CLASSIFICATION OF DERMATOSCOPIC IMAGES USING CONVOLUTIONAL NEURAL NETWORK

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ACTUALITY

Skin cancer is one of the most frequently diagnosed malignant neoplasms [1]. Malignant melanoma is one of the most dangerous types of cancer. Although it is less common than other skin malignancies, due to the high probability of metastasis, melanoma has a mortality rate of about 74%. Basal cell carcinoma accounts for 75% of nonmelanoma malignancies [2].

MATERIALS AND METHODS

Dermatoscopic image data sets were used in this research. The first dataset is a freely available image set HAM10K. It contains 1113 images of malignant melanomas and 8902 images of other neoplasms.The second dataset consists of 310 images, of which 100 images of malignant melanoma and 210 images of pigmented neoplasms. Images of the second dataset were acquired using a dermatoscope layout [7].

The images obtained with the dermatoscope layout have distorted color reproduction (see Fig. 1, b) and may not be suitable for use with the first dataset in the same classifier. Color correction was performed in accordance with the presented coefficients.

$$R = 0{,}85 * R + 0{,}15 * (1{,}8 * B)$$
$$G = 0{,}75 * G$$
$$B = 1{,}8 * B$$

The R, G, B are the red, green, and blue color channels, respectively. An example of color correction is shown in Fig.1(c).

The dermatoscopic image classifier is based on a convolutional neural network and implemented in Python. Initially, the neural network was trained and tested on the first HAM10K dataset. The saved model was then used to re-train and test on a second set of images.

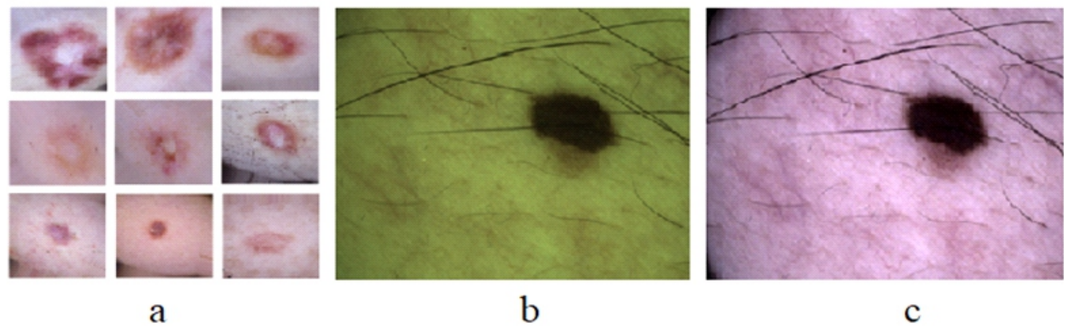

Fig. 1. Images taken with polarized light: a) images from the HAM10K set (size 600x450); b) images taken with the dermatoscope before color correction (size 1920x1080); c) images taken with the dermatoscope after color correction (size 1920x1080)

RESULTS

The figures show the result of neural network training. Accuracy and cross entropy loss are used to evaluate the model.

The model should probably not be trained longer than 12 epochs (see Fig. 2).The accuracy value on the validation dataset does not change, but the cross-entropy loss increases, which may indicate overtraining of the neural network. The model was trained on 12 epochs and saved it for use later.

The image classification accuracy on the first HAM10K dataset on the test was 90%. The resulting model was used for pre-training and testing on a second set of images. To improve the model's ability to generalize the data, an augmentation method is used. As a result, the classification accuracy on the second set of data was 80% (see Fig. 3).

It can be concluded that the model needs to be trained on more epochs to see if it is prone to overtraining.

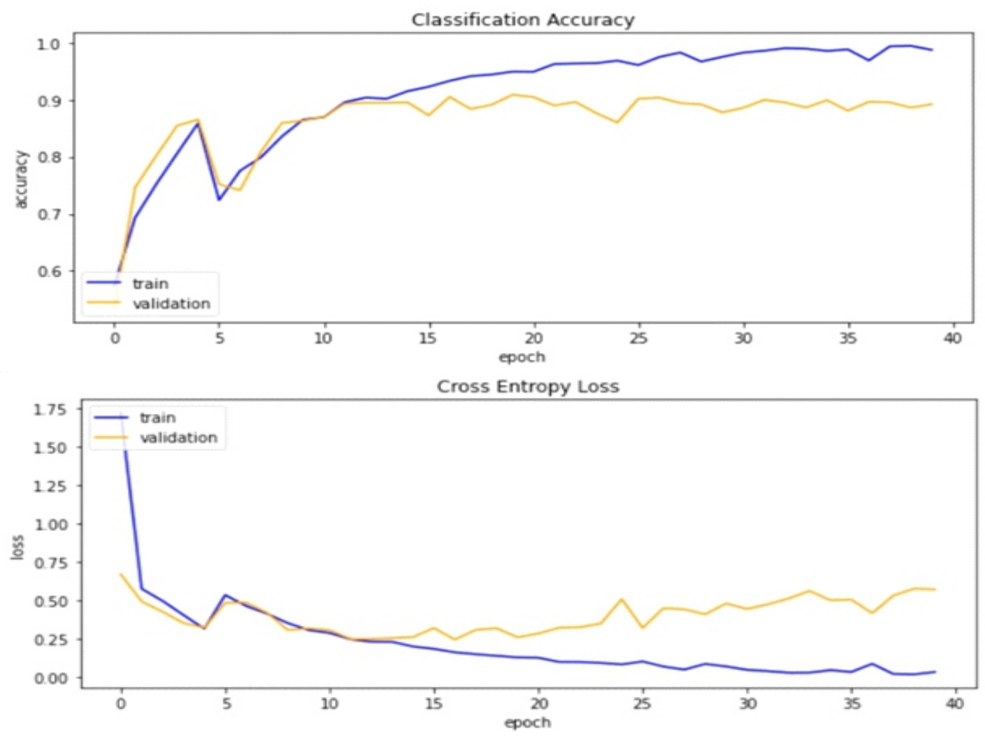

Fig. 2. Accuracy and cross entropy loss learning of the neural network after training using the first dataset.

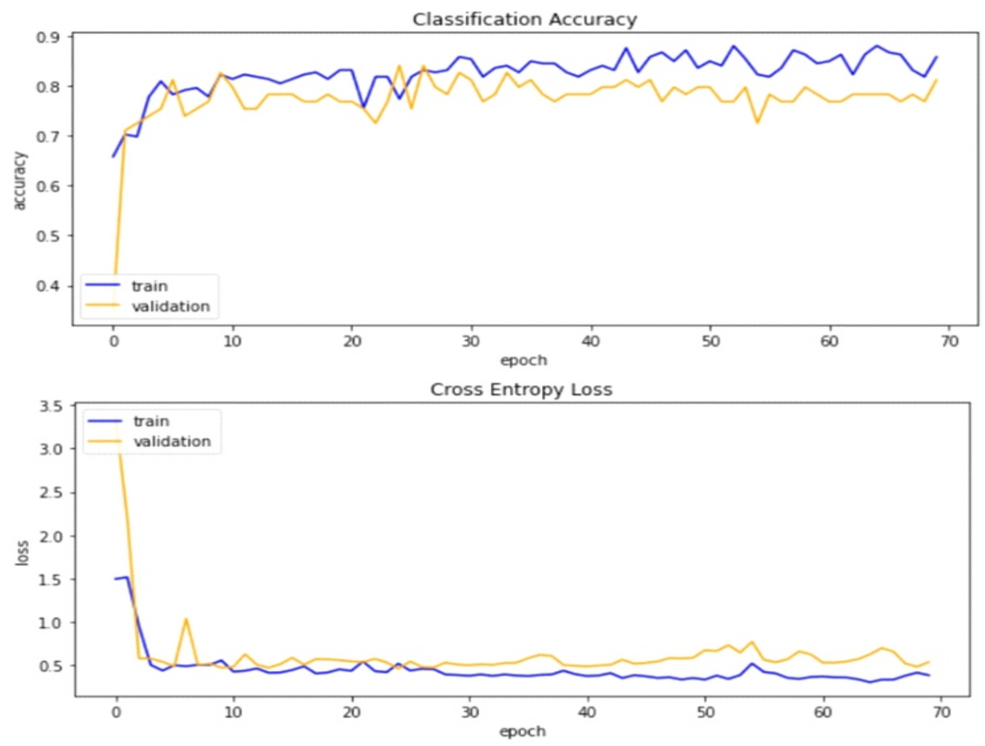

Fig. 3. Accuracy and cross entropy loss learning of the neural network after training using the second dataset.

CONCLUSION

In the next stages of the study, the neural network model will be simplified to find out whether the architecture of the neural network affects its tendency to overlearn.

Thus, this work showed the possibility of classifying dermatoscopic images of skin neoplasms using a convolutional neural network. The obtained learning accuracy is more than 80%, which indicates that this algorithm can potentially be used as an expert system for doctors in the diagnosis of skin neoplasms.

FULL VERSION