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Detection of Skin Diseases from Dermoscopy Image Using the combination of Convolutional Neural Network and One-versus-All

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Abstract

The use of deep learning in the field of image processing is increasing. In this study, a new method based on Convolutional Neural Network is proposed to detect skin diseases automatically from Dermoscopy images. Skin cancer is one of the common diseases in the community. In this article, the skin images were taken from the data HAM10000 dataset prepared by Philipp Tschandl. There are seven classes in the skin disease data set; Actinic keratoses and intraepithelial carcinoma, Basal cell carcinoma, Benign keratosis, Dermatofibroma, Melanoma, Melanocytic type and Vascular lesions. To classify the skin diseases automatically, two different methods have been proposed: i) Alone Convolutional Neural Network model, and ii) the combination of Convolutional Neural Network and one- versus- all. In the proposed method, we have not used any pre-processing method to classify them. The raw dermatology images taken from the dataset have been given to the input of Convolutional Neural Network and then trained and tested by these images. In the second proposed method, seven different models having two-classes have been composed and then combined with the one-versus-all approach. While alone, Convolutional Neural Network obtained 77% classification accuracy in the detection of skin disease with seven classes, the combination of Convolutional Neural Network and one-versus-all approach achieved 92.90% accuracy. The obtained results have shown that the proposed method is very promising in the classification of skin disease from Dermoscopy images.

Keywords

Deep Learning, Skin Cancer, Convolutional Neural Network, Artificial Neural Networks, Image Processing.

1. Introduction

In this paper, skin disease classification has been done using two different methods including the alone Convolutional Neural Network and the combination of CNN and one-versus-all (OVA).

Malignant melanoma occurring in skin tissue and to death is a type of skin cancer that can cause [1, 2]. With early diagnosis, the disease can be cured. In the detection of medical diseases, Computer-Aided Diagnosis (Computer) Aided Diagnosis - CAD) systems for the detection of skin cancer can also help patients and physicians [2]. Dermoscopy is a non-invasive skin imaging technique. Malignant melanoma is one of the fastest-growing cancers in the world. Early diagnosis is especially important because if diagnosed early, melanoma can be treated with a simple excision [3].

In this study, we have used the convolutional neural network (CNN) as the classifier method. Convolutional neural network (CNN) is one of the best among deep artificial intelligence methods used in image processing. CNN takes an input image to train its network and produces an output that matches the input image using the existing image dataset. A neural network draws a path based on similarity connections of biological nerves interconnected with each other and thus creates a learning structure. The performance of CNN also varies depending on how many input images there are and how many convolutions are used [4]. Deep learning methods can be seen as a useful tool for dermatologists to detect lesions better. A CNN model that works to obtain a diagnostic result from an image is similar to the training and learning process of a dermatologist [4].

In the literature, there are many works regarding skin disease diagnosis using deep learning and machine learning techniques. Suhail M.Odeh et al. used four different models including k-NN (k-Nearest Neighbor), the combination of k-NN and genetic algorithm, Artificial Neural Networks with Genetic Algorithm, and Adaptive Neuro-Fuzzy Inference System to diagnose the skin cancer from the lesion images [5]. In the work of Fekrache Dalila et al. [6], they proposed a hybrid approach to diagnosing melanoma and benign skin lesions. In their method, to segment, the images, ant colony optimization method has been used to extract the features from these lesions and then used the K-Nearest Neighbor (KNN) and Artificial Neural Network (ANN) to classify the melanoma and benign skin lesions [6]. Wiem Abbes et al. proposed an ontology-based classification model for the classification of skin lesions. In their method, they used the Bag-of-Words (BoW) modeling to extract the features from the images. Then, the support vector machine (SVM) has been used to classify the skin lesions [7]. Pedro Pedrosa Rebouças Filho et al. proposed a different model based on structural co-occurrence matrix (SCM) to classify the skin lesions from dermoscopy images. They applied their method to the ISIC 2016, 2017 and PH2 datasets and then obtained very good results in the classification of skin lesions [8]. Jose Luis Garcia-Arroyo et al. proposed a segmentation method for skin lesions in the classification of melanoma disease from dermoscopy images. In their method, this approach has been based on the fuzzy classification of pixels and subsequent histogram thresholding [9]. In the other work [10], Serkan Sete et al. proposed a Gabor wavelet-based deep convolutional neural network for the classification of malignant melanoma and seborrheic keratosis from the dermoscopy images. Saptarshi Chatterjee et al. used a hybrid method for the classification of skin type lesions. In their method, for the feature extraction from the images, they used the gray level co-occurrence matrix (GLCM) and a fractal-based regional texture analysis (FRTA) algorithm. Then, to select important features from all feature sets, recursive feature elimination (RFE) has been used. To classify the skin lesions, the support vector machine with radial basis function (RBF) has been used in this paper [11]. Nazia Hameed et al. proposed a Multi-Class Multi-Level (MCML) classification algorithm for multi skin lesions [21]. In the other work of

Pedro M.M. Pereira et al. [22], they used the Local Binary Pattern Clustering (LBPC) for segmentation of dermoscopy images. Then, they extracted some shape features from these images and classified them using the support vector machine and Feed Forward Network [22]. Javeria Amin et al. proposed a different method for localization and classification of skin cancer [23]. They applied the PCA to the images and then obtained new features to detect the skin cancer [23]. Ghasem Shakourian Ghalejoogh et al. proposed the Stacking Ensemble Method based on the Meta Learning algorithm for skin disease classification from the dermoscopy images. In this dataset, three classes including benign, dysplastic and melanoma have been used [24]. In the work of Muhammad Attique Khan et al. [25], they proposed a hybrid approach including faster region based convolutional neural network (RCNN), deep feature extraction, and feature selection by IcNR approach for skin lesion classification. Fengying Xie et al. proposed a new segmentation method called the Convolutional neural network and then applied it to skin images dataset [26]. Ahmed Refaat Hawas et al. proposed a histogram-based clustering estimation (HBCE) algorithm for skin lesion segmentation. And then, they combined it with neutrosophic c-means (NCM) for segmentation of dermoscopic images [27]. As for the work of Teck Yan Tan et al. [28], they proposed a hybrid Particle Swarm Optimization (HPSO) for the segmentation of skin lesions and then combined it with CNN algorithm for detection of skin lesions.

Apart from the literature works, we have classified the seven different skin diseases including Actinic keratoses and intraepithelial carcinoma (akiec), Basal cell carcinoma (bcc), Benign keratosis (bkl), Dermatofibroma (df), Melanoma (mel), Melanocytic type (nv) and Vascular lesions (vasc) using two different CNN models. In general, in the conducted works in the literature, two different skin diseases have been classified using the dermoscopy images. In this paper, we have focused on the multi-class classification problem named skin disease detection using two different approaches.

The novelty and the contributions of this work are:

- Two different models have been proposed for seven different skin diseases using deep learning methods. In the literature, generally, two different skin diseases have been classified.
- We have firstly combined the convolutional neural network (CNN) and one-versus-all (OVA) to classify the multi-class skin disease dataset with high performance.
- We have not used any pre-processing method in the dermoscopy images.

The rest of this study is organized as follows: the details of the dataset and methods are given in Section 2. The experimental results and discussion are presented in Section 3. Lastly, concluding remarks are given in Section 4.

2. Material and Method

2.1. Dataset

In this study, we have used the HAM10000 dataset for dermoscopy images [12]. It contains pigmented lesions in different populations. This data set consists of 10015 images in total. The image sizes are scaled to 150x200 pixels to reduce network input and reduce the number of network parameters. The diagnostic classes in this dataset are given as follows [12].

a) Actinic keratoses and intraepithelial carcinoma - akiec
b) Basal cell carcinoma - bcc
c) Benign keratosis - bkl
d) Dermatofibroma - df
e) Melanoma -mel
f) Melanocytic type - nv
g) Vascular lesions – vasc

Figure 1 shows the akiec example taken from [12]. Figure 2 denotes the bcc example taken from [12]. Figure 3 gives the bkl example taken from [12]. As for figure 4, the df example is shown. Figure 5 shows the mel example taken from [12]. Figure 6 explains the nv example taken from [12]. The vasc example is given in Figure 7.

Figure 1. The dataset example taken from: akiec [12]

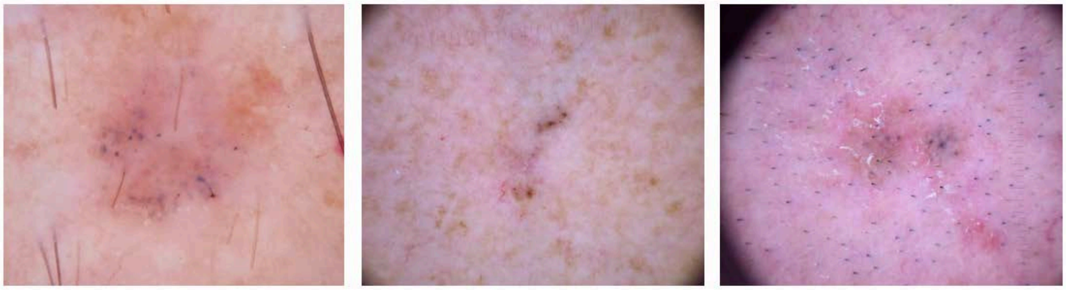

Figure 2. The dataset example taken from: bcc [12]

Figure 3. The dataset example taken from: bkl [12]

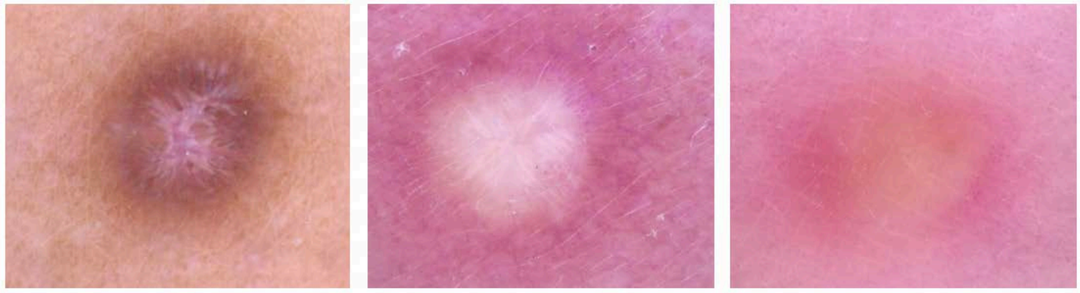

Figure 4. The dataset example taken from: df [12]

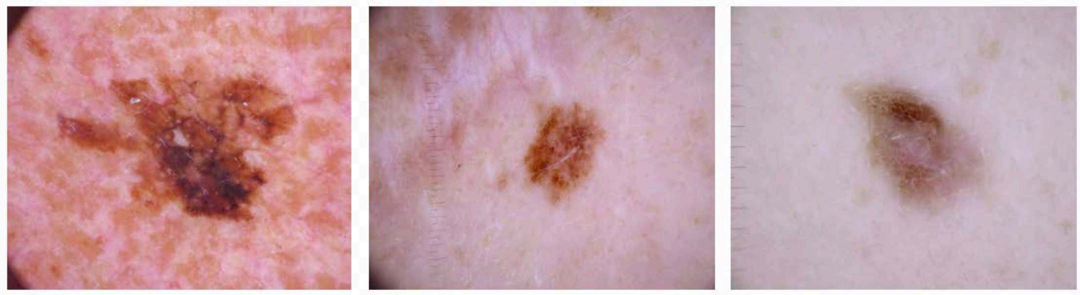

Figure 5. The dataset example taken from: mel [12]

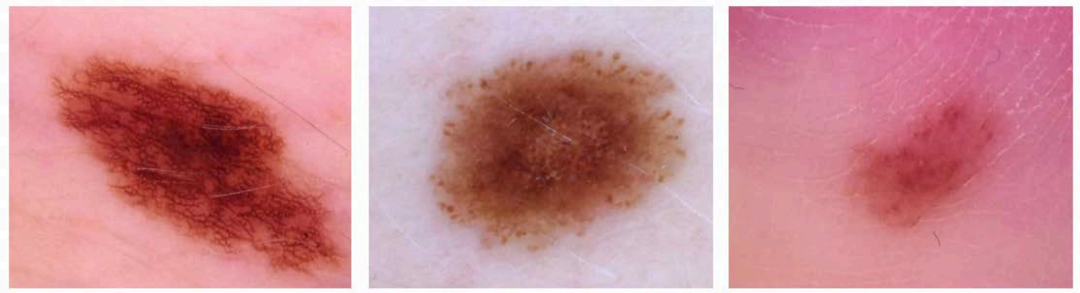

Figure 6. The dataset example taken from: nv [12]

Figure 7. The dataset example taken from: vasc [12]

Information about which class belongs to each image in the dataset is also provided with the dataset. The sets to be used in the portions of the dataset were obtained from the entire data set to 75%, 5%, and 20%, respectively, training, verification and testing. Data indicating how much data each set contains are listed in Table 1.

Table 1. Data indicating how many data each set contains in the dataset [12]

Diagnosis Class in the dataset	Train	Validity	Test
Akiec	243	17	67
Bcc	386	25	103
Bkl	814	59	225
Df	79	9	27
Mel	844	52	217
Nv	5034	328	1343
Vasc	111	10	21
Total	7511	500	2003

As can be seen in the table, most of the data in the dataset belong to the sixth grade, and there is no equal distribution between classes. During this training phase, it will lead to more learning of the 6th grade and the network to learn this information and to learn this class. In order to overcome this problem, the number of images in the training set has been increased by using the data duplication method. The resulting training set contains 10015 images.

2.2. The Proposed Method

To classify the skin diseases automatically, two different methods have been proposed: i) Alone CNN model, and ii) the combination of CNN and one-versus- all (OVA). In the proposed method, we have not used any pre-processing method to classify them. The raw dermatology images taken from the dataset have been given to the input of Convolutional Neural Network and then trained and tested by these images. In the second proposed method, seven different models having two-classes have been composed and then combined with the one-versus-all approach. As the pre-processing stage, we have just used the normalization method.

In this paper, the first method has been proposed to classify the images in the dataset as multi-class using the convolutional neural network (CNN). In this method, the input image has been normalized in the range of 0-1, then applied as an input to the designed CNN network. At the output of the CNN, information about which class the image belongs to is obtained. The flow diagram of the first method is given in Figure 8.

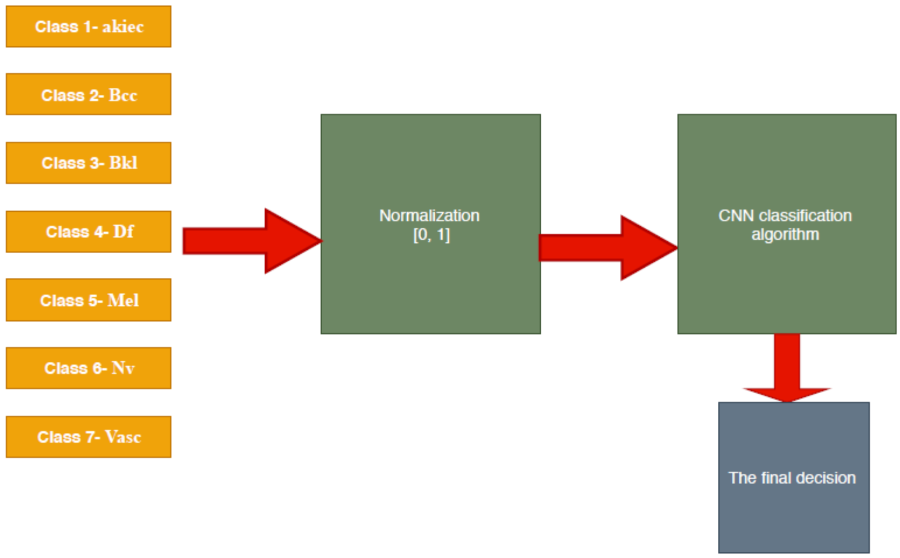

Figure 8. The flow diagram of the first method (alone CNN)

In the second method, CNN has been combined with one versus all approach to improving the classification performance. In this method, we have classified all the classes as the pairwise: Class 1 - other (a combination of other classes in the dataset), C2- other (a combination of other classes in the dataset), C3- other (a combination of other classes in the dataset), and so on. Then, we have taken an average of all the pairwise results. Thanks to the proposed second method, the classification performance has been increased from 77% accuracy to 92.90% accuracy. The flow diagram of the second method is given in Figure 9.

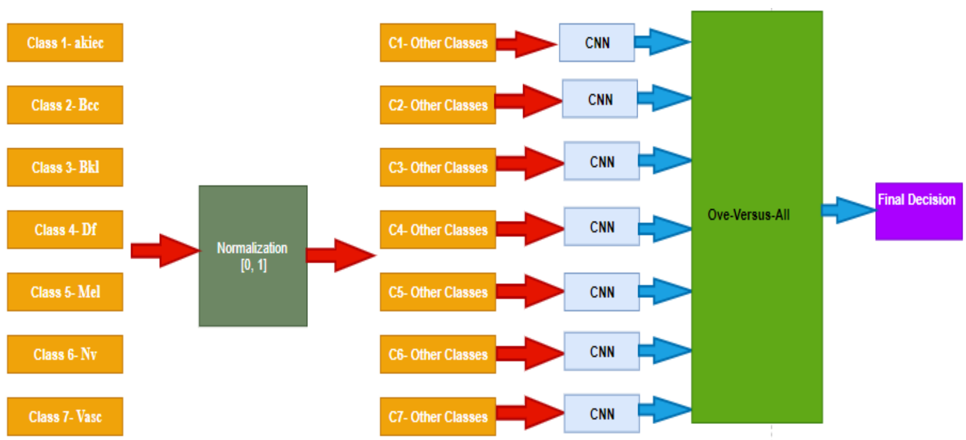

Figure 9. The flow diagram of the second method (the combination of CNN and OVA)

With the introduction of deep convolutional neural networks in image processing applications, high-performance results have begun to be achieved in many image processing problems [9]. These networks mainly contain two different structures, namely convolution and neural network. While convolutional structures allow imitation of the capabilities of image processing techniques by networks, neural networks are used to make sense of this data obtained from images. These structures are mentioned in the next subsections.

The first network structure consists of four different evolutionary layers and fully connected layers added to the output of these layers. This network structure includes 1,243,463 parameters in total, and the visualized structure of the network is given in Figure 10.

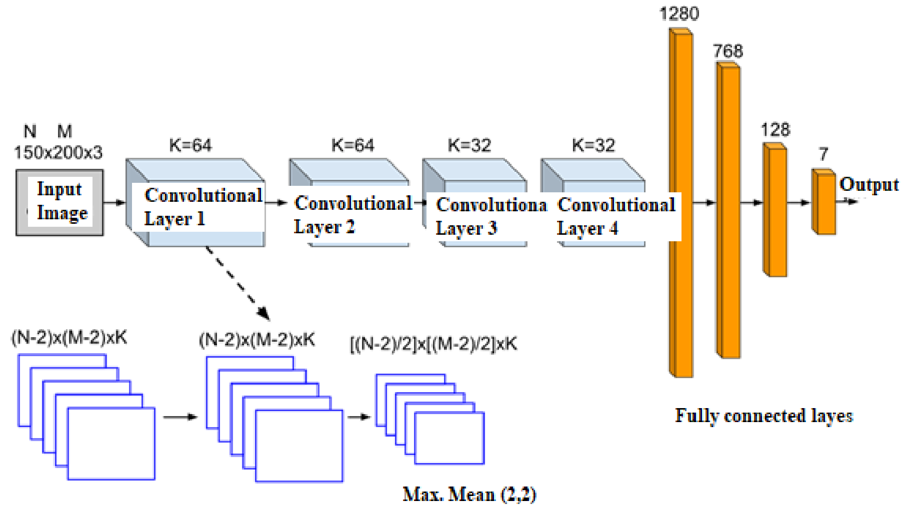

Figure 10. The proposed network structure model-1 for our problem

Using the network structure given in the figure, training was carried out for each class by using a data set consisting of all other classes against one class. For each class, binary (coded as 10-true, 01-false in the study) classification is made at the output of the network. In this way, seven different pieces of training were carried out for seven classes. It can be understood whether an input image of the relevant class is given at the exit of each network. This network structure contains 153090 parameters in total, and the visualized structure of the network is given in Figure 11.

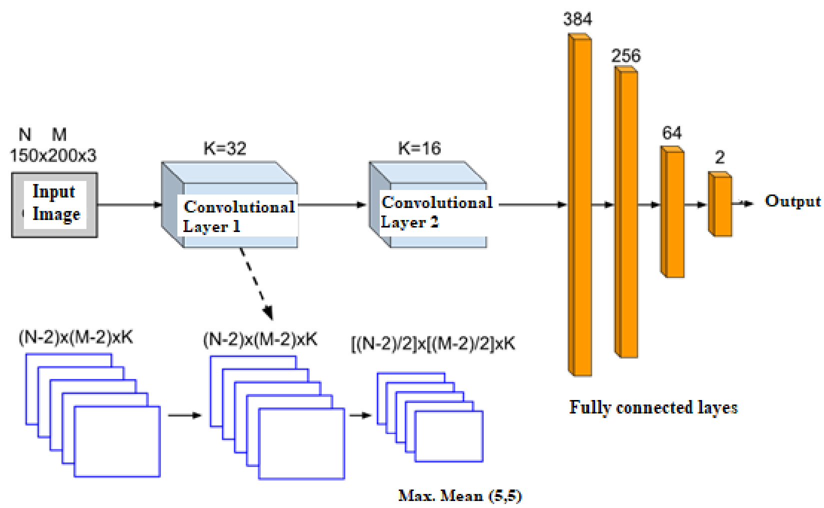

Figure 11. The proposed network structure model-2 for our problem

2.2.1. Data Augmentation

Neural networks need to be well trained to achieve successful results from processing large amounts of data [15]. The number of images used for education may have insufficient or unbalanced distribution. In order to increase the number of insufficient data used in education, replication is performed in the data set. The data replication process is used to create additional data for the training set. It is realized by different approaches such as rotating, scaling, translation, adding noise on the original image, or combining these approaches in combination [15, 29, 30]. The training set with the data replication process has the number of images in Table 2. The specified training set was used for the training. A cycle is completed using the entire training dataset in groups of 32 images for training. A total of 15 cycles were made for training. At the end of each cycle, verification results are obtained by using the verification set. This value indicates how the network has achieved the data it has not seen before. The education coefficient was chosen as 0.0001.

Table 2. The distribution of data after the data augmentation

Diagnosis Class in the dataset	Number of data after the augmentation
Akiec	4800
Bcc	5018
Bkl	4884
Df	4977
Mel	4220
Nv	5034
Vasc	4995
Total	33998

3. The Experimental Results and Discussion

In this study, the confusion matrix is used to calculate several metrics. This matrix forms four indices which are true positive (TP), false positive (FP), false negative (FN) and true negative (TN). TP and TN match the number of correctly predicted hypoxic and normal samples whereas the FP and FN match the number of incorrectly predicted hypoxic and normal samples, respectively. These metrics, their mathematical forms, and short descriptions are given in Table 3.

Table 3. The used performance metrics with their descriptions in this work

Metrics	Equations	Descriptions
Accuracy	$\frac{TP+TN}{TP+FP+FN+TN}$	The overall accuracy of the model.
Sensitivity (Recall)	$\frac{TP}{TP+FN}$	The capacity of the model on the prediction of the hypoxic fetus.
Specificity	$\frac{TN}{TN+FP}$	The capacity of the model on the prediction of the normal fetus.

Precision	$\frac{TP}{TP+FP}$	The correctly predicted hypoxic fetus.
F-Score	$\frac{2*P*R}{P+R}$	The harmonic mean between precision and recall.

The meanings of the classification results obtained from the trained networks and their outlets are shown in the figure. The education of a dataset containing two classes is easier than a multi-class dataset. There is no need for the wide network structure used previously. You can see the test achievements obtained from the network structures trained for each class in Table 4 and Table 5. The simulations were conducted in the TensorFlow Deep learning. The computation cost for each model is approximately 4 hours.

Table 4. Performance indicators of the first network for each class in the detection of skin diseases using CNN model-1

Diagnosis Class in the dataset	Precision	Recall	F score
Akiec	0.58	0.21	0.31
Bcc	0.64	0.59	0.62
Bkl	0.48	0.61	0.54
Df	0.39	0.41	0.40
Mel	0.51	0.42	0.46
Nv	0.89	0.91	0.90
Vasc	1.00	0.48	0.65

Table 5. Performance indicators of the second network for each class in the detection of skin diseases using CNN model-2

Diagnosis Class in the dataset	Precision
Akiec	96.9%
Bcc	95%
Bkl	89.7%
Df	98.9%
Mel	87.70%
Nv	82.90%
Vasc	99.20%
Average	92.90%

Figure 12 shows the performance graph of the proposed first model (alone CNN) in the classification of skin diseases having seven classes. As for the other proposed method called the combination of CNN and OVA, the obtained performance graphs are given in Figures 13 through 19. for each class in the skin disease dataset. Figure 20 shows the error diagram of each class in the classification of skin diseases using the CNN method.

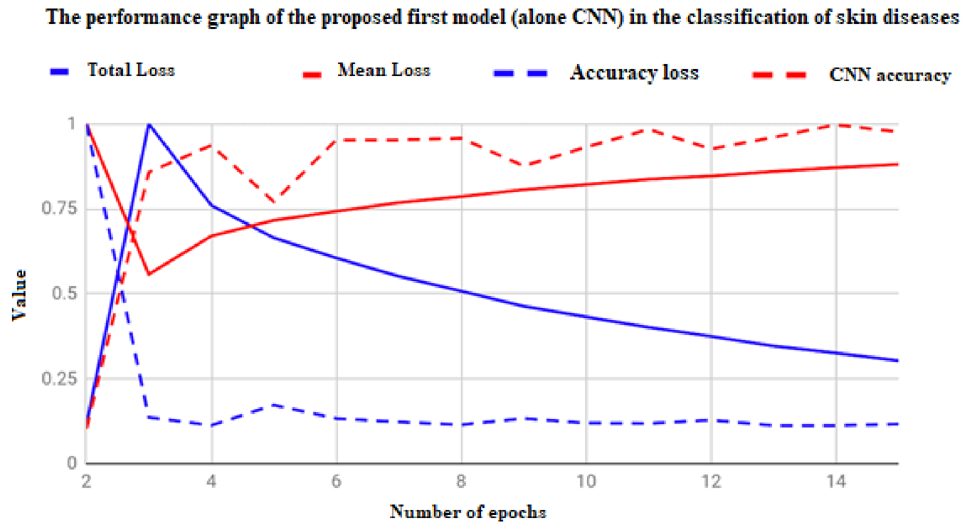

Figure 12. The performance graph of the proposed first model (alone CNN) in the classification of skin diseases having seven classes

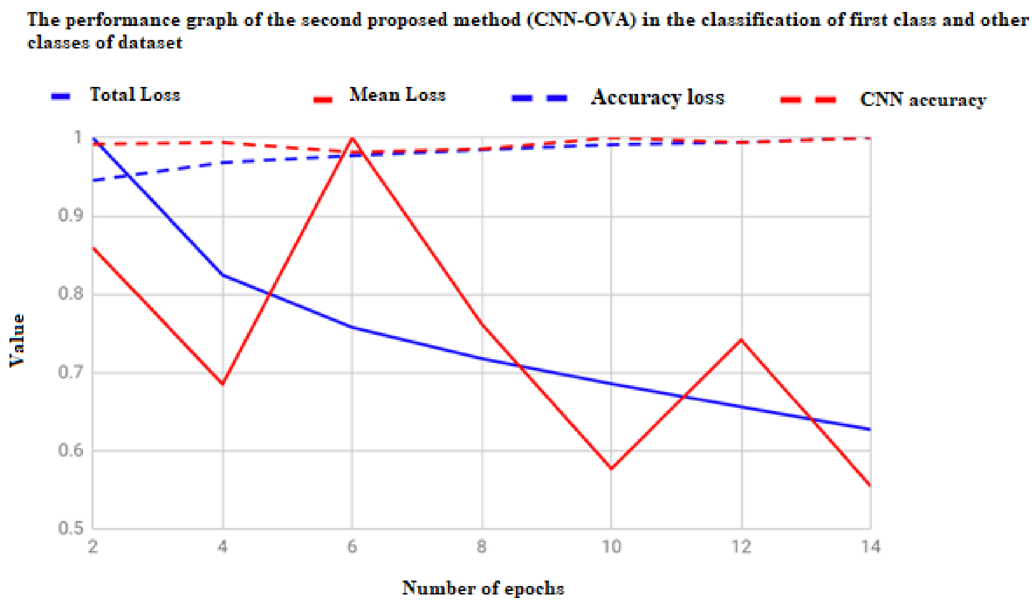

Figure 13. The performance graph of the proposed second model (the combination of CNN and OVA) in the classification of first class (Akiec) from skin diseases having seven classes

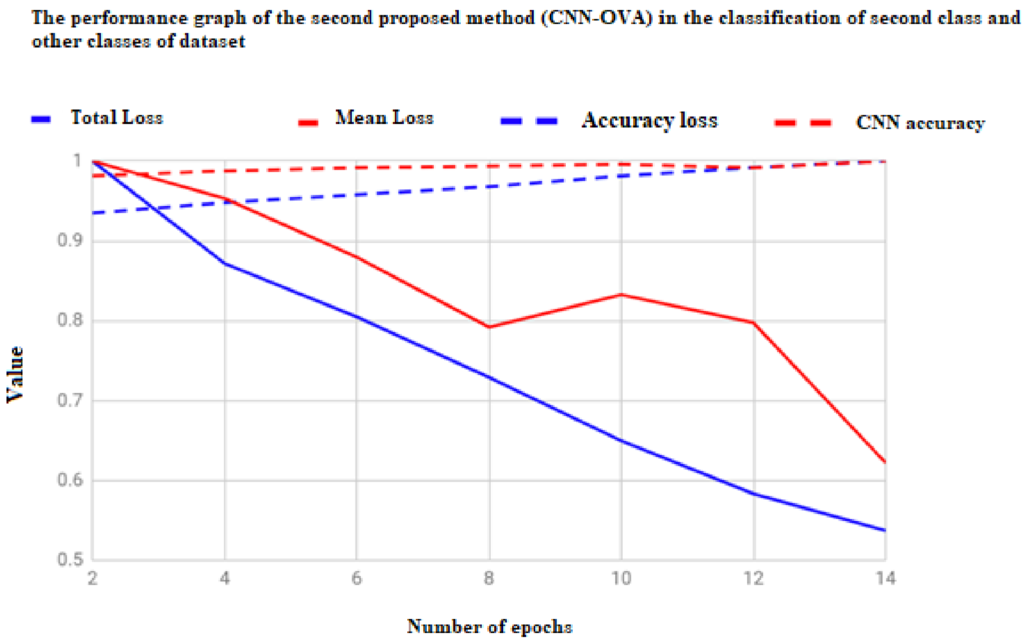

Figure 14. The performance graph of the proposed second model (the combination of CNN and OVA) in the classification of second class (Bcc) from skin diseases having seven classes

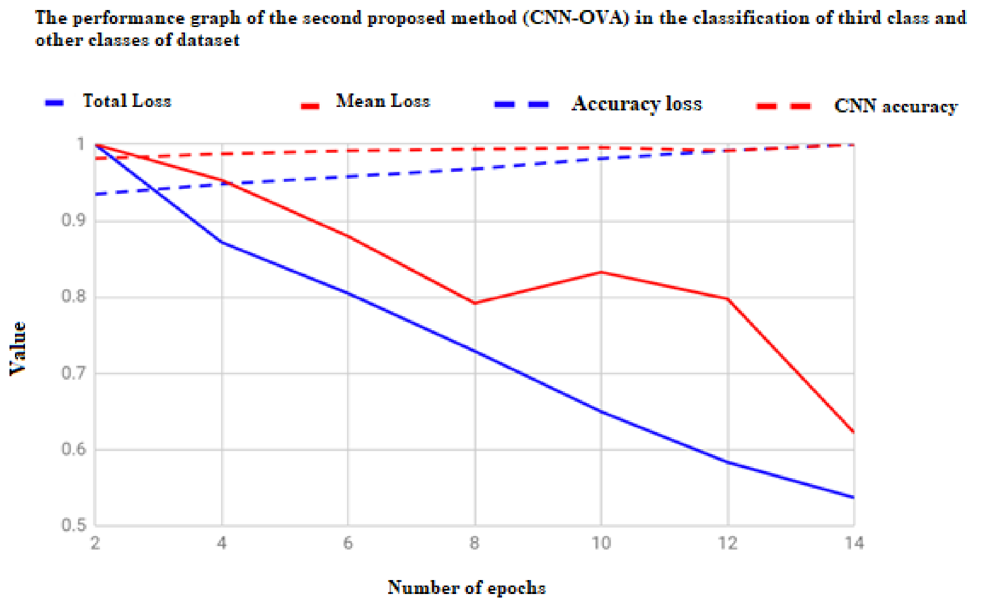

Figure 15. The performance graph of the proposed second model (the combination of CNN and OVA) in the classification of third class (Bkl) from skin diseases having seven classes

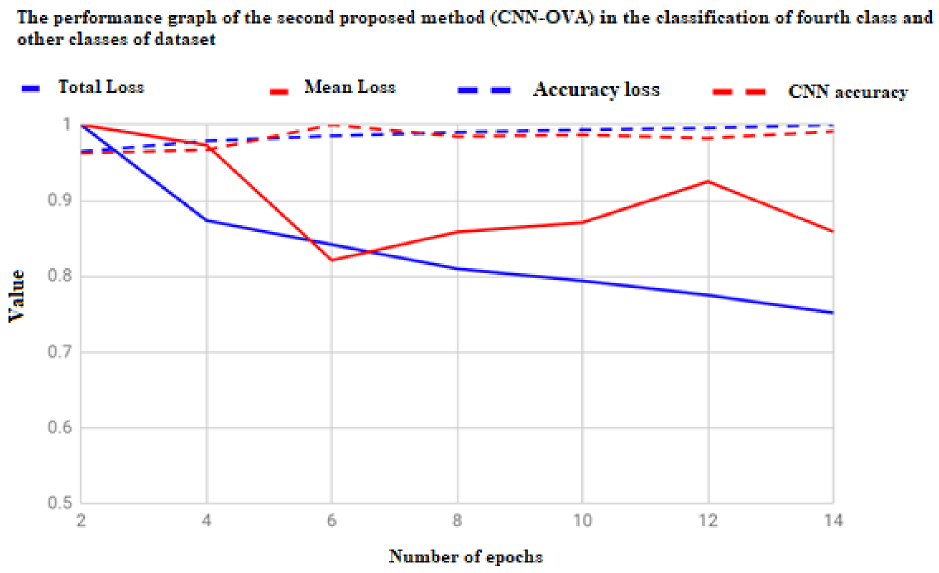

Figure 16. The performance graph of the proposed second model (the combination of CNN and OVA) in the classification of fourth class (Df) from skin diseases having seven classes

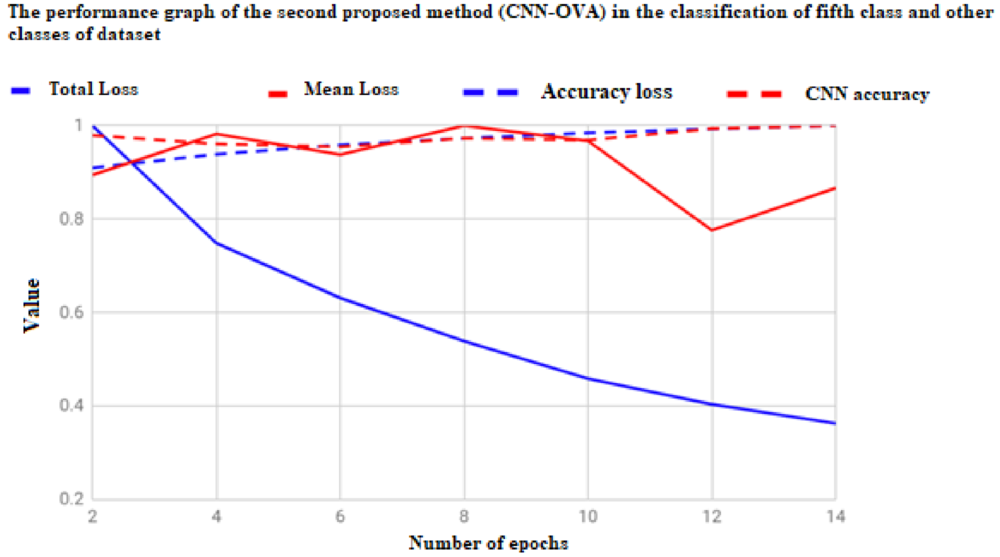

Figure 17. The performance graph of the proposed second model (the combination of CNN and OVA) in the classification of fifth class (Mel) from skin diseases having seven classes

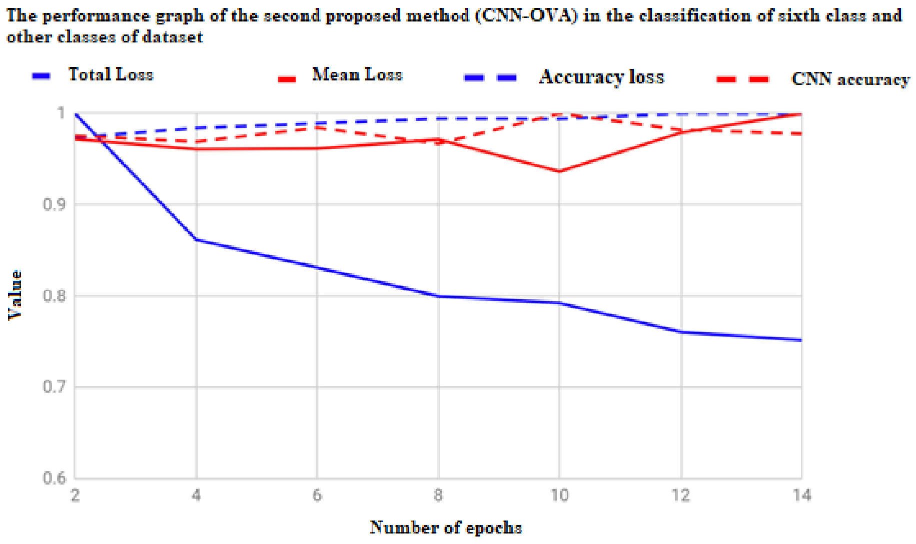

Figure 18. The performance graph of the proposed second model (the combination of CNN and OVA) in the classification of sixth class (Nv) from skin diseases having seven classes

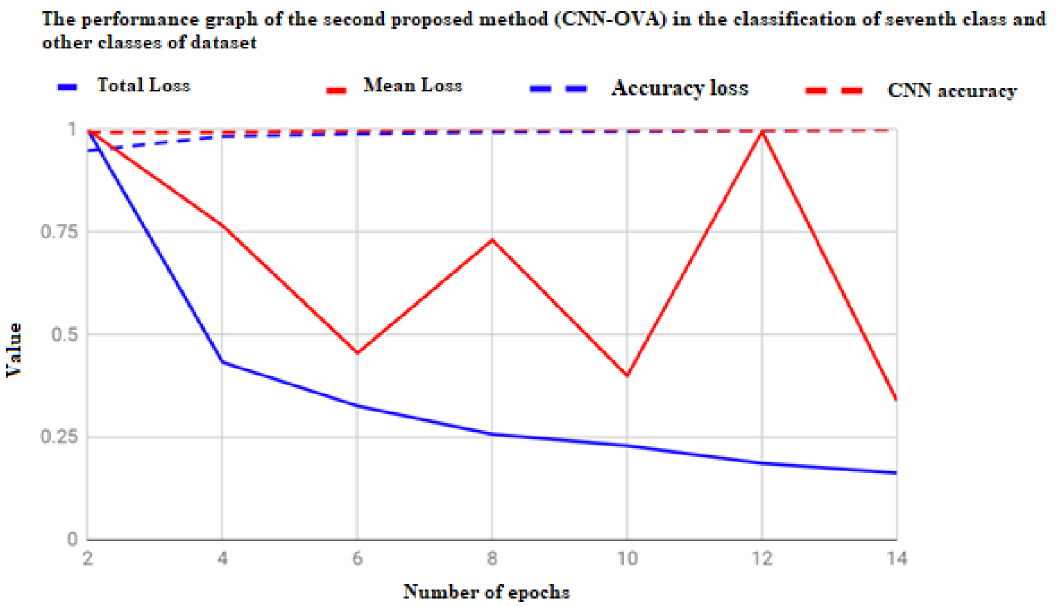

Figure 19. The performance graph of the proposed second model (the combination of CNN and OVA) in the classification of seventh class (Vasc) from skin diseases having seven classes

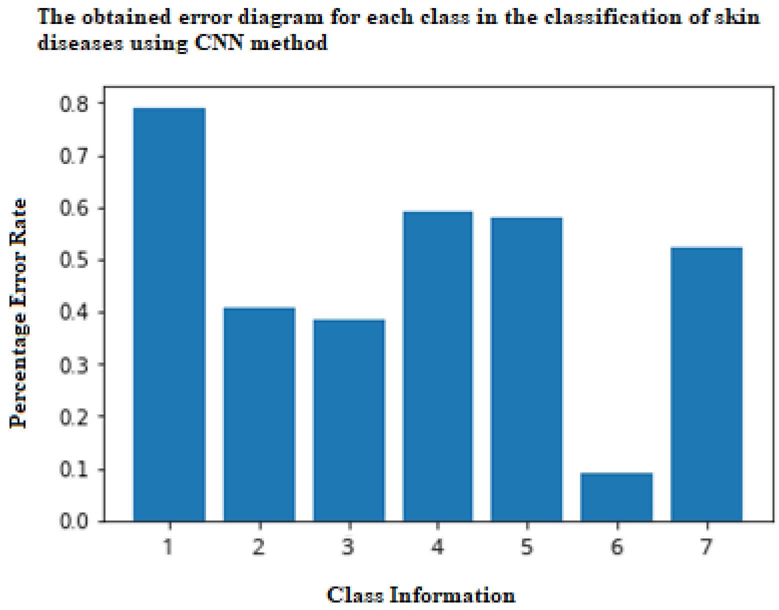

Figure 20. The error diagram of each class in the classification of skin diseases using CNN method

When the two proposed models in the study are compared; the first network structure has achieved 77% success as a result of separating and classifying seven classes in total. In the second model, when each class is evaluated as one, respectively, higher success rates are observed. By collecting the success rates of the mentioned seven classes, the average of the proposed second network was 92.9%. When the second network, which is among the proposed networks, is evaluated by considering similar studies in the literature, it has achieved success in a value that will contribute to the literature. The values related to the comparison are shown in Table 6. As can be seen from the obtained results, the best method is our method called the combination of CNN and one versus all (OVA) in the classification of skin diseases from the dermoscopy images.

Table 6. Performance comparison of the second model (the combination of CNN and one versus all) with the literature

The relevant work	The obtained classification accuracy (%)
Aleksey Nozdryn-Plotnick et al. [16]	88.50
Nils Gessert et al. [17]	85.60
Iaxin Zhuang et al. [18]	84.50
Mohammed K. Amro et al. [19]	81.20
Philipp Tschandl et al. [14]	80.20
Yeong Chan Lee et al. [20]	78.50
Aminur Rab Ratul et al. [13]	87.42
Aminur Rab Ratul et al. [13]	85.02

Aminur Rab Ratul et al. [13]	88.22
Aminur Rab Ratul et al. [13]	89.81
Our study (2020)	92.90

4. Conclusions

In the paper, we have proposed two different approaches based on CNN and one-versus-all (OVA) for the classification of skin diseases from dermoscopy images. Apart from the literature, the skin diseases dataset having seven classes has been classified by the combination of CNN and OVA with a high classification performance. The simulations of this work have been done in Tensor Flow deep learning. Without using any filtering and any feature extraction, we have obtained very promising results in the detection of skin lesions. The advantage of OVA is that classification has been made based on true and false for each class. Therefore, it caused the complexity to decrease. Thus, the accuracy rate values in multiple classifications increased when each class was evaluated separately. While alone CNN obtained 77% classification accuracy in the detection of skin disease with 7 classes, the combination of CNN and one-versus-all approach achieved 92.90% accuracy. The proposed method, called the combination of CNN and OVA could be used in many medical imaging classification problems.

Conflicts of Interest

There is no conflict of interest.

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