Skin Cancer Detection and Classification using Machine Learning Techniques

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Abstract: Skin cancer is the most common type of cancer, which affects the life of millions of people every year. About three million people are diagnosed with the disease every year in the United States alone. The rate of survival decreases steeply as the disease progresses. However, detection of skin cancer in the early stages is a difficult and expensive process. In this study, we propose a methodology that detects and identifies skin lesions as benign or malignant based upon images taken from general cameras. The images are segmented, features extracted by applying the rule and a Neural Network is trained to classify the lesions to a high degree of accuracy. artificial neural networks (ANNs) were used as diagnosis method for Skin cancer detection from magnetic resonance image. The detection of the cancer is performed in two stages: Preprocessing and enhancement in the first stage and segmentation and classification in the second stage which using different stages of statistical method; feature extraction which one of texture analysis and the last used this feature as input parameters to the feed-forward back propagation Artificial neural networks which designed by the neural networks toolbox in implemented all the result.

Keywords— Skin Cancer, Image Processing, Feature Extraction, Neural Networks, Classification.

I. INTRODUCTION

Skin cancer is the most common and prevalent type of cancer over the world. Over 3.5 million cases of Melanoma, Basal Cell Carcinoma and Squamous Cell Carcinoma are diagnosed every year. This is more than the combined counts of breast cancer, lung cancer and colon cancers. In fact, a person falls victim to Melanoma every 57 seconds. [1] As it is with every variety of cancer, early screening and detection of skin cancer is the most hopeful sign of making a full recovery. Early detection of skin cancer yields a ten-year survival rate of 94%. However, this survival rate drops drastically as the cancer progresses and reaches then Ext stages. Ten-year survival rates come to a meagre 15% in the case of Melanoma, when it is detected in the final stage. [2] However, early detection of skin cancer is an expensive affair. As skin lesions look quite similar to each other, it is difficult to determine whether a lesion is benign or malignant. Extensive analysis needs to be performed to identify the category of the lesion. Traditionally, an image using a special device, known as a dreamscape, is taken to study the lesion closely. Unfortunately, thermoscopes are expensive and not widely available with dermatologists. One of the challenges of visual screening is the visual similarity between skin diseases. In the last few years, significant advancements have taken place in the domain of computer vision. With the advent of new algorithms, it has become possible to differentiate between clinically similar in conditions. These algorithms do not require the images to be taken from special purpose devices, such as thermoscopes, and can be applied on images obtained from general purpose cameras [3].an approach to pre-process and segment lesions, extract features from the segmented lesions and train an artificial neural network, which would then classify the lesions into their respective categories. We consider three variants each of benign and malignant lesions. The benign lesion category comprises of Melanocytic Nevi, Seborrheic Keratoses and Acrochordon, whereas the malignant lesion category comprises of Melanoma, Basal Cell Carcinoma and Squamous Cell Carcinoma.

II. RELATED MATERIAL AND METHOD

Extensive work has been done in classifying skin lesions from dermoscopic images, however little work can be found on classification performed using general images. [4] consists of the most extensive work in the area of classification of skin lesions into multiple categories. They have categorized the lesions into 23 distinct classes. They use Convolutional Neural Networks to perform this classification. They use the 16 layer and 19-layer models, VGG-16 and VGG-19 [5] respectively, created by the Visual Geometry Group, to perform this classification used a pre trained VGG model and improved its performance with the help of transfer learning. They achieved an accuracy rate of 90% on binary classification of lesions into cancerous and non-cancerous. However, a

lot of work has been done in the detection of Melanoma specifically. Various approaches have been taken for this purpose. Moussa et. al. detected Melanoma using its geometric features and using the k-Nearest Neighbors algorithm to classify it from benign lesions [6]. They achieved an accuracy rate of 89%, however their dataset was limited. Other approaches have seen the calculation of a Total Dermatoscopy Score (TDS), which has then been used to differentiate the malignant and benign skin lesions. Azmi et. al. [7] worked on this approach and assigned a TDS score based on the extracted features based on the ABCD rule. The TDS scored ranged between 1.0 - 8.9 and a score above 5.45 meant the lesion was highly suggestive of Melanoma. Masood et. al. [8] classified a set of 135 images into cancerous and non-cancerous lesions with the help of an Artificial Neural Network system. They segmented images using the Histogram Analysis based Fuzzy C Mean Algorithm for Level Set Initialization and extracted features using histogram features and statistical features obtained using the Grey Level Co-occurrence Matrix. They then trained a two-layer feed forward Neural Network with three training algorithms which were Levenberg-Marquardt, Scaled-Conjugate Gradient and Resilient Back Propagation. They obtained an accuracy of 91.9% using the Scaled Conjugate Gradient training algorithm [9].

III. PROPOSED METHODOLOGY

The MATLAB platform, along with its Image Processing and Neural Network Toolboxes, is a great resource for image based medical diagnosis systems. The images are processed and their features evaluated using the Image Processing Toolbox, whereas the Neural Network Toolbox is used to train a model of feedforward Neural Network, which is used to classify the images into its respective malignant and benign categories. A set of 463 images were acquired from different web sources, mainly from, which is the largest independent photo dermatology source dedicated to online medical education. [10] Since, the acquired images are captured using general purpose digital cameras, they suffer from noise and face inconsistencies in background illumination. Apart from these issues, some lesions also have hair over them, which makes their identification difficult.

A. Preprocessing and Cleaning Before the images can be segmented, they need to be preprocessed and cleaned so as to improve the performance of the segmentation algorithm. First, the image is converted to grayscale and a homomorphic filter is applied on it. The homomorphic filter consists of performing a fast Fourier transform on the image and passing it through a high pass filter. We have used Butterworth's high pass filter for this purpose. The homomorphic filter improves the inconsistency in the background illumination [11], thus making it easier to segment the image. The image is subsequently passed through a median filter to remove any presence of salt and pepper noise. [12] The pre-processed image is then passed through a bottom hat filter [13] followed by erosion and dilation, which remove any presence of hair in the image. The results of the preprocessing steps are depicted.

B. Segmentation The cleaned image is then segmented using Otsu's thresholding algorithm, a global thresholding algorithm [14]. Otsu's algorithm differentiates between the background and the foreground of the image by thresholding the image above a computed grey scale value. Otsu's algorithm requires us to computer a grey level histogram of an image before running the segmentation algorithm. Otsu's method aims to find a threshold which minimizes the intra-class variance, which is defined as the weighted sum of variances of the two classes as:

$$\sigma^2 \omega = \omega_0(t)\sigma^2_0(t) + \omega_1(t)\sigma^2_1(t) \qquad (1)$$

Weights ω_0 and ω_1 are the probabilities of the classes separated by a threshold t and σ^2_0 and σ^2_1 are the variances of these two classes. The image is then binarized above the threshold value and morphological operations are performed to fill holes in the segmented image [15]. The segmented image is then masked upon the original image and a segmented colored lesion is obtained. Results of the segmentation process are depicted.

C. Feature Extraction Once the image is successfully segmented, features are to be extracted from it based on the ABCD rule, where ABCD stands for Asymmetry, Border, Colour and Diameter [16]. The features are extracted as below: 1) Asymmetry: An asymmetry index is calculated which deduces the symmetry of a lesion. Since, malignant lesions are generally asymmetrical in nature, it is an important feature that can be used to differentiate between malignant and benign tumors. The asymmetry index is calculated about the major and minor axes of the lesion [17]. To calculate the index, first the lesion is translated to the center of the image and is rotated in such a manner that the major axis of the lesion lies along the x-axis of the image. The image is then flipped about the x-axis and the difference between the overlapping area (Ax) is calculated. The same procedure is repeated about the y-axis as well to find the required area (Ay). The asymmetry index is then calculated as:

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$$AI = \frac{(A_x + A_y)}{A} \qquad (2)$$

D. Border: Generally, the borders of malignant lesions are irregular in nature, whereas the borders of their benign counterparts are round and smooth. The irregularity of the border is considered by calculating the compactness index of a lesion. The compactness index is the ratio of the square of the perimeter (p) of the lesion to the area of the lesion (A) [18]. It is calculated as follows:

$$CI = \frac{p^2}{4\pi A} \qquad (3)$$

E. Colour: Lesions which have the presence of six suspicious colours, white, black, red, light-brown, dark-brown and blue-grey, are said to be suggestive of Melanoma. The colours are represented by their Red, Green and Blue (RGB) pixel values as per Table I [19]. The values are normalized before finding the Euclidean distance between the pixels of the lesion and the colours. A threshold is decided which is roughly equal to the normalized distance between the white and black pixel values. The threshold is set to 0.35 in our case. If the number of pixels of a certain colour exceed more than 5% of the total pixels in the lesion [20], then the colour is said to be present in the lesion. A count of the total colours present in a lesion is maintained. Malignant lesions possess

Fig. 1: Results of Preprocessing and Segmentation of Lesion Images. (Left to Right) (i) Original Image (ii)

Homomorphic Filtered Image (iii) Noise and Hair Removed Image (iv) Segmented Image (v) Masked Segmented Image a high number of colours, whereas their benign counterparts only possess one or two colours.

F. Diameter: To find the diameter of the lesion, only the points along the edge of the lesion are to be considered. For this purpose, the perimeter of the lesion is found. After the points along the perimeter have been determined, the distances between all these points is computed. The maximum distance between any two points is the diameter of the lesion. [21] D. Classification as the number of classes increase, it becomes difficult to classify lesions into their appropriate classes accurately. From previous studies, it has been found that Neural Networks work well for medical diagnostic systems [22], thus in our approach, classification would be performed using a feedforward Artificial Neural Network (ANN). Neural Networks inherently possess better capability of handling complex relationships between different parameters and making classification based on learning from the provided training data. Success of a Neural Network based classification system depends on the model architecture of the network and the training algorithm used to train the network. The model used in this study consists of an input layer, a single hidden layer of ten neurons and an output layer. More number of hidden layers do not guarantee a better result, the number of hidden layers in a network are decided by trial and error. Three training algorithms were used to train the model and their performance was compared. The algorithms used were Levenberg-Marquardt (LM), Scaled Conjugate Gradient (SCG) and Bayesian Regularization (BR). All three algorithms are variants of the backpropagation algorithm Scaled Conjugate Gradient: Moller [16], developed the Scaled Conjugate Gradient (SCG) method to implement nonlinear search techniques with the conjugate gradient approach [23]. This decreased the computations in an epoch and thus is faster than traditional conjugate gradient methods which implement linear search.

TABLE I: Class Distribution of Dataset

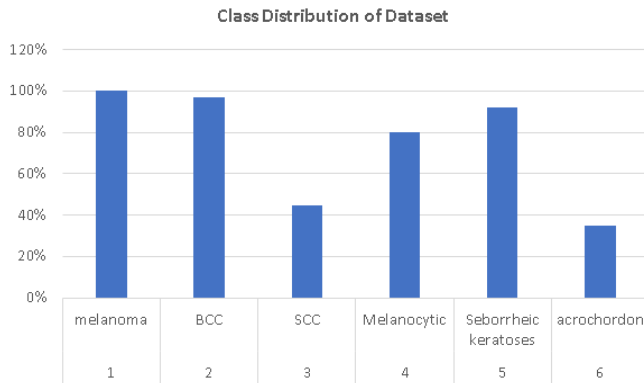| index	class	Number of Images
1	melanoma	100%
2	BCC	97%
3	SCC	45%
4	Melanocytic	80%
5	Seborrheic keratoses	92%
6	acrochordon	35%

Fig. 2: graph of Class Distribution of Dataset

The idea behind SCG is to combine the model-trust region approach, which is used in the LM algorithm, with the conjugate gradient approach. [24] 2) Levenberg-Marquardt: Levenberg-Marquardt (LM) algorithm [24] is an approximation of Newton's method which finds the minimum value of a function that is expressed in the form of sum of squares of linear functions. The LM method approximates the error of the function as a first order expression [25]. The LM method is very simple, fast and thus is widely used in the training of Artificial Neural Networks.

3) Bayesian Regularization: In typical neural networks, the weights are tuned by minimizing an error function, however, the Bayesian approach involves a probability distribution of network weights. Thus, the predictions of the network are also a probability distribution [17]. Bayesian Regularization (BR) uses an objective function to penalize large weights. The parameters of the objective function dictate the emphasis for training, whether the errors need to be reduced or the weight size need to be reduced [18]. Bayesian models tackle the overfitting problem effectively.

IV. EXPERIMENTAL RESULTS

For experimental analysis, a dataset consisting of 463 images was used. The class distribution of images followed Table II. The dataset was divided into training, testing and validation sets, each consisting of 80%, 10% and 10% of the dataset, respectively. The neural network was independently trained on the aforementioned training algorithms and its accuracy, specificity and sensitivity were measured. Sensitivity is the proportion of positives which were identified as such. Whereas, specificity measures the proportion of negatives which were identified as such. The formula for sensitivity and specificity is as follows:
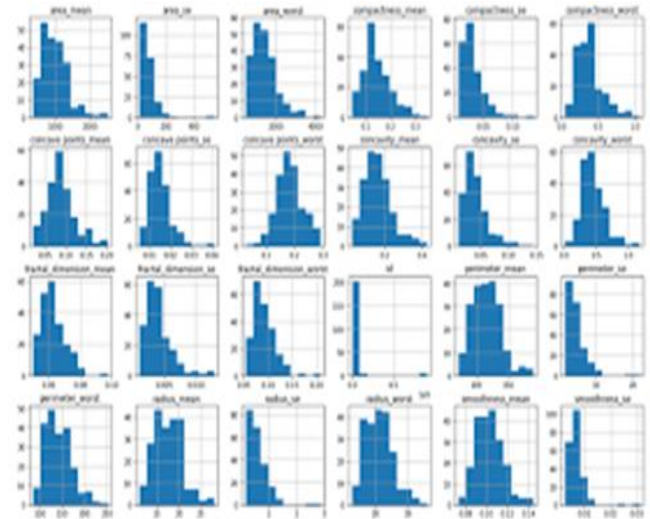

Fig.3: Results of Preprocessing and Segmentation of Lesion.

Where TP stands for True Positive, TN for True Negative, FP for False Positive and FN for False Negative. The sensitivity and specificity for SCG, LM and BR training algorithms are given in Table III, Table IV and Table V respectively. The confusion matrix contains more details about the accuracy and performance of the training algorithms; thus, they need to be studied to better understand the results.

TABLE II: Results of Scaled Conjugate Gradient Training Algorithm.

index	class	sensitivity	specificity
1	melanoma	91%	74.6%
2	BCC	71%	89.4%
3	SCC	0%	98%
4	Melanocytic	0%	97%
5	Seborrheic keratoses	82%	89.2%
6	acrochordon	98%	98.1%

It can be observed from Fig. 2, the confusion matrix of SCG, that an overall classification accuracy of 60.9% was achieved, however it completely misclassified two out of the six classes. The LM algorithm improved on the performance of SCG and achieved an overall classification accuracy of 68.9%. Unfortunately, it also misclassified an entire class, as can be seen in Fig. 3. The BR algorithm achieved the best result amongst the three algorithms and recorded an overall classification accuracy of
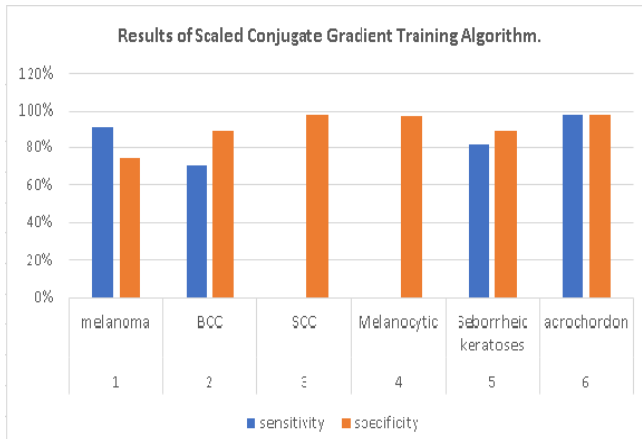
Fig.4: Results of Scaled Conjugate Gradient Training.
TABLE III: Results of Levenberg-Marquardt Training Algorithm

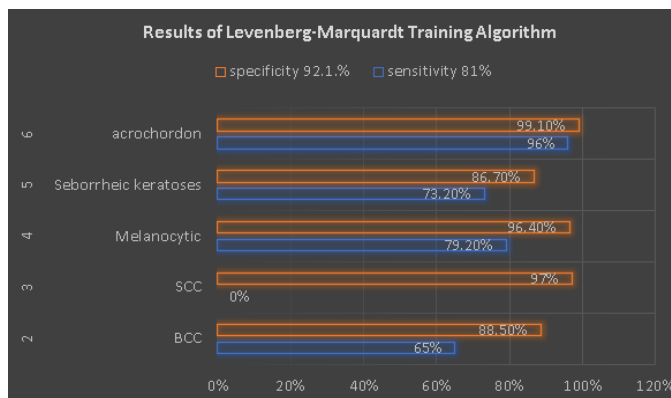| index	class	sensitivity	specificity
1	melanoma	81%	92.1.%
2	BCC	65%	88.5%
3	SCC	0%	97%
4	Melanocytic	79.2%	96.4%
5	Seborrheic keratoses	73.2%	86.7%
6	acrochordon	96%	99.1%

Fig.5: Results of Levenberg-Marquardt Training.

V. CONCLUSION AND FUTURE WORK

It Can Be Observed From Fig. 4 That Br Did Not Suffer From Complete Misclassification Of A Class, Unlike The Previous Training Algorithms, And Achieved A Sensitivity Of 33% For Class 3, Which Was Completely Misclassified By Both The Prior Training Algorithms. It Can Be Observed, From Table Vi, That Though Moussa Et. Al. And Masood Et. Al. Obtained A Higher Rate Of Accuracy, They Only Performed Binary Classification And Used A Very Small Dataset. Classification Accuracy Decreases As The Number Of Classes Increase, As In The Case. This Is Due To The Complexity And Low Inter Class Variance In The Classes. Our Study Achieved An Overall Accuracy Rate Of 76.9%. The Overall Accuracy Rate And Performance Of The System Can Be Improved By Training The Neural Network On A Much Larger And Diverse Dataset With High Intra-Class Variability. This Would Decrease The Misclassification And Positively Impact The Accuracy Rate. An Alternative To Diversifying The Dataset Is Increasing The Number Of Features Extracted From The Images.

Encouraged by these results, future work will involve the improvement of classification result and overall accuracy. The number of output classes can also be increased as more data is available. Convolutional Neural Network (CNN) models can be used for performing this classification without segmentation and extraction of features independently. The input images can be directly fed to the CNN model, which would perform the classification automatically and give better results.

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