Early Detection of Skin Cancer Using Deep Learning Architectures: Resnet-101 and Inception-v3

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***Abstract*— Skin cancer is one of the most prevalently seen cancer type in human beings. Skin cancer occurs due to the uncontrollable growing of mutations taking place in DNAs owing to some reasons. Recognizing the cancer in early stages could increase the chance of a successful treatment. Nowadays, computer aided diagnosis applications are used almost at every field. One of the mostly used areas is health sector. Biomedical datasets are created by saving the data of illness people in computers. Our goal is to obtain an effective way for early diagnosis of skin cancer by classifying our dataset images as benign or malignant. Our dataset consists of 2437 training images, 660 test images and lastly 200 validation images. ResNet-101 and Inception-v3 deep learning architectures are used for the classification task. Once the acquired results are examined, an accuracy rate of 84.09% is get in ResNet-101 architecture, and an accuracy rate of 87.42% is get in Inception-v3 architecture.**

Keywords — skin cancer; classification; ResNet-121; Inception-v3

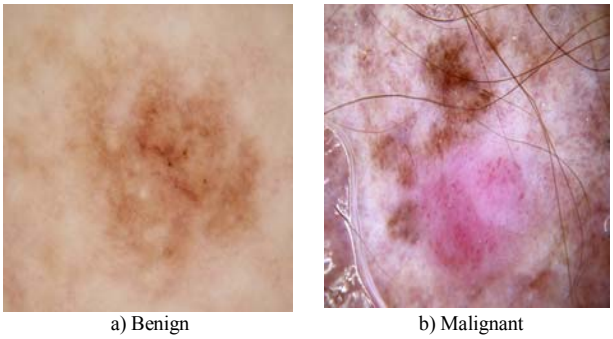
I. INTRODUCTION

Skin cancer is the most common seen cancer type in the world and the prevalence of having this type of cancer is increasing gradually [1]. Malignant cancer type is seen in human body as a result of comprising of mutations in human DNA. Sun light has an important point in arising skin cancer and so the risk of occurring of this type of cancer can be diminished by saving the human body from sunlight by means of some methods saving the body from sunlight [2]. Doctors do the first remedy by some observations on skin for skin disease and then do the medical examinations by dermoscopy method. Dermoscopy is an assistant diagnosis method which is done by taking some pictures with the help of computer systems. Probability of a human being skin cancer is determined by using the results obtained as a result of dermoscopy and naked eye. Diagnosis of skin cancer with this method has an accuracy rate of almost 75-80% [3]. In addition to that, accurate diagnosis rate decreases when skin cancered people are checked up by some doctors who are not expert on this area [4-5]. Exact diagnosis of skin cancer is done as a result of pathological examination of tissue taken by some surgical methods.

It is vital that cancer diagnosis is being timely and accurate by the help of some experts and a number of necessary equipments. Thereby, some computer support systems are used to help to the experts in this area. Nowadays, machine learning and deep learning techniques are used in a great number of areas in addition to the health area. After taking some images from the people coming to hospital, these images are saved and formed a biomedical database by using them.

Structural differences of skin lesions and their color changes are some distinguishing features for the classification of skin cancer. In a study, classification operation is done after obtaining lesions' geometry, color, and tissue features for the diagnosis of skin cancer by using nerve system [6-7]. In an another study, an artificial neural network classifier is used for skin cancer classification [8]. A study using SVM and k-NN classifiers for the classification of skin cancer acquires an accurate diagnosis rate of 61% [9]. In an another study, an accurate diagnosis rate of 78% is acquired by using HOG method for feature extraction and then using LDA and k-NN classifiers for the classification of benign and malignant skin cancer [10]. CNN is used for the classification of four different skin lesions and an accurate diagnosis rate of 77% is obtained for four different classification tasks separately [11].

In this study, malignant and benign images are used. A benign skin cancer image example is given in figure 1.a and a malignant skin cancer image example is given in figure 1.b. These images are trained by using two different deep learning methods and then made classification.



a) Benign b) Malignant

Figure 1. Example test set images

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II. MATERIAL AND METHOD

Skin cancer dataset used for the classification aim is taken from ISIC-Archive [12]. This dataset contains a balanced dataset of images of benign skin moles and malignant skin moles. Each of the images in this dataset is 224x224x3 pixels in size. The skin cancer images in the dataset consist of two different classes: benign skin moles and malignant skin moles. The training data set contains 2437 images in total, 1330 for benign class and 1107 for malignant class. A total of 660 images, 360 benign and 300 malignant, are used in the test process. And lastly 200 images, 110 of which is in benign class and 90 of which is in malignant class, taken from training part of our original dataset randomly is used in the validation step. ResNet-101 and Inception-v3 neural network architectures are used to evaluate the classification performance.

A. *ResNet-101 Model*

The employed structure for our classification task, ResNet, stands for Residual Networks and has an important point on computer vision problems. ResNet network uses residual connections which the gradients can flow directly through to inhibit the gradients to become zero after the applications of chain rule [13]. ResNet-101 contains 104 convolutional layers in total. Along with, it consists of 33 blocks of layers in total and 29 of these blocks use previous block's output directly which is defined as residual connections above and these residuals are used as the first operand of summation operator used at the end of each block to get the input of the following blocks. The remaining 4 blocks take the previous block's output and use it in a convolution layer with a filter size of 1x1 and a stride of 1 followed by a batch normalization layer which performs normalization operation and the resultant output is sent to the summation operator at the output of that block. Dense block depths are different as shown in Table I.

B. *Inception-v3 Model*

It is a commonly used image recognition model that has been shown to attain an accuracy rate of greater than 78.1% on the ImageNet dataset. The model is the culmination of many ideas developed by multiple researchers over the years [14].

The Inception-v3 is composed of a 42-layer deep neural network. Inception-v3 model consists of symmetric and asymmetric building blocks, including convolutions, max pooling layers, average pooling, dropouts, and fully connected layers. The Inception-v3 architecture is shown in Figure 2.

TABLE I. RESNET ARCHITECTURE [13]

Layer Name	Output Size	101-Layer
conv1	112×112	7×7,64, stride 2
conv2	56×56	3×3 max pool, stride 2
		$\begin{bmatrix} 1\times1,64 \\ 3\times3,64 \\ 1\times1,256 \end{bmatrix}\times3$
conv3	28×28	$\begin{bmatrix} 1\times1,128 \\ 3\times3,128 \\ 1\times1,512 \end{bmatrix}\times4$
conv4	14×14	$\begin{bmatrix} 1\times1,256 \\ 3\times3,256 \\ 1\times1,1024 \end{bmatrix}\times23$
conv5	7×7	$\begin{bmatrix} 1\times1,512 \\ 3\times3,512 \\ 1\times1,2048 \end{bmatrix}\times3$
	1×1	average pool, 1000-D fc, softmax
FLOPs		7.6×10^9

III. EXPERIMENT

The classification performance of two different convolutional neural network architectures is evaluated in the skin cancer dataset.

A. *Classification Results of ResNet-101 and Inception-v3*

Training process of these two architectures is completed in 60 epochs. Learning rate is determined as 0.001 at the beginning of the training process and this ratio diminishes gradually at every stage of training. Figure 3.a suggests the graph of accuracy and loss values obtained by using Resnet-101 architecture. According to this graph, train and loss lines are almost constant after 50 epochs. Furthermore, rise of training accuracy reaches a saturation point after this epoch. Validation loss is nearly constant after 30 epochs. Figure 3.b shows the accuracy and loss graph acquired by using Inception-v3 architecture. It can be seen once the graph is examined that train loss and validation loss is scarcely constant after 40 epochs. Hence, it can be said that train and validation accuracy saturation points are reached after 40 epochs. Figure 4 shows the accurate and inaccurate prediction numbers of whether the test images are benign or malignant.

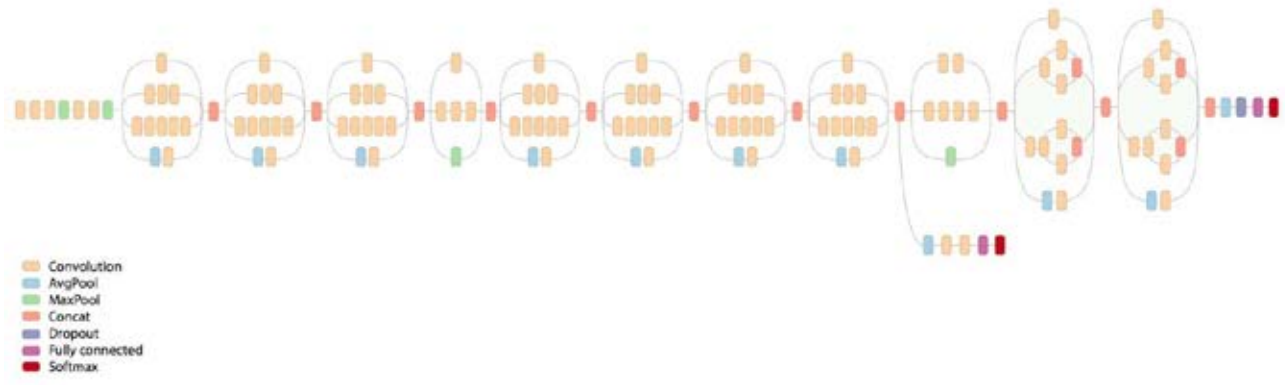
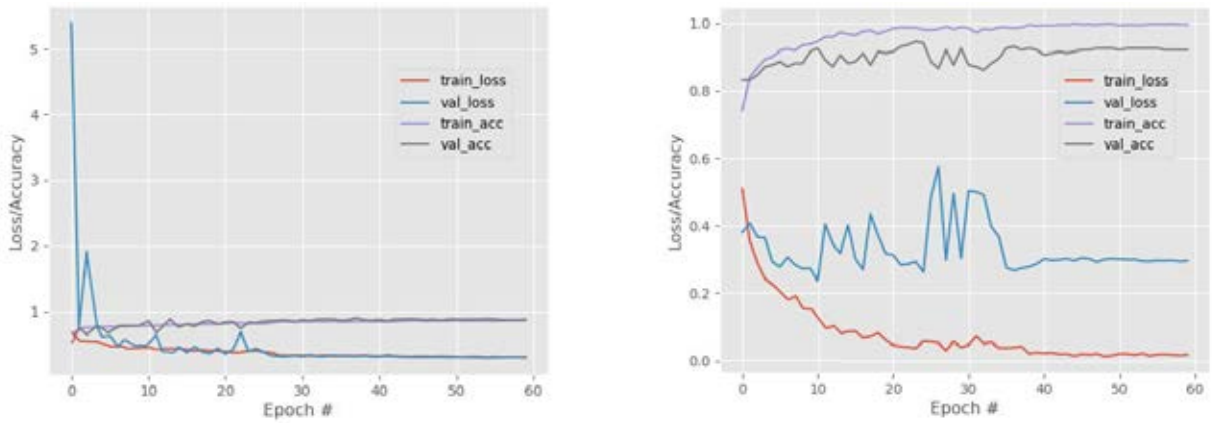
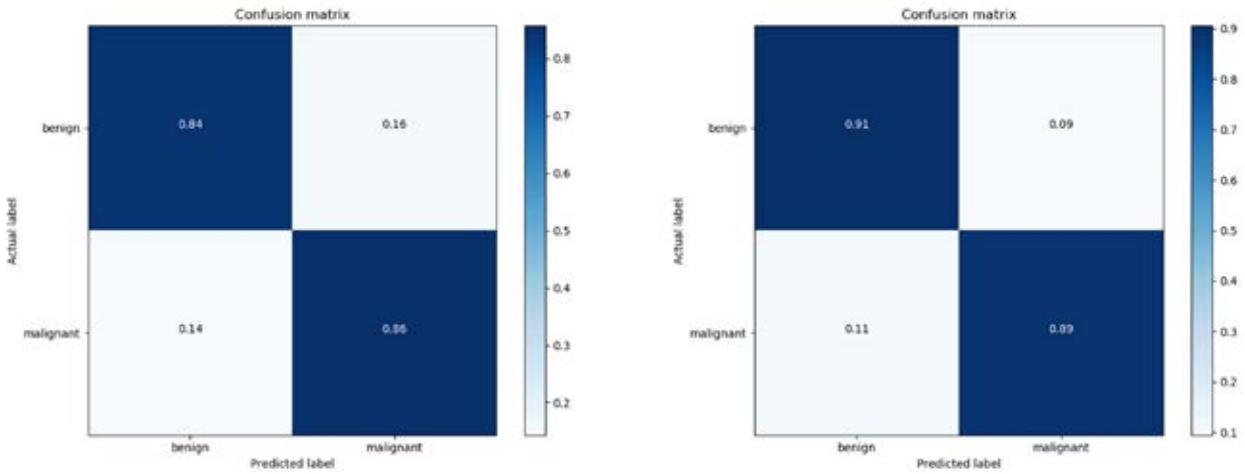


Figure 2. Inception-v3 architecture [14]



a) Resnet-101 b) Inception-v3

Figure 3. Accuracy and loss graphs



a) Resnet-101 b) Inception-v3

Figure 4. Confusion matrix

TABLE II. CLASSIFICATION RESULTS

Model	Validation Accuracy	Benign Accuracy	Malign Accuracy	F-1 Score
ResNet-101	0.8900	0.8277	0.8566	0.8409
Inception-V3	0.9000	0.8861	0.8600	0.8742

IV. CONCLUSION

In this study, we show that two different deep learning methods can be used to diagnose skin cancer with high accuracy rates. The results obtained by using these two algorithms are given in Table II. According to the results, accuracy value obtained in Resnet-101 model is 84.09%, and accuracy value obtained in Inception-v3 model is 87.42%. The results show that the classification performance with Inception-v3 model is better than the classification performance with ResNet-101 model.

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