Skin Cancer Classification Using CNN Skin Cancer Classification Using CNN View project

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Skin Cancer Classification Using CNN

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Abstract
In the world wide mostly of the cancer are skin cancer, essentially, there are two kinds of skin cancer called malignance and non-malignance.In this paper , design a system to detection and classification skin cancer with high accuracy and sensitivity by using Convolution Neural Network (CNN) which able to diagnose different types of cancer in a human skin. With the objective of utilizing more meaningful information to improve skin cancer and help physicians in the clinical diagnosis and accurate detection of the disease. The system supports physicians to prevent errors while identifying and classifying cancer. This is motivated by potential performance improvement in the general automatic and giving reliability in decision-making and rapid detection of skin cancer this technology is of great and economic importance to physicians.The system divided in two type which contain the following stages: image acquisition, preprocessing, and classification, while the second part consist of image acquisition, classification.There is a significant change between the classification with preprocessing and without preprocessing, as with preprocessing the accuracy decreased that return to the reason that the pictures that were taken to the skin are too close and the do not require any preprocessing.
Keyword: Skin , Cancer , Algorithm CNN

1Introduction

In the world wide mostly of the cancerare skin cancer [1, 3, 4]. Essentially, there are two kinds of skin cancer called malignance and non-malignance. Recently,malignance frequency has raised veryhighly,lead to become the main concern in public health. Nevertheless, if the patients were diagnosis early there may be higher degree of curing, particularly if thediagnosis done in the initial stage ofthe cancer, the ratio of curing may be more than 90%. [1,2]

If both visual inspection and dermato-scopic images are used for the diagnosis the accuracy 75%-84% by dermatologists [5,6].some time the issue of skin classifying has also stimulatedto the emphasis of thecommunity of the machine learning. The physicians can be supported by both classification with using automated lesion and daily clinical routine that give the capability for quick and less expensive diagnoses, even if the patients were not in the hospital, through installation of apps on mobile devices. [7,8]

There are many studies try to diagnose skin cancer with more speedily and in the initial stage, by evolving computer image analysis algorithms [9].Thedetection of skin cancer andimage classification have been suggested by the studies suggest, there exists anembarrassment of research papers. A comprehensive survey of these approaches is available in Refs. [10,11,12]. Every one of theses papers [10,11,12] used available state-of-art approaches andimprovementsof claim performance. The most knownapproaches used for classifications of image differ from application of algorithms ofdecision tree [13,14] Bayesian classifiers [15,16], support vector machines [20,17], to a diversity of Artificial Intelligence based approaches [18,19].

In this paper,design a system to detection and classification skin cancer with high accuracy and sensitivity by using Convolution Neural Network (CNN) which able to diagnose different types of cancer in a human skin. With the objective of utilizing more meaningful information to improve skin cancer and help physicians in the clinical diagnosis and accurate detection of the disease. The system supports physicians to prevent errors while identifying and classifying cancer. This is motivated by potential performance improvement in the general automatic and giving reliability in decision-making and rapid detection of skin cancer this technology is of great and economic importance to physicians.

CNNs are neural networks with a that have architecturethat consider very prevailing in areas like recognition andclassification of image [21]. CNNs have been establishedfoe faces, objects, and traffic signsidentification with much improvedway than humans and therefore can be found in robots and self-driving cars.

for the issue ofclassification malignancy[22]. the most used algorithm is CNN. It encompassed of two key parts that are feature extractor and classifier. features of Images are investigated and précised by diverseCNN layers, features in every layer characterize the abstraction level of the object, the lower-level features are taking out by the earlier layer, and the higher-level features are taking out by the next layer of CNN.

Titus J. et al 2018[23] introduce the first methodical appraisal of the unique research on skin lesions classifying with CNNs. In specific, approaches that used a CNN for segmentationonly or for the dermoscopic patterns classification are not measured.

Rina R. et al 2019 [24] proposed a system for Skin Cancer classification of dermoscopy examination and to increase the accuracy of the results with lesstime. The proposed system usesCNN and LeNet-5 architecture for classifying image data. The research using 44 images data from the results oftraining with a diverse number of training and epoch caused that 93% for training and 100% in testing, that the number of raining data used of 176 images and 100 epochs.

2. Proposed System

The proposed approach depends on three main steps to detect and classify the skin cancer. The input to the system is an image, and the output is a classification of skin cancer.

The proposed system has several main stages and each stage has several steps that work together to achieve the system goals. The system divided in two two type which contain the following stages: image acquisition, preprocessing, and classification, while the second part consist of image acquisition, classification. Figure (1) shows the general diagram of the proposed system to classification using CNN the skin cancer from images.

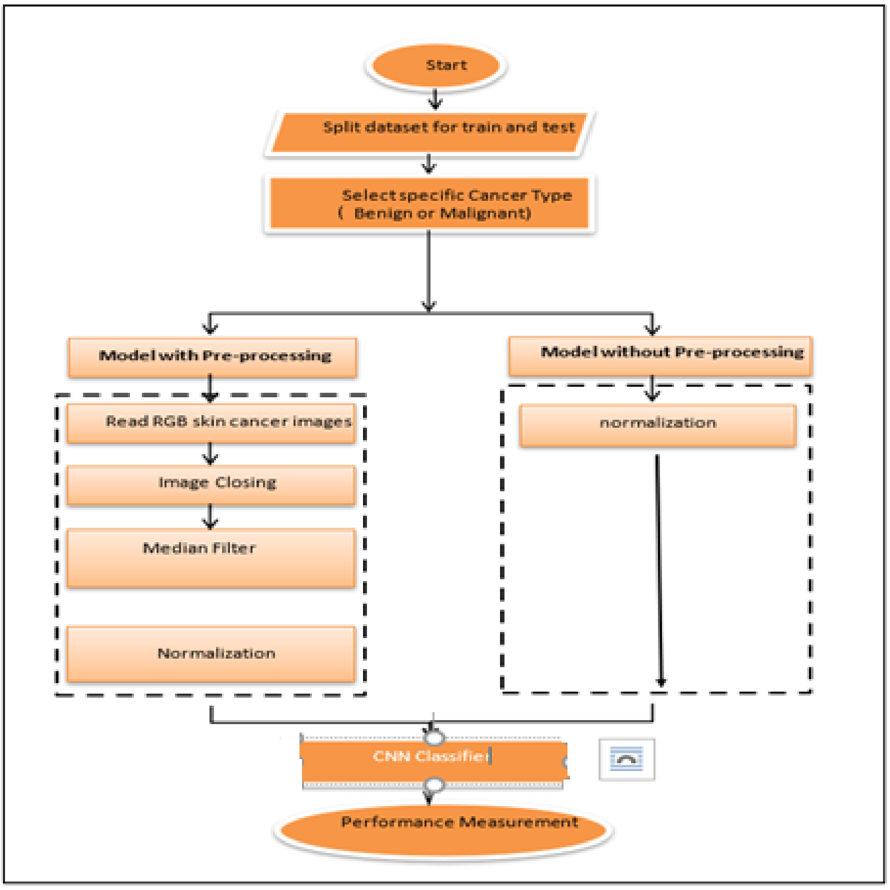


Figure (1) Block Diagram of the first proposed system

In order the method for skin cancer detection and classification for the proposed system, images of skin cancer, a dataset was collected from the source for different categories of the most common skin cancer.

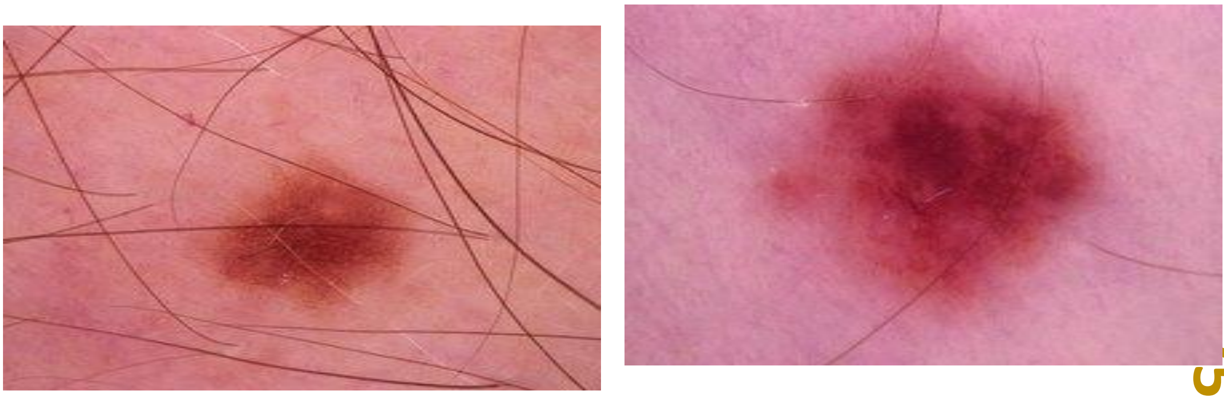


Figure (2): Samples of Different skin cancer Images

3. Image Preprocessing Stage

In preprocessing image step the proposed system consists of multiple steps, they are:

3.1 Normalization for image

Picture are loaded and convert them into numerical python array using their RGB values. As the pictures have already been resized to 224*224 and there is no need them to resize them. Because the picture do not have any label then the picture is loaded, then normalize in rang [0,1] all values images by dividing them RGB values of images by 255.

3.2 Removal of hair by image closing operation and median filter

In dermoscopic images, the most common artifact, and necessary to remove, is the hair. Many methods and algorithms are presented in the literature to remove the hair when it is not shaved before the acquisition step. Therefore, the typical algorithm of hair removal methods is based on two main steps:

1. First use simple morphological closing operation with a disk-shaped structuring element. Based on the assumption that hair segments are thin structures, a simple morphological technique is applied.
2.Next, a hair mask is retained by using a global automatically threshold over the image intensity information. Each hair pixel from the resulted mask is replaced by an average mean of the neighbor's pixels. (using median filter after closing operation).

4. CNN

The CNN algorithm is used to classify skin cancer Figure (3) represents the block diagram of the CNN model that used both pre and without preprocessing.

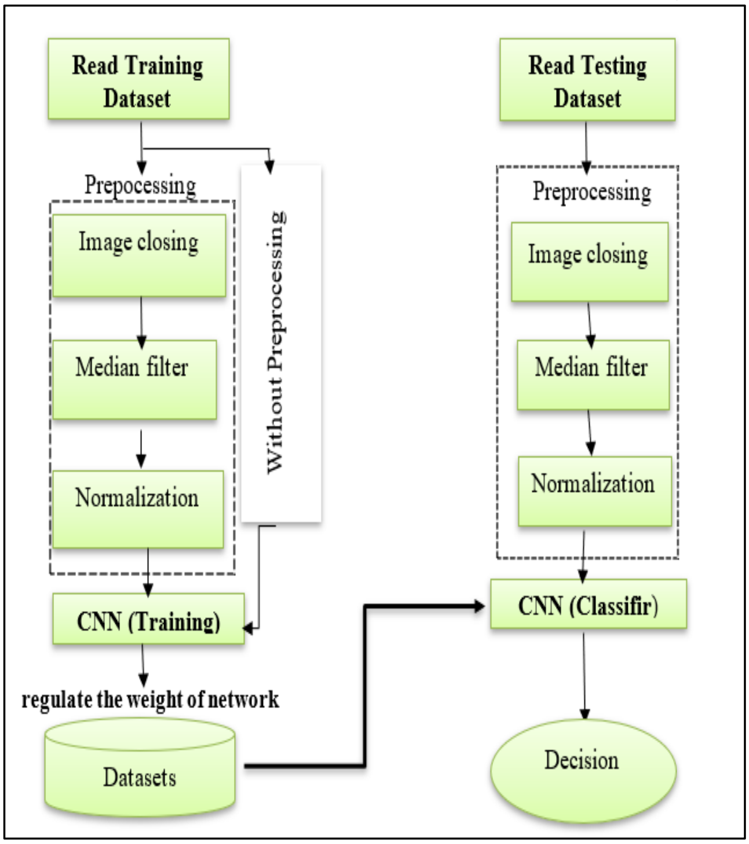


Figure (3): Represents the block diagram of the CNN model

CNNs are applied to distinguish between the two classes of the skin cancer (benign and malignant) by producing such as a vector of probabilities for all tested images. The effective and correct the performance of the CNN for the correct class (Y) using the image (x) is by the loss function (classification error). Conv2D layers that have the parameters are learned using a Stochastic Gradient Descent (SGD) approach and a Backpropagation Algorithms for fine tuning the whole parameter in the CNN fully connected layer. This section explores the performance results of CNN. In order to perform the backpropagation method for each epoch to achieve the parameter fine-tuning operation. A fully connected layer to perform the classification tasks has been designed as a last layer of the proposed CNN structure.

Figure (4) Shows the CNN architecture of the multi-channel input image to the output function exploiting full color information in RGB stained images, and includes a pooling layer which improves the classification.

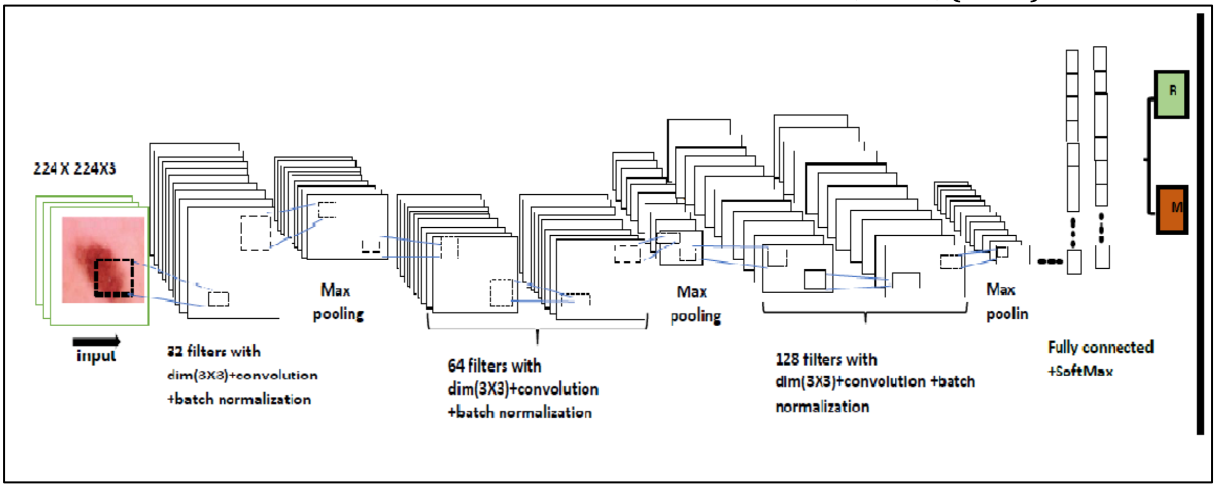


Figure (4): Represents the Architecture of CNN

The first is the convolutional (Conv2D) layer. It is like a set of learnable filters. I choose to set 64 filters for the two firsts conv2D layers. Each filter transforms a part of the image (defined 3 by the kernel size) using the kernel filter. The kernel filter matrix is applied on the whole image. Filters can be seen as a transformation of the image. The CNN can isolate features that are useful everywhere from these transformed images (feature maps). The second important layer in CNN is the pooling (MaxPool2D) layer. This layer simply acts as a downsampling filter. It looks at the 2 neighboring pixels and picks the maximal value. These are used to reduce computational cost, and to some extent also reduce overfitting. We have to choose the pooling size (i.e the area size pooled each time) more the pooling dimension is high, more the downsampling is important. Combining convolutional and pooling layers, CNN are able to combine local features and learn more global features of the image. Dropout is a regularization method, where a proportion of nodes in the layer are randomly ignored (setting their wieghts to zero) for each training sample. This drops randomly a propotion of the network and forces the network to learn features in a distributed way. This technique also improves generalization and reduces the overfitting. 'relu' is the rectifier (activation function max(0,x). The rectifier activation function is used to add non linearity to the network. The Flatten layer is use to convert the final feature maps into a one single 1D vector. This flattening step is needed so that you can make use of fully connected layers after some convolutional/maxpool layers. It combines all the found local features of the previous convolutional layers. The implementation of CNN is shown in figure (4) which show the input layer, hidden layers with neurons sequentially, and an output layer that has a number of neurons.

5. Results and Discussion

In this stage, the results of the model is explained , the model is divided into two part , the first part without preprocessing and the results as follow :

Skin Cancer Images Pre-processing Results

In this stage, two processes are performed on skin cancer images in order to make them ready for the next stages first step is closing operation applied then median filter figure (5) show hair Remove by image closing followed by median filter and the image after and before applied the hair removal algorithm.

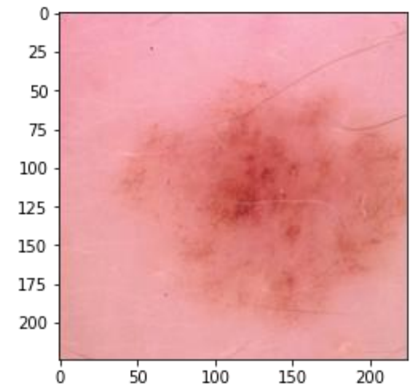


Image before preprocessing

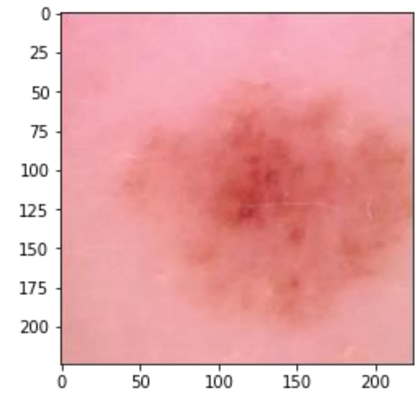


Image after preprocessing

figure (5) show skin cancer image Preprocessing

A- Without Preprocessing:

The first proposed model is implemented and trained by using the dataset, where the (2637) images are selected for training and (660) for testing. Figures (6) shows the variation in the loss and accuracy of the model without preprocessing, using training images, in 30 training epochs. The classification accuracy of the firstproposed model without preprocessing and in 30-epoch, using the test images, is 85.00%, and the total time is 9637.1 seconds.

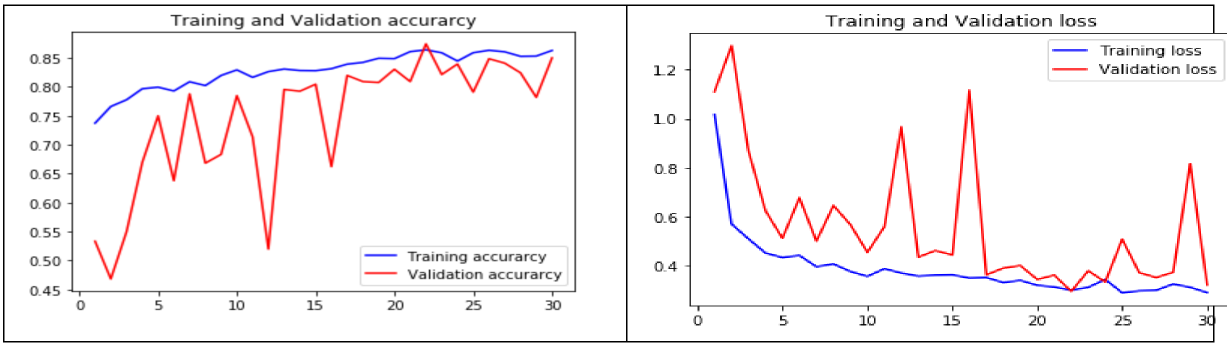


Figure (6): Accuracy and Loss Validation Change Against Training Epochs using CNN Model(30-Epoch) without preprocessing.

Table (1) The accuracy and loss for each training in 30-Epoch

Epoch	Time	Loss	Accuracy	Val _loss	Val _accuracy
1	318s 8s/step	1.0479	0.7373	1.1103	0.5333
2	319s 8s/step	0.5662	0.7660	1.2979	0.4682
3	318s 8s/step	0.5212	0.7777	0.8681	0.5500
4	316s 8s/step	0.4485	0.7967	0.6237	0.6697
5	318s 8s/step	0.4319	0.7995	0.5115	0.7500
6	318s 8s/step	0.4356	0.7928	0.6773	0.6379
7	316s 8s/step	0.4127	0.8088	0.4996	0.7879
8	318s 8s/step	0.4040	0.8022	0.6455	0.6682
9	317s 8s/step	0.3778	0.8197	0.5669	0.6833
10	323s 8s/step	0.3557	0.8293	0.4535	0.7848
11	313s 8s/step	0.3962	0.8164	0.5586	0.7136
12	320s 8s/step	0.3689	0.8263	0.9665	0.5197
13	324s 8s/step	0.3568	0.8308	0.4344	0.7955
14	317s 8s/step	0.3681	0.8282	0.4611	0.7924
15	315s 8s/step	0.3571	0.8279	0.4433	0.8045
16	318s 8s/step	0.3492	0.8313	1.1160	0.6621
17	323s 8s/step	0.3508	0.8392	0.3621	0.8197
18	321s 8s/step	0.3392	0.8422	0.3895	0.8091
19	315s 8s/step	0.3461	0.8493	0.4001	0.8076
20	323s 8s/step	0.3193	0.8487	0.3433	0.8303
21	315s 8s/step	0.3152	0.8608	0.3608	0.8091
22	323s 8s/step	0.2994	0.8639	0.2947	0.8742
23	312s 8s/step	0.3104	0.8588	0.3787	0.8212
24	319s 8s/step	0.3424	0.8445	0.3329	0.8394
25	317s 8s/step	0.2931	0.8589	0.5074	0.7909
26	324s 8s/step	0.2967	0.8632	0.3709	0.8485
27	318s 8s/step	0.3018	0.8605	0.3510	0.8409
28	317s 8s/step	0.3265	0.8527	0.3725	0.8242
29	316s 8s/step	0.3160	0.8531	0.8157	0.7818
30	317s 8s/step	0.2880	0.8628	0.3208	0.8500

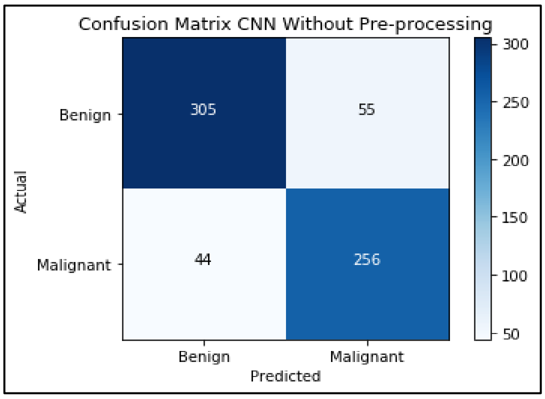
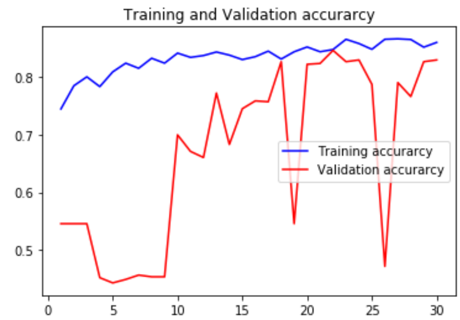


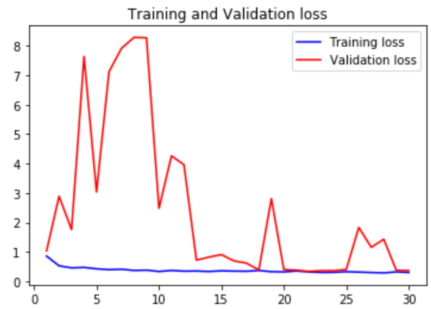
Figure (7): confusion matrix for the CNN training without Preprocessing CNN trainingIn 30- Epoch.

B- With preprocessing

The second part consist of CNN with the preprocessing that is evaluated by using the same dataset, the values of the loss and accuracy of the second model (with preprocessing) during 30 training epochs are illustrated in figure (8).The classification accuracy of the firstproposed model with preprocessing in 30-epoch, using the test images, is 83.03%, and the total time is 9868.3 seconds.



b- The Training and validation accuracy (30-epoch)



a- The Training and validation loss(30- epoch)

Figure (8): Accuracy and Loss Validation Change Against Training Epochs using CNN Model(30-Epoch) with preprocessing.

Table (2) The accuracy and loss for each training in 30-Epoch

Epoch	Time	Loss	Accuracy	val_loss	val_accuracy
1	314s 8s/step	0.8577	0.7450	1.0363	0.5455
2	340s 8s/step	0.5260	0.7854	2.8886	0.5455
3	306s 7s/step	0.4520	0.8010	1.7552	0.5455
4	323s 8s/step	0.4714	0.7839	7.6366	0.4515
5	313s 8s/step	0.4227	0.8096	3.0361	0.4424
6	326s 8s/step	0.3916	0.8247	7.1229	0.4485
7	311s 8s/step	0.4065	0.8158	7.9149	0.4561
8	330s 8s/step	0.3690	0.8333	8.2854	0.4530

9	312s 8s/step	0.3755	0.8247	8.2729	0.4530
10	330s 8s/step	0.3337	0.8422	2.4790	0.7000
11	314s 8s/step	0.3927	0.8348	4.2600	0.6712
12	327s 8s/step	0.3489	0.8379	3.9604	0.6606
13	308s 8s/step	0.3464	0.8442	0.7187	0.7727
14	325s 8s/step	0.3365	0.8387	0.8228	0.6833
15	314s 8s/step	0.3520	0.8309	0.9062	0.7455
16	328s 8s/step	0.3537	0.8360	0.6934	0.7591
17	319s 8s/step	0.3413	0.8457	0.6164	0.7576
18	321s 8s/step	0.3773	0.8319	0.3890	0.8273
19	313s 8s/step	0.3291	0.8445	2.8096	0.5455
20	332s 8s/step	0.3189	0.8529	0.3993	0.8227
21	309s 8s/step	0.3441	0.8446	0.3795	0.8242
22	326s 8s/step	0.3191	0.8484	0.3370	0.8470
23	312s 8s/step	0.3013	0.8662	0.3624	0.8273
24	324s 8s/step	0.3028	0.8588	0.3607	0.8303
25	320s 8s/step	0.3323	0.8488	0.4031	0.7879
26	325s 8s/step	0.3203	0.8663	1.8288	0.4712
27	325s 8s/step	0.2996	0.8671	1.1552	0.7909
28	316s 8s/step	0.2843	0.8659	1.4289	0.7667
29	332s 8s/step	0.3191	0.8525	0.3777	0.8273
30	311s 8s/step	0.3014	0.8608	0.3639	0.8303

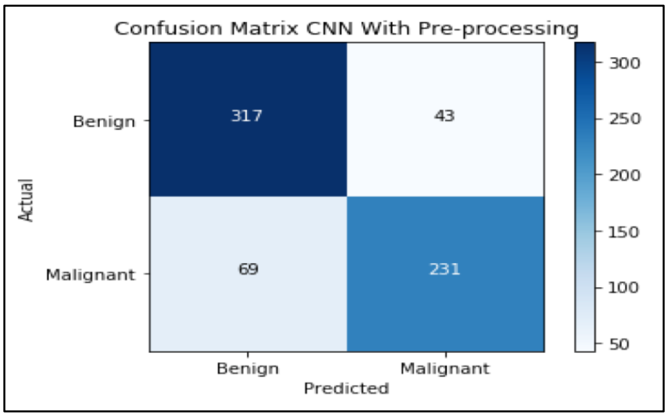


Figure (9): confusion matrix for the CNN training with Preprocessing CNN trainingIn 30- Epoch.

Through the figures (6), and (4.8), and compared to the tables (1), and (2), we notice that the first model with the preprocessing, the classification accuracy has decreased and fluctuation in loss function. As well as the training time, the model with the preprocessing takes more time than it is in model without preprocessing.

Table (4.8) difference between CNN with and without processing

Type	No. epoch	Test Accuracy	Total run Time
CNN without preprocessing	30 -Epoch	85.00%	9637.1 seconds
CNN with preprocessing	30 -Epoch	83. 03%	9868.3 seconds

There is a significant change between the classification with preprocessing and without preprocessing, as with preprocessing the accuracy decreased that return to the reason that the pictures that were taken to the skin are too close and the do not require any processing.

Conclusion and Future work

Skin cancer is classified in both benign and malignant types using a model such as CNN and its proposed system with or without pre-Processing. Where the data is initially trained to obtain a trained model then test this model with test data and displays the results of the prediction in the form of the probability of each type of skin cancer.

The experiment showed that the data used in the training affect the level of accuracy in the classification of images for skin cancer patients, as it turned out that the model without pre-processing data had a higher classification accuracy than the model when using pre-data processing. The reason is that the training data set does not need to be pre-processing.

As a future work, we suggest that other types of dermal cancer data set be used, as well as other methods of pre-processing the data and comparing our findings.

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