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DERMATOLOGICAL DISEASES PREDICTION USING HYBRIDIZED PIXEL SCALING, SYNTHETIC MINORITY OVERSAMPLING AND CONVOLUTIONAL NEURAL NETWORK TECHNIQUES Keywords: Dermatological diseases, image pixel scaling, classification, data balancing ABSTRACT The fast growing and acceptability of Artificial Intelligence in medical sector has provided for an improvement in the detection and treatment of many kinds of ailments including skin diseases. Pixel scaling is a key operation in the

12**classification of skin diseases** imagesß. To improve **the** performance **of** our **skin disease** detection **and**

clasffication model, this paper presents a new pixel scaling technique called Mean Pixel Division. The work uses the

1**HAM10000 Dermatological dataset** obtained **from the** University **of**

Harvard

1**to train** a **carefully designed CNN** architecture. At **the**

preprocessing stage, each pixel value is divided by the mean of the entire channel in scaling the image

1**pixel values to** reduce **the range of the values to a** manageable level. Realizing **the**

challenge of imbalanced data and insufficient of data in the sector of Medicine, data balancing technique is required to improve and balance the data classes to provide fair recognition for all classes of data during training. Synthetic Minority Oversampling Techniques (SMOTE) is adopted to overcome the challenge of unbalancing in the data classes' distribution. The designed CNN architecture was trained with the proposed technique as well as with some existing scaling techniques; Unscaled Pixels, Local Centering and Global Centering. At the end of the experiments, it is observed that the proposed technique; Mean Pixel Division outperforms the existing ones having recorded 99.62%, 98.66% and 99.78% performance accuracy, sensitivity and specificity respectively. INTRODUCTION The

2**adoption of Artificial Intelligence (AI) in medicine**

has made activities of the experts in health sector easy. The medical personnel have been able to utilise the acquisition of digital medical images, store the acquired images and process them to solve problems arisen from traditional methods of diagnosis, treatment, patients monitoring, drug administration, medical data collection, selecting appropriate treatment approach and in analysing the collated results (Mendeley, 2018). Dermatological images are among the clinical images faced by the aforementioned problems prior the empowerment of medical systems with the state-of-the-art in detecting and classifying disease symptoms. The cancer of the skin has been generally proven to be the most common and dangerous of all types of cancers (ACS, 2019). In spite of the deadly nature of the skin cancer, it is 1 curable if it is promptly and accurately detected and treated precisely. But the procedure involved in detecting cancer undergoes a multi-stage (ABC, 2013), this always leads to time, efforts and cost consuming. Traditionally, detecting and classifying skin diseases undergo a three step procedure the first is that the pathologists, who are the experts in managing skin infections, use any of the available approaches in carrying out

1**prognosis examination on the** infectious **part of the skin**

(Mayo Clinic, 1998). The prognosis is followed by biopsies where the cell

11**sample is** removed **from the** suspected infectious **part of the skin to** undergo **laboratory**

analysis (NBCF, 2019) to confirm the presence of cancer. If it is established that the skin portion is infected, it undergoes another process known as staging where additional examination is carried out to grade the degree of spread of the disease in the skin (NCI, 2020). The classification of the diagnosed tumour is carried out by histopathologists who are other medical experts responsible for autopsies examination (AnaPath, 2019). This process consumes times and the results always lack accuracy, which invariably leads to wrong management of the skin lesion which is more calamitous. The adoption of Machine Learning technique and continuous acceptability of automating power have proffered simplified solutions to the problems of time consumption, high cost of resources involved and that of the misclassification (Yanming et al., 2016, Shin et al, 2006), hence mismanagement of skin related issues overcome. The machine learning algorithm most suitable for image classification is the Convolutional Neural Network (CNN) because of its ability to group images by matching and also to identify substances. It extracts and learns special features (or representations) of the image and maps them from the upper layer of the algorithm to the lower layer down to the output point where the detection and classification are performed. Features contained in an image

1**make a great impact on the performance** accuracy **of**

any classifying algorithm (Wang et al., 2019). Efforts were made in the past to establish the influences of some these image attributes on image classifiers in some existing research works. Samuel and Lina (2016) worked on the effect of image quality distortions, Mathieu et al. (2017) explored the effect of compression of image, Sanchez

14**et al. (2016**) studied **the impact of** illumination **feature. The** attention **of**

(Chavalier et al., 2015) was on the image resolution, Suresh & Gaurav (2018) examined the effect of image spatial resolution in the study. However, the amount of data and structure of datasets have a noticeable impact as well in the classification performance accuracy of a classifier (Foody et al, 1995, Soleyman, 2018). The performance of a classifier, where some classes dominate others by having more instances, will be biased towards these classes with higher samples and while little or no attention will be paid to the minority classes. Medical images are generally scarce, and sometimes irregularity in the number of instances in the various classes of the dataset (Belarouci & Chikh, 2017) are some of the challenges faced when classifying medical data and the ones related to dermatology is not an exception, this necessitates data resampling in this study to improve the performance of the classifier. 2 Many researchers

2in the field of Artificial Intelligence (AI) have

come up with different scaling techniques in attempts to proffer computer vision solutions to diagnosing and classifying the skin infections. However, low performances recorded by these techniques are indications that they are deficient and there is need to improve on their performances to enable the reliabilities of the classifying algorithms. However, the hybridization of the existing scaling techniques with the popular augmentation method of generating data has not improved the performances of the models to an acceptable level, as most of the existing studies persistently augmented image samples to compliment the available ones. Hence, there is need to look inward to other scaling technique hybridized by another method of data generation to improve the performance of the image classifier. Therefore, this system is capable of extracting the pixels from dermatological images,

1**calculating some statistics on the pixel values**, synthesizing additional samples **to the**

minority classes using a more robust image sample generating technique, processing them and classifying the skin samples, on high performance rates, into seven classes of skin related issues. The

2**aim of this** research **work is to develop a**

hybridized image scaling, synthetic oversampling and Convolutional Neural Network techniques to detect dermatological diseases. RELATED STUDIES

4**Deep Learning is fast becoming a key instrument in Artificial** Intelligent (**LeCun et al., 2015**

).

4**One of the** problem areas **where deep learning excels is image** processing **classification (Rawat** and **Wang, 2017). The goal** of **image classification is to classify a specific** image object **according to a set of possible categories**

. This has been emphasised in numerous literatures. The attempts were to provide computerized systems capable of performing skin issues diagnosis as performed by human dermatologists, but in an effective and more accurate manner. Several studies carried out for classifying the skin diseases have established that the use of instant based algorithm is more robust and accurate than the traditional method of classification carried out by the human experts. Some of these previous studies are reviewed as reported in the literature. Pathiranage (2017) developed as many as four different CNN models which were trained for the classification of skin diseases with varying various required parameters. Each of the trained CNNs was trained with various number of layers arranged in different forms, number of training steps as well as learning rates of various values. The architectures were equally designed to use different activation functions and optimizers different from each other. The author in his effort considered classifying only two types of skin diseases out of many, the system may fail to produce accurate classification if an image of a skin lesion different from the ones it was trained with is fed into the architectures. 3 Arkadiusz et al. (2017) as well carried out analyses on three pre-trained CNN architectures; VGG19, RESNET and and hybrid of VGG19 with SVM. The research work used over ten thousand skin images in classifying benign and malignant in the experiment. In evaluating the performance of the experiment, the k-fold validation technique was used to compare the pre-trained structures using specificity, sensitivity and accuracy metrics. The research work also emphasised on the categorisation of skin diseases into two classes. Xinyuan et al. (2017) combined methods of expert knowledge and deep learning to classify skin disease images. The skin image data collected from the Hospital of Peking Union Medical College were screen by two or more dermatologists before being finally diagnosed. The skin images were processed using the GoogleNet network architecture. The study, while preprocessing the data flattened the pixels values, divided into two subsets A and B, and then fed theses into the network for classification. At the end of the experiments, an average of 87.25% and 86.63% respectively were obtained for data sub- sets A and B. The misclassified images were analysed by the group of experts in attempt to improve on the diagnosis results. The study sees importance in exploiting the image pixel values, but did not scale the values to reduce the range. Another study work was carried out by Han et al. (2018) classifying the uniqueness of skin lesions classes. The study process was emphasized on identifying twelve different skin lesions either belong to the benign and malignant meta classes. A total of nineteen thousand, three hundred and ninety-eight (19,298) image samples used for experimentation were obtained from five different sources which are the Asan skin image dataset, public/biopsy proven data, the Edinburgh Image Dataset, Hallym Image Dataset and Atlas Dermatological data sites. The training experiments were performed by fine tuning the CNN MS-ResNet 152 on the ImageNet pre-trained model using the Asan training set, Atlas and MED-NODE image samples, while the validation process was performed with the samples from Hallym, Edinburgh and the test dataset of the Asan. The results of the experiments were later compared with the diagnosis carried out by a team of sixteen (16) human experts who made their observations through assessment of the original image. The results of the experiments reveal that the system’s Area Under the Curve performances values for the Asian skin samples are 0.96, 0.83, 0.82 and 0.96 in classifying BCC,

7**squamous cell carcinoma, intraepithelial carcinoma and melanoma** respectively. On **the**

use of the Edinburgh samples, the AUC values are 0.90, 0.91 and 0.83 respectively. The limitation of the study could be categorisations of skin infections into two classes, as well as not minding the exploration of the skin features. Danilo and Nilton (2018) as well proposed a model for the classification of twelve skins related issues. This study chosen to use three sets of dermatological datasets, the first is the MED-MODE, containing one hundred and seventy skin samples which were classified into one hundred nevus and seventy melanoma cases. Another dermatological dataset used by the study is Edinburg, made available by the Edinburg Dermofit Image 4 Library (EDIL). It consists of one thousand, three hundred skin related samples of ten types of skin diseases. Also used are the skin samples from the Atlas Skin Image dataset, which contains skin issues of six types. The collection of the three datasets did not produce enough samples for training, hence were augmented and fed into the pre-trained RESNET152 architecture for classification. The results of the experiment show that the accuracy of the training was 78% which can still be improved on. In the recent time, Agilandeeswari et al., (2019) used texture based segmentation to classify skin lesions. In approaching the classification process, they applied filters to segregate the lesion area of the skin and the unwanted background from the skin image. The Gray Level Co-occurence Matrix (GLCM) was after this used to extract the features from the lesions area before being forwarded for processing in a CNN classifier. The study obtained an average of 96% accuracy of skin classification. The study did not explore the image pixels and the accuracy can be improved upon. In most recent time, Sriwong et al. (2019) employs the integration of the skin image data with patients' details to determine the performance of Convolution Neural Network. The study made use of the skin images collected from the Medical University of Vienna, Harvard and published by Tschandl et al. (2008). A deep learning approach was utilised in designing the process of the skin diseases classification. To achieve their aim, Feature Extraction Support Vector Machine (FESVM) was pre-trained along the AlexNet CNN image classifier that was employed for the training. At the training and validation stage, five rounds of experiments were performed, one each for the AlexNet transfer learning, FESVM, FESVM+Age, FESVM +Age+Sex and FESVM+Age+Sex+Location. The results reveal that the pre-trained AlexNet model produced

16**training accuracy of** 84.94% **and testing accuracy of** 79.29%, while **the**

FESVM performed 100% training accuracy and 78.7% testing accuracy. The results obtained when the description of the patients were added indicate that each of the FESVM+Age and FESVM+Age+Sex produced 100% training accuracy and 80.16 testing accuracy. The training and testing accuracies obtained from the addition of the three attributes to the image samples are 100% and 80.39% respectively; hence the combination that performs the best among the five scenarios. The concern here is that the system may not be efficient when the details of the patients are not available. Majority of the previous studies except Sriwong et al. (2019) classified skin diseases into either malignant or benign skin lesions. Above all, there is deficiency in the existing image pixel techniques and the various performances can be improved upon. Therefore, this study seeks to propose an image pixel scaling technique capable of improving

1**on the** existing **accuracy of image classifiers**

. MATERIALS AND METHODOLOGY The proposed technique predicts the diseases related to human skin into seven classes. The tecnique

1**is designed to classify dermatological** HAM10000 **dataset into 'Akiec**', 5
'Bcc', 'Blk', 'Df', 'Mel', 'Nv', and 'Vasc

'. The

2**Convolutional Neural Network (CNN**) architecture **used for**

this study was carefully designed. The

1**image data** were **preprocessed by** scaling **the pixel values**

in order

1**to bring the range of the pixel values to a bearable size**

. Every class contributes to the performance of the model, the sample distribution that the classes are imbalanced, classifiers biased against the minority classes while more recognition is accorded the majority classes, so the issue of class imbalancing is addressed by synthesizing the samples in the minority classes using Synthetic Minority Oversampling Technique (SMOTE). The CNN architecture

1**designed for this study** is **then trained with the** synthesized values **and tested with the testing set to evaluate the performance of the** proposed technique. **Performance**

metrics used

19**to evaluate the model** are **accuracy**, sensitivity **and**

specificity. Figure 1

1**shows the architecture of the designed model of skin diseases classification**

. Data Collection Image Pixel Scaling Data Balancing Image Preprocessing Training and Evaluation

1**Skin Diseases Classification** 6 Figure **1: The** process structure **of the**

model (A) Data Collection The dermatological HAM10000

1**dataset collected from the Medical** University **of**

Vienna, Harvard (Tschandl, et al, 2008) is used for the study. It consists of

1**a total** number **of 10,015 images collected from different populations**

over different locations and races and is presented in Table 1.

1**Table 1: The distribution table** for **the skin disease types S/N DISEASE ACCRONYM NUMBER 1**

. 2. 3. 4. 5. 6. 7.

6**Actinic keratoses and intraepithelial carcinoma/Bowen's disease Basal cell carcinoma Benign keratosis-like lesions Dermatofibroma Melanoma Melanocytic nevi Vascular lesions**

13**Akiec Bcc Bkl Df Mel Nv Vasc 327 514**

1,099 115 1,113 6,705 142 Total 10,015 The

1**distribution of the** diseases **in the HAM10000 dataset**

is represented in a bar chart as shown in Figure 2.

1**Chart Showing the Distribution of the Skin** Samples **in the HAM10000 Dataset**

8000 7000 6,705 Akiec 6000 Frequency Bcc 5000 4000 Bkl 3000 Df 2000 1,099 1,113 Mel 1000 327 514 115 142 Nv 0 Vasc NUMBER Linear (Akiec) Disease Type Figure 2. A Chart Representing the Original Skin Distribution in the Dataset The samples of the dermatological images are as shown in Figure 3. 7 (

3**a) Melanocytic nevus; (b) benign keratosis; (c) vascular lesion; (d) dermatofibroma; (e) intraepithelial carcinoma; (f) basal cell carcinoma; and (g) melanoma. Legends inside each image represents clinical data such as age, sex and localization associated to the image. F: female; M: male; LE: lower extremity; B: back; H: hand; T: trunk. Figure** 3. Sample picture **of the**

seven Skin types in the HAM10000 Dataset (B) Data Preprocessing Preprocessing of data is highly required in the development of machine learning model as a result of the huge size of the datasets. This is necessary to improve the features of the images by removing undesirable representations of the images so as

17**to enhance the performance of the image**

classifier. In this study, some data preprocessing techniques were applied on the HAM10000 dataset in simplifying the samples for processing and in improving the performance of the proposed model. (B) Image Pixel Scaling It is observed from the vector representation of the images that there exists a very large range in the pixel values as presented in the matrices. It is therefore necessary to reduce the range of the values by scaling down pixel values. The following pixel scaling techniques are applied on the image pixels. (i)

1**Unscaled Pixel** Values **Here the original pixel values of the image data are directly** used in training **the** model without being subjected to any manipulation. The

1**motive of using the original pixel values of the images is to**

establish or otherwise the impact of the computed statistics on the performance of the classifier. It is on the performance of the model using other values 8 are based upon for analysis. The mathematical representation for the non-scaled (original) pixel value is as defined in Equation (1). f(x) = x (1) (ii)

1**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** image channels **values from each** pixel value across **the** colour channels. **The**

approach is called centering because the pixel values are centered on the value zero. Here, the whole mean is subtracted from each of the pixel value and the values

1**are computed before being normalized to avoid feeding the network with negative values**

. The

1**function for this** technique **is: f(x**

) = xi – μ (2) (iii) Local Centering: Determining a

1**mean per channel arrays. With this technique, the mean of the pixel values of each** colour **channel is** calculated **and subtracted**

from the pixel values within the particular Channel thereby causing centering to the pixel values

1**in the channel**. This **technique does not** zero **center the** mean but **to**

a value nearest to zero. The mathematical function derived for this technique is in Equation (3) f(x) = xi – μchanneli (3) (iv) Mean Pixel Division: As the name implies, the mean of the entire channel is determined (otherwise called global centering), and each of the pixel values in the particular channel is divided by the mean to obtain a transformed array of pixel values, which is then used to train and

9**evaluate the performance of** the classifier. **The** function **of the** proposed scaling **is defined as** stated in Equation (4). f(x) = xi μ (4) where f(x) = the function defined on the pixel values, xi = a pixel value on the image, μ = mean of the colour channel, μchanneli = mean per channel. (C) Data Balancing The method of

2Synthetic Minority Oversampling Technique (SMOTE) is applied on the

original data distribution to improve on the amount of instances available in the minority classes, and

1on the performance accuracy of the proposed classifier. 9 The use of SMOTE technique of

sampling balancing has enabled the duplication of samples in the minority classes and made the amount of instances across the classes be equal. The training set of 9,015 instances is synthesized to 42,469. Table 2 reveals the amount of samples, before and after synthesizing in each class. Table 2: Original and synthesized samples of the training set SN Skin Type Acronyms Original Frequency Frequency before synthesised Frequency after synthesised 1 Akiec 327 292 6,067 2 Bcc 514 449 6,067 3 Bkl 1,099 985 6,067 4 Df 115 103 6,067 5 Mel 1,113 991 6,067 6 Nv 6,705 6,067 6,067 7 Vasc 142 128 6,067 Total 10,015 9015 42,469 (D) Implementing the CNN Architecture The architecture is implemented with Python Anaconda library 3.5.2 based and keras 1.1.0 with the TensorFlow backend 0.3 high level API

10on a server with Intel Core i5 processor with 16 GB of RAM

. In order to classify the seven dermascopic images into their various classes, the CNN architecture designed for the classification task is trained with the statistical values obtained from the image pixels. The performance of the classifier is evaluated. The output node used is softmax because of

1its probabilistic interpretation in classifying values (Ayyuce, 2019), especially when the number of labels are

multiple as it is the case in this study. The architecture of the designed CNN image based classifier adopted is as shown in Figure 4. Vectiorisation SKIN IMAGE 64 x 64 x 3 Input Image Vectors Conv 32 Average Pool 2 x 2 64 x 64 x 32 32 x 32 x 32 Output Conv 64 Average Pool 2 x 2 FC 1 6 3 FC 1 6 3 Dense Blk Akiec Bcc 32 x 32 x 64 16 x 16 x 64 8 8 Df Mel 4 4 Nv 10 FC = Fully Connected Figure 4. The Architecture of the CNN Classifier Implemented for this Study (E) Classification After training testing stage, the results of the image processing are produced. The results obtained at this processing level are the types of the skin diseases to which each of the skin samples belongs. They are categorised into various categories as follows: -

5Actinic keratoses and intraepithelial carcinoma/Bowen's disease (Akiec) - Basal cell carcinoma (Bcc) - Benign keratosis-like lesions (Bkl) - Dermatofibroma (Df) - Melanoma (Mel) - Melanocytic nevi (Nv) - Vascular lesions (Vasc

) (F) Performance Evaluation Performance of a classifier is quantified by an evaluation metric. Confusion matrix analyses the performances of the model, the correct predicted classes, and the incorrect ones as well as the errors made during the classification process, this enables the measurement of the quality of the classifier. Hence, the quality of the classifier designed for this study is measured using accuracy,

2**sensitivity and specificity metrics. RESULTS** AND **ANALYSIS**

(A) Results In this section, the results obtained from the experiments performed for this study are presented. In an attempt towards achieving the aim and objectives of this study,

2**a Convolutional Neural Network (CNN**) based image architecture **was trained**

and evaluated over

18**training and validation sets. The** performance accuracies **of**

the experiments on some existing techniques and the proposed scaling method as well as on various data structures were monitored. 11 The CNN architecture was trained with various forms of sample distributions which include the original data structure of the dataset, weigh balancing technique and Synthetic Minority Oversampling Technique (SMOTE). The results obtained from various experiments

15**are presented in Table 4. Table 4**: The **Results of**

the Experiments Statistics Accuracies (%) Original Data Structure Weight Balancing SMOTE Unscaled Values 54.2 75.3 73.6 Local Centering 59.4 73.1 72.5 Global Centering 61.0 72.8 72.9 Division by Mean (Proposed) 59.8 73.8 74.3 The unscaled pixel values technique performed 54.2% training accuracy, the local centering technique recorded accuracy of 59.4% and while with the technique of global centering, the accuracy is 61.0%. Similarly, the results reveal that the proposed scaling technique; mean pixel division, during the evaluation period recorded the training accuracy of 59.8% accuracy. The performance of the unscaled pixel scaling technique, when trained and tested with balanced weights as shown Table 4 is 75.3%. Also from Table 4, it is observed that the accuracy of local centering is 73.1%, while that of the global centering model is 72.8% and that of the proposed technique; mean pixel division was able to make 73.8% accuracy. The results presented in Table 4 as well reveal that the unscaled pixel values technique performed 73.6% accuracy, local centering performed 72.5% and the global centering recorded accuracy of 72.9%, mean pixel division technique recorded 74.3% accuracy. (B) Results Analysis It is observed from Table 4 that the classifier is sensitive to the data structure. The sensitivity to the structure of the dataset is connected to the class balancing and the amount of data used in training the classifier. According to the results presented,

2**it is observed that the** architecture **performed better** when **the**

data were synthesized

2**with the Synthetic Minority Oversampling Technique (SMOTE**). The confusion matrices **for**

the techniques and SMOTE techniques are presented in presented in figures 5, 6, 7 and 8. 12 Unscaled Pixel Values Technique The confusion matrix for the technique of unscaled pixel values is shown in Figure 5. Figure 5: Confusion Matrix for the Unscaled Pixel Values technique From Figure 5, 589 samples, representing 99.83%, were correctly classified as 'Akiec', while 1; 0.17% was wrongly classified to be 'Bkl'. In the second row, 585 samples representing 100% were correctly classified as 'Bcc' and no instance from the class was wrongly classified. Out of 610 'Blk' present for classification, 607 were correctly classified and 3 were mis-classified to be 'Nv' and 'Bcc'. The model was able to classify the entire 610 'Df' samples correctly representing 100%. 581 of the 585 'Mel' samples, representing 99.32% were classified to be 'Mel', while 4, 2 each were classified as 'Bkl' and 'Nv' respectively. The original pixel value technique was unable to classify a total of 101, which is 15.47% of the samples belonging to class 'Nv' correctly, but was able classify up to 552 samples representing 84.53% correctly. However, the entire samples totalling 614 belonging to the 'Vasc' class was classified into 'Vasc' class. In overall, out of the total 4,247 samples classified, the model was able to classify a total of 4,138 samples correctly and 109 wrongly to achieve 99.27% performance accuracy. Local Centering Scaling Technique Figure 6 shows the confusion matrix for the local centering method. 13

8**Figure 6: Confusion matrix for the** local centering technique **The** confusion matric for **the**

method of local centering in Figure 6 has shown that all 590 'Akiec' samples were correctly classified representing 100% classification. Similarly, the model achieved 100% classification in classifying the instances belonging to the class 'Bcc'. The model was able to classify 606 out of 610 samples of the class 'Bkl' correctly, and the remaining 4 which represent 0.66% of the samples in the class. Also, the entire 610 samples of the class 'Df' was correctly classified, but 98.46% of the of 'Mel' samples totalled 576 instances were classified correctly. In the 'Nv' class, the classification performance as shown in the table indicates that the model was able to classify a sum of 550 representing 78.24% of the class correctly while the remaining 103 samples were mis-classified. However, all the 614 samples contained in the class 'Vasc' were correctly classified. With these classifications, the model was able to classify a total number of 4,131 samples correctly and 116 wrongly to achieve a performance accuracy of 99.22% Global Centering Technique 14 The confusion matrix of the global centering technique is shown in Figure 7.

8**Figure 7: Confusion matrix for the** method **of** global centering **The**

global centering technique classified all the samples belonging to 'Akiec' and 'Bcc' classes correctly to achieve 100% classification in each case. In the case of the ''Bkl' class, it was able to classify 99.67% standing for a sum of 608 out of 610 samples in the class correctly, and only 2 were not correctly classified. The method was able to classify the entire samples in the class 'Df' correctly as 'Df' samples hence, recording 100% accuracy. The instances of the class 'Mel' were 585, the method was able to classify up to 584 correctly but only 1 to the class 'Bkl', to achieve a performance accuracy of 99.83%. Also, it records 84.53% accuracy for classifying 552 samples belonging to the class 'Nv' correctly, while it mis-classified 101 of the samples representing 15.47% to other various classes. The classification performance of the technique in classifying the class 'Vasc' is accurate, classifying the entire 614 samples of the class correctly, to obtain 100% classification accuracy. In all, the technique was able to classify a sum of 4,143 instances correctly, which represents 99.30% of the classified samples and was unable to classify 104 samples representing 0.70% correctly. The Division of Pixels by the Mean Technique The confusion matrix for the method of division of pixel value by mean is presented in Figure 8. 15 Figure 8: Confusion matrix for the technique mean pixel division The classification results in Figure 4.4 show that the technique was able to classify 637 samples out of the 639 of the class 'Akiec' correctly, to achieve 99.68% classification accuracy. The method records a classification accuracy of 89.19% while classifying the 'Bcc' class for have classified 582 instances correctly. Furthermore, 604 of the 616 samples of the 'Bkl' class were correctly classified to belong to the class, recording 98.05% classification accuracy. The technique records classification accuracy of 98.71% for classifying up to 614 samples of 622 samples contained in the class 'Df'. 593 samples were correctly classified to belong to 'Mel' class representing 96.42% classification accuracy, it misses 22 representing 3.58% of the entire samples in the class. 597 instances of the 598 samples present for classification in the class 'Nv' were correctly classified representing 99.83%, while 99.62% of the 565 samples of the class 'Vasc' was correctly classified to belong to the 'Vasc' class. Overall performance shows that the pixel scaling technique achieves a classification accuracy of 99.62%. 4.5 Performance Evaluation The training and testing accuracy performances of the pixels scaling techniques were monitored during the experiments. The techniques were further evaluated using accuracy, specificity and sensitivity performance metrics computed from various confusion matrices. The performance evaluation of the image scaling techniques were performed and presented in Table 5. Table 5: Summary of the Results for Performance Evaluation 16 Scaling Technique Accuracy Sensitivity Performance Measure (%) Specificity Unscaled Pixel Value 99.27 97.43 99.57 Local Centering 99.22 97.27 95.55 Global Centering 99.30 97.55 99.59 Mean Pixel Division 99.62 98.66 99.78 Figure 9 shows in summary the visual presentations of the accuracy, sensitivity and specificity results of the performance evaluation. Chart Showing the Results of Model Evaluation 101 100 99 98 97 96 95 94 93 Accuracy (%) Original Value Local Centering Sensitivity (%) Global Centering Specificity (%) Division by Mean Figure 8: Chart showing the performances of the models From the results presented in Table 5 and as shown on Figure 8, it is obvious that the Mean Pixel division scaling technique out performed other models with 99.62% performance accuracy, 98.66% sensitivity and 99.78% specificity, hence can be adopted for the classification of dermatological skin diseases. CONCLUSION AND RECOMMENDATION (A) Conclusion This study proposed and implemented

2**a Convolutional Neural Network (CNN) based**

image classifier, enhanced with image scaling and image data synthesising techniques. 17 The model is capable of classifying dermatological images of skin diseases into seven classes;

7**akiec, bcc, bkl, df, mel, nv and vasc. The**

aim was achieved having fulfilled the objectives enlisted to pursue the goal of this research work. The CNN architecture was trained using a number of techniques, which are unscaled value, local centering, global centering and mean pixel division. The performances of the techniques were further evaluated to enable the adoption of the best performing one using accuracy, sensitivity and specificity performance measures. The evaluation results obtained indicated that the model mean pixel division outperforms others having scored 99.62% accuracy, 98.66% sensitivity and 99.78% specificity. (B) Contribution to Knowledge The study has been able to contribute to existing knowledge by developing and successfully implementing a CNN image detecting architecture enhanced with pixel mean division technique for classifying skin diseases. (C)

Recommendation This study has been able to introduce a new pixel scaling technique in classifying skin diseases and by extension, image classification. However, there is room for improvement, research can further be carried out on finding the root of the division to see if the reduction in the pixel values will bring any improvement to the results obtained. The model can still be evaluated using other algorithms.

REFERENCES Mendeley. (2018). Retrieved from https://www.mendeley.com/careers/news/careers- jobs-field/artificial-intelligence-medicine. Accessed on 12/4/2021 All About Cancer (2013). Cancer Detection. Retrieved from www.allaboutcancer.fi>detection. American Cancer Society. (2019) Skin Cancer. Retrieved from www.amp.cancer.org>cancer AnaPath (2019). Things to know about Histopathology. Retrieved from https://anapath.ch/things-to-know-about-histopathology/. Accessed 12 – 11 - 2020 Mayo Clinic (1998). Diagnosis: Cancer Screening. Retrieved from www.mayoclinic.org. National Breast Cancer Foundation (2019). Inc. About Breast Cancer. Retrieved from www.nationalbreastcancer.org 18 National Cancer Institute (2020). Skin Cancer Treatment (PDQ). – Patient Version. Retrieved from www.cancer.gov. Shin, H. C., Roth, H. R., Lu, L. Xu, Z., Nogues, I., Yao, J., Mollura, D., and Summers, R. M. (2006). Deep Convolution Network for Computer Aided Detection: CNN Architectures, Dataset Characteristics and Transfer Learning. IEEE Transactions on Image Processing. Vol 15, issue 2, pp.430-444. Yanming, G, Yu, I., Ard,O., Songyang, L.,Song, W., and Micheal, S. L. (2016). Deep Learning for Visual Understanding: A Review. Neurocomputing. Vol. 187, pp.27-48. Wang, H., Chong, D., Huang, D., and Zou, Y.(2019). What Affects the Performance of Convolutional Neural Networks for Audio Event and Classification. 2019 8th International Conference on Affective Computing and Intelligent Interaction Workshops and Demos (ACIIW). Pp.140-146, doi: 10.1109/ACIIW.2019.8925277. Samuel, D., and Lina, K. (2016). Understanding How Image Quality Affects Deep Neural Networks. Quality of Multimedia Experience (QoMEX). 2016 Eighth International Conference on IEEE. Sanchez, A., Moreno, A. B., and Velez, J. (2016). Analysing the Influence of Contrast in Large-Scale Recognition of Neural Images. Integrated Computer-Aided Engineering. vol.23, issue 3, pp.221-235. Mathieu, D., Karol, D., Kamel, A., Wassim, H., Lucc, M., and Maxime, P. (2017). Study of the Impact of Standard Image Compression Techniques on Performance of Image Classification with a Convolutional Neural Network. Diss. INSA Rennes; Univ Rennes; IETR; Institut Pasca. Chevalier, M., Nicolas, T., Matheu, C., Jerome, F., Gilles, H., and Elodie, D. (2004). LR_CNN for Fine-Grained Classification with Varying Resolution, Image Processing (ICIP). IEEE International Conference. Suresh, P. K., and Gaurav, J. (2018). Effects of Varying Resolution on Performance of CNN Based Image Classification: An Experimental Study. JCSE international Journal of Computer Sciences and Engineering. vol 6, issue 9, 451-456. Belarouci, S. and Chikh, M. (2017). Medical Imbalanced Data Classification. Advances in Science, Technology and Engineering Systems Journal. DO - 10.25046/aj020316. Vol.2, pp 116-124. Rawat & Wang. (2017). Deep Convolutional Networks for Image Classification: A Comprehensive Review. PubMed. Retrieved from www.ncbi.nlm.nih.gov. LeCun, Y., Bengio, Y and Hinton, G. (2015). Deep Learning. Retrieved from www.nature.com, pp 436 – 444. Pathiranage, A. J. (2017). Convolutional Neural Networks for Predicting Skin Lesions of Melanoma. ePublications at Regis University, availaible on www.epublications.regis.edu/theses 19 Xinyuan, Z., Shiqi, W., Jie, L. and Cui, T. (2017). Towards Improving Diagnosis of Skin Diseases by Combining Deep Neural Network and Human Knowledge. BMC Medical Informatics and Decision Making, doi: 10.1186/s12911-018- 0631-9. Han, S. S., Kim, M. S., Lim, W., Park, G. H., Park, I., and Chang, S. U. (2018). Classification of the clinical images for benign and malignant cutaneous tumors using a deep learning algorithm. The Journal of Investigative Dermatology. Arkadiusz, K., Agnieszka, M., and Michal, G. (2017). Deep Neural Networks Approach to Sking Lesions Classification – A Comparative Analysis. Conference on Methods and Models in Automation and Robotics (MMAR). DOI: 10.1109/MMAR.2017.8046978 Agilandeeswari, L., Mahajan,T. S., and Keerthana, N. (2019). Skin Lesion Detection using Texture Based Segmentation and Classification by Convolutional Neural Networks (CNN). International Journal of Innovative Technology and Exploring Engineering (IJITEEE). ISSN: 2278-3075, vol.9, issue 2, pp.2117- 2120. Danilo, B. M., Nilton, C. S. (2018). Skin Lesions Classification Using Convolutional Neural Networks in Clinical Images. Computer Vision and Pattern Recognition. arXiv:1812.02316. Sriwong, K., Bunrit, S., Kerdprasop, K. and Kerdprasop, N. (2019). Dermatological

Classification Using Deep Learning of Skin Image and Patent Background Knowledge. IJML&C, vol 9, no 6. Foody, G. M., McCulloch, M. b>, and Yates, W. B. (1995). The effect of training set size and composition on artificial neural network classification. Int. J. Remote Sensing, vol. 16, no. 9. Pp.1707 – 1723. Soleyman, S. (2018). Effect of Dataset Size on Image Classification Accuracy. Online available: http://seansoleyman.com /effect-of-dataset-size-on-image- classification-accuracy/ 20