INTELLIGENT CLASSIFICATION OF PLAQUE LESION WITH EMULATION OF HUMAN VISION PERCEPTION

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Abstract - The HSV color model is fundamentally different from the widely known RGB color model since it separates out the intensity (luminance) from the color information (chromaticity). This paper presents contribution in the field of digital image processing in medical application. Previous work has studied and analyzed psoriasis lesion digital images using HSV color model. The images were processed to show performance of color component in terms of pixel gradation indices that can discriminate plaque from other psoriasis lesion. The findings were based on visual observation of statistical error plots and independent t-test applied. As an extension, this work proposed that the pixel gradation indices representing the respective HSV component being used in the development of an intelligent classification model for plaque lesion. Optimizations of the model by observing the performance indicators regularly applied in medical research.

Keywords: Psoriasis, Plaque, HSV, RGB

1.0 INTRODUCTION

Dermatology is about medical study on skin diseases or lesions. Dermatologist determines the type of lesions by using the color representation, therefore color variegation or variation conveys important diagnostic information for a lesion [1].

Psoriasis is an immune-mediated disease which affects the skin and joints. Psoriasis is characterized by an increased rate of skin cell turnover resulting in thick scales appearing on the skin. The affected skin becomes dry and unsightly. Itching is often experienced in our hot and humid climate. The four major group of psoriasis is plaque, guttate, erythoderma and pustular [2].

In recent years, artificial neural networks (ANNs) have also been used as pattern classifiers in medical diagnosis [3]. Most of these decision models were validated based on the receiver operating characteristic (ROC) curve, which is a popular tool in medical and imaging research. It conveniently displays diagnostic accuracy expressed in terms of sensitivity (or true-positive rate) against 1-specificity (or false-positive rate) at all possible threshold values. Important significant in ROC analysis concerns the comparison of two (or more) diagnostic tests [4].

Most operating systems, image processing programs and texts treat images as collections of pixels comprised of red, green and blue values. This is very convenient for display purposes, since computer monitors output color by combining different amounts of red, green and blue. However, most users don’t think of color in these terms. Users tend to think about color the same way they perceive it - in terms of hue (“reddish” or “greenish”), purity (pastels are “washed out”, saturated colors are “vibrant”), and brightness. So scientists came up with what they call perceptual color spaces [5].

In this research, major psoriasis lesions such as plaque, guttage and erythroderma are being experimented and tested in order to produce an automated diagnosis model for plaque. Digital image processing technique is applied to produce quantitative color measurements that are very helpful when investigating the lesion from early diagnosis. So far previous researchers have used RGB (true color) to distinguish the skin lesions [6]. As an extension, this work proposed that pixel gradation indices are represented in terms of HSV components in the development of the intelligent classification model. These color components are chosen because of they can emulate closely to the human vision perception [7].
2.0 METHODOLOGY

In this research, three sets of 900 digital images of psoriasis lesions representing guttate, plaque and erythroderma captured from psoriasis patients under controlled environment at the Hospital Universiti Kebangsaan Malaysia (HUKM) and Hospital Melaka. These images were later cropped and divided into sets of 400:400:100 representing each lesion respectively.

2.1 Instruments and Measuring Procedure

The Red, Green, Blue (RGB) component color images were acquired using FinePix 6900 Zoom (FujiFilm) digital camera, with pixel resolution of 786x512. This size is sufficient for analysis, as all relevant details of the lesions are shown. During the photo session, the camera was placed at a distance of one foot directly above the patient’s skin. The light intensity was controlled by a standard low flash having mean lux of 224 ± 50 [7].

2.2 Digital Image Processing

The procedure started with each image from the stored database being filtered. In this case, median filter technique was recommended to remove artifacts such as small white ellipse lines or dots. These artifacts can be considered as impulsive noise and may thus be reduced using a median filter given by:

\[
P_{med}(m,n) = \text{median}\left(P_{m-k,n-l}\right) \text{ where } l \leq \frac{N_{med}-1}{2} \leq k,
\]

where \(N_{med}\) is odd and indicates the size of the two dimensional median filter. \(P\) represents all the three color components. After the filtering process, region of interest (ROI) which includes a sample of normal skin and three samples of lesion area were selected. Each image was carefully studied and observed. Once the regions have been identified, they were cropped out sequentially with the normal skin first and followed by the other lesion sample. All samples were then been resized to a dimension of 256 by 256 pixel area. The differential method of gathering lesion sample color indices is defined as:

\[
P_{hsv}(i,j) = \left[ P_{hsv \; \text{lesion} \; (i,j)} - X_{hsv \; \text{skin}} \right]
\]

where \(X_{hsv}\) are the computed mean index for each color component of the selected ROI normal skin sample. For the color transformation process, RGB color is derived non linearly to obtain the HSV parameters. The mathematical models for the conversion are as follows;

\[
H = \begin{cases} 
\text{undefined} & \text{if } \text{Max} = \text{Min} \\
60 \times \frac{G - B}{\text{Max} - \text{Min}} + 0 & \text{if } \text{Max} = R \\
60 \times \frac{G - B}{\text{Max} - \text{Min}} + 360 & \text{if } \text{Max} = R \\
60 \times \frac{B - R}{\text{Max} - \text{Min}} + 120 & \text{if } \text{Max} = G \\
60 \times \frac{R - G}{\text{Max} - \text{Min}} + 240 & \text{if } \text{Max} = B \\
\end{cases}
\]

\[
S = \begin{cases} 
0 & \text{if } \text{Max} = 0 \\
1 - \frac{\text{Min}}{\text{Max}}, & \text{otherwise} \\
\end{cases}
\]

\[
V = \text{Max} \left[R, G, B\right]
\]

2.3 RGB transformation to HSV image

Figure 1 shows the transformation of the sampled psoriasis image from RGB color space to HSV color space. In this experiment, 400 lesion samples from the later color space were selected for training while 186 for testing. The trained data set consist of 250 of plaque samples while 150 were chosen from guttate and erythroderma lesion (categorized as non-plaque). While, the testing data set consists of 93 plaque samples and 93 non-plaque samples. Thus, the ratio for plaque and non-plaque lesion training samples is 250:150 and the testing set ratio is 93:93.
2.4 Designing of ANN Diagnosis Model

The development of ANN started more than 50 years ago. However, recently NN is considered successful and strong potential in many applications such as powerful software tools and power hardware technology. Neural networks are composed of simple elements operating in parallel. These elements are inspired by biological nervous systems. Neural networks can be train by performing a particular function that adjusts the weight between elements. The success of neural networks largely depends on the architecture, algorithm, and the choice of features used in training. This research model is straightforward built from the data using the backpropagation (BP) algorithm method. The type of network that best fits in the diagnosis application is the multilayered perceptron (MLP) network with one hidden layer based on the fact that it has been widely satisfactorily applied by many researchers [4]. The motive of this work is to discriminate between plaque and non-plaque lesion based on differential mean parameter indices extracted from sample images. Since it is also necessary to classify the indices into a discrete category, feedforward neural networks were ideally suited for such purpose [8].

The network is shown as in Figure 2 and the output can be expressed by the following equations:

$$\hat{z}_i = \frac{1}{1 + e^{-\sum_{j=1}^{m} w_{ij}^2 f \left( \sum_{k=1}^{n} w_{jk}^1 a_k^0 + b_j \right)}}$$

(6)

where $i = 1$ and $w_{ij}^2, w_{jk}^1, b_j$ denotes the adaptive variables to be optimized and their values are changed many times during the network training process. Sensitivity and specificity are commonly used terms that generally describe the accuracy of a test [9]. Sensitivity is a measure of the ratio or percentage of ‘true’ lesions ($TP$) and a positive diagnostic test result ($D+$). It represents the actual percentage of a ‘true’ lesion disease realized by a positive test result and is also known as true positive rate ($TPR$), defined as:

Sensitivity: $TPR = \frac{TP}{D+}$

(7)

Specificity measures the ratio or percentage of ‘false’ lesions ($TN$) and with a negative diagnostic test result ($D−$). It is actually represents the actual percentage of a ‘false’ lesion condition realized by a negative diagnostic test. Specificity is also termed as true negative rate ($TNR$) and is given as:

Specificity: $TNR = \frac{TN}{D−}$

(8)

The percentage for diagnostic accuracy ($DA$) refers to the percentage of samples that have been correctly classified or diagnosed, and have output values within the predefined threshold range for the respective output level. It can be derived as:

$$DA = \frac{1}{N} \sum_{i=1}^{N} c_i \times 100 \%$$

(9)

Variable $c_i$ serves as counter for the proposed ANN model output, $z$ at sample $i$. $c_j$ is defined as:
During the training phase process, the ANN application was optimized via four steps where each of these steps was implemented to find optimum value or setting for the number of neurons, learning rate, momentum, and lastly the number of iterations or epochs. Selection of the optimum parameter value for each step was based on the performance evaluation of the model through the sum-squared error (SSE) analysis as well the diagnostic accuracy (DA). For simplicity, threshold for the output logic levels was fixed to ±0.5 for each model in this initial work. At a later stage, the most appropriate threshold level would be decided by analyzing the minimum Euclidean Distance (ED) values form the receiver operating characteristic (ROC) plot [10]. Comparisons between experimented models such as RGB and YCbCr were made to choose which model given the best performance. This performance would indicate the highest accuracy, specificity, sensitivity, large area under the curve (AUC) and shorter ED.

3.0 RESULTS AND DISCUSSIONS

Figure 3 shows an example of SSE performance with respect to epoch iterations during training of best hidden layer size. Shown only are selected number of neurons where their respective SSE are observed to be converging. Thus, implying that training of the model is successful for each experiment.

![Figure 3: Training of ANN Model](image)

Shown from Figure 4 to Figure 7, are the performance results for each training parameter in terms sensitivity, specificity, and accuracy. The threshold set for this evaluation is at ±0.5 for each parameter. Figure 4 depicts the performance of hidden layer size. Model with the best value obtained that is 3 neurons is selected. This is because at that point, the automated model results in the highest accuracy for this automated model that is 61.83%. In addition, at this point, the values for sensitivity and specificity are 82.2% and 40.86% respectively in which sensitivity indicates that the ANN model is able to recognize plaque lesions while specificity shows that the model can recognize non-plaque lesions. This model was then selected for the next training for finding the best learning rate.

![Figure 4: ANN model HSV showing the training and testing results of neurons.](image)

Performance of learning rate can be observed in Figure 5. The number of neuron is taken from the previous optimized value that is 3 neurons. The momentum rate is 0.95 and epoch cycle is set to 10000. The learning rate is varied from 0.01 to 1.00.

![Figure 5: ANN model HSV showing the training and testing results of learning rate.](image)

Figure 6 shows the performance of momentum rate. The number of neurons and learning rate are taken from the previous optimized values. The momentum rate is varied from 0.45 to 0.99.

![Figure 6: ANN model HSV showing the training and testing results of learning rate.](image)
During the training of epoch performance, it can be observed from the Figure 7, that the highest accuracy is 61.83% where the optimum model only needs 10000 of iterations.

After getting the optimized models, the receiver operating characteristic (ROC) graph is plotted as shown in Figure 8. The threshold value that is nearest to the ideal point of the top left-hand corner of the plot is found to be 0.4. All the models have about the same slope in the FPR axis, implying they have the same capability in recognizing non-plaque samples. The figure also shows the HSV has the lowest AUC, thus indicating that it is not a good model for recognizing plaque lesion.

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### Table 1: Performance comparison between ANN models

<table>
<thead>
<tr>
<th>Model with Threshold 0.4</th>
<th>Model</th>
<th>RGB</th>
<th>YCbCr</th>
<th>HSV</th>
</tr>
</thead>
<tbody>
<tr>
<td>ANN (No. of Connections)</td>
<td>56</td>
<td>24</td>
<td>16</td>
<td></td>
</tr>
<tr>
<td>Sensitivity(%)</td>
<td>73.00</td>
<td>73.00</td>
<td>62.37</td>
<td></td>
</tr>
<tr>
<td>Specificity(%)</td>
<td>29.00</td>
<td>29.00</td>
<td>22.58</td>
<td></td>
</tr>
<tr>
<td>DA (%)</td>
<td>51.50</td>
<td>51.00</td>
<td>42.47</td>
<td></td>
</tr>
<tr>
<td>AUC (%)</td>
<td>69</td>
<td>71</td>
<td>64</td>
<td></td>
</tr>
<tr>
<td>ROC Plot: ED from point (0,1)</td>
<td>0.426</td>
<td>0.426</td>
<td>0.596</td>
<td></td>
</tr>
</tbody>
</table>

This model has 62.37% for sensitivity, 22.58%
for specificity, 42.47% for diagnostic accuracy and 64% for AUC. The total number of connections in HSV model is 16, much smaller if compared to RGB and YCbCr. However, it has poorer diagnostic performance. Thus, this color space has difficulty in recognizing plaque lesion and so, not recommended for such purpose in the future.

4.0 CONCLUSION

This project research mainly presents a contribution in the field of color image processing of selected skin lesions for dermatologists. It proposed pixel gradation indices represented in terms of HSV components in the development of the intelligent classification model. These color components were chosen because of they could emulate closely to human vision perception. The extracted HSV color indices were then used to produce intelligent model system for plaque classification.

It can be concluded that the performance of the plaque analysis by using HSV model does not improve the total accuracy although there were numerous number of samples trained for these models analysis. The factor affecting the result of the analysis was the unsupervised cropping processes as there possibly muddled the identification of plaque lesion. Beside that, the HSV model is commonly used in computer graphics applications rather than other applications.

5.0 ACKNOWLEDGEMENT

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References: