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Classification of Skin Images with Respect to Melanoma and Non-Melanoma Using the Deep Neural Network

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Abstract: Melanoma is the most common type of skin cancer. At first, for the diagnosis of melanoma, clinical screening is performed and then diagnosis is made by clinical imaging. It is followed up by dermoscopic analysis, biopsy and histopathological examination. Early diagnosis is important in the treatment of melanoma. Automatic recognition of melanoma from dermoscopy images is a difficult task. Therefore, computer aided systems are recommended to reduce time ,cost and accuracy diagnosis. In this paper, a deep learning-based system is used to classify melanoma in color images taken from dermoscopy devices. With this system, differentiation from previous studies can be done with good accuracy without segmentation step and feature extraction. This system provides a significant advantage in hardware implementation. Because there are no pre-processing and segmentation steps. The International Skin Imaging Collaboration database for the designed system is used and includes 1483 training, 517 test data(ISIC). As a result of the classification of these data, the success rate is reached 86-85%.

Keywords: Deep learning, image classification, melanoma, CNN.

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I. INTRODUCTION

Studies on the use of deep learning in the medical field are increasing day by day. The lack of adequate study in this area is due to problems such as the hardware inadequacy of computers in calculations of deep learning networks, and the difficulties in storing and using of very large data [1]. These problems are overcame with the development of technology, and the very complex processes are solved in a very short time. The structures that the human eye can not perceive are found and solved very easily with the development of technology. In this context; in recent studies in the field of health, it is detected that the use of machine learning methods in the analysis of structures beyond human perception provides success [2]. Deep learning is the general name given to machine learning algorithms used to create systems that thinks and make decision like human [3]. Deep learning aims to perform learning and decision making by modeling a structure similar to the human brain. The main subject of deep learning is based on calculating gradually the characteristics or representations of the observational data in which the high-level features or factors are defined from low-level features. The family of deep learning methods includes neural networks, progressive probability models, supervised and unsupervised feature learning algorithms[4]. The Convolutional Neural Network (CNN) is one of the most popular deep learning structure that can extract features of the images without user intervention [5]. CNNs are generally used for classification, localization, detection, segmentation, and registration of medical images [6]. While the first studies using CNN were published in the late 70s, one of the first studies that applied CNN to medical images was performed in 1995 by Lo et al.[7]. In study published in December 2012 by Krizhevsky et al., ImageNet was a turning point for both deep learning algorithms and CNN. In the following years, further progress was achieved using deeper learning structures [8-9]. AlexNet, the newer CNN architecture, is considered as a recent algorithm in the relevant literature to perform the classification tasks on image data. AlexNet took advantage of many techniques to obtain good features from the image automatically. AlexNet network structure is shown in Figure-1 [10].

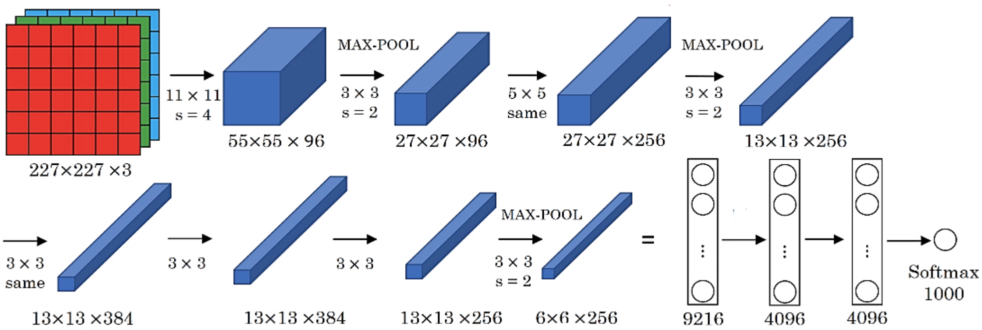


Figure 1: *AlexNet network structure [10]*

This paper is organized as follows; section two is about previous study and section three is about developed material and method,next section give conclusion.

II. RELATED WORKS

Since the 2000s, a large number of studies were performed on the detection of melanoma from the images. In the first studies, classical machine learning techniques such as k-nearest neighbor (kNN) and support vector machines (SVM) were used. Austrian researchers divided 5393 different images into three classes as healthy, diseased and suspicious. As a result of this research, they reached 90% sensitivity [11]. In another study conducted in 2007, the binary classification as healthy and diseased was made using support vector machines (SVM) after the process such as edge detection and color subtraction performed for lesion segmentation. In this study performed using classical methods, a value of 92% accuracy was reached [12]. After the success of deep learning in the field of image processing was proven, a lot of research was started in this area. J. Kawahara et al. achieved 80% accuracy by applying deep learning to images of 10 different skin diseases [13]. In another study, classification was carried out by performing the feature extraction using deep learning methods and classical machine learning methods, and a 93% accuracy value was reached [14]. In a study published in 2017, the classification of skin lesions was performed using a single CNN and using only pixels and disease labels as inputs. A CNN was trained using a dataset of 129,450 clinical images consisting of 2,032 different diseases. In this study, it reached approximately 90% accuracy [15]. Study published by Li and Shen in 2017,two deep learning methods were proposed for tasks such as lesion segmentation, lesion dermoscopic feature extraction and lesion classification. The proposed deep learning frameworks were evaluated in the ISIC 2017 dataset. Accuracy value was obtained as 0.753 in task 1, 0.848 in task 2, 0.9123 in task 3 [16].

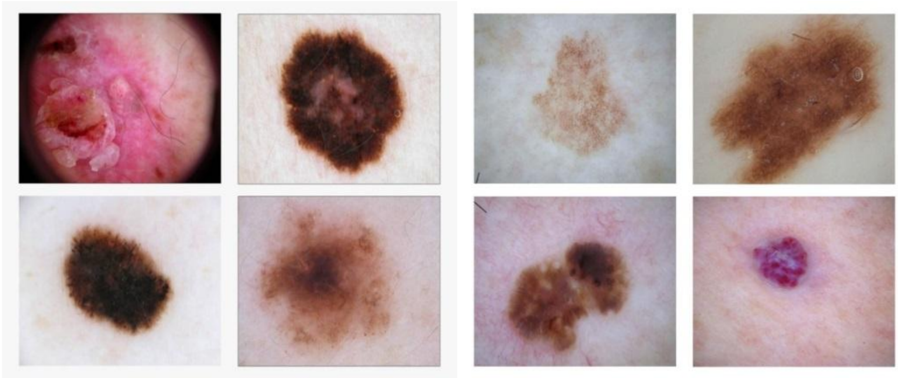
III. MATERIAL AND METHOD

The ISIC (International Skin Imaging Collaboration) archive have been used for the formation of dataset [17]. A total of 2000 color images are used for training and testing. The distribution of the images in the dataset is shown in Table-1. Firstly, binary classification as melanoma and non-melanoma are executed. While this classification is made, specialist doctor information is consulted.

Table 1: The distribution of dataset

Dataset Category	Melanoma	Non-melanoma
Test	93	400
Training	281	1226

The melanoma and non-melanoma in the dataset, i.e. the disease and healthy image samples are shown in Figure-2. The purpose of this dataset is to test the performance of binary classification using multiple data. For that reason, more than one CNN method is used and their success is evaluated.



a.Melanoma **b.**Non-melanoma

Figure 2: a.*Diseased images ,***b.***Healthy images [17]*

In this system, AlexNet is used as a deep learning model. 'ReLU' activation function is used until the last layer and 'Softmax' is used in the last layer. Dropout (0.5) is optionally available before fully connected layers. Dropout is a method use to prevent the deep learning network from becoming over-compatible with the dataset due to over-training. Optionally, the Normalization layer can be used after the max pooling layers. As the optimization function the Adam, Sgd and Rmsprop functions are used.

Accuracy and error values obtained by changing the number of steps, activation function and error optimization method are shown in Figure-3 and Figure-4.

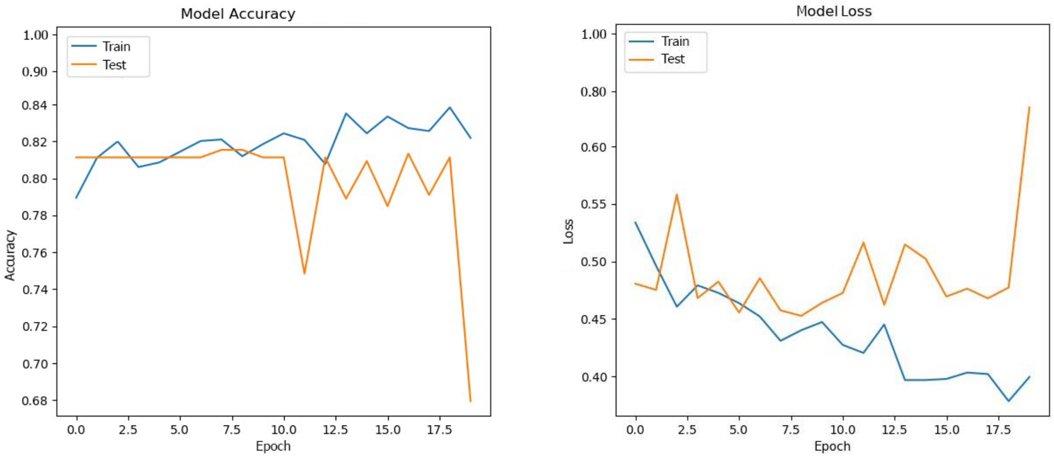


Figure 3: *Performance (Left) and Error (Right) Rates of AlexNET*

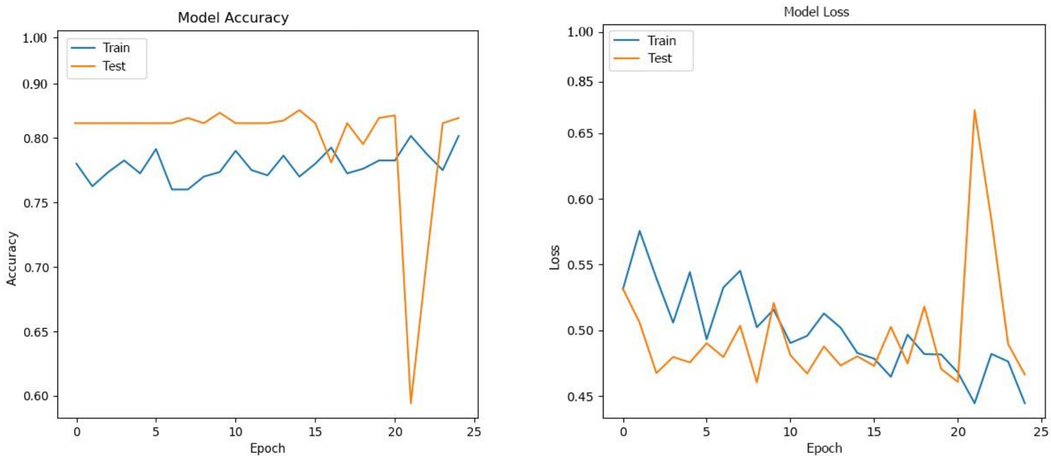


Figure 4: *Performance (Left) and Error (Right) Rates Charts of AlexNET*

In the second classification, seborrheic keratosis, nevus and melanoma images are used. The image samples are shown in Figure-5. The distribution of the images in the dataset is shown in Table-2.

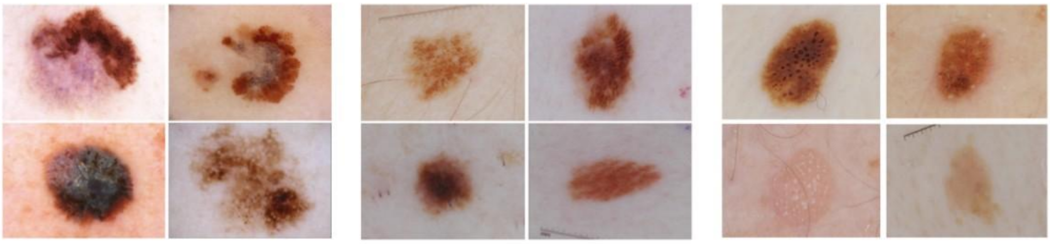


Figure 5: *Image samples [17]*

Table 2: The distribution of the images in the dataset

Dataset Category	Melanoma	Nevus	Seborrheic Keratosis
Test	74	393	50
Training	300	979	204

New results are obtained with 50 and 100 steps. Sgd and Rmsprop optimizer methods are tried with Softmax and Sigmoid activation functions. Approximately 76% accuracy is achieved in 50 steps, with an accuracy of approximately 85% in 100 steps. The results of accuracy and error value are shown in Figure-6, Figure-7 and Figure-8.

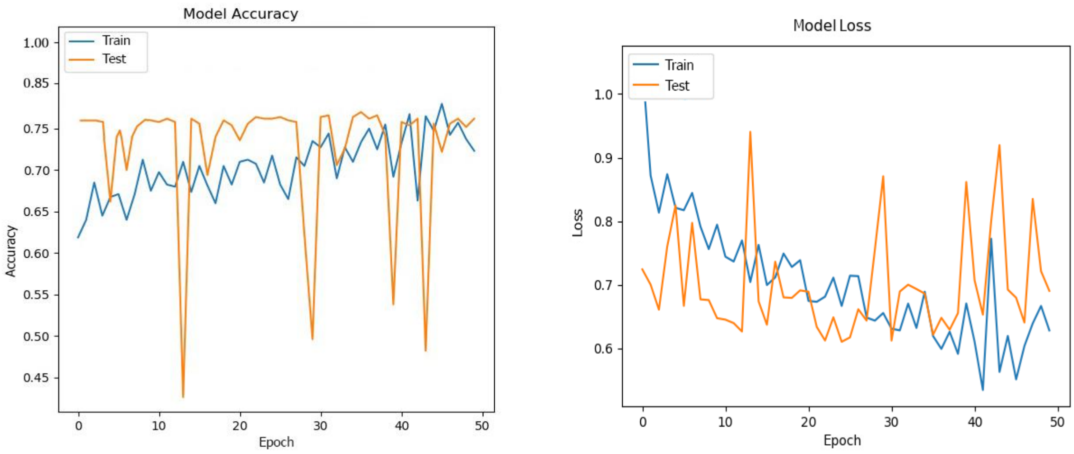


Figure 6: *Performance (Left) and Error (Right) Rates Charts in 50 Steps*

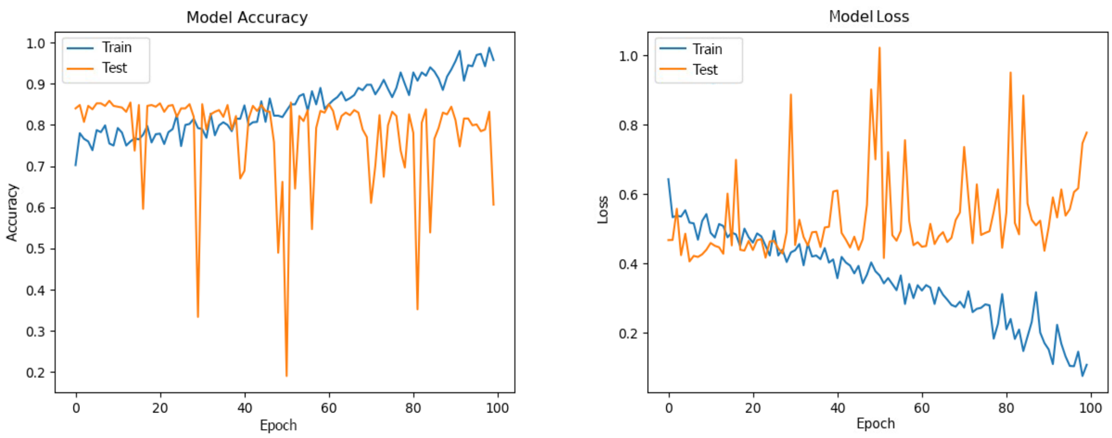


Figure 7: *Performance (Left) and Error (Right) Rates Charts in 100 Steps*

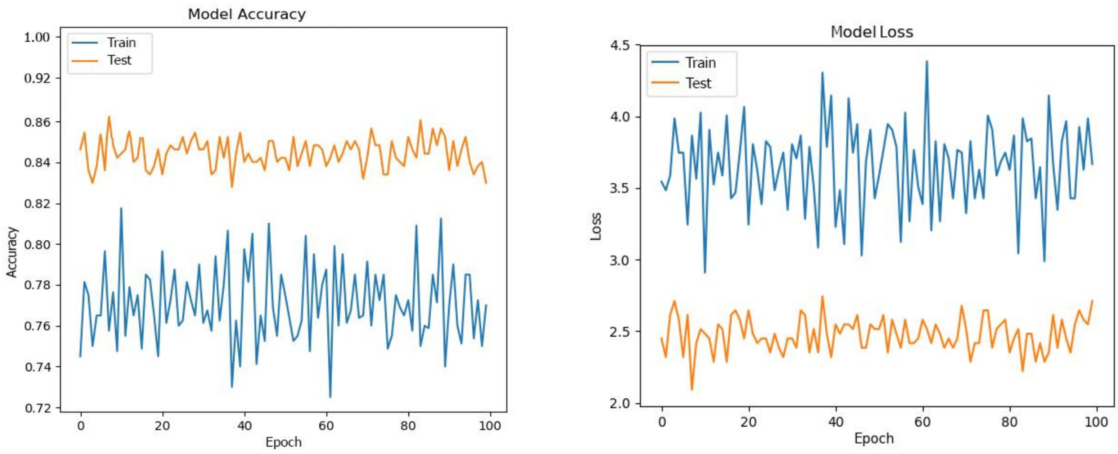


Figure 8: *Performance (Left) and Error (Right) Rates Charts in 100 Steps*

IV. CONCLUSION

In this study, a system that makes diagnosis of melanoma using skin images was proposed. The proposed method was tried using one of the largest datasets usable by everyone. The data set contains 517 different images for testing and 1483 different images for training. In deep learning applications, a large number of images are needed to achieve high success values. CNN based classification was related without any segmentation technique and any preprocessing. Therefore running time was decreased. However, the system was successfully trained with this dataset consisted of a small number of images. As result of various testing, the best accuracy value was found to be 86% and the average accuracy value was 81%.

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