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CUSTOMIZED ALEXNET MODELS FOR AUTOMATIC CLASSIFICATION OF SKIN DISEASES

AUDREY K. C. HUONG*, K. G. TAY, XAVIER T. I. NGU

Faculty of Electrical and Electronic Engineering,
Universiti Tun Hussein Onn Malaysia, 86400 Parit Raja, Johor, Malaysia
*Corresponding Author: audrey@uthm.edu.my

Abstract

Most of the skin diseases exhibit complex, visually indiscernible features and characteristics, rendering traditional physical inspection technique fails. Meanwhile extraction of handcrafted features used in machine learning (ML) for prediction purposes may involve tedious manual labour. Different viable adaptations of deep convolutional neural network (CNN) system for automatic classification of skin diseases have not been extensively and systematically explored in the past. This could be due to the various degree of classification accuracy with complexity of the model, which also affects its modifiability, using the limited training data available. This work presents the use of AlexNet-SVM and Alex-KNN model trained with a limited data set for computer aided skin disease diagnosis. The performance of these models was also compared with that from transfer-learned AlexNet using images of skin disorders namely acne, eczema, psoriasis and rosacea. This work observed considerably consistent and good mean classification accuracy ranged in between 85 and 92 % produced by these customized models. Even though there is no correlation found between the models used in this research and their performance metrics using ANOVA t-test ($\rho > 0.05$), visual examination showed superiority of AlexNet-SVM over other models. In the concluding remark it is suggested that the highest adaptability of AlexNet-SVM to the considered task, combined with its robust and time effective advantages, make this approach an attractive tool for skin disease diagnosis. This model may be incorporated into skin health innovation as an added feature to allow accurate clinical decisions available rapidly and efficiently.

Keywords: AlexNet, Computer Aided Diagnosis, KNN, Skin disease, SVM, Transfer-learned.

1. Introduction

Skin disorders or lesions that plague integumentary system have reported in [1] to affect around one third of human population (~1.9 billion people) at a time. These skin conditions particularly that on facial region have negative impact on its bearer's life and are strongly retarding their psycho-social and emotional wellbeing. While some (such as melanomas) can be easily recognized, classifying others required domain expertise, expert knowledge and specialized equipment and modalities [2]. Acne, psoriasis, rosacea and eczema are among the commonly encountered dermatologic diagnoses [3]; they usually appear as red colour and inflamed, and sometimes accompany with pustules or blisters, whose characteristic features can be hard to unambiguously classify.

Following geographical heterogeneity in the shortage of professional dermatologists [4, 5], dermatological screening and treatment are mostly done by general practitioners who are not sufficiently trained in the area [6]. In many cases misdiagnosis or late treatment often exacerbates skin conditions that may contribute to impeded healing. This has not only led to increased financial burden to the individuals but also resources to manage them, especially those living in low-income countries [7]. Human skin disorders can be caused by either bacterial infections or overgrowth of skin flora. Some other (intrinsic/extrinsic) factors include physiological change (such as stress and hormonal status) [8] and external agents such as drugs, cosmetics, chemical or food.

The typical characteristic features used by dermatologists or medical personnel in the diagnosis including colour, size, location and shape of the lesion. Very often, this examination is accomplished with the use of other assistive devices such as dermoscopy, Wood lamp, or through clinical procedure such as biopsy. These efforts should be compounded with a great deal of experience and expertise before an appropriate treatment is instituted. Tissue oxygen saturation, which is known to be essential for any metabolic process and successful wound (lesion) healing, is commonly used to evaluate effectiveness of clinical treatment and intervention programmes. For that reason recent research and innovations [9-11] have been established in the field of adjunctive technology for dermal health screening using tissue oxygen as outcome parameter. It is of great significance that the function of these innovations is able to be extended to the classification of skin lesions to further elucidate the effectiveness of interventions or therapeutic products used on treated lesions.

Current artificial intelligence (AI) technology has gained increasing importance in works related to prediction and decision-making such as in health industry to assist in medical diagnosis processes, in economic affairs to predict the financial market, in agriculture and food industries to manage market demands and food supply-demand balance through data mining methods (see [12, 13] for a comprehensive review of recent advances of AI). This is mainly driven by the increased capacity of technology in computing systems (e.g. both distributed and cloud), Graphical Processing Unit (GPU) and edge devices (e.g., Intel® MovidiusTM NCS for inference purposes).

Computerized classification systems or computer aided detection (CAD) of skin disorders using metaheuristic approach, machine learning (ML) techniques [14, 15], deep learning convolution neural network (DL-CNN) [7, 16], and transfer learning approaches [9, 17, 18] have been performed with considerable success in the past. The earliest approach is the human-engineered optimization algorithms

proposed through either domain knowledge or simulations. This method has its fair share of uses and applications in the past decades before it was replaced by ML technique, which classification and prediction depends on the extracted hand-crafted features, a process that can be labour-intensive.

Deep learning is the current state of art of the machine learning technique, where layers of data are arranged in hierarchical structure to automatically extract important features for predictions. Prior studies demonstrated the ability of CAD to match or even surpass human performance in many computers vision tasks, such as in skin cancer diagnosis [19], in playing board games [20] and for autonomous driving vehicles [21]. It must be noted that the use improved pretrained CNN models (such as AlexNet, GoogleNet, VGG16, Xception, ResNet18) with Support Vector Machines (SVM), K-Nearest Neighbour (KNN) and gradient boosting classifiers have been shown to achieve significant success in recent years [14, 22-24]. These algorithms were also reported in [22] to have superior performance than classification output of a transfer-learned CNN model. The differences separating these approaches are in the strategy these classifiers adopted.

SVM is based on construction of single or multiple hyperplanes in solving highly dimensional and nonlinear problems by closely matching attributes of observations to the class label. KNN approximates the distribution of data in non-parametric fashion (based on spatial neighbourhood information) while gradient boosting is an iterative functional gradient descent algorithm. In the latter approach, cost function is optimized via iterative selection of points in negative gradient directions. A review and discussions of these classifiers in data mining can be found in [25-26]. T

he reported works on the use of these classifiers with pretrained CNN models and comparisons of different architectures of CNN in the field of dermatology are, however, far and few in between. This is primarily because of the variation in classification accuracy with the model complexity, whose learning requires a huge volume of data to enhance its inference performance.

A systematic comparison of different network architectures by [27] showed an increased classification accuracy at the price of higher model complexity (i.e., using VGG, Inception, etc) using abundance of data collected from several sources and exhaustive computational resources. Therefore this work is motivated to compare the performance of transfer-learned AlexNet with AlexNet-SVM and AlexNet-KNN models trained using a limited data set for computer aided skin disease diagnosis. This choice of CNN model is because of its comparatively simple and shallow architecture, resulting in much faster training speed with less memory demand [28].

Since facial dermatological diseases were reported to cause stress, depression and can adversely impact both social and psychological wellbeing of its sufferers [29, 30], only facial images are used here. We believe that the outcomes of this work may be integrated into the skin health monitor developed within this laboratory [10] to further enriching the application of this innovation. Meanwhile the relatively shallow network structure of AlexNet model making it a much preferable choice in our design for fast retraining of the model at the edge using new and updated images collected from the device. All the following simulations were carried out using MATLAB 2019b.

2.Materials and Methods

This section discusses the research methods used in the study. The first subsection summarizes the preparation of dataset required for deep learning. This is followed by the discussions of AlexNet models used in this work in section 2.2.

2.1. Dataset description

Images of skin diseases studied in this work were reproduced and used with permission from DermNet NZ (www.dermnet.org). Only facial skin images were used in this present study, so images were manually chosen from acne, eczema, psoriasis and rosacea image database. There were 206 images collected for acnes, 22 on eczema, and 33 and 49 images, respectively, on psoriasis and rosacea. The dataset for eczema, psoriasis and rosacea were enlarged by quintuple (n = 5) through augmentation during preprocessing stage. This is through rotation of main images in four directions (-10˚, 10˚, 20˚ and -20˚) and the flip of the images in horizontal direction. These augmented images of different classes were stored separately but in the same folder as their main images. In each run, we used 70 % of randomized split of data for training and 30 % for the testing. This split ratio is following the heuristic suggestion by [31] for balance training/testing proportion percentage and the results of previous investigation in [32] who reported improved classification accuracies using this ratio. The distribution of images of different skin disease classes for the training and testing process is shown in Table 1. An example of 249 sets of images used in net testing is shown in Fig. 1.

Table 1. Distribution of training and testing data.

Skin disease	Number	Total (incl. augmented)	Training data	Testing data
Acne	206	206	144	62
Eczema	22	132	92	40
Psoriasis	33	198	139	59
Rosacea	49	294	206	88
Total	**830**	**581**	**249**	

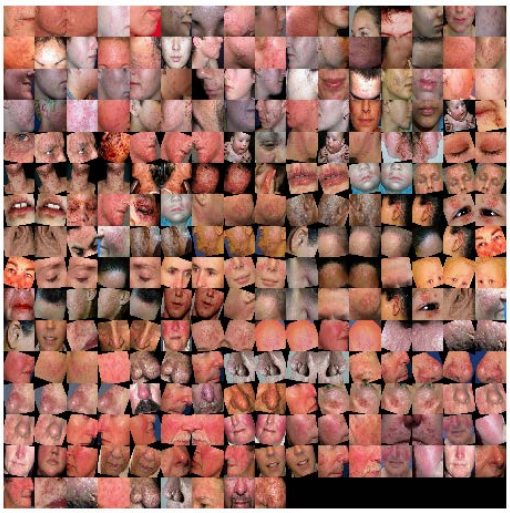

Fig. 1. Random images chosen for testing the nets.

2.2. AlexNet based CNN models

The architecture of pretrained AlexNet is shown in Fig. 2. This system consists of 25 layers of 8 main blocks comprising of 5 convolution layers (Conv) each followed by ReLU activations, and 3 max pooling layers (Pool) at 1st, 2nd and 5th block. The function of convolution networks is to apply learnt filters to input image to create feature maps, the pooling layers operate upon each feature map to create new set of pooled feature maps. The output from the 5th block is passed to two fully connected networks, fc6 and fc7, each has fixed 4096 feature vectors. These fully connected layers, fcl, take input from the pooled features and applied weights to predict the correct label.

The fc8 consists of 1000 nodes followed by Softmax that calculates the probability of class label distribution. Even though features from any fcl can be extracted, stored in features vectors, and used by classifiers (i.e., SVM and KNN) in Fig. 2 for classification, fc6 is chosen for analysis and further processes in the current study. This is on the basis that it was proved in [33] to contain most information for wide range of computer vision applications and object detection tasks. Besides, our experimentation showed evidence of a slight superiority in classification accuracy using fc6 compared to fc7 and fc8 (mean accuracy difference of < 4 %).

The three different AlexNet based CNN systems considered are: model 1, Transfer-learned AlexNet; model 2, AlexNet-SVM; and model 3, AlexNet-KNN. Both SVM and KNN approaches used error-correcting output codes (ECOC) method, whose main function is to decompose a multiclass classification problem into several binary ones, in classifying deep features according to their class label.

The AlexNet system takes only images of size 227×227×3 as its input. All images (the final total from main and augmented in Table 1) were first resized using the MATLAB's imprecise function to match the input dimension of the net. The resized images were then zero-center normalized by subtracting the mean image of dataset from every input image to bring dataset to uniformity before training and testing the nets.

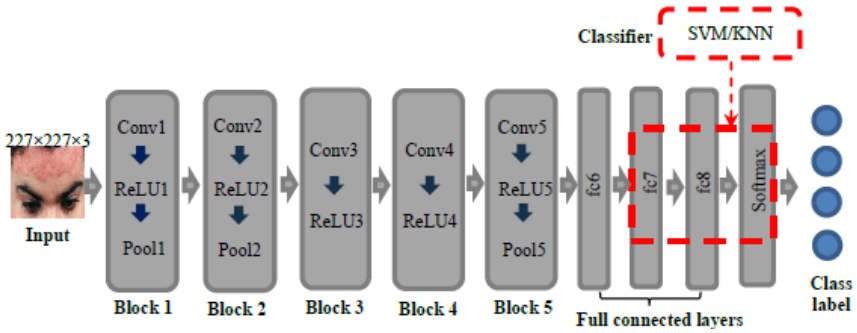

Fig. 2. CNN based AlexNet architecture. The SVM and KNN replacing classification output layers are marked by the red dashed-line boxes.

2.2.1. Transfer-learned AlexNet

The present study used transfer learning concept for retraining the AlexNet in Fig.2 using dataset in Table 1. Stochastic gradient descent with momentum (SGDM)

optimizer was used with initial learn rate of 0.01 and gradient threshold of 1 due to its shortest computational time as compared to other training methods (RMSProp and Adam) [34]. In effort to minimize the possibility of underfitting, 20 epochs and mini batch-size of 20 were chosen for the training set. These hyperparameter values were based on the acceptable ranges previously reported by [35, 36] in investigating overfitting and underfitting problems. Thus no attempts or trial runs have been made to optimize the experimental conditions. Meanwhile the number of outputs in fc8 layer was replaced with 4 nodes, each label is associated with a skin disease class in Table 1.

2.2.2. AlexNet-ECOC SVM

The SVM designed for two classes classification is combined with ECOC method (using the MATLAB *fitcecoc* function) that utilized one against one encoding scheme. The ECOC technique generates ($k(k$-1))/2 learners for k classes. Each learner is trained on the SVM classified feature vectors of training data of two class labels shown in Table 2. For example, in the case of learner 1, this learner groups all the observations (i.e., features) in acne class into a positive class (+1), eczema into a negative class (-1) and ignores observations in other classes (i.e., psoriasis and rosacea) before it was trained (on this set). The same applies to the remaining learners. During classification of a new observation (unseen sample), outputs of binary classifiers are combined to form the output codeword. This code is compared to the 6 bits codes in Table 2 by optimizing the aggregated losses using the quadratic loss function, L, given in Eq. (1) [37]. The class that has the nearest code to it is assumed as the class label of the new observation.

$$L = \sum_{i=1}^{n} w_i \left(1 - y_i f(X_i)\right)^2 \quad (1)$$

where n is the sample size, w_i is the weight for observation i, y_i is the corresponding class label and $f(Xi)$ is the classification score for observation i of the predictor data X. Readers are advised to refer to the published articles [38, 39] for the full account of the design behind the ECOC model.

Table 2. One against one binary coding scheme.

	Binary learner					
Class	**1**	**2**	**3**	**4**	**5**	**6**
Acne	1	1	1	0	0	0
Eczema	-1	0	0	1	1	0
Psoriasis	0	-1	0	-1	0	1
Rosacea	0	0	-1	0	-1	-1

2.2.3. AlexNet-ECOC KNN

Similar to the case of ECOC SVM model, this method allows binary learners to learn via KNN clustered feature vectors of different classes using one by one scheme. The binary scheme for each learner and the loss function used in the training phase are the same as that in previous section. The predictor data was standardized prior to training the learners. During experimentation, various numbers of nearest neighbour (i.e., K = 5, 7 and 9) used in KNN learner were attempted, but only for number 5 did the model perform well for testing dataset. We, therefore, discarded result from other K values, whose accuracy is inferior by a factor of at least 1.1, in the subsequent analysis.

3. Results and analysis

Due to randomization in the selection of training/testing dataset, each simulation was executed three times to effectively evaluate the performance of each model. Figure 3 shows the temporal evolution of accuracy and loss function of transfer-learned AlexNet training state versus iteration during one of its runs. The model achieved near 100 % accuracy and 0 % loss function at iteration number of 300. The average computing time taken for each run in training the AlexNet, AlexNet-SVM and AlexNet-KNN on a 64-bit operating system with processor Intel®Core i7-4600U CPU@2.10GHz are recorded and presented in Table 3.

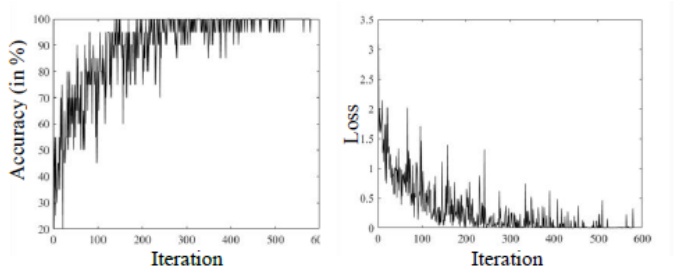

Fig. 3. (Left) Percent accuracy and (right) loss function of modified AlexNet during the training session.

The classification outputs of these models for each skin disease category from one of the runs is shown in Fig. 4. This investigation is necessary to gain a deeper understanding of the models' performances in diagnosis of each skin disease. The extended study of the classification results in Fig. 4 revealed that there were five same images (i.e., one image each from acne, eczema and psoriasis class and two from rosacea) misclassified by all the classifiers in our study. Very interestingly, all models misclassified psoriasis and eczema images as rosacea, while the rosacea images were misclassified as acne. Almost always, we recognize four potential reasons of errors in these images: (i) rarity of lesion in the image (ii) overlapping features or attributes with other class, (iii) regions that were unclear due to facial expression (canine smile), and (iv) low resolution image.

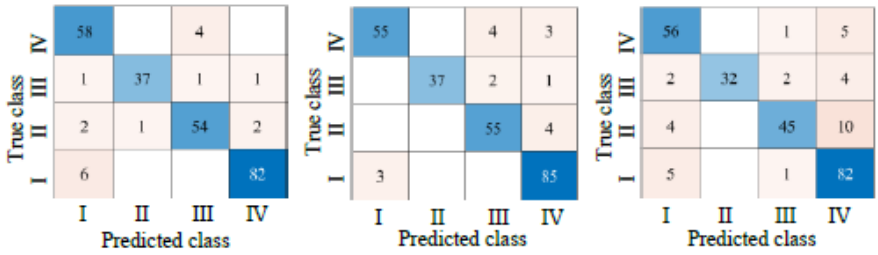

Fig. 4. Confusion matrix of prediction results (class label I: Acne, II: eczema, III: psoriasis, IV: rosacea). From left to right: modified AlexNet, AlexNet-SVM, AlexNet-KNN.

The performance of these models is further compared using misclassification error rate, ε, and classification accuracy, Acc, given in Eqs. (2) and (3). The mean

(standard deviation, SD) of the calculated performance metrics for three simulation runs are summarized in Table 3.

$$\varepsilon = \sum_{i=1}^{4} \frac{P_i n_i}{M_i} \times 100\ \% \quad (2)$$

$$Acc = \sum_{i=1}^{4} \frac{c_i}{M_i} \times 100\ \% \quad (3)$$

where n_i and c_i represent number of misclassified and correctly classified images, respectively, and Mi is the total samples in a specific class label i. P_i is the class prevalence given by the ratio between sample size in a class and total sample in all classes. Also shown in Table 3 are the reported classification accuracy of skin lesions from previous research that used similar network architectures.

Even though the SVM and KNN classifiers are observed in Table 3 to produce similar classification performance at a fraction of computation time as compared to the conventional AlexNet, it is necessary to use statistical method to confirm if the significance difference (or similarity) exists in the means of the computed outputs. To test the equality of mean classification outputs, the differences in prediction accuracy and misclassification in each class in Fig. 5 are evaluated using a one-way ANOVA test in SPSS 23 software with confidence level, σ, of 95%. The results showed statistical insignificance in accuracy performance of different models in our study (ρ = 0.498), while ρ = 0.38 was calculated for the association test between the models used herein and misclassification rate.

Table 3. Comparison of classification performance and training time of AlexNet models used in this study and in literature.

Model	Classification accuracy, *Acc*	Misclassification rate, ε	Training time (s)
Transfer-learned AlexNet†	91.36(**4.42**) %	2.34(**1.25**) %	3,780
AlexNet-SVM†	92.91(**3.6**) %	1.63(**0.93**) %	138
AlexNet-KNN †	85.53(**6.09**) %	3.21(**1.37**)%	98
Transfer-learned AlexNet [9]	84.6(**0.08**) %	-	-
Transfer-learned AlexNet [17]	91.02(**3.57**) %	-	-
AlexNet-SVM [7]	86.21 %	-	-
AlexNet-SVM [40]	94.45 (**1.96**) %	-	-
AlexNet [41]	94.55 %	-	-

†Results from this work

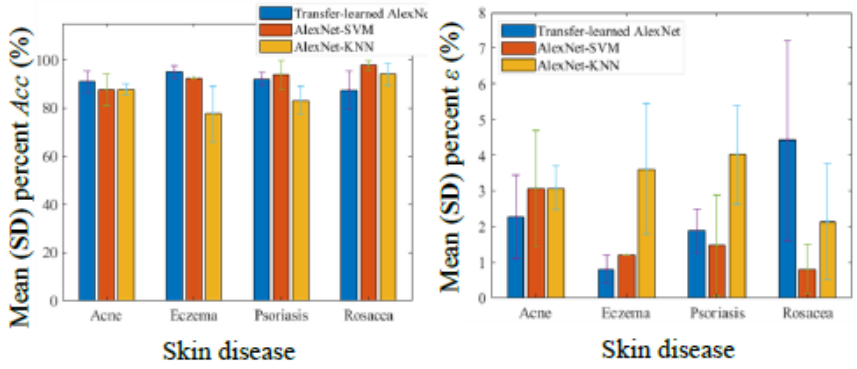

Fig. 5. Mean and standard deviation (SD) of percent (left) classification accuracy, Acc, and (right) misclassification rate, ε, for each skin disease class given by transfer-learned AlexNet, AlexNet-SVM and AlexNet-KNN.

4. Discussion

Even though the hyperparameters used in CNN training in section 2.2.2 have not been meticulously fine-tuned as that demonstrated in [42] prior to the retraining session, Fig. 3 shows the accuracy of the modified network started to saturate at 100 % at iteration number 300. This may suggest appropriate selection of parameter values for the model. This is supported by the considerably high accuracy in the prediction of the unseen test data using this modified pretrained model with mean percent classification accuracy ranged in between 85- 95 % in Fig. 5 for different skin disease class. Meanwhile in the case of AlexNet-SVM and AlexNet-KNN models, both the algorithms replaced the functions of fully connected networks. These models took results from fc6 layer without retraining the pretrained model and use them to classify image into defined classes. Thus, this has significantly reduced the computing time (up to twentyfold faster than transfer-trained approach) required in training data.

The similarity in the results of the customized AlexNets in Fig. 5 was supported by the statistical testing of the relationship between the models and their performance metrics, which ρ values showed that they are of statistical insignificance ($\rho>0.05$). However, it is evidence through the visual inspection of the plots that AlexNet-KNN model gives overall inferior results, especially for eczema. This is likely affected by the size of this particular class, as the latter has the smallest data sample of the four. Since the KNN algorithm relies on the extracted spatial information of the pixels in its clustering process [43], small training data leads to insufficient mapping of clustering assignments to the target label. It is hypothesized that the performance of this classifier may be improved through fine-tuning of the parameters used and with an increased in data size. Meanwhile in the case of transfer-learned AlexNet, the misclassification error in rosacea class is notably larger than the rest. Notably, AlexNet-SVM is shown capable of giving consistent and accurate results (i.e., accuracy 90-95 %) with rapid training time. Based on the above research findings, it can be inferred that AlexNet-SVM has better adaptability to the current dataset and may have better future of clinical application compared to other models.

Based on the comparison with the literature in Table 3, consistent results were observed for similar AlexNet architectures used in the past in [17]. The AlexNet-SVM used in [7] is similar to that used in this work, but a lower performance was reported in the precedent study. This is attributed to the differences in the choice of fcl where feature vectors are extracted, in addition to a larger number of classes considered in the study. In contrary, prior research in [41] handled smaller class groups (i.e., 3 groups) thus a slight superior performance was found. Meanwhile improvement in results of [40] is due to the advanced techniques implemented in preprocessing stage to enhance quality of the images before the training and testing sessions.

It is interesting also to note that although augmentation strategies, commonly known as a critical component of training process, have not implemented on acne image class, a considerable good accuracy with percent misclassification error of less than 3 % is calculated for this class. This further confirms the feasibility of augmentation methods used in this work to overcome the imbalanced dataset, as the considerably good classification performance in Fig. 5 (i.e., 85-92 %) showed that the augmented data served sufficiently as new and unseen dataset for training and

testing of the models. Nonetheless, it should be noted on the considerably higher rate of skin lesion images misclassified as rosacea in all models such as that shown in Fig. 4. We, therefore, do not rule out the possibility of overfitting/underfitting problems in our training. We suspected that our models suffer from overfitting to larger training sample class (i.e., rosacea). This problem may be obviated with a larger dataset used in training the model. The future of this work includes incorporate the classification system into the skin health innovation developed within this group in [10] to widen and enrich its application. This is in addition to the further enhancement of AlexNet-SVM to include closed-loop feedback system to include new/updated information given to it for retraining at edge devices.

5. Conclusions

This study demonstrated the performances of different customized AlexNet models in the classification of four skin disease classes. The results revealed a striking similarity in the performance of the retrained AlexNet, AlexNet-SVM and AlexNet-KNN ($\rho>0.05$). It was found that the performance of AlexNet-KNN depends on the data size used. This study recommended that the performance of these classification models can be improved by fine-tuning the hyperparameters and including more data in the training. The contribution of this research are our findings on the rapid training time (~2 minutes), good inference accuracy and high adaptability of AlexNet-SVM for dermatological application that suggest its excellent potential for embedding into skin oxygen innovation. All these attributes allow this model to be used for future edge retraining using new and updated images. This classifier would be useful as an added feature to the adjunctive technology for automatic and rapid skin disease classification, and for use as an assistive tool in dermatology research.

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