs of pixels with explicit values and in a particular spatial connection are present in the image. SGLD matrix can be created and then statistical texture features are extracted from the SGLD matrix. SGLD shows how different combinations of pixel brightness values which are also known as grey levels are present in the image. It defines the probability of a particular grey level is present in the surrounding area of other grey levels. In this paper, the SGLD is extracted first from the image for all three color spaces i.e. RGB, CIE L*u*v, and YCbCr. Then the SGLD matrix is calculated in four directions which are 135º, 90º,45º, and 0º degrees. In the following formulas, let a, b be several rows and columns of matrix respectively, $S_{a,b}$be the probability value recorded for the cell (a, b), and the number of gray levels in the image be 'N'. Then several textural features can be extracted from these matrices, extracted textural features are as shown in the following equations:

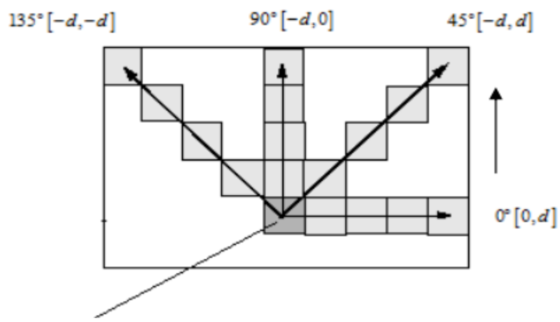

Fig 2: Orientations and distance to compute GLCM

1. Mean (μ) =$\frac{1}{N^2}\sum_{i,j=1}^{N} I(i,j)$
2. Variance =$\sum_{i,j=1}^{N}(i-\mu)^2\, I(i,j)$
3. Standard Deviation (σ) =$\sqrt{\frac{\sum_{i,j=1}^{N}[I(i,j)-\mu]^2}{N^2}}$
4. Skewness= $\frac{1}{\sigma^4}\sum_{i,j=1}^{N}(i-j)^3\, I(i,j)$
5. Kurtosis= $\frac{1}{\sigma^4}\sum_{i,j=1}^{N}(i-j)^4\, I(i,j)$
6. Contrast =$\sum_{a,b=0}^{N-1} S_{a,b}\,(a-b)^2$
7. Correlation =$\sum_{a,b=0}^{N-1} S_{a,b}\left[\frac{(a-\mu_a)(b-\mu_b)}{\sqrt{(\sigma_a^2)(\sigma_b^2)}}\right]$

   hereμ_a and μ_b are mean and $\sigma_a and \sigma_b are standard deviation.$
8. Dissimilarity = $\sum_{a,b=0}^{N-1} S_{a,b}|a-b|$
9. Homogeneity =$\sum_{a,b=0}^{N-1}\frac{s_{a,b}}{1+(a-b)^2}$
10. Angular Second Moment (ASM) = $\sum_{a,b=0}^{N-1} s_{a,b}^2$ and Energy =$\sqrt{ASM}$

3.4 Texture Analysis Of Features

Feature of lesion: According to previous work on skin lesion feature extraction, computing the variance and mean of various color channels would assist in classifying the melanoma from non-melanoma images. Hence on segmenting the skin lesion image, the binary image is converted into a red, green, and blue (RGB) scale, Hue, Saturation Value

(HSV), and grayscale. Thus computing the mean, variance, histograms, and non-zero bins of skin lesions in different color spaces.

Border feature of lesion: The border feature of the lesion is essential as melanoma has a highly irregular border as compared to the normal skin lesions. Border features can be computed by using the solidity, convex area, entropy, and convexity features.

- Solidity- It is defined as the area of the image divided by the area of its convex hull, and it is used to quantify the size and the cavities in an object boundary.
- Entropy: It is defined as the randomness of the texture of the skin lesion.
- Convex Area: It is defined as the area of the skin lesion

3.5 Classification of Cancer

Neural networks have been effectively applied across a range of problem domains like finance, medicine, engineering, geology, physics, and biology. From a statistical viewpoint, neural networks are interesting because of their potential use in prediction and classification problems. The neurons are connected in the pre-defined architecture for effectively performing the classification operation. Depending on the SGLD features, the weights of the neurons are created. Then, the relationships between weights are identified using their characteristic features. The quantity of weights decides the levels of layers for the suggested network. The architecture of Artificial Neural Networks, BP-ANN consists of two stages for classification such as training and testing. The process of training will be performed based on the layer-based architecture. The input layer is used to perform the mapping operation on the input dataset; the features of this dataset are categorized into weight distributions.

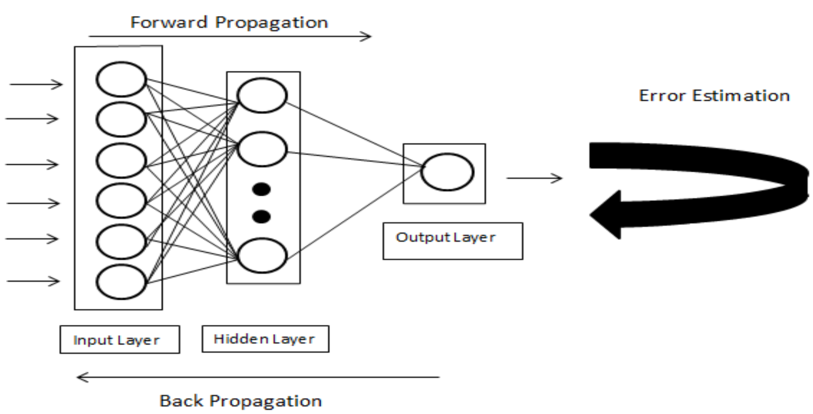

Fig 3: Layered architecture of BP-ANN model

The BP-ANN architecture has eight layers with weights. It contains the sequence of three alternating Convolutional 2D layers and the Maxpooling2D layer and three fully connected layers. The first convolutional 2D layer of the net takes in 224 * 224*3 pixels skin lesion images and applies 96 11×11 filters at stride 4 pixels, followed by a ReLU activation layer and cross channel normalization layer. The second layer (Max Pooling) contains 3*3 filters applied at stride 2 pixels and zero paddings. Next convolutional 2D layer applies 5 256*256 pixel filters at stride 4 pixels, followed by max pooling2D layer which contains 3×3 pixels filters applied at stride 2 pixels and zero paddings. The third convolutional2D layer of the net takes applies 384 3×3 filters at stride 1 pixel and one padding. The last dense layer of the BP-ANN contains three fully connected layers with ReLU activation and a 50% dropout to give 60 million parameters.

Then the classification operation was implemented in the two levels of the hidden layer. The two levels of hidden layer hold individually normality and abnormalities of the skin cancer characteristic information. Based on the segmentation criteria, it is categorized as a normal and abnormal classification stage. These two levels are mapped as labels in the output layer. Again the hidden layer also contains the abnormal cancer types separately; it also holds the benign and malignant cancer weights in the second stage of the hidden layer. Similarly, these benign and malignant weights are also mapped as labels into the output layer. When the test image is applied, its SGLD features are applied for testing purposes in the classification stage. Based on the maximum feature matching criteria utilizing the Euclidean distance manner it will function. If the feature match occurred with hidden layer 1labels, then it is classified as a normal skin image. If the feature match occurred with hidden layer 2 labels with maximum weight distribution, then it is classified as a benign effected cancer image. If the feature match occurred with hidden layer 2 labels with minimum weight distribution, then it is classified as a malignant affected cancer image.

5. Conclusion

Finally, this article concludes the following challenges presented in the various literatures. They are,

- By using the standard filters in preprocessing stage, they were effectively removed the noise from the images. But they are failed to remove the hair artifacts from the dermoscopy images. This results in effective segmentation.
- As the Melanoma is a life threatenskin cancer, it should be segmented very precisely with exact localization of borders. But conventional approaches failed to detect the cancer region accurately.
- The feature extraction should be done very accurately for proper classification. The state of art approaches focusing on only few categories of features but not all the types of features.
- The training of either deep learning or machine learning model should be done with variety of skin cancer types. But, the conventional methods failed to provide the maximum accuracy for various types of cancer. For this purpose a multi layer and error resilient back propagation based artificial network will be effectively used.

To solve this challenges, this article suggests a computational methodology for the detection & classification of skin cancer from dermoscopy images using a deep learning-based approach. Here, sharpening and smoothing filters are utilized for preprocessing, which eliminates any unwanted noise elements or artifacts innovated while imaging acquisition. These filtering methods can effectively removes the hair from the skin images. Then otsu segmentation is employed for ROI extraction and detection of cancerous cells with the accurate borders. Then SGLD matrix method was developed for the extraction of all kind of statistical and texture features from segmented images respectively. Finally, BP-ANN was employed to classify the type of cancer as normal, benign, or malignant using the trained network model.

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