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Study of Effects of Image Enhancement Techniques on Early Detection of Skin Cancer

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Abstract: *Worldwide, an estimated 19.3 million new cancer cases and almost 10.0 million cancer deaths occurred in 2020[1]. Cancer begins when healthy cells change and grow out of control, forming a mass called a tumor. A tumor can be cancerous or benign. A cancerous tumor is malignant, meaning it can grow and spread to other parts of the body. A benign tumor means the tumor can grow but will not spread. If skin cancer is found early, it can usually be treated with topical medications, procedures done in the office by a dermatologist, or an outpatient surgery. In this paper, we attempt to approach the early detection of skin cancer using image enhancement techniques and image classification model (VGG-16). The dataset used in this paper is International Skin Imaging Collaboration (ISIC) Dataset 2019. The main objective of this paper is to compare the results obtained from the classifier when it is given images without any enhancement or images after applying CLAHE (Contrast Limited Adaptive Histogram Equalization) and MSRCR (Multiscale Retinex with Color Restoration). The results show that the accuracy of the model is relatively similar in all cases though CLAHE gives marginally better results.*

Key Words: Benign, CLAHE, ISIC, Malignant, MSRCR, Skin Cancer, VGG-16.

1.INTRODUCTION

Skin cancer is one of the most dangerous forms of cancer. The World Health Organization estimates that skin cancer is so common that it accounts for one third of all the diagnosed cancers worldwide[2]. Skin cancer tends to gradually spread to other body parts, so it is more curable in initial stages, which is why early detection is important. The increasing rate of skin cancer cases and expensive medical treatment only increases the need for early diagnosis. It is one of the most active types of cancer in the present decade. As the skin is the body's largest organ, the point of considering skin cancer as the most common type of cancer among humans is understandable. Considering the seriousness of these issues, researchers have developed various early detection techniques for skin cancer.

The gold standard to diagnose skin cancer is skin biopsy with histopathology. However, this procedure is painful due to invasive techniques to get the skin tissue sample[3]. Mobile skin cancer apps that are equipped with machine learning can revolutionize the diagnosis system in the near future [4], and can provide low-cost diagnostic care. The main problem with skin image acquisition using a smartphone is the image quality that depends on the environmental conditions, such as lighting and skin color. The example of these skin color images is shown in Figure 1. The issue of low quality images can be addressed using image enhancement techniques, i.e. Multi-scale retinex with color restoration or histogram equalization due to its simplicity. Another image enhancement technique that is commonly used is Contrast-Limited Adaptive Histogram Equalization (CLAHE) which eliminates non-uniform illumination in RGB skin image.

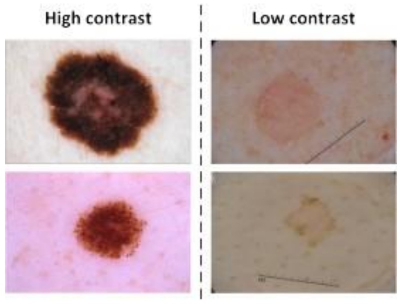

Fig -1: Different skin color contrasts

Recent researches that fused hand-crafted and deep learning techniques to diagnose skin cancer have shown successful results in terms of accuracy [5], [6], [7], [8]. Other techniques used in computer-aided diagnostic systems include steps like dermoscopic image pre-processing, segmentation, extraction and selection of peculiar features, and relegation of skin lesions[9].
This study explores a new possibility of lightweight image processing and deep learning techniques in the early detection of skin cancer. Common image enhancement techniques, CLAHE and Multiscale Retinex Color Restoration (MSRCR), are used in this study. The main purpose of this research is to compare the effect of image enhancement using CLAHE and MSRCR in the early detection of skin cancer using deep learning techniques. The main limitation of the study is only two classes of classification that are addressed, i.e. benign and malignant, due to the focus on the early detection of skin cancer.

1.1 Dataset:

In this paper, we have used the ISIC dataset. The International Skin Imaging Collaboration (ISIC) is an academia and industry partnership designed to facilitate the application of digital skin imaging to help reduce melanoma mortality[10]. The dataset consists 25331 RGB images each having size of 256*256. Each image is classified into benign and malignant out of which 20771 images are benign and 4560 images are malignant.

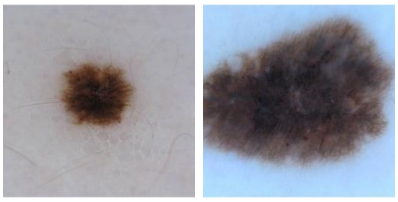

Fig -2: Benign

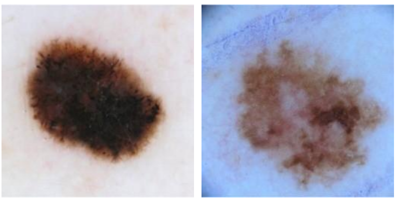

Fig -3: Malignant

If the cells are not cancerous, the tumor is benign. It won't invade nearby tissues or spread to other areas of the body. A benign tumor is less worrisome unless it is pressing on nearby tissues, nerves, or blood vessels and causing damage. Malignant means that the tumor is made of cancer cells, and it can invade nearby tissues[11].

2. METHODOLOGY:

2.1 VGG-16

We used Convolutional Neural Network (CNN) as a classifier in this study because this is a popular method in image classification, providing higher classification accuracy. VGG16 is used in this study as CNN architecture.The most unique thing about VGG16 is that instead of having a large number of hyperparameters the model focuses on having convolution layers of 3x3 filter with stride=1 and always uses the same padding and maxpool layer of 2x2 filter of stride 2. In the VGG-16 architecture, there is an arrangement of convolution and max pool layers consistently. In the end it has 2 FC(fully connected layers) followed by a softmax for output to determine the prediction. The 16 in VGG-16 means there are 16 layers that have weights.

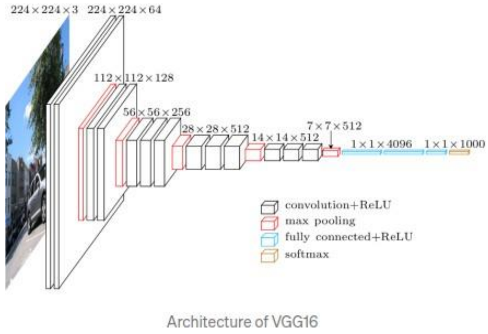

Fig -4: VGG-16 architecture

Deep Convolutional Neural networks may take days to train and require lots of computational resources. So to overcome this we used Transfer Learning for implementing VGG16 with Keras. Transfer learning is a technique whereby a deep neural network model that was trained earlier on a similar problem is leveraged to create a new model at hand.

We reused the model weights from pre-trained models that were developed for standard computer vision benchmark datasets like ImageNet. We used the downloaded pre-trained weights that do not have top layers weights and replaced the last three layers by our own layer and pre-trained weights do not contain the weights of newly three dense layers.

2.2 CLAHE

Contrast Limited Adaptive Histogram Equalisation(CLAHE)[12] is a type of histogram equalization used to improve contrast in an image to improve chances of cancer detection. Histogram Equalization adjusts the contrast in an image by manipulating its histogram. It improves the global contrast of the image by changing the intensities in the image to be more uniformly distributed overall. This allows for areas of lower local contrast to gain a higher contrast. Histogram equalization accomplishes this by effectively spreading out the highly populated intensity values throughout the entire histogram. The histogram of a grayscale image is calculated as follows:

$$(k) = (L - 1) * \frac{\sum n(j)}{n}$$

where k = 0,1,2,3,...,L-1

L = number of gray levels in image
j = 0,1,2,… ,k
n(j) = number of pixels of gray level j
n = total number of pixels
n(j)/n = CDF for pixel value k

However, one of the drawbacks of histogram equalisation is that it only makes changes based on the pixel intensities of the entire image without taking into account the intensity around the local environment of each pixel. This can lead to generation of unrealistic and in some cases amplify the noise.

This can be solved using the adaptive histogram equalisation technique. In this technique, multiple histograms are generated for different parts of the image and the intensity of pixels in each part is manipulated accordingly. Since two different histograms are used for some two neighbouring parts of the image, this may lead to generation of superficial boundaries within the image. To avoid this phenomenon, binary interpolation is used at the boundary pixels within each part. This leads to a histogram equalized image that has much better contrast but Ordinary adaptive histogram equalisation tends to overamplify the contrast in near-constant regions of the image, since the histogram in such regions is highly concentrated. Contrast limited adaptive histogram equalization helps fix this issue by putting an upper limit on the intensity values of the pixels to prevent excessive contrast in uniform regions. CLAHE limits the amplification by clipping the histogram at a predefined value before computing the CDF. This predefined value is called the clip limit. Part of the histogram above the clip limit is cut and redistributed uniformly throughout the histogram.

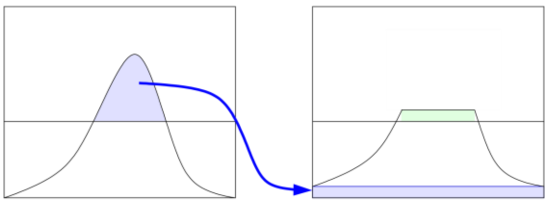

Fig -5: Clip Limit(CLAHE)

This gives us a near perfect contrast limited equalised image in which it is easier to classify the tumor as either malignant or benign.

2.3 MSRCR

The camera perceives a scene differently than how the scene would have looked to a naked eye. The human visual system can distinguish between different colors in different illumination conditions. But this is not the case with a camera. This is mainly because of the difference between the dynamic range of a camera and the human visual system. Dynamic range is basically the difference between the largest and smallest value a certain quantity can assume. Multiscale Retinex with Color Restoration (MSRCR)[13] is a technique that enhances images taken under different illumination conditions to the level that a human eye has perceived it in real time. The property that MSRCR tries to achieve is called 'color constancy' .

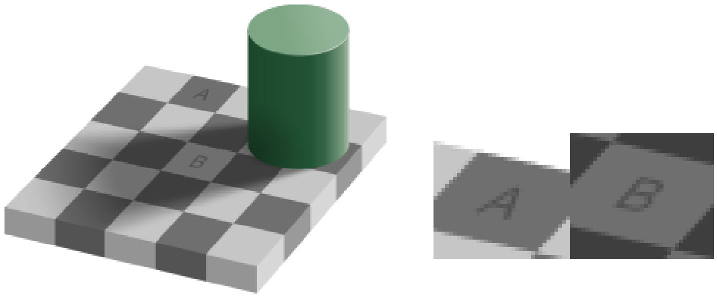

Fig -6: Color constancy

In Fig. 6, there are two blocks 'A' and 'B'. The block 'B' is under the shadow of the cylinder. It can be observed that the color of block 'A' appears darker as compared to color of block 'B'. This is because of the difference in illumination. But in fact both blocks 'A' and 'B' have the same color. This effect is known as color constancy.

MSRCR is a combination of three techniques: 1) Single Scale Retinex (SCR), 2) Multi Scale Retinex (MSR) and 3) Color Restoration.

1) Single Scale Retinex: The SCR equations can be represented as,

$$R_i(x, y) = log[I_i(x, y)] - log[F(x, y) * I_i(x, y)]$$

where, Ri(x,y) is the retinex output, Ii(x,y) is the input image, F(x,y) is the Gaussian Blur kernel and '*' is the convolution operation. The Gaussian Blur uses a constant which can be varied to produce desired results. For SCR, this constant is fixed to a certain value.

2) Multi Scale Retinex: MSR is basically the weighted sum of outputs produced by SCR for different values of Gaussian Blur constant. The equation for the same can be represented as,

$$R_{MSR_i} = \sum_{n=1}^{N} w_n R_{ni}$$

where, N is the number of constants, Rni is the output for nth constant and wn is the weighted associated with nth constant.

3) Color Restoration: This step is mainly required because of the 'gray world assumption'. It states that an image with enough color variations, the average value of RGB pixel values should be a common gray value. In images where a certain color may dominate, the MSR step may produce a grayish image. Hence, to solve this problem, Color Restoration is required. The color restoration process is defined as a function of chromaticity. Chromaticity can be found by

$$C_i(x, y) = \beta lo[\alpha . I_i^{'}(x, y)]$$

where, Ci is the chromaticity, β is the gain constant and α controls the strength of nonlinearity. The term I'i(x,y) is given as,

$$I_i^{'}(x, y) = \frac{I_i(x,y)}{\sum_{j=1}^{S} I_j(x,y)}$$

where, S = 3 for RGB image

Finally, the chromaticity of the image is multiplied to the output of MSR to produce MSRCR output. MSRCR is represented as,

$$R_{MSRCR_i}(x, y) = C_i(x, y) . R_{MSR_I}(x, y)$$

The R_{MSRCR}(x,y) is then normalized using a minmax scaler.

3. Implementation:

As discussed before, we have trained our VGG-16 model using three techniques: 1) Without applying any image enhancement, 2) Applying CLAHE to images before training, 3) Applying MSRCR to images before training. The ISIC dataset consists of 25331 images. The following table gives the configuration of the model.

Table -1: Model Configuration

Optimizer	Adam
Loss	Binary Cross-Entropy
Metrics	Accuracy
# Training Images	80% (20265)
# Validation Images	20% (5066)
Batch Size	120
# Epochs	50

This configuration is the same for all 3 cases mentioned above.

Our problem is a binary classification problem to classify images into benign and malignant, so we used binary_crossentropy.
The binary cross entropy loss function calculates the loss of an example by computing the following average:

$$Loss = \frac{-1}{output\ size} \sum_{i=1}^{output\ size} y_i . \log y_i + (1 - \ )_i . lo(1 - y_i)$$

where yi is the scalar value in the model output, yi is the corresponding target value, and output size is the number of scalar values in the model output.

We used the Adam Optimizer for the training and compiling the model. The goal of using an optimisation function is essentially to optimize the loss function and arrive at ideal weights. The adam optimizer uses an algorithm in which the stochastic gradient descent method is leveraged for performing the optimization process. It is efficient to use and consumes very little memory.

3.1 CLAHE

Fig.7 shows the original image on which we are going to apply clahe image enhancement technique. Fig.8 is the corresponding image histogram of the original image.

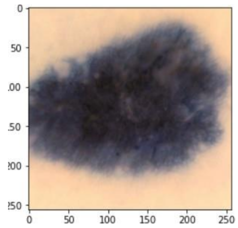

Fig. 7 Original Image

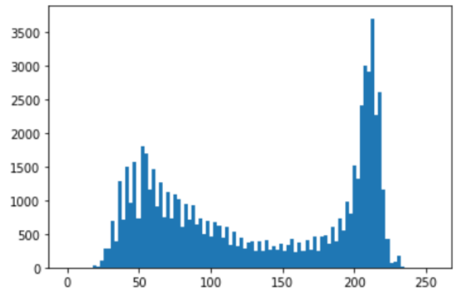

Fig. 8 Original Image Histogram

We then apply histogram equalization on the original image to improve the contrast of the image. Fig.10 shows the histogram of the image after applying histogram equalization and Fig.9 corresponds to the image of the equalized histogram.

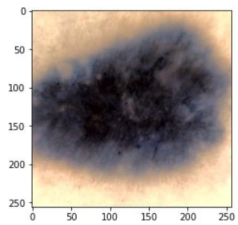

Fig. 9 Image after applying Histogram equalization

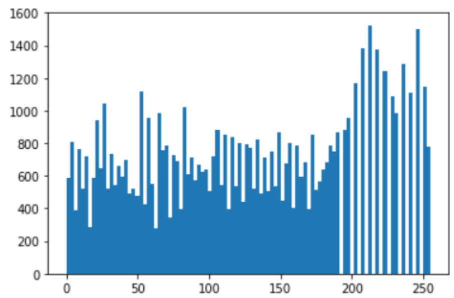

Fig.10 Image Histogram after applying Histogram equalization

We then apply clahe image enhancement technique as discussed before on the histogram equalized image.

Fig. 11 shows the difference between the original image and the enhanced image obtained after applying the Clahe technique.

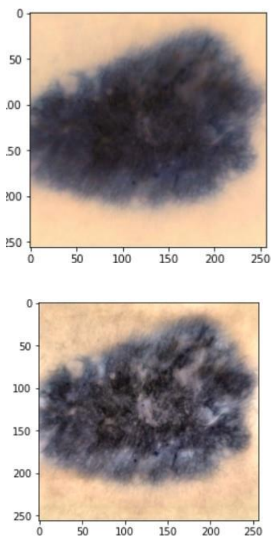

Fig. 11 Original Image(top) vs Image(bottom) after applying CLAHE enhancement technique

By using the CLAHE enhancement technique the visibility of the image has significantly increased, and all distinct parts of the image can be easily differentiated.

3.2. MSRCR

The MSRCR image enhancement technique discussed before was applied on all the images. Fig. 12 shows the difference between the original image and the enhanced image obtained after applying the MSRCR technique. The original image seems to be low in brightness. The enhanced image obtained after applying MSRCR has an increased brightness and contrast.

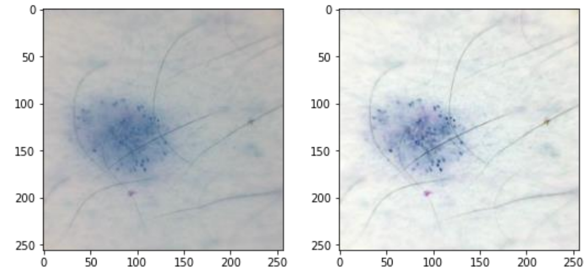

Fig -12: MSRCR

4. Results :

4.1 VGG16

The training and validation accuracy obtained without applying any image enhancement on the dataset is shown in Fig.13 (top). We trained our model for 50 epochs for a batch size of 120 images. The training accuracy gradually increases approximately from 0.81 (81%) in the #1 epoch to 0.92 (92%). The best training accuracy, 0.925 (92.5%), is achieved at epoch #44. The training accuracy is steady at around 0.92(92%). The value of validation accuracy is a little bit different from the training. In Fig. 13, the validation accuracy of the dataset is steady at around 0.83(83%). The best validation accuracy is 0.85(85%) that achieved in epoch #20. In Fig.13 (bottom), the training and validation loss is plotted. As the number of epoch increases, the loss decreases exponentially for both training and validation sets. After the 50th epoch we see that the validation loss (0.624) is slightly greater than the training loss (0.316).

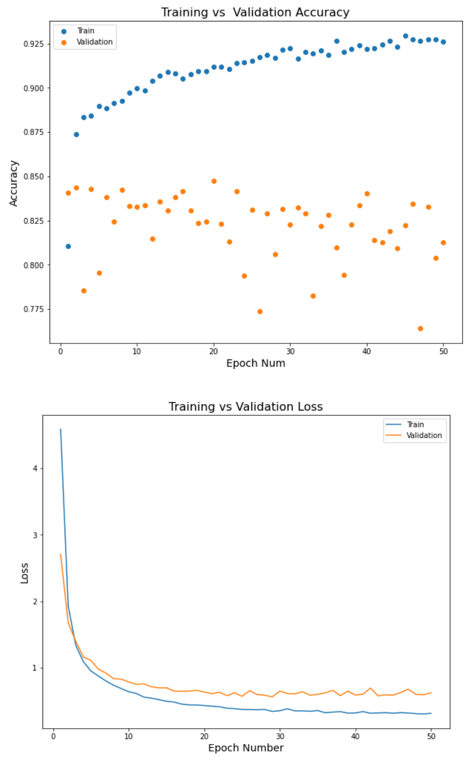

Fig -13: VGG-16 model results

4.2 CLAHE

The training and validation accuracy obtained by applying CLAHE image enhancement on the dataset is shown in Fig.14(top). We trained our model for 50 epochs for a batch size of 120 images, as in the previous case. We see that the training accuracy gradually increases approximately from 0.80 (80%) in the first epoch to 0.93 (93%). The best training accuracy, 0.93 (93.0%), is achieved at epoch #47. From the graph, the training accuracy is steady at around 0.925 (92.5%). The value of validation accuracy is a little bit different from the training but steadier as compared to the VGG16 trained model. In Fig.14, the validation accuracy of the dataset is steady at around 0.83(83%). The best validation accuracy is 0.84(84%) that achieved in epoch #20. In Fig.14 (bottom), the training and validation loss is plotted. We see that as the number of epoch increases, the loss decreases exponentially for both training and validation sets. After the 50th epoch we see that the validation loss (0.710) is slightly greater than the training loss (0.377).

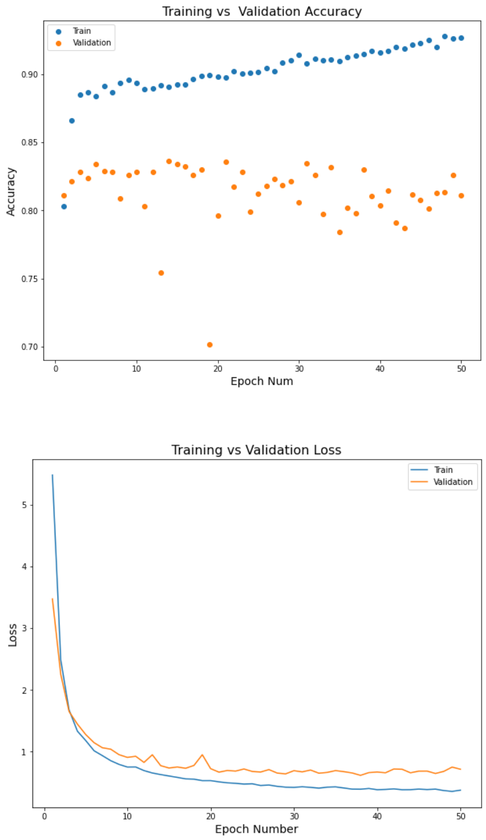

Fig -14: CLAHE results

4.3 MSRCR

The training and validation accuracy obtained by applying MSRCR image enhancement on the dataset is shown in Fig.15(top) We trained our model for 50 epochs for a batch size of 120 images, as in the previous case. We see that the training accuracy gradually increases approximately from 0.805 (80.5%) in the first epoch to 0.918 (91.8%). The best training accuracy, 0.923 (92.3%), is achieved at epoch #49. From the graph, the training accuracy is steady at around 0.91 (91%). The difference between the validation and training accuracy is more than that of the VGG16 trained model, but lesser than that of the CLAHE trained model. In Fig.15, the validation accuracy of the dataset is steady at around 0.82(82%). The best validation accuracy is 0.83(83%) that achieved in epoch #19. In Fig.15(bottom),the training and validation loss is plotted. We see that as the number of epoch increases, the loss decreases exponentially for both training and validation sets. After the 50th epoch we see that the validation loss (0.795) is slightly greater than the training loss (0.377).

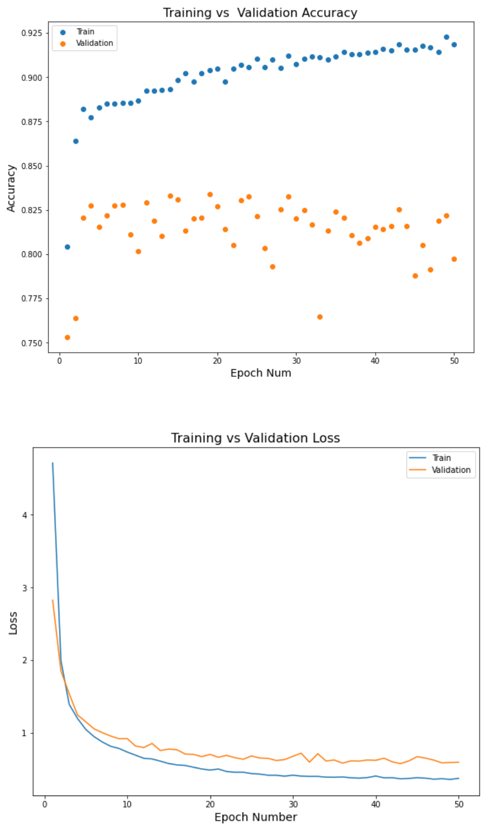

Fig -15: MSRCR results

5. CONCLUSIONS

In this study, we applied and studied the effects of applying two image enhancement techniques, CLAHE and MSRCR, on the ISIC Skin Cancer Dataset. Table 2 shows the training and validation accuracy obtained at the 50th epoch for each of the methods.

Table -2: Model Accuracy

Methodology	Training Accuracy	Validation Accuracy
VGG-16	92%	81.2%
CLAHE	92.6%	81.3%
MSRCR	91.9%	80%

We conclude that the accuracy of the model after applying all the techniques is similar although the CLAHE model gives a marginally better accuracy as compared to other models.

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