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Skin Cancer Diagnosis using Cascaded Correlation Neural Network

Sethulekshmi R*[1], Arul Linsely[2]

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Abstract: In recent days, Melanoma is found to be the most unpredictable and fatal form of skin disease. But it is curable if detected at the rudimentary stage. In this paper, Cascaded Correlation Neural Network, a new method of automatic classification of the skin images is presented. CCNN is self-organizing networks which by itself trains and add on new hidden layers consecutively till the error is minimized. By adopting this particular feature, an accurate and efficient image processing technique is implemented in this paper for cancer detection. As a preprocessing step, noise is filtered, and contrast enhancement is done using histogram equalization method. The color attributes are taken from RGB and opponent color space in the skin lesion and are provided as input to the CCNN. The proposed approach is tested on the ISIC database of melanoma images. Receiver Operating Characteristic curve is used to detect the performance of the suggested system. In the results obtained with 91.1 % accuracy, the sensitivity is 91.7% and the specificity is 89.2%. The result shows the potential of the proposed CCNN network.

Keywords: *Malignant Melanoma, Histogram equalization, feature extraction, colour space, cascaded correlation neural network, Receiver Operating Characteristic*

1. Introduction

Melanoma, a malignant melanocyte tumor is the rampant and life threatening category of skin cancer. Overexposure to the sun, having fair skin is some of the risk factors of melanoma [1]. But with the early detection, the disease is curable. Hence it is beneficial to screen for Melanoma using automated screening algorithms which analysis the image taken by a digital camera [2]. The preprocessing, segmentation, feature extraction and classification are the significant methods in automatic dermoscopic image analysis [3].

Dermoscopy, a more precise and noninvasive advance imaging technique, became popular for the study of skin lesions later on. At present, computer-aided diagnostic systems have become more popular to overcome the limitations of dermoscopy, like high expenses, lack of specialized training. [4]

Many types of research have been going on in computer-aided diagnostic schemes for lesion detection and classification. Diwakar Gautam and Mushtaq Ahmed proposed a system using Support Vector Machine with Sequential Minimal Optimization classifier to classify color images of Melanoma as normal and abnormal. For extracting ABCD features of the lesion, illumination compensation technique for segmentation and iterative dilation technique for noise removal were used [5]. Suleiman Mustafa et al. deployed color space to enhance the Melanoma images and Grab Cut technique for image segmentation. The asymmetry and border rules were used to take out geometric and corner characteristics to train SVM classifier in identifying melanoma [6]. S. Mohan Kumar et al. proposed a melanoma classification system using Shearlet transform and naïve Bayes classifier. Statistical t-test was applied on the Shearlet decomposed sub-bands for selecting Shearlet transform coefficients which are given as inputs to the classifier [7]. Nima Fassihi et al. proposed a Neural Network system where wavelet coefficients like variance and mean were used to extract image features which were given as inputs to a Neural Network [8]. Aya Abu Ali and Hasan Al-Marzouqi deployed LightNet to categorized skin lesions into normal and abnormal. ABCD rule is used to extract input features which are given to convolutional Neural Networks for classification [9].

Rahil Garnavi et al. presented a CAD system built on Gain-Ratio method for the optimized selection of texture, border and geometrical features for the diagnosis of Melanoma. Wavelet decomposition was used for deriving the texture features; Shape indexes were used for deriving the geometry features and border features for making a boundary series model of the skin image border. Hidden Naïve Bayes, Logistic Model Tree, SVM and Random Forest were the four classifiers used for classification of Melanoma [10]. Achim Hekler et al. analyzed the benefit of combining artificial intelligence and human for the classification of skin cancer [11].J. Premaladha and K.S. Ravichandran in their study, analyzed different techniques to quantify asymmetric properties of the skin image in detecting Melanoma [12].

Nudrat Nida et al. proposed region-based convolutional neural network using Fuzzy C-Mean segmentation algorithm in classifying melanoma images into normal and abnormal[13]. Lequan Yu et al. constructed a fully convolutional residual network for segmenting and detecting skin lesion [14].

[1] Department of Electronics and Communication Engineering,
Noorul Islam Centre for Higher Education, Kumaracoil, TamilNadu, India.
[2]Department of Electrical and Electronics Engineering,
Noorul Islam Centre for HigherEducation, Kumaracoil, TamilNadu, India.
** Corresponding Author Email: lekshmisethur@gmail.com*

The commonly used visual features are shape, texture and colour. In this, colour represents the visual content of the images and colour spaces are used to manipulate colours [15]. By implementing different filtering techniques, the unnecessary noises are filtered using a low pass, high pass, mean, median filters etc. There exists a different spatial and transform domain technique for analyzing the enhancement processes. Histogram enhancement, a spacial domain enhancement method, directly processes the image pixels to change the image and gives a better effect. The histogram also can retain schematic information of an image. Histogram equalization, a contrast enhancement methods produce uniform histogram which redistributes intensities [16]. Both grayscale histogram and colour histogram equalization are applicable to spatial and colour space [17].

In this paper, a colour histogram is generated, which represents the colour distribution of the image in a particular colour space, RGB and opponent colour space[18]. The colour invariance properties of the histogram can be studied by the colour constancy of the colour space.

This work mainly aims at constructing a Cascaded Correlation Neural Network (CCNN) [19] structure to accurately classify Melanoma as malignant or benign and thus evaluating, the performance of CCNN. The first step of the developed architecture is to preprocess the skin lesion and Region of Interest is taken. In the next step, histogram equalization technique is adopted to take out the colour features of lesion image and subsequently they are given as inputs to CCNN in classifying the skin lesion. The Melanoma images are taken from ISIC database consisting of 24,000 images. Using MATLAB, the proposed system is implemented.

2. Proposed Methodology

The proposed methodology block diagram is presented in the Figure 1. Preprocessing, feature extraction and detection are the three stages of the proposed network. The skin lesion is chosen as the ROI for further processing, thus effectively reducing the storage space. The skin image is preprocessed to increase its quality, while retaining all essential details by histogram equalization. In colour histogram equalization, the colour of the image is mapped to different colour spaces, intensity and chromaticity are decoupled, and equalization is applied to intensity channel. The skin lesion is de-noised by a median filter [20]. The lesion is classified as normal or abnormal using CCNN classifier.

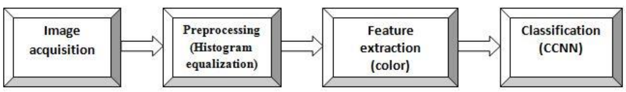

Figure 1 Proposed System block diagram

3. Feature extraction

After the preprocessing phase, feature extraction is done to get the vital details in the image. Here color is given prime importance to identify ROI. Four color features, taken from the color component of the skin lesion are given as the input to the CCNN classifier. [21-22]. Color histograms are used to get the best attributes from the original images taken under different imaging conditions. They are computed from the skin lesions in the RGB colour space. RGB values are calculated, and normalized rg values are calculated from equation 1 and 2

$$r = \frac{R}{(R+G+B)} \quad (1)$$

$$g = \frac{G}{(R+G+B)} \quad (2)$$

For an improved colour perception, two components are also used from the opponent colour space as feature set.

$$O_1(R,G,B) = \frac{R-G}{2} \quad (3)$$

$$O_2(R,G,B) = \frac{2B-R-G}{24} \quad (4)$$

Where $O_1$is the luminance channel and O_2 is the red-green (referred to as G-R) channel.

4. Proposed CCNN based classification

Classification is the most important stage of image processing techniques, which distinguishes normal skin from the abnormal. A specific class inside Neural Network function approximators is CCNN, which automatically adapts to the application with efficient training, is used in this proposed system. The CCNN has input hidden and output units with adjustable weighted connections. The algorithm starts with only input and output layers. While the learning process goes on, each newly added neuron is placed into a new hidden layer, its input connection freezes. Then the neuron is activated, thus training all the output connections. This process goes on until the desired network accuracy is attained

For the proposed system,1600 ROI, which has both normal and abnormal conditions are used as the training dataset. The input to train the network is the four colour features extracted from the ROI. Here the CCNN classifier is designed to have an input layer with 25 neurons, a hidden layer and a output layer with a neuron. The CCNN network chooses the hidden layer neuron, which uses tan sigmoid activation function. The input colour feature pattern and the output normal or abnormal patterns are present during training. The difference between these patterns produces an error signal at the output, relying on neurons weights values in every layer. During the process, this error is reduced, and new weights values are obtained. The momentum constant at 0.9 and the learning rate at 0.01 were set. The training was stopped at the point when the root mean square error value was less than 0.1 per training or when it reached 500 epochs. The network was assessed with test cases after training. The input layer of the CCNN structure designed with 25 neurons is shown in figure 2. Cascaded architecture of the network is shown in the figure as, the input layer neurons connected to the hidden and output layer neurons. The b is the bias, and w is the weights connecting the neurons.

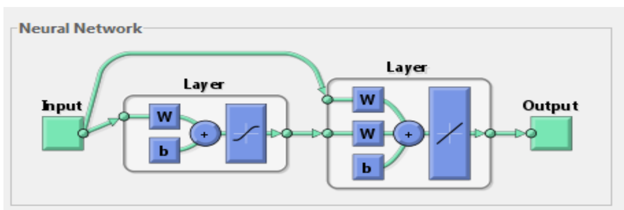

Figure 2 Proposed Design of Cascaded Correlation N.N

Cascaded correlation learning algorithm

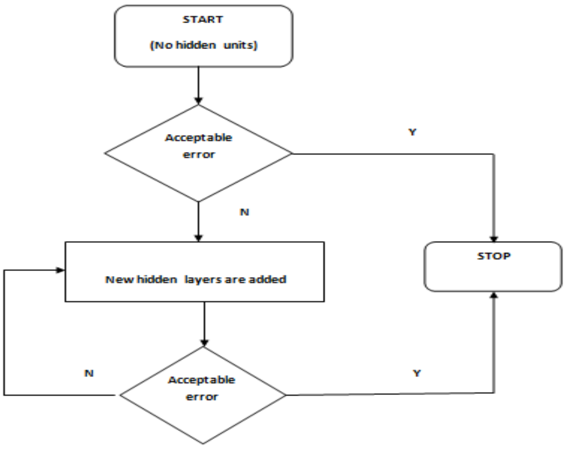

Figure 3 Cascaded correlation learning algorithm

Steps involved in the Cascaded correlation learning algorithm shown in figure 3.

1. The network starts with colour features as the input and an output layer to classify the lesion and has no hidden layer.
2. After training the network, the error is evaluated.
3. The input unit is connected to a newly added candidate unit and their weights are adjusted.
4. When the training procedure is finished, the weights freezes, and the candidate unit gets converted into new hidden unit.
5. The output unit is joined with the new hidden unit, and weights are adjusted and then the error is evaluated after training the network.

Whole process is repeated until the error is acceptably small.

5. Results and analysis

The suggested system performance was evaluated on skin lesions from ISIC database. It includes 2000 dermoscopic images out of which 374 are Melanoma. The database is reduced to 200micron pixel edge, which makes all images 1024 x1024. The components given as input to the classifier is four colour features obtained from the equalized R and G color histogram and the opponent colour space (O_1andO_2). Using MATLAB, the dataset is randomly divided into training (80% of the dataset) and the rest for testing using MATLAB. In the training period, for the classification of images, the classifier uses a known output. During testing, previously unknown lesions are classified. The training dataset contains 1600skin lesion images which have malignant and benign pixels and 400 images for testing. The proposed CCNN system identifies the input images as normal or abnormal. The classification results are shown in figure 4, which shows malignant skin lesions.

ROC, a graph of true positive rate against false positive rate is adopted in assessing the performance of the recommended system in determining the presence of Melanoma [23]. ROC analysis is used in biomedical applications to quantify how accurately medical diagnostic tests can discriminate between normal and abnormal conditions. TPR is the fraction of patients having malignancy and classified as positive, and FPR is the fraction of patients without malignancy and classified as positive. The area under curve (AUC) helped in assessing the system by showing its potentiality to recognize normal and abnormal cases. From the ROC curve in figure 5, the AUC value obtained is 0.95187. Confusion matrix for classification algorithm is shown in figure 6.Rose plots an effective technique for displaying the data in confusion matrix is also shown in figure 7.

In this work, MATLAB R2018a is used. The processor specification is an Intel (R) Core (T.M.) i5-7200U x64 dual-core processor, 2.50 GHz CPU, 8 G.B. installed memory (RAM), and Intel H.D. Graphics 620 IGP graphical processing unit.

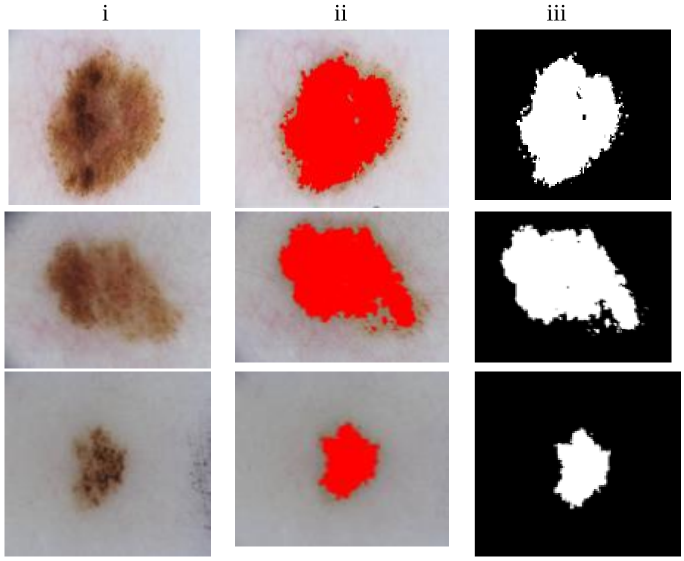

Figure 4 Detection results i) ISIC database image ii) ROI iii) Detected malignant image.

From the confusion matrix, classification performance is also evaluated using sensitivity, specificity, accuracy, Misclassification Rate, F-Measure and Youden's Index [24]. With the equations and the following conventions described below, the measures are assessed.

$$\text{Sensitivity} = \frac{\text{TP}}{(\text{TP+FN})}$$

$$\text{Specificity} = \frac{\text{TN}}{(\text{TN+FP})}$$

$$\text{Accuracy} = \frac{(\text{TP +TN})}{(\text{TP+FP+TN+FN})}$$

Youden's index (J) = sensitivity + specificity -1

$$\text{F measure} = 2*\frac{\text{Precision}*\text{Recall}}{\text{recision+Recall}}$$

$$\text{Where precision} = \frac{\text{TP}}{(\text{TN+FP})}\text{and}$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP+FP+TN+FN)}}$$

$$\text{Misclassification rate} = \frac{(\text{FP+FN})}{(\text{TP+FP+TN+FN})}$$

Table. 1 shows system's performance measures for ISIC dataset using MATLAB. Results are obtained using four colour features.

Parameters	***CCNN***
Sensitivity	91.7%
Specificity	89.2 %
F-Measure	0.941
Accuracy	91.1 %
Youden's index	0.8092
Misclassification rate	0.089

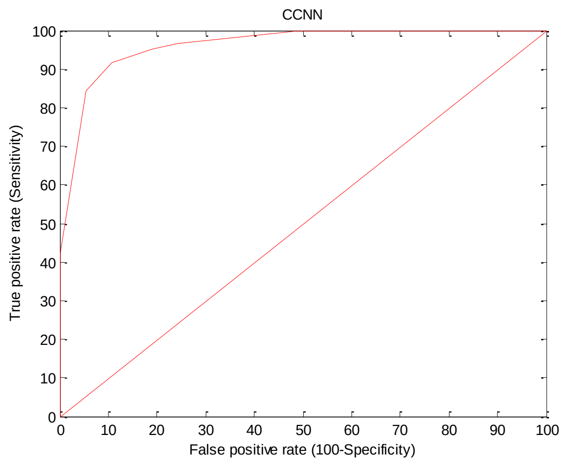

Figure 5 ROC curve for CCNN classifier

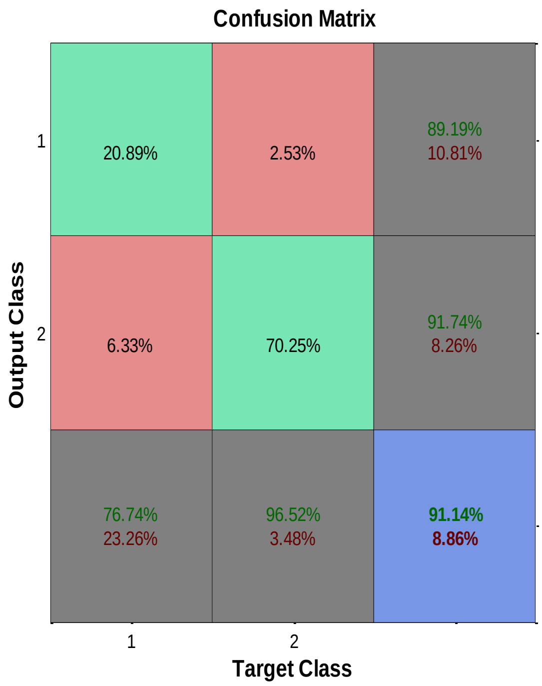

Figure 6 Confusion matrix for CCNN classifier

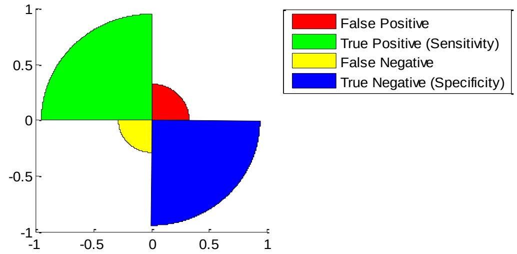

Figure 7 ROSE plot for the classifier

6. Conclusion

The proposed method in this paper gives an improved classification accuracy of 91.1% for the detection of Melanoma. The Melanoma images are taken from the ISIC dataset. The system classifies the given skin images as normal and abnormal. Preprocessing is done using histogram equalization, and the region of interest is identified. The classifier input is the colour features extracted from the ROI. The results show the excellent performance of CCNN network. Receiver Operating Characteristic curve is adopted for the detection performance. Performance evaluation shows AUC value as 0.95187 with sensitivity of 91.7% and specificity and accuracy of 89.2% and 91.1 % respectively for the images taken from ISIC dataset.

Conflicts of interest

The authors declare no conflicts of interest.

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