Multi-Class Skin Diseases Classification Using Deep Convolutional Neural Network and Support Vector Machine

Nazia Hameed*
Anglia Ruskin Research IT Institute
Anglia Ruskin University
Chelmsford
nazia.hameed@pgr.anglia.ac.uk

Antesar M. Shabut
Anglia Ruskin Research IT Institute
Anglia Ruskin University
Chelmsford
antesar.shabut@anglia.ac.uk

M. A. Hossain
Anglia Ruskin Research IT Institute
Anglia Ruskin University
Chelmsford
alamgir.hossain@anglia.ac.uk

Abstract— **Globally, skin diseases are the fourth leading cause of non-fatal disease burden. Both high and low-income countries suffer from this burden; indicates the prevention of skin diseases should be prioritised. In this research work, an intelligent diagnosis scheme is proposed for multi-class skin lesion classification. The proposed scheme is implemented using a hybrid approach i.e. using deep convolution neural network and error-correcting output codes (ECOC) support vector machine (SVM). The proposed scheme is designed, implemented and tested to classify skin lesion image into one of five categories, i.e. healthy, acne, eczema, benign, or malignant melanoma. Experiments were performed on 9,144 images obtained from different sources. AlexNET, a pre-trained CNN model was used to extract the features. For classification, the ECOC SVM classifier was used. Using ECOC SVM, the overall accuracy achieved is 86.21%. 10-fold cross validation technique was used to avoid overfitting. The results indicate that features obtained from the convolutional neural network are capable of enhancing the classification performance of multiple skin lesions.**

Keywords—skin lesion classification, convolutional neural network, skin lesion detection, melanoma classification, eczema classification, acne classification, support vector machine, error-correcting output codes model

I. Introduction

Skin diseases are a major health problem in both high and low-income countries and are the fourth leading cause of non-fatal skin disease burden [1]. Skin diseases may occur due to several factors like exposure to ultraviolet radiation, tanning, family history, environmental factors, alcohol etc. [2][3]. These factors affect the skin and have a devastating impact on its well-being. Skin diseases cause several problems like isolation, physical impairment, self-harm, body changes, difficulty in a relationship, unemployment, alcoholism and even death in case of malignant melanoma. An increased rate of suicidal attempts is also seen in patients suffering from skin diseases [4]. In the United Kingdom, sixty per cent of the population suffers from skin diseases in their life-span [5]. Classifying skin diseases require domain expertise, specialised equipment and expert knowledge and there is a gross mismatch between the burden of the skin patients and resources required to manage them [6]. Especially people living in low-income countries do not have access to these resources. Therefore, to lessen the problems caused by skin diseases, there is a strong need for intelligent expert systems that can perform multi-class skin lesion classification to help the people in early diagnosis. Acne, eczema and melanoma (benign and malignant) are among the top five most occurred skin diseases [7] in the world, hence the target of this research work is to propose and develop an intelligent expert system that can classify these skin diseases. In our previous study, we investigated the skin lesion classification using traditional machine learning approach [8]. By traditional machine learning approach, we meant a computational approach for skin lesion classification that constitutes different phases and classification is performed using manually extracted features. In this research, we have investigated the classification accuracy of the convolutional neural network, a subfield of the deep neural network. We have used a pre-trained network title "AlexNET" for extracting the features and used linear error-correcting output codes (ECOC) support vector machine (SVM) classifier to perform the classification task. An ECOC classifier reduces the multi-class classification problem to a set of binary classification problem [9]. SVM is the most used machine learning technique for skin lesion classification [10] that is why we are using SVM to perform classification. The proposed intelligent expert system is capable of classifying healthy, acne, eczema, benign and malignant skin lesions.

The rest of the paper is organized as follows. In section II, a critical analysis of the literature review is presented. Dataset used in this research work is explained in section III. Intelligent expert system methodology is explained in section IV. In section V, the results are discussed. Conclusions and future work are presented in section VI.

II. Literature Review

In literature, multiple skin lesions are classified using different image processing and machine learning techniques. The most used machine learning techniques used for skin lesion classification are SVM [11][24], trees [20], artificial neural network K-nearest neighbour [18][19], ensemble classifiers and convolution neural network(CNN) [15][16][17].

Dorj et al. used the SVM classifier on the features obtained by CNN to classify the skin cancer into four classes. They trained and tested their algorithm on 3753 images which were collected from the internet, and 94.2% accuracy was achieved by the proposed algorithm [16], but they only perform skin cancer classification. Zhang et al. used a combination of deep neural network and human knowledge to classify the melanocytic nevus, seborrheic keratosis, basal cell carcinoma and psoriasis. Their algorithm achieved 87.25% accuracy with 1067 images. Although they provide multi-class skin lesion classification, they used domain expert knowledge which cost more and not easily available to people with limited resources. Esteva et al. [15] presented an expert system trained on a data set of 129,450 clinical images of different skin cancers and compared its diagnostic performance against 21 board-certified dermatologists. They found that the expert system is proficient in classifying skin cancer at a level of competence comparable to the dermatologists. Their system was trained on an extensive dataset which makes it adaptive to the new skin lesion image, but at the same time, it can only classify different forms of skin cancer. A multi-layered system was designed and evaluated by Guzman et al. ANN was used to design the single layered and multi-layered system for eczema detection. The single-layer system classifies the images into eczema vs non-eczema images, and multi-model system classifies the images into three different types, i.e., spotted, scattered, and dried eczema. ANN was applied to the extracted features, and 85.71% to 96.03% accuracy was achieved for the single-layered system, and 87.30% - 92.46% accuracy was achieved for the multi-layered system [22]. Their system also provides a multi-class classification of a single skin lesion, i.e. eczema.

Sultana et al. used the deep residual network for the classification of melanoma lesions. They evaluated their proposed algorithm on ISBI, MED-NODE, and PH^2 databased and achieve the 98.5% accuracy using PH^2 dataset [21]. They also considered only the melanoma lesions. Alam et al. presented a framework for multi-class classification and skin lesion is classified as “mild” or “severe” on the basis of extracted features with an accuracy of 93% for healthy images and 92% for the classified images in the first stage and 80% for mild eczema and 93% for severe eczema in the second stage [24]. They evaluated their proposed framework on a limited dataset, so it lacks adaptability. Due to the limitations discussed, there is a need for an intelligent expert system that can perform the multi-class classification of a different range of skin lesions.

III. DATASET

To develop an expert system for multi-class classification, the dataset is collected from different sources. Some of the images related to the healthy category are collected by the authors. The data collection details for each category are given in Table 1.

[1] The images are from different sources. Images from DermIS, DermQuest and DermNZ are free to use for educational purpose

Table 1: Image categories with their sources

Category	Source
Healthy	1) 11K dataset [23] 2) Collected by the authors 3) Alam et al. [24]
Acne	1) DermIS[1] [25] 2) DermQuest [26] 3) DermNZ [27]
Eczema	1) DermIS 2) DermQuest 3) DermNZ 4) Alam et. al.
Benign	1) PH2 dataset [28] 2) ISIC Image challenge [29] 3) DermIS 4) DermQuest
Malignant	1) PH2 dataset 2) ISIC Image challenge 3) DermIS 4) DermQuest

The number of images in each category is different. The total number of images used in this research work is 15,546. In each category, the number of images is divided into two sets, i.e. training and testing. Some of the images from each category are graphically presented in Figure 1.

Figure 1. Image subset used to evaluate the proposed expert system

IV. METHOD

To develop the expert system, data collection is the first step. Images of healthy, acne, eczema, benign and malignant lesions are collected from different sources, and an image data store is created. The images in the data store are divided into training and testing dataset in the ratio 70:30, i.e. 70% of images are used for training the classifier, and 30% of data is used for testing. The division of training and testing data with respect to each category is given in Table 2.

Table 2: Training and testing data division

	Total	Training Images	Testing Images
Healthy	3014	2110	904
Acne	913	639	274
Eczema	967	677	290
Benign	3015	2111	904
Malignant	1235	865	370
Total	**9144**	**6402**	**2742**

The methodology of the proposed intelligent expert system is presented in Figure 2. There are two phases of the proposed intelligent expert system, i.e. the training phase and the testing phase. In the training phase, the images are preprocessed and resized into 227x227. After pre-processing, features are extracted using the deep CNN. We used the transfer learning approach and used a pre-trained CNN model titled "AlexNET" for feature extraction. Transfer learning approach is a deep learning approach in which a pre-trained model is used as a starting point to train a model for similar task [30]. The process of feature extraction using the convolutional neural network is graphically represented in Figure 3. For classification, ECOC linear SVM is applied to the extracted features. As discussed in section I, an ECOC model reduces the multi-class classification problem to a set of the binary classification problem. The coding design used for the ECOC model is one-verses-one and presented in Table 3. Learner 1 trains on observation having acne class and benign class. Learner 2-10 are trained using their respective classes.

Table 3: One-verses-one coding scheme used in ECOC model

Class	Learner 1	Learner 2	Learner 3	Learner 4	Learner 5	Learner 6	Learner 7	Learner 8	Learner 9	Learner 10
Acne	1	1	1	1	0	0	0	0	0	0
Benign	-1	0	0	0	1	1	1	0	0	0
Eczema	0	-1	0	0	-1	0	0	1	1	0
Healthy	0	0	-1	0	0	-1	0	-1	0	1
Malignant	0	0	0	-1	0	0	-1	0	-1	-1

A new observation is assigned the class K that minimises the aggregation of the losses for the L binary learners by using (1).

$$K = arg_K min \frac{\sum_{l-1}^{L} |m_{Kl}| g(m_{Kl}, s_l)}{\sum_{l-1}^{L} |m_{Kl}|} \ldots (1)$$

Where M is the coding design matrix with elements m_{kl}, and s_l be the predicted classification score for the positive class of learner l. The output of the training phase is the learned classifier. In the testing phase, the images in the testing dataset are also pre-processed and resized into 227 x 227 x 3. Afterwards, the features are extracted from the images and stored in the feature vector. The extracted feature vector are sent to the learned classifier, and the image is classified as healthy, acne, eczema, benign, or malignant.

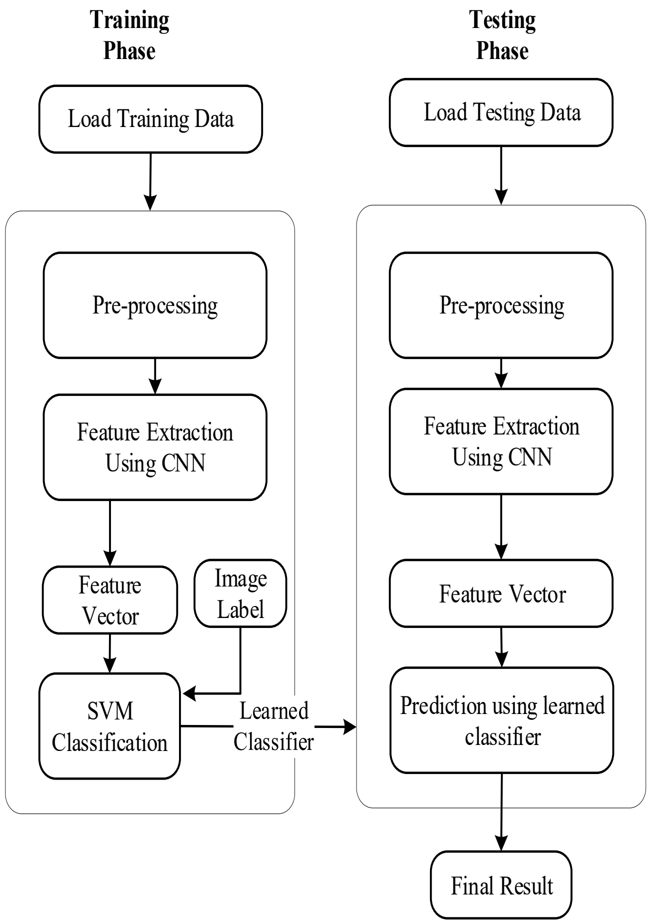

Figure 2. Intelligent expert system methodology

V. EXPERIMENTS & RESULTS

In this paper, our primary focus is to develop an intelligent expert system that can classify skin lesions using deep CNN and SVM. The proposed intelligent expert system is implemented using MATLAB 2018a. Experiments are performed on an Intel(R) Core(TM) i7-4770 CPU @ 3.40GHz with 16 GB of RAM, running Microsoft Windows 10 Enterprise 64 bits. The dataset is divided into two parts, i.e. training data and testing data in the ratio of 70:30.

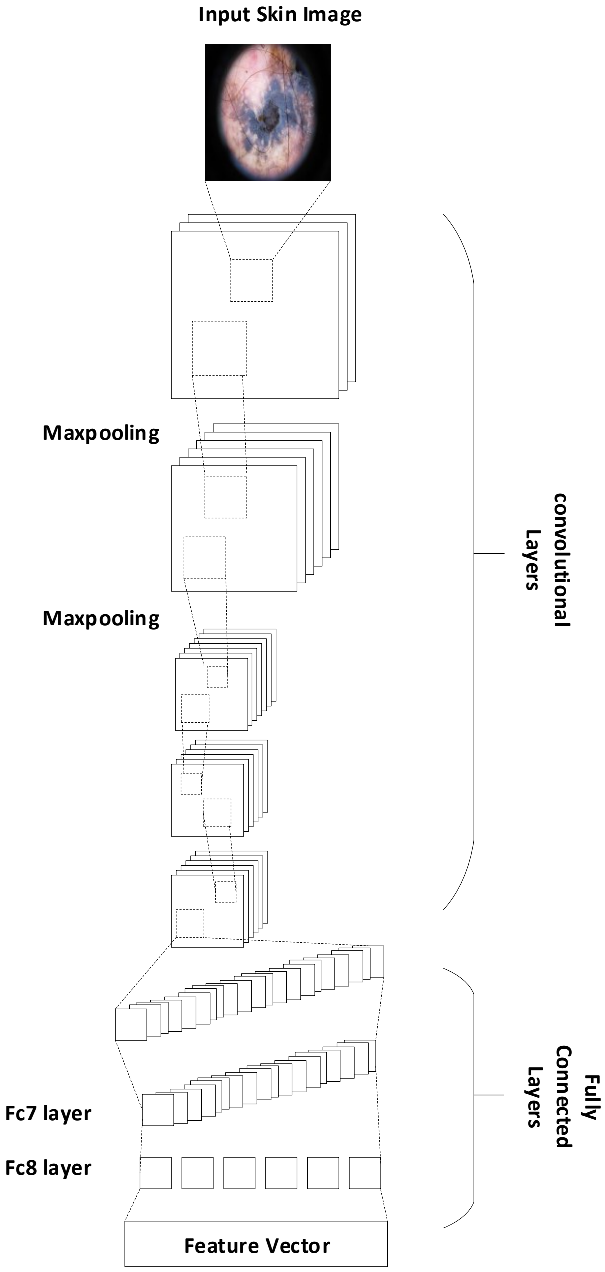

Figure 3. Feature extraction using AlexNET (Convolutional Neural Network)

The results performance is measured using sensitivity, specificity, precision and accuracy. The formula's to measure the sensitivity, specificity, precision and accuracy are given in equation (2), (3), (4) and (5).

$$Sensitivity = \frac{TP}{TP + FN} \text{x100} \ldots \ldots \ldots (2)$$

$$Specificity = \frac{TN}{TN + FP} \text{x100} \ldots \ldots \ldots (3)$$

$$Precion = \frac{TP}{TP + FP} \text{x100} \ldots \ldots \ldots (4)$$

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \text{x100} \ldots \ldots \ldots (5)$$

The terms true positive, true negative, false positive and false negative are explained in Table 4.

Table 4. Terms used for measuring the performance metrics

Term	Meaning
True Positive (TP)	Healthy image classified as healthy
True Negative (TN)	Unhealthy image classified as unhealthy
False Positive (FP)	Healthy image classified as unhealthy
False Negative (FN)	Unhealthy image classified as healthy

When the classification is performed using ECOC SVM, 86.21% accuracy is achieved. To avoid the overfitting, we used the 10-fold cross-validation. In 10-fold cross-validation, the data is divided into ten equal subsets, and the holdout method is repeated ten times. Each time, the 10th subset is used for the testing, and 9 subsets are used for training, and finally, the average error across all ten trial is calculated. The generalisation error using 10-fold cross validation is 0.1593. The confusion matrix obtained by SVM is presented in Table 5. The sensitivity, specificity, precision and accuracy of a linear ECOC classification model is given in Table 6.

Table 5. Confusion matrix of ECOC SVM classifier

	Healthy	**Acne**	**Eczema**	**Benign**	**Malignant**
Healthy	**901**	1	2	0	0
Acne	0	**244**	27	2	1
Eczema	0	19	**263**	7	1
Benign	1	1	2	**738**	162
Malignant	0	1	3	148	**218**

Table 6. Sensitivity, specificity, precision and accuracy for healthy, acne, eczema, benign and, malignant

	Sensitivity	Specificity	Precision	Accuracy
Healthy	99.76	99.97	99.89	99.9
Acne	89.05	99.11	91.73	98.1
Eczema	90.69	98.61	88.55	97.78
Benign	81.64	91.46	82.46	88.22
Malignant	58.92	93.08	57.07	88.47

The accuracy along with the number of images in each category are graphically presented in Figure 4.

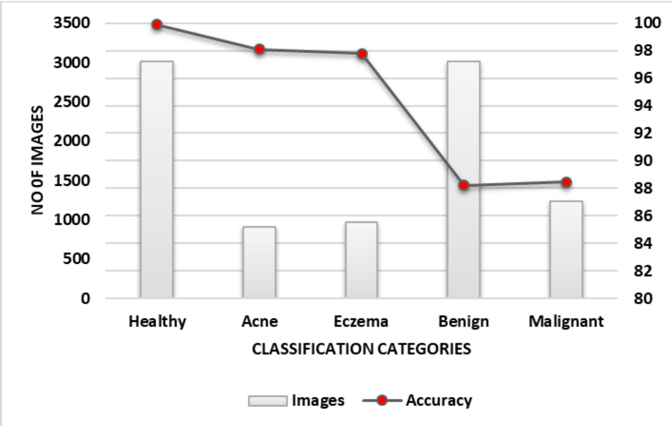

Figure 4. Comparison of categories w.r.t. images and accuracy

While comparing the proposed research work with existing work in literature (Table 7), we can see that in most cases, proposed intelligent expert system classify more diseases than the existing work in literature. Although, [8] classify more diseases, but their accuracy is less than our work. The accuracy of [24] is superior to us, but they trained their model on only 80 images, but the proposed expert system is trained on 9,144 images, so it is more adaptable to new and unseen images then model proposed in [24].

Table 7. Comparison of the proposed system with existing work in literature

Reference	**Diseases**	**No of images**	**Technique**	**Resilts**
[3]	Malignant lesions	369	Genetic Algorithm	Acc*: 76.17%
[8]	**Acne, Eczema, psoriasis, benign and malignant**	1800	SVM	Acc: 83%
[22]	Eczema	126	ANN	Acc: 81.34% - 85.71%
[24]	Eczema	80	SVM	**Acc: 90%**
Proposed	Acne, Eczema, benign and malignant	**9,144**	CNN and SVM	Acc: 86.21%

Acc*= Accuracy

VI. Conclusion and Future Work

This paper has been presented as an intelligent expert to perform the multi-class classification of skin diseases using machine learning algorithms. The proposed expert system can classify healthy, acne, eczema, benign, and malignant skin lesions. In this research work, we investigated the features obtained by the deep convolutional neural network for the multi-class classification task. The features are extracted using the AlexNET; a pre-trained convolutional neural network model. An ECOC SVM classifier was applied on the extracted features for the classification task. The overall accuracy achieved by the SVM classifier is 86.21%, and the generalisation error after performing 10-fold cross validation is ~0.16. The proposed intelligent expert system outperforms our existing work with an increase in accuracy of 3.21%.

In our future work, we will explore the effect of data balancing for multi-class skin lesion classification. We will also focus on the development of a smartphone based expert system for the multi-class skin lesion classification to make the intelligent expert system accessible for people living in remote areas and with limited resources.

VII. Acknowledgement

This research work is funded by Erasmus Mundus FUSION (Featured eUrope and South asIa mObility Network) project Grant reference number:2013-32541/001001.

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