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Deep Learning Can Improve Early Skin Cancer Detection

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***Abstract*—Skin cancer is the most common form of cancer affecting humans. Melanoma is the most dangerous type of skin cancer; and early diagnosis is extremely vital in curing the disease. So far, the human knowledge in this field is very limited, thus, developing a mechanism capable of identifying the disease early on can save lives, reduce intervention and cut unnecessary costs. In this paper, the researchers developed a new learning technique to classify skin lesions, with the purpose of observing and identifying the presence of melanoma. This new technique is based on a convolutional neural network solution with multiple configurations; where the researchers employed an International Skin Imaging Collaboration (ISIC) dataset. Optimal results are achieved through a convolutional neural network composed of 14 layers. This proposed system can successfully and reliably predict the correct classification of dermoscopic lesions with 97.78% accuracy.**

***Keywords*—technology, dermoscopic lesions, convolutional neural network, ISIC dataset, deep learning, neural networks**

I. INTRODUCTION

IN the last 10 years, from 2008 till 2018, the annual number of people diagnosed with skin cancer increased by 53%; this is partly due to increased exposure to ultraviolet radiation [1, 2]. Although, Melanoma is one of the most deadly types of skin cancer, a prompt diagnosis can lead to a very high probability of survival. Melanoma occurs in the melanocytes, which are melanin-producing cells that give the skin its color. However, malignant melanoma, at an early stage, can be treated; meaning that, the majority of malignant melanoma cases will be treated. Analysis of Dermoscopic Malonic lesions (i.e. moles) to detect malignant melanoma is currently the normal procedure in clinical follow-up. However, dermatologists specialized in diagnosing skin cancer must take into consideration new or dynamic moles and lesions which may appear on the patients' skin [3].

Yet, many of the dermoscopic features and algorithms are complex, confusing and difficult to discover [4]. As such, many dermatologists do not use dermoscopic tools correctly or accurately; which can result in clinical care risk. Completely different imaging techniques, such as multi-spectral imaging and confocal research, are forced to deal with the problems encountered while detecting melanoma tumors.

Nevertheless, these imaging devices and techniques are expensive, heavy, and the specialist working with such devices and techniques needs to be trained in these imaging modalities. It is proven that dermoscopic examination by trained and experienced doctors yields higher sensitivity and specificity [5] in the diagnosis of skin lesion. Therefore, the automated technique for robust analysis of dermoscopic dataset will be extremely helpful for physicians.

The development of advanced dermoscopic algorithms [6], such as "chaos and clues", "3-point checklist", "ABCD rule", "Menzies method", "7-point checklist", and "CASH" were intended to facilitate the novice ability to distinguish and diagnose benign melanoma accurately.

To this end, in 2018 the International Skin Imaging Collaboration (ISIC) hosted a challenge divided into 3 separate tasks to diagnose malignant melanoma employing mechanically dermoscopic images.

In the last few years, deep convolutional neural networks (CNN) become very popular in feature learning and object classification. Additionally, it has been widely used in medicine dataset, such as skin lesion analysis [7]. The fact that, totally different features get detected at the various convolutional layers, permit the network to be handled automatically; therefore, resolving the difficulties of feature detection work present in convolutional pattern analysis techniques.

Deep learning, particularly the convolutional neural network (CNN), has been widely applied to unravel several issues in computer vision. Varied CNN primarily based models developed for object classification and detection, such as Alex Net [8], VGG [9], GoogleNet [10], or ResNet [11]; are trained via the large image database ImageNet and have over 1000 training images for each training session.

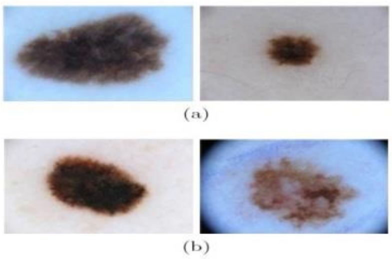

Fig. 1. Illustration of (a) benign Nevus, (b) melanoma

One of the most effective ways to overcome similar challenges in automating the diagnosis of medical imaging is to simplify the objective of analysis, and to take advantage of some reasonable theoretical information dealing with imaging structures. The images may then be categorized using morphological, color, fractional, and texture characteristics. Some researches started to apply deep learning approaches for melanoma recognition.

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Deepti et al., used statistical region merging (SRM) to rule on region growing and merging. Traditional skin is then removed from the affected skin area and the cancer cell is also left within the image. Recognition accuracy of the 3- layers back-propagation neural network classifier is 91% and the auto-associative neural network is 82.6% within the image database that adopt dermoscopy image and digital images. The advantage of this technique is the unique features of the segmented images extracted using 2-D Wavelet Transform. Based on these features, the images were classified as cancerous and non-cancerous. This methodology has good accuracy; however, by changing the image processing methods and classifiers, the accuracy of this technique can be improved [12].

Xulei et al. studied the multi-tasked learning model and proposed deep learning which was assessed on dermoscopic image collections of the International Skin Imaging Collaboration (ISIC) 2017 Challenge. The typical value of the Jaccard index is for lesion segmentation of the 0.724; while the typical values area under the curve (AUC) in the 2 individual best classifications are 0.880 and 0.972. The advantages of this system are the power and efficiency of the multi-task system compared with the traditional deep convolutional neural networks (DCNN). The integration of different annotations from the skin dataset allows the network to detect features that can describe the different attribute of the skin dataset. This allows for the powerful detection of lesion in the skin dataset [13].

Another method proposed by Pieter et al., used a CNN consisting of 4 convolutional blocks formed by 2 convolutional layers, followed by a max pooling of each. They have got a performance evaluation resulting from the CNN's set of test-holding departures, consisting of 600 dermoscopy images (483 benign lesions, 117 malignant lesions), and AUC 0.75. The advantages of this method is the fact that the visualizing feature maps and the CNN result in observing that high-level convolutional layers are activated on similar concepts as those used by doctors; for example, lesion boundaries, dark areas within the lesion, the surrounding skin, etc. They also found that some maps feature activation on various image artifacts, gel application, and rulers. They believe that further research is needed in this area in order to make CNN's decision a better tool for dermatologists [14].

Qaisar et al., studied a clinically-oriented assisted system supported by deep-learning (COE-Deep) algorithms used to mechanically differentiate between melanocytic and non-melanocytic (MnM) skin lesions. Convolutional neural network (CNN) is employed to extract deep features. The statistical results obtained on average reveal 90% of sensitivity, 93% of specificity, 91.5% of accuracy, and 0.92 of the area under the receiver operating curve (AUC) of (ROC) values. Such results were obtained once they used a 10-fold cross-validation test. The proposed deep COE system is best suited to the classification of non-melanocytic skin lesions to improve accuracy, reliability, and accessibility of pigmented skin lesions screening system [15].

Haofu et al., on the other hand, investigated building a global dermatologic classification system using deep CNN. They tend to address this problem by ImageNet pre-trained model's refinement (VGG16, VGG19, and GoogleNet) with Dermnet dataset. Their experiments show that this state of the art CNN models can be done up to 73.1% from top-1 accuracy (VGG19) and 91.0% from top-5 accuracies (GoogleNet) once tested on the Dermnet dataset. They also demonstrated that by increasing variance in the Top-1 training group; their top-5 accuracies can be improved to 31.1% and 69.5%. For future work, the size of the training set must increase. We should also take note that images retrieved by networks must be as realistic as can be [16].

Henceforth, Section II deals with the theoretical background and identifies the different types of neural networks that currently exist; whereas Section III discusses the methodology used by the researchers for this current research. Section IV, on the other hand, highlights the results obtained and discusses the advantages of the method employed for this research. Finally, we present the conclusion of the research.

II. Theoretical Background

A. Neural Networks

Artificial neural networks (ANN) are an attempt to imitate or mimic neurons in the brain. However, the models used have many simplifications; thus, they do not reflect or mirror the true and actual behavior of the brain. ANN's initial development took place in the 1940s and, ever since, this development has been witnessing ups and downs [17].

ANNs mathematical model is:

$$y = f\left(\sum_{j=1}^{n}(w_j x_j) + u\right)$$

ANNs use a mathematical model where the input nerve impulse (x_j) is multiplied by a learnable matrix of weights (w_j), which represents the synaptic strengths of neurons. The second parameter learned by the model is called the bias term (u), which is directly added to the elementwise multiplication of previous matrices. The mathematical model of the neuron will fire the output signal ($x_j w_j$) according to an activation function (f), which introduces a non-linearity to the equation. Considering the multiple impulses a neuron can receive as an input; the output of the mathematical model can be expressed as(y).

Different signals calculate the weighted total from the nodes connected to the model and consist of neurons. The nodes are connected in two main patterns. In feed-forward networks, loops do not occur in continuous loop networks. In addition, there is a multi-layered feeder network forward wherever their initial input stage is reflected to the hidden layers and reach an output layer.

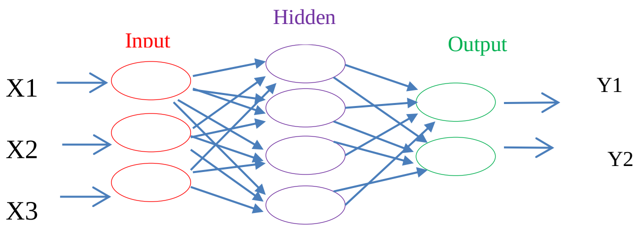

Fig. 2. A feed-forward network with one hidden layer [17]

Learning the part of ANN comes once we find what weight all neurons must have so as to induce the desired result. Within the learning of artificial neural networks, there is a tendency to look for patterns within the examples provided. The way to learn using ANN is through supervised learning (with a named training set), unsupervised learning (discover patterns in unnamed data and enhance learning), and reinforcement learning.

B. *Deep Neural Networks*

The deep neural network (DNN) may consist of one input, one output and fully-connected multiple layers in between. DNN thought about it for several years, but, only recently, a lot of technology-related issues have been solved. This can be mainly due to new learning algorithms and increased computer power. There are three major issues of multilayer networks: vanishing gradient, over-fitting, and computational load [18]. The easiest way to improve deep neural networks (DNN) is by increasing its size both in depth and width; however, this simple solution has two disadvantages; the increased volume can make the networks more efficient, but this shall require a dramatic increase in the power of computer. [19]

C. *Convolutional Neural Networks*

Convolutional neural networks (CNN) are one of the most powerful classes of the deep neural networks in image processing application; where the neurons are arranged in 3 dimensions (width, height, and depth). CNN structure consists of several layers.

D. *CNN Architecture Layers*

Convolutional neural networks are currently one of the most prominent deep learning algorithms with image data. While for traditional machine learning the related features will be manually extracted, deep learning, on the other hand, uses raw images as an input to know certain features.

CNN consist of input layers, output layer, and several hidden layers between inputs and outputs. Examples of intermediate layers are, convolutional layers, max-pooling layers, and fully connected layers.

CNN architectures differ in the number and type of layers implemented to apply them, specifically based on the purpose of its application. For continuous responses, the network should include a gradient layer at the end of the network; whereas for conclusive responses, the system must include a classification function and layer. Neurons are arranged in each CNN layer in 3D order and convert the three-dimensional output of the three-dimensional input. For the specific application of this current research, the input layer holds images as 3D inputs, with height, width and RGB values as dimensions. Figure 3 below outlines the convolutional neural layer attached to the image regions, where it is converted to a three-dimensional output.

In this CNN configuration, the red input layer consisting of an image is transformed into a 3D arrangement. The height and width of the hidden layer are the dimensions of the image, and the depth consists of the three RGB channels [20].

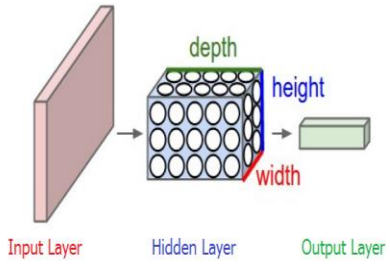

Fig. 3. CNN configuration [20]

In this CNN configuration, the red input layer consisting of an image is transformed into a 3D arrangement. The height and width of the hidden layer are the dimensions of the image, and the depth consists of the three RGB channels [20].

CNN configurations also include a multitude of hidden layers. In each layer, the activation sizes are changed with the use of different functions. There are four types of layer principles used to build CNN configurations described below:

1. Convolutional Layer (CONV): where filters are used to extract an activation map from the input data.
2. Rectified Linear Unit Layer (ReLU): where filters for negative values are used to provide only positive values for much faster training time.
3. Pooling Layer (POOL): performs nonlinear down-sampling and cuts down the number of parameters for a simpler output.
4. Fully Connected Layer (FC): computes the class probability scores by outputting a vector of C dimensions, with C being the number of classes. All neurons are connected to this layer.

E. *Learning Transfer*

Stuart J. Russell, a professor of technology at the University of California, Berkeley,mentioned as stated in [21], that it is easier to learn to play chess, knowing already a way to play checkers; or to learn Spanish with already Italian knowledge. This can be the only thing you will benefit from using learning transfer. Either the CNN's are trained from scratch when the parameters are adjusted for the matter; or they will be turned towards the issue of CNN pre-training. Learning transfer with CNN is usually used within the means that all layers, except the last one, are retained; that is training for a particular problem. This methodology may be very useful for medical applications because it does not require the maximum amount of training data, which may be slow to induce in medical issues [22]. Both [23] and [24] are sampled once there is the higher performance with learning transfer compared to learning CNN with a small dataset.

III. METHOD

A. *Image Dataset*

Through (ISIC) 2018 Challenge and the ISIC Archive, a number of 13,000 dermoscopic image dataset are available to the public. The dataset [25] on skin lesion was used to detect skin cancer throughout this work. The images were obtained from the dataset using the dermoscope. The used images were saved in JPG format (compressed image format). These are 24-bit color RGB images with a resolution of 227x227pixels. The used samples contain a total of 600 images divided into 50% images of melanomas and 50% images of benign lesions.

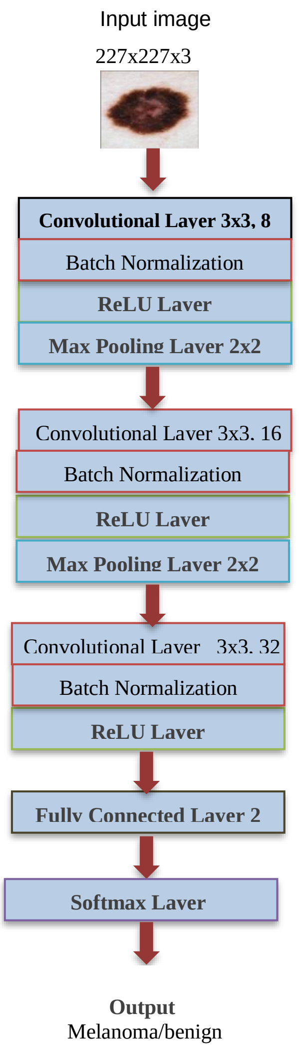

Fig. 4. A systematic flow diagram of the proposed system for classification of melanocytic and non-melanocytic skin lesions

B. Pre-Processing

Before feeding the dermoscopic images into the CNN architecture, the raw input images are exposed to a set of pre-processing transformations. In this paper, the pre-processing procedures applied to the input images are as follows:

1- Mean subtraction: to center the cloud of RGB values from input data on zero along each dimension of the image, subtraction is applied to the image features.

2- Image normalization: through dividing each RGB dimension from input images by its standard deviation, the normalization of the original 0 and 255-pixel values are obtained to 1 of 0 normalization values. This technique is processed avoiding other issues caused by poor contrast of images.

3- Image cropping & resizing: the input image is preprocessed to be accepted by the architecture, thus, the image is cropped to the needed same aspect ratio and the original image size is changed to 227x227.

4- When using the dataset obtained through (ISIC), including 600 dermoscopic images, the images are enlarged and minimized using a convolutional neural network with 14 layers. The results of this process will be displayed at the result and discussion section of this paper.

C. CNN Network Layer Configuration

A common approach is to use a CNN pre-trained on a large image database. CNN will also contain a lot of uninformative filters. Thus, we enter an image with a size of 227x227x3; corresponding to the height, width, and channel size. The CNN used for this research consists of 3 convolutional blocks, each block is formed by 3 convolutional layers, followed by 3 batch normalization, 3 RELU layers, 1 fully connected layer; and Softmax layer.

Convolutional layers are used as feature identifiers and they are sometimes followed by a down-sampling operation that reduces the spatial size of the feature map and removes redundant spatial information. Down-sampling makes it possible to increase the number of filters in deeper convolutional layers without increasing the required amount of computation per layer. One way of down-sampling is by using a max pooling layer created using maxPooling2dLayer.

The max pooling layer returns the maximum values of rectangular regions of inputs, specified by pool size. In this system, the size of the rectangular region is (2, 2). The 'Stride' name-value pair argument specifies the step size that the training function takes as it scans along the input. The convolutional layers in each block have a kernel size of 3x3 and have 8, 16, and 32 filters, respectively. It uses the number of filters (numFilters), which is the number of neurons connected to the same region of the input. This parameter determines the number of feature maps.

Batch Normalization is a technique to provide any layer in a Neural Network with inputs which are zero mean /unit variance. It also used for speeding the training process.

Following this, 2 fully connected layers are used to compute the class probability scores by outputting a vector of C dimensions; with C being the number of classes. All neurons are connected to this layer. The first layer consists of 100 neurons, while the second layer consists of 2 neurons. All layers have rectified linear units (ReLU) as non-linear activation function; ReLU consists of filters for negative values to provide only positive values for much faster training time. As a final step, the researchers insert the output of the layer on (Fc) and SOFTMAX to make the classifier. For this process, data from the publicly available ISIC Archive was used [25], to compose a training set of 600 dermoscopic images, spread over two classes (50% benign lesions, 50% malignant lesions). In a preprocessing step, the images are downscaled to a resolution of 227x227 pixels. Additionally, the researchers trained the network for 50 epochs with a learning rate of 0.01, while CPU was used as the hardware.

IV. RESULTS & DISCUSSION

This paper proposes an automatically dermoscopic detection pattern using deep convolutional neural networks. The system used was trained by using different numbers of images, where the accuracy increases with increasing the number of images; then the accuracy starts to decrease, and this is called over-fitting and is illustrated in Figure 5. The dataset obtained through (ISIC), including 600 dermoscopic images and 300 samples in each class, when employed; the results obtained show that 50% of images are melanoma, while the other 50% are benign. The best results achieved by a convolutional neural network with 14 layers are 97.78%. In this paper, the results of the pre-processing procedures applied to the input images achieved by a convolutional neural network when enlarged and minimized will be as shown in Figure 6:

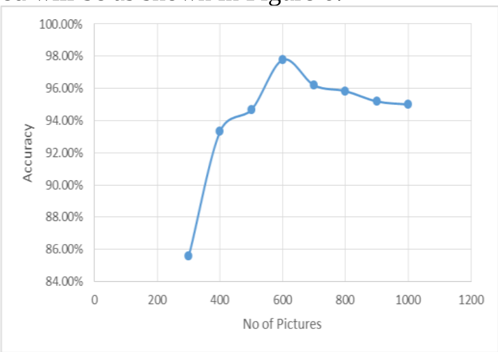

Fig. 5. Accuracy result of different amount of dataset

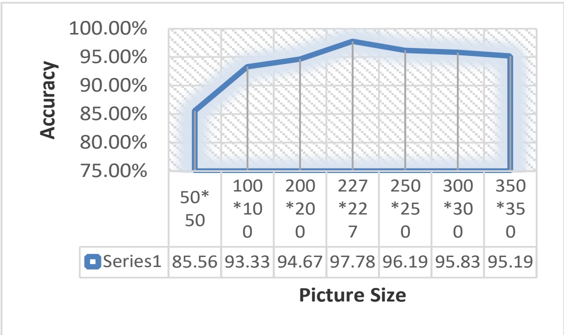

Fig. 6. The result of the pre-processing accuracy

When we are cropping and resizing the images; input images are preprocessed to be accepted by the architecture; thus, the image is cropped to the needed same aspect ratio and the original image size is changed to 227x227 when using the dataset obtained through (ISIC). Upon minimizing the images, the accuracy increases and the best accuracy achieved is 97.78% at size 227x227; however, when we enlarged the images, the accuracy decreases causing over-fitting.

Comparison between No. of pictures and accuracy:

The system used in this research was trained using different numbers of images. The accuracies of the training phase can be seen in Figure (5) above, where the accuracy increases with the increased number of images; then the accuracy starts decreasing. Therefore, we conclude that the system is *over-fitting*. The used system achieved high accuracy of 97.78% with the used dataset consisting of 600 dermoscopic images.

When using 14 layers, the accuracy achieved scored 97.78%; however, when we used the same number of images increasing the layers to 22 layers, and 30 layers, the accuracy becomes 97.92% and 98.34%, respectively. This means that when we are increasing the number of layers the performance becomes better. For the purpose of this research, the optimum number of layers used is 14 layers, as increasing the number of layers beyond 14 layers results in more computation and consumes more resources.

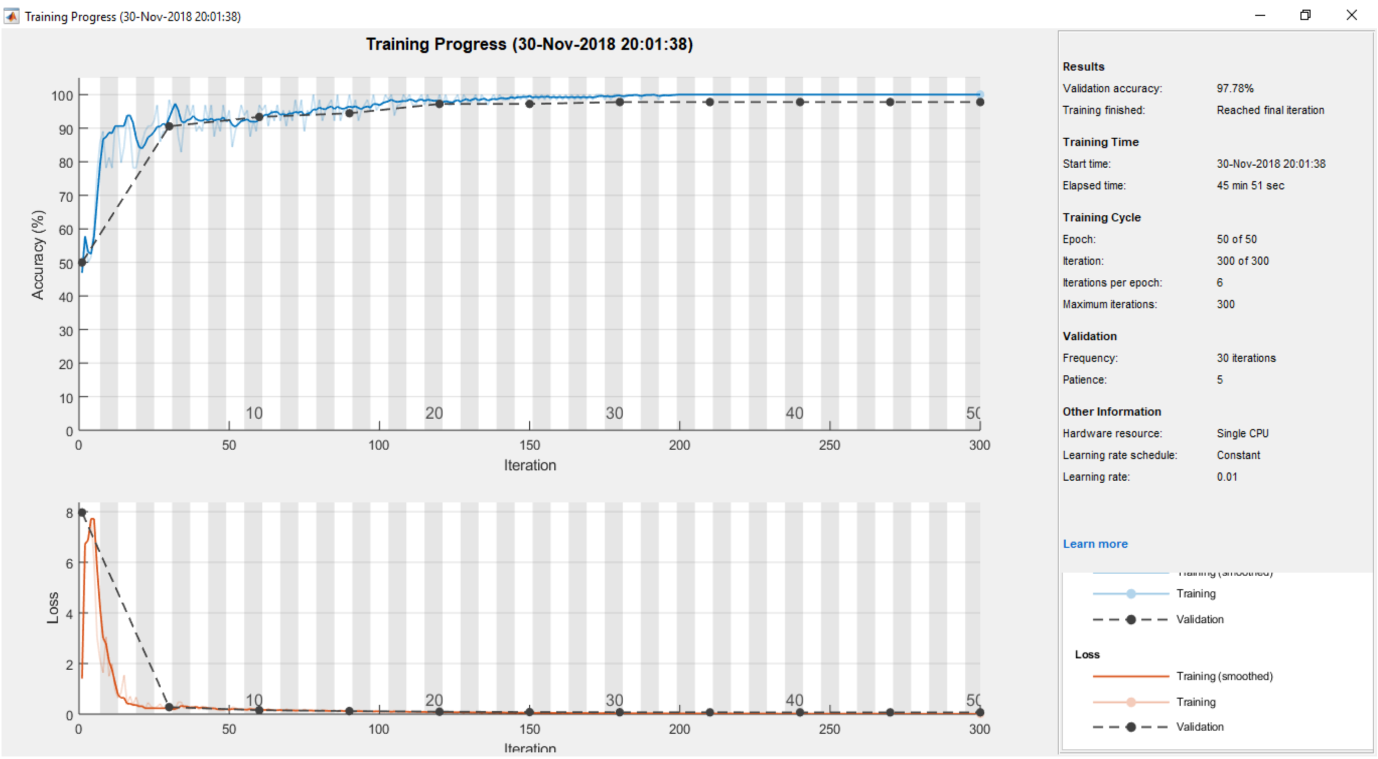

Fig. 7: Depiction of the accuracy of the training phase

TABLE I
COMPARISON BETWEEN NO. OF LAYERS AND ACCURACY

No of layers	Accuracy
14	97.78 %
22	97.92 %
30	98.34%

TABLE II
COMPARISON OF SKIN LESION CLASSIFICATION USING DEEP LEARNING TECHNIQUES

Authors	Accuracy
Qaisar Abbas [13]	91.5%
Deepti Sharma [14]	Recognition accuracy 91% and 82.6%
Andreas Nylund [26]	89.3%
Haofu Liao [17]	31.1% and 69.5%
Doaa A. Shoieb [27]	93.75%,94.12% and 98.04%
The Proposed System	97.78%

To validate the results of this current research, the researchers, as illustrated in Table II, compared between the results obtained through this current research and the results from recent published papers in the same field. The comparison proved that the method used for this research achieved the highest accuracy; entailing that the CNN designed by the researchers for the purpose of this research is well designed. Furthermore, the newly introduced method employed by the researchers in this research achieved better accuracy because a two-class classifier was designed and implemented taking skin lesion images labeled as malignant or benign as an input. Additionally, a model using deep convolutional neural networks was built. This built model was used to predict whether an image of a skin lesion is malignant or benign. The number of layers was increased and a pre-processing method was used to show the effect of these layers on the images. The achieved accuracy scored is 97.78%.

For sake of completeness, finally, the method used in this research is compared with the conventional method for melanoma classification. The comparison is done according to the same dataset consisting of 600 dermoscopic images. In the conventional system; the total number of images is [600 images]; 214 images were classified true positive, 238 images were classified true negative; whereas, 86 images were classified false positive and 62 images were classified false negative. So, an accuracy of 75.3% is achieved. While in this work, the CNN method, achieved a better accuracy of 97.78%.

CONCLUSION

In this paper, the researchers investigated the possibility of automatically distinguishing between melanocytic and non-melanocytic (MnM) skin lesions. The method employed proposed a solution to assist dermatologists during the diagnosis of skin lesions. A two-class classifier was designed and implemented taking skin lesion images labeled as malignant or benign as an input. Additionally, a model using deep convolutional neural networks was built. This built model was used to predict whether an image of a skin lesion is malignant or benign. The number of layers was increased and a pre-processing method was used to show the effect of these layers on the images. The achieved accuracy scored is 97.78%. Finally, the researchers believe that the proposed classification system can achieve promising results on the validation set and has the potential to be a computer-aid diagnosis system for melanoma detection.

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