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Table of Contents

Impact of Pixel Scaling on Classification Accuracy of Dermatological Skin Diseases Detection

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***Abstract*—Images are made up of many features on which the performance of the system used in processing them depends. Image pixel values are one of such important features which are often not considered. This study investigates the importance of image preprocessing using some calculated statistics on the pixels of skin images in classifying images using HAM10000 dataset. Image pixel values make a great impact on the classification performance of Convolutional Neural Network (CNN) based image classifiers. In this study, the 'original pixel values' of the skin images are used to train three carefully designed CNN architectures. The designed architectures are further trained with some calculated statistical values using 'global centering', 'local centering', 'dividing pixel values by the mean' and 'root of the division' techniques of data normalization. The results obtained have shown that, out of the five different forms of values used in training the architectures, the CNNs trained with the original (unscaled) image pixel values perform below those trained with calculated statistics that are computed on the image pixel values.**

Keywords—image pixel scaling, image preprocessing, classification accuracy, dermatological skin diseases

I. INTRODUCTION

Skin infections have been rated to be the most common of all diseases [1] and dangerous of all cancers [2]. There are many skin conditions that affect man, which are diagnoseable and identifiable by their various symptoms [3] and are accordingly treated by skin experts. The traditional process of screening skin infection for classification involves a pathologist performing prognosis examination on the infected part of the skin [4]. This is followed by biopsies which involve removal of the affected skin portion for laboratory investigation [5] to establish cancer presence in the skin area. To further classify the infections to appropriate types, another group of medical experts specialized in autopsy performs histopathology on the skin sample [6] to grade the diseases for appropriate medical administration. This process requires the patient to wait for some period of times thereby his condition becomes more severe, unbearable financial burdens committed and wrong classification may be specified at the end which will subsequently lead to administering wrong medication. The adoption of deep learning and the continuous growth and availability of computing power have made the classification of image models more efficient [7], [8]. The representations (features) learnt by an image classifier have been proven to have noticeable effect on the performance accuracy of the classifier [9]. The effects of some of these image features as discussed in some literatures include image quality distortions [10], image compressions [11], illumination quality [12], image resolution [13], [14] and spatial resolution [15]. One other feature that has direct impact on image classification is the pixel which has not got much attentions of the researchers, especially on dermatological images.

A pixel in digital imaging is the smallest addressable element in an all points addressable display device, so it is the smallest controllable element of a dermatological skin image. Each pixel is a sample, and represents the original image more accurately [16]. The variation in the pixel values denotes the intensity of the color representation presence at a particular point of an image. Image pixel scaling involves generation of new image with higher or lower number of pixels without loss in the quality of the image [17]. The need for scaling the pixel information of an image is necessary to remove the unwanted pixels from the image [18] thereby preparing the images for processing. Image preprocessing is highly required in preparing image data to bring improvement to the features of the image data. This improvement suppresses unwanted distortions and/or enhancing some important image features which can result in improved data to work on [19]. Data normalization is an imperative measure taken in image pre-processing. The goal of normalizing image values is to change the values of numeric columns in the dataset to a common scale especially when there are different ranges in the features of the data [20].

This study aims at analyzing the experimental study of applying different statistical scaled values and their effects on the classification accuracy of dermatological skin diseases detection. To achieve this, a proposal of an experimental methodology is designed. In the designed experiment, the Convolutional Neural Network (CNN) architectures used are built to make up of different convolutional filter sizes. In each of the experiments, the network is trained and evaluated using the calculated statistics computed on the pixel values of the HAM10000 dermatological dataset collected from the Medical University of Vienna. The result of this study may be different from the ones obtained in the previous investigations for the fact that the features used in training the networks in this work are directly extracted from the images, and not transformed nor deformed in any form.

The remaining part of the paper is organized as follows: Section 2 highlights some previous related research works, while section 3 describes the methodology and the experimental set up used in performing the experiment for the study. The results and discussion are carried out in Section 4 of the paper while Section 5 presents the conclusion and future work.

II. RELATED STUDIES

As the application of deep learning pathological skin diseases classification and diagnosis has become widespread, many researchers have put on the responsibility of investigating the contribution of some features on the processing of skin images and consequently, on the resulting accurate classifications. For example, authors in [21], examine the effect of image compression on telepathology. In carrying out the task, they selected ten diagnosed cases from the teaching files of Department of Pathology, University of Illinoise Hospital, Chicago. Each of these ten samples was then snapshot in six different forms and captured with a Polaroid DMC 1 digital camera. The original (uncompressed) images were saved in Windows bit-map and later compressed using Adobe PhotoShop 5.0. These images were compiled and sent on the internet. The selected sets were monitored on the net by a group of ten experts according to a laid down protocol. The final diagnosis based on the glass slides from UIC was used as the reference diagnosis. Independently, three among the authors did compare the correspondents' diagnoses blindly with the reference diagnosis using four categories of classification evaluations: no diagnosis (n=0) when no diagnosis was provided, no difference (n=1) if there was total agreement with the reference diagnosis, minor difference (n=2) if the disagreement to the reference diagnosis was minor and did not require any change in the management of the skin diseases, and (n=3) when the difference in the correspondence diagnosis required that a major alteration be carried out in the malignant administration. The work equally adopts the following four categories of confidence levels and these are n=0, when no response was provided by an expert, n=1 for very confidence, n=2 for quite confident while n=3 when there was no confidence. Assessment of images quality were placed on five categories; n=0 (no response), n=1 (excellent response), n=2 (very good response), n=3 (fair response) and n=4 (poor performance). The results were analyzed using comparison of proportions. The results from the analysis show that there were no statistical differences at the rates of acceptability for both compressed and uncompressed image samples at 95% level of confidence interval. Similarly, there was no difference statistically at the rates of accuracy for the samples at the same 95% level of confidence interval. The results further reveal that no notable deviation was observed when the assessment was carried out on the quality of both the compressed and uncompressed images at 95% level of confidence interval. This investigative work considers the ability of pathologists in diagnosing skin disease using telepathology if the original samples are manipulated with compression technique of image preprocess. The experiments performances were evaluated using statistical analyses, does not employ an algorithmic process and does not work on the pixel values of the pathological images.

In another studies, [22] carries out investigation on the effect of lossless compression of JPEG2000 on diagnostic virtual microscopy. The authors have previously in one of their efforts, established that image quality is not destructed by lossless compression. In this new work, evaluation was carried out on virtual 3-dimentional microscopy using JPEG2000 whole slide images of gastric biopsy specimens. The authors collected specimens of gastric biopsy from the Department of Pathology, Otto-vonantrum mucosa (VM) and scanned to 0.23µm resolution. With the aid of Kakadu software, 3D slides of uncompressed (that is lossless compression; 1:1) images were created, as well as samples derived from lossy compression using ratios 5:1, 10:1, 20:1. These compressed slides were mixed up and diagnosed by three senior pathologists in a blinded manner according to the updated Sydney classification. The consultants made use of a Windows XP system which was connected to monitor resolved to 1600 x 1200 pixels for VM. SPSS software was used in performing the statistical analysis considering 0.5 level of significant. The results obtained from the pathologists reveal that there exists significant variation from the observation made by Consultant B while grading the density of Helicobater pylori gastritis (H pylori), but in the detection of H pylori, there was no significant difference. In the grading of neutrophil inflammation and in the evaluation of its presence, the significant difference was obtained from the observations made by Pathologist C. It was also shown from the results that out of 46 observations, maximum of 2 false negatives were observed by Pathologists A and B, while C claimed to have observed as much as 9 false negatives. The results further revealed that Pathologists A and B diagnosis specificity performance was over 0.9, while that of C was not beyond 0.9. Similarly, Pathologists A and B recorded above 0.85 while determining the sensitivity performance of their diagnoses, but the highest recorded by pathologist C was 0.8. The results of the K-values show that A and B achieved up to 0.8, while that of C was rated to be 0.77. The observations made by the three pathologists indicate that there is no better performance in the diagnosis of H pylori of the same malignant with the use of lossy compression. It is summarily established that there is no any significant effect made by JPEG2000 compression ratio up to 20 on the detection of H phlori. This study only shows the relative performances of human diagnosis ability using statistical analysis.

Moreover, [23] explores the need to define a clinical task in the valuation of quality of digital pathology image. In the research work, an experiment was performed (at the pre-study level) to select an appropriate test parameters for image alterations. In the main study, three experimental cases were conducted using the same samples of pathology and were overseen by six pathologists. These three experiments were designed to function using different protocols. The images used were collected from animal pathological samples, magnified by 40 with the use of a BX50 Olympus microscope. An approximate area of 1200 x 750 was removed from the original pixel images dimensioned 2776 x 2074 to fit the image presentation requirements. The image qualities were effected with the methods of Gaussian blur, unsharp masking, decreasing/increasing gamma, increasing/decreasing color saturation, adding low/high frequency white Gaussian noise, and JPG compression. These were applied on every reference image once at a time. In an attempt to achieve the set goal, the six pathologists selected to evaluate the experiment were screened for color vision deficiencies but all passed the examination. These observers performed three experiments each, and to answer some questions as regard the quality of color digital images from pathological clinics. The questions are :– (1) what are the effects of image alterations on clinical performance? (2) How sensitive are pathologists to image alterations? And (3) how do pathologists judge IQ and its attributes? Analysis carried out on the image data was performed with the use of median and inter-quartile range while Kruskal-Wallis testing was performed to take the level of statistical significance. The results obtained revealed that the findings are in agreement with the experimental question 1. However the findings in experiments (2) and (3) do not agree with the questions set. While the results from experiment (2) indicate that the pathologist could not notice the JPG artifacts similarity with high similarity M-JPG and M-NONE, the PIQ results from experiment (3) show that the observers failed to observe what had previously been observed in (1). The authors made use of animal skin samples, did not use any preprocessing technique to ensure full control over the alteration of the images, the experiment was not algorithimic as well.

The first study that adopts a conventional algorithm to evaluate human related skin problem is [24]. Visiopharm HER2-Connect image algorithm is used to evaluate the level of Human Epidermal Growth Factor Receptor 2 (HER2) in immunohistochemical images. In their own efforts, the authors collected and digitalized samples of 55 different patients diagnosed with breast cancer. Of these 55 samples, 30 were analyzed with score 0, 10 samples with 1+, 5 samples were analyzed with 2+ and the remaining 10 were analyzed with 3+. Four image variation parameters which include brightness, contrast, JPEG2000 compression and out-of-focus blurring were applied on each of the images to obtain HER2 scores. The Visiopharm HER2-Connect image algorithm was utilized and its robustness against images serially degraded with the four image parameters was graded. This algorithm was to detect and quantify the amount of HER2/neu (c-erb2-2) in formalin-fixed, paraffin-embedded breast tissue. While the successively degraded images were generated by computer simulation using Matlab. The results obtained show that HER2 scores reduced when illumination increases, compression ratios are higher and when blurring is increased, but inflated with high contrast. It is also established that image adjustment did not affect the cases with no HER 2 score. While the study utilizes a conventional algorithm to solve epidermal problem, it is observed that the problem solved is limited to the breast cancer only which excluded the other parts of the human skin.

Moreover, the authors of [25] explore the impact of JPEG 2000 compression on deep convolutional neural networks for metastatic cancer detection in histopathological images. They proposed an algorithmic CNN based image classifier to detect cancer metastases in the lymph nodes of human breast. The effect of reducing the quality of the image data was monitored by applying different ratios of compression on the image samples used for both training and testing of the algorithm. The dataset used for the experiment is CAMELYON16 image dataset, collected from some clinics in the Netherlands. The images consist of WSIs of pixels resolved to approximately 0.243µm. A total of 650 thousand of size 300 x 300 pixels patched image data was generated with the aid of CNN patched classifier. The proposed CNN which uses Inception_v3 architecture was used to perform binary classification on the inputted data. In training the network, 14 different compression ratios of JPEG algorithm were used to compress samples of 150 thousand from the regions with positive WSIs and 500 thousand from the negative regions. The effect of changing compression ratios of JPEG on the performances of the classifier was measured in three different instances. In the first instance, the system was trained with the original images and its performance was measured using degraded quality images of different ratios of compression. Here, the performances of the CNN in both F1 score and AUC evaluation metrics were observed to be decreasing as the image quality decreases due to increase in compression ratio though of no considerable changes. The performance values of 0.927 was recorded for F1 score and 0.981 for AUC at the compression ratio of 24:1, the point where high disparity exists between performance and compression. In the second instance, the quality of the training and testing images were made to be the same, the performance of the CNN image based classifier shows that a CNN is efficient in handling images compressed with higher ratio as there exists manageable differences under various ratios. The results show that there is significant improvement in the performances as the compression ratios increase. The experiment in the third scenario examined the performance of the CNN on images of various qualities when trained with a fixed compressed images. The results obtained here indicate that the performance recorded for F1 score; 93.4% is the highest at the compression ratio of 48. The implication of this is that the ratio of 48:1 is capable of performing almost equal well on all higher and low quality samples. This study establishes the fact that the CNN is adaptable to maintaining its efficiency on images of different qualities once its parameters have successfully learnt. Though, the study utilizes an analytical algorithm to assess performance of classification on degraded pathological images, which were transformed into another form which might have defected the pixels contained in the images. To our conviction, the effort and all the previous ones have not studied the effect of the original pixels of the skin images in the performance accuracy of the skin diseases classification.

III. METHODOLOGY

A. Materials

In carrying out this study, dermatological HAM10000 dataset, published by the Medical University of Vienna, Harvard is used. The dataset is adopted in examining the performance of CNNs to classify dermatological skin diseases into seven different classes.

The dataset contains a total of 10,015 samples of skin images collected from different populations of various background. This sum is obtained from the total frequency of the disease types as shown in *Table 1*. These images were manually cropped with lesion centered to 800 x 600px at 720PDI. Manual histogram corrections as well were applied to enhance visual contrast and color reproduction [26].

TABLE 1. THE FREQUENCY DISTRIBUTION TABLE OF THE SKIN DISEASE TYPES

S/N	DISEASE TYPES	ACCRONYM	NUMBER
1.	Actinic keratoses and intraepithelial carcinoma disease	Akiec	327
2.	Basal cell carcinoma	Bcc	514
3.	Benign keratosis-like lesions	Bkl	1,099
4.	Dermatofibroma	Df	115
5.	Melanoma	Mel	1,113
6.	Melanocytic nevi	Nv	6,705
7.	Vascular lesions	Vsasc	142
Total			10,015

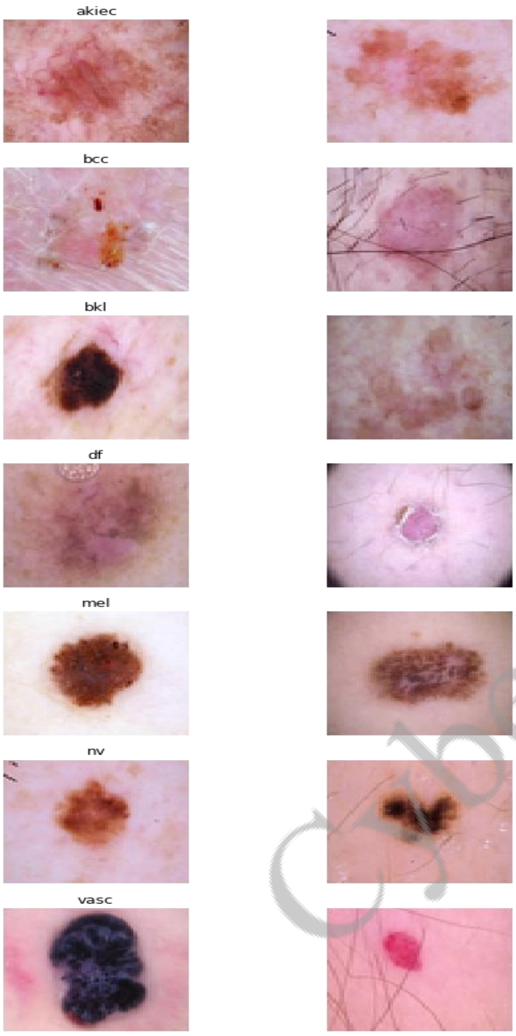


Fig. 1. Samples of infected skin image caption

The number of samples in the Melanocytic nevi (Nv) class is reduced by 5,000 to 1,705 to check its dominance over others, the number of samples considered for the study is 5,015.

B. *CNN Architectural Design*

In order to make a difference, three architectural networks are carefully designed for the purpose of realizing the set goal on image data. The scaled and unscaled pixel values of the images are then used to train the designed network architectures. The performance metric accuracy, which is the metric used in measuring the performance of the network architecture is observed in each case. The activation function used in output node is softmax. The choice for choosing softmax as the activation function is informed by its probabilistic interpretation in classifying values [27], especially when the values are more than two.

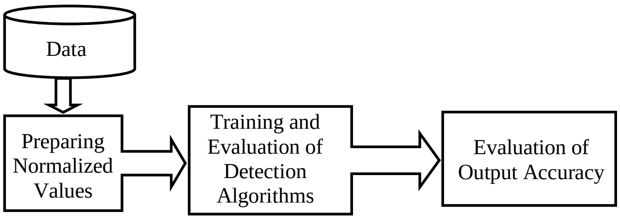


Fig. 2. Architecture of the detection process

C. *Preparing Normalized values for the images*

In preparing the data for processing, the pixel values of the skin images are extracted, some statistics are performed on the pixel values. The classifiers are then trained with the original (unscaled) and scaled pixel values.

To scale the pixels of the images for the training and evaluation of the CNN based image classifiers; 'global centering' and 'local centering' techniques are used. Also, 'division of image pixel value by the mean' and 'root of the division' are determined on the image pixel values. These statistics are discussed as follows:

1) Unscaled pixel

Here the original pixel values of the image data are directly fed into the classifier to train the model. The motive of using the original pixel values of the images is to set a base line for comparative analogy to meet the goal of this study. The function for this method is:

$$f(x) = x \tag{1}$$

2) Global Centering

Scaling of pixel values to have a zero mean. This is one of the popular data preparation techniques for image data. The method involves subtraction of the mean of the entire pixel values from each of the pixel values across the color dimension or channels. These are computed before being normalized to avoid feeding the network with negative values. Equation (2) below defines the global centering function.

$$f(x) = x - mean(x) \tag{2}$$

3) Local Centering

Calculating one mean per channel arrays. With this technique, the mean of the pixel values of each color channel is determined and subtracted per channel hereby centering the values of the pixels in the particular channel. The technique does not center the pixel values to zero but to values nearest to zero. Equation (3) defines the computational function for this technique.

$$f(x_i) = x_i - mean_{ichannel}(x) \tag{3}$$

4) *Dividing by mean*

The pixels are scaled by dividing the values of the pixels by their means. The function used here is defined (4)

$$f(x) = \frac{x}{mean(x)} \tag{4}$$

5) *Root of the mean division*

After dividing the value of a pixel by the mean, the square root of the division is further taken to reduce the value to more appreciable real computable values. The function applied to obtain the values used here is

$$f(x) = \sqrt{\frac{x}{mean(x)}} \tag{5}$$

D. Training and Testing

Different sessions of training and testing were performed to analyze the effects of different computed statistics on the performances of the classifiers. The standard classification performance metric accuracy is used to evaluate the classifiers' performances. Accuracy is the most intuitive performance measure which is a ratio of correctly predicted observation to the total observations.

After the preparation, each of the CNN based image classifiers is implemented using Python Anaconda library and Keras with the Tensorflow backend. The architectures of the designed CNN image based classifiers are detailed in *Tables 2, 3* and *4*.

TABLE 2. ARCHITECTURE 1

Convolutional Filter	Filter Size	Activation Function
Conv2D Conv2D maxPooling2D	(32, (3, 3)) (32, (3, 3)) (2, 2)	Relu Relu
Conv2D Conv2D maxPooling2D	(32, (3, 3)) (32, (3, 3)) (2, 2)	Relu Relu
Dense Dropout	128 0.2	Relu
Dense Dropout	64 0.2	Relu
Dense	7	Softmax
Number of Parameters	1,680,807	

TABLE 3. ARCHITECTURE 2

Convolutional Filter	Filter Size	Activation Function
Conv2D Conv2D maxPooling2D	(32, (3, 3)) (32, (3, 3)) (2, 2)	Relu Relu
Conv2D Conv2D maxPooling2D	(64, (3, 3)) (64, (3, 3)) (2, 2)	Relu Relu
Dense Dropout	128 0.2	Relu
Dense Dropout	64 0.2	Relu
Dense	7	Softmax
Number of Parameters	840,807	

TABLE 4. ARCHITECTURE 3

Convolutional Filter	Filter Size	Activation Function
Conv2D Conv2D maxPooling2D	(32, (3, 3)) (32, (3, 3)) (2, 2)	Relu Relu
Conv2D Conv2D maxPooling2D	(64, (3, 3)) (64, (3, 3)) (2, 2)	Relu Relu
Conv2D Conv2D maxPooling2D	(128, (3, 3)) (128, (3, 3)) (2, 2)	Relu Relu
Dense Dropout	128 0.2	Relu
Dense Dropout	64 0.2	Relu
Dense	7	Softmax
Number of Parameters	707,239	

IV. RESULTS AND DISCUSSION

Performance metric accuracy is considered in measuring the performance of the CNN based image classifiers in the experiments. The results obtained from an experiment are the ratios of the correctly predicted observations to the total observations. The results of the training testing performance are shown in *Table 5*.

TABLE 5. THE RESULTS OF THE EXPERIMENTS

Statistics	**CNN Classifier**		
	Architecture 1 (Accuracy)	**Architecture 2 (Accuracy)**	**Architecture 3 (Accuracy)**
Unscaled pixel values	50.4	54.2	54.5
Local centering	58.39	59.4	56.8
Global centering	55.39	61.0	58.2
Division by mean	58.4	59.8	56.8
Root of division	60.0	61.8	60.8

It is observed from *Table 5* that all networks are very sensitive to the image pixels despite non-specific pattern of performances across the calculated statistics. The sensitivity to the values may be connected to the weights of the pixel values in each experiment. The network is more sensitive to smaller real values.

According to the results obtained in *Architecture 1*, classification accuracy rate of 60% is obtained from training the network with 'root of the division of x values by the mean(x)'. The training with 'division of x by the mean(x)' and 'local centering' perform higher after the 'root of the division' with approximate scores of 58.4% classification accuracy. The network performs lower when trained with 'global centering' with performance rate of 55.39% and least performance is obtained when it is trained with the 'original pixel values' of the skin images with an accuracy of 50.4%.

Similarly, in *Architecture 2*, the network performs best when trained with the 'root of the division of the x values by the mean(x)' with 61.8% and performs very low with 54.2% when trained with 'unscaled pixel values'. In contrast to the order of the performance in the *Architecture 1*, the performance of the network with 'global centering' comes next to the leading grade with 61%, while the training with the 'division of x value by the mean' comes third having performed at 59.8%. The network records 59.4% accurate performance when trained with ‘local centering’, which is the fourth grade in performance record.

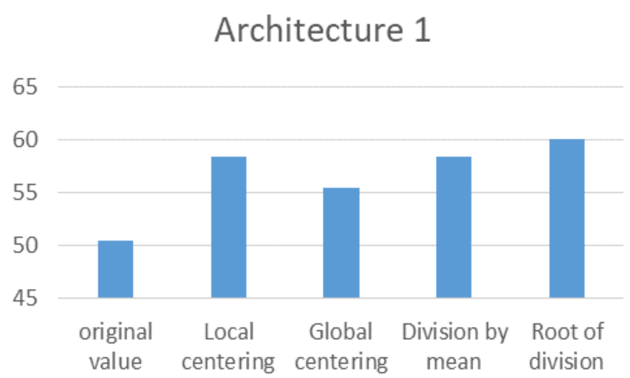
The results obtained from *Architecture 3* show that the network equally performs better when trained with the ‘root of the division of x value with the mean(x)’ than with trainings on other calculated statistics by producing an accuracy of 60.8%. As recorded in *Architecture 2*, the ‘global centering’ comes second in ranking with 58.2%. This time, the performances with both the ‘local centering’ and ‘division by mean(x)’ come third with accurate performance of 56.8% each while training with the ‘original pixel values’ records the least accuracy performance with 54.5%.

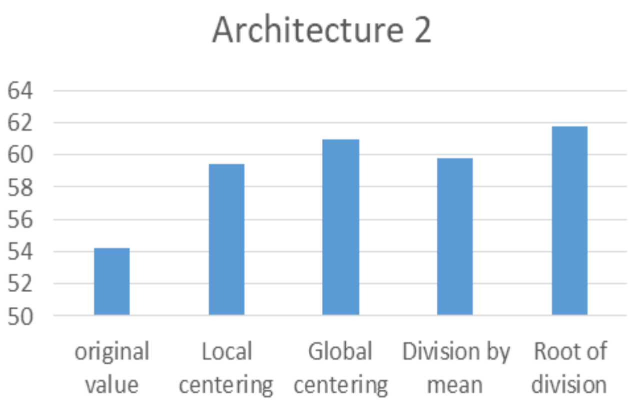
It is expected that the order of performance be maintained in the three network architectures, but this was not. While ‘local centering’ and ‘division of x value by the mean(x)’ techniques perform better than ‘global centering’ technique in the first *Architecture 1*, the performances of the ‘global centering’ technique in *Architectures 2* and *3* are better than the performances of ‘local centering’ and ‘division by mean(x)’ techniques. The discrepancy in the performance patterns across the three CNNs may be attributed to the small number of image data set used for the training [28].

However, it can be seen that the CNN architectures performances are consistently high when trained with the technique of ‘root of the division of x value by the mean(x)’ over other calculated statistics. The best performance with this technique can be attributed to the values involved whose range is very minimal due to the small sizes of the values of the calculated statistics which is very easy for an instance based algorithm like CNN.

Also, the performances of the networks when trained with the ‘unscaled pixel values’ of the skin images are generally low across all the CNN architectures. The networks perform the least on the original pixel values of the images. This is obviously connected to the fact that the values are only not preprocessed, but equally very diverse big, expectedly having a big range of values.

Pictorial representations of the results obtained from the experiments are further made in the comparison graphs in Fig. 3. The graphs provide visual analysis of the performances of the *Architectures 1, 2* and *3* on the statistics calculated on the image pixel values.





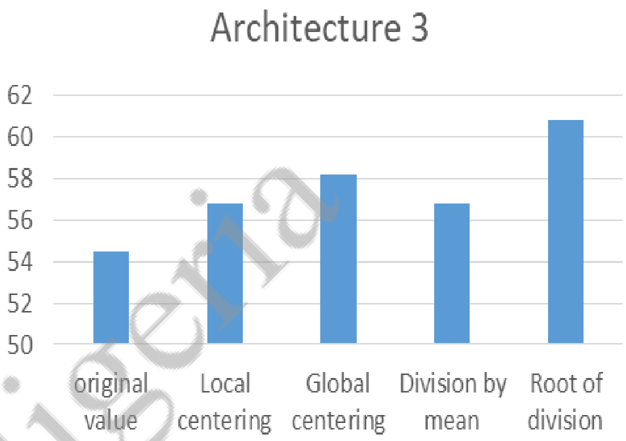


Fig. 3. Charts showing visual interpretations of the results

V. CONCLUSION AND FUTURE WORK

This study proposed a methodology and implemented on HAM10000 dataset for the study of effects of pixel scaling on the performance accuracy of CNN based image classifiers. The results obtained have thereby provided solution to the problem. From the analysis presented above, it is revealed that ‘the root of the division of the x value by the mean(x)’ outperforms all other calculated statistics, while the ‘original pixel values’ performs the least in all network architectures. Our results also show that a CNN image classifier performance is lower when trained with the original image pixel values but greater when the pixel values are scaled, irrespective of statistics calculated on the pixel values of the images. Finally, it is empirically being established that performance of the classifier is obviously affected by the image pixel values. This finding can assist in designing a more efficient skin disease classifier in the future.

The results obtained here emphasize the impact of calculated statistics on skin image pixel values using CNN architectures. With these results, having observed that there is no specific pattern in the order of performances of the network architectures on those calculated statistical values, it is a future task to enquire whether the parameters trained in an architecture have effect on performance accuracy of the skin diseases classification.

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