Analysis and Classification of Skin Cancer Images using Convolutional Neural Network Approach

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***Abstract*—In this modern era skin cancer is a serious problem around the globe and so it is the age of technology and it is important to solve this problem through intelligence machines which using different algorithms rather than conventional method. Intelligent machine using different algorithms to classify the skin cancer images in a reliable way to save effort, time and ease human life. For this purpose, deep learning (CNN) algorithm is used by intelligent machine to classify the skin cancer images according to its types. In this current research work there are three types of skin cancer types name is Basal cell Carcinoma (BBC), Melanocytic Nevus (NV) and Vascular Lesion (VASC) are used. The study showed that implementing deep learning in the field of cancer diseases may be the most appropriate way to classify and recognize the images of skin cancer according to their type, which can be very useful in the field of medicine for early diagnosis and improve the exact result of the diagnosis. This current work has shown and produced results with 98.89% accuracy**.

Keywords—Convolutional Neural Network, Skin Cancer, Machine Learning, Deep Learning

I. INTRODUCTION

Nowadays in the field of medical technology machine learning algorithm play a great role in diagnosis of different diseases. In the field of medical one of the skin cancer disease can be classify according to their types while using machine learning algorithms. There is a deep learning algorithms (CNN) using for skin cancer images which can ease the diagnosis for doctors of different skin cancer types. While using this algorithm technique doctor just take a picture of patient and pass through it from CNN architecture in order to shows or help the doctor to find the skin cancer disease type. It is the key feature of deep learning (CNN) which can ease the diagnosis without any other type of lab test and cost. More ever, CNN architecture is suited for any computing devices where a lacking of computing power.

Deep convolutional neural networks (CNN) are a new different type of artificial neural networks that give solid results for general and highly variable tasks in different image processing applications. In recent years there are some different applications of deep neural networks for medical imaging [1]. For example, [2] proposed a dermatologist-level classification for melanoma based on deep neural networks. They used CNN to classify melanoma using a single CNN, training directly end-to-end from the images. The effectiveness of the method was tested by 21 board certified dermatologists on biopsy proven clinical images. On account of the high precision of CNN, they have many applications in different parts of medical images, such as magnetic resonance imaging fusion [3], lesion classification [4], tumor diagnosis [5], cancer breast [6] and panoptic analysis. [7] For the CNN-based methods explained, the image was first divided into several small super pixels, and then the operator was applied to each of the super pixels. Based on the previous literature, it has been observed that the use of CNN models develops the efficiency of the diagnostic system [8].Another method to improve the efficiency of the system is to combine them using optimization algorithms [9].

For this purpose, deep learning (CNN) algorithm is used by intelligent machine to classify the skin cancer images according to its types. In this current research work there are three types of skin cancer types name is Basal cell Carcinoma (BBC), Melanocytic Nevus (NV) and Vascular Lesion (VASC) are used.

The proposed method based on convolutional neural networks for classification of skin cancer images. This method used a dataset of existent skin cancer images of different types. This dataset used to training the CNN architecture then check the training accuracy, after they test the accuracy of the trained network for better cancer images analysis and classification. Results showed approximately 98.89% accuracy for this current convolutional neural network.

II. LITRATURE REVIEW

The skin is the largest organ in the body that protects it from heat, light, and infection. It also helps control body temperature and conserves fat and water. One of the most important skin problems in the body is the risk of infection with skin cancer. Skin cancer begins in cells, the main components that make up the skin; skin cells grow and divide to form new cells. Every day skin cells age and die and new cells take their place. Sometimes this systematic process does the wrong thing. New cells are created when the skin does not need it, and old cells die when it is not needed. These additional cells form a mass of tissue called a tumor [10]. Melanoma is the most malignant and most serious type of skin cancer and is the reason for most skin

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cancer deaths. The underlying cause of melanoma is unknown. But several factors, including genetic factors, ultraviolet radiation, and environmental contact, are involved in the cause of the disease. Melanoma originates from skin melanocytes that have undergone a malignant transformation. Melanocytes produce dark pigments in the skin, hair, eyes, and body spots. Therefore, melanoma tumors are predominantly brown or black. But in some cases, melanomas do not produce pigments and appear pink, red, or purple [11]. Melanoma is the nineteenth tumor that occurs most frequently among humanity such that around 300,000 new cases have been found 2018. On average, 2490 women and 4740 men lost their lives due to melanoma in 2019. An important problem is that the early diagnosis of melanoma, even by specialists, is a fundamental process. Therefore, the use of a method to simplify the diagnosis can be useful for specialists. During the last decade, the application of image processing and artificial vision for a different use of medical images has increased exponentially. Using these techniques increases the speed of the diagnostic process and reduces human error. It can also improve the quality and convenience of melanoma diagnosis by doctors and radiologists. For example, in 2016 proposed segmentation of the melanoma image based on Delaunay triangulation. The method was automatic melanoma detection. They analyzed the method at a benchmark of publicly available dermoscopic images [12]. In 2018, they proposed a method based on morphological characteristics for the detection of melanoma. The method resulted in a computerized diagnostic system to detect skin cancer [13]. In 2016 they proposed a method based on artificial neural networks for the diagnosis of skin cancer. This method used skewness, edge, color, diameter (ABCD ruler) for better cancer analysis. This method also is used to assess the classification of the cancer [14].

Convolutional Neural Networks (CNNs) are computer models inspired by biological visual cortex. These models have been proven to be very efficient, accurate and reliable in image classification. They have already achieved near-human performance in many challenging natural image stratification tasks [15],[16] and have also been used to classify diseases from medical images [17].Towards automated skin disease classification, [18] employed CNNs to extract features and trained a linear classifier on them using 1300 images of Dermofit Image Library to perform 10-ary classification. Similar approach was used by [19] on MoleMap dataset to do 15-ary classification. The sensitivity and specificity of their Deep Neural Network (DNN) model is certainly higher than that of dermatologists' mean performance on two private test sets, however, their performance on publicly available International Symposium on Biomedical Imaging (ISBI) 2016 Challenge [20] test data is below the performance of first two winning entries in that challenge. To address the scarcity of available data for tracking and detecting skin diseases [21] developed a domain-specific data augmentation technique by merging individual lesions with full body images to generate large volume of synthetic data. Li and Shen [22] also used DNN to segment lesions, extract their dermoscopic features and classify them.

III. DATA SET

We have 3150 images in the current dataset, which have size of 28x28 pixels of RGB images. The data set which is use in the current simulation downloaded from the public Github website. This website provides free data set for simulation. The data set which contains is divided by three classes and each class has 1050 images. In each class 800 images (75%) data for training and 300 images (25%) for validation. After that convolutional neural network (CNN) is apply on the data set which results shows in result section.

The methodology of skin cancer of images of the current work shows in Fig 1. For the CNN network training the size of images specification is very important key. During simulation of the data for the input if we have a large size images then the training of network will take more time than a small size images. So for the current work there is the image size 28x28 pixel of RGB image. Fig 2 shows the skin cancer RGB images for the input data to the network for simulation. We load RGB image data as an image-data-store. Image-data-store loads stores and automatically label them based on folder names. It is very important to note that during the training of CNN network, the image-data-store efficiently reads batches of images.

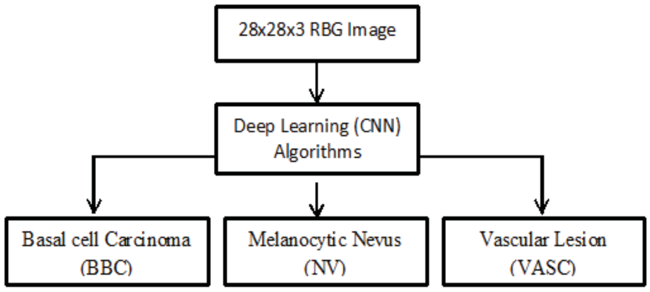

Fig. 1. Block diagram Classification of the Skin Cancer Images

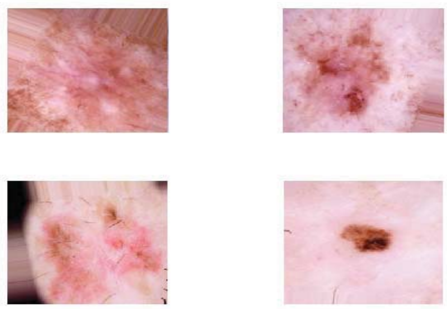

Fig. 2. Random images of skin cancer from Data Set

IV. SIMULATIONS AND RESULTS

A. CNN for One Convolutional Layers

The Fig 3 shows three convolutional layer CNN algorithm architecture. In this algorithm architecture one convolution, one max pooling and one fully connected layer are used. Fig 6 shows the training progress plot of the CNN with10 epochs, training time is 51 sec. In the plot one part of validation accuracy and second part shows the loss (accuracy/mini batch) of the data. This architecture used convolution layer of filter size 3x3 and channel size is 8 with the same padding, 2x2 max pooling layer with (Stride2) and fully connected layer and obtained classification accuracy 80.15 after training the CNN network.

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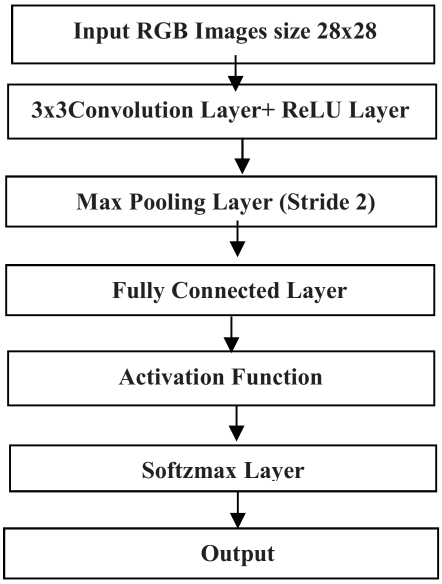

Fig.3. CNN architecture for one Convolution Layers

B. *CNN for Two Convolutional Layers*

The Fig 4 shows three convolutional layer CNN algorithm architecture. In this algorithm architecture two convolution, two max pooling and one fully connected layer are used. Fig 7 shows the training progress plot of the CNN with10 epochs, training time is 2 minutes and 28 sec. This plot shows one part of validation accuracy and second part shows the loss (accuracy/mini batch) of the data. This architecture first used convolution layer of filter size 5x5 and channel size is 8 with the same padding 2x2 and max pooling layer with (Stride2).Then applied convolution layer of filter size 3x3 and channel size is 8 with the same padding 2x2 and max pooling layer with (Stride2) and fully connected layer and obtained classification accuracy 95.79 after training the CNN network.

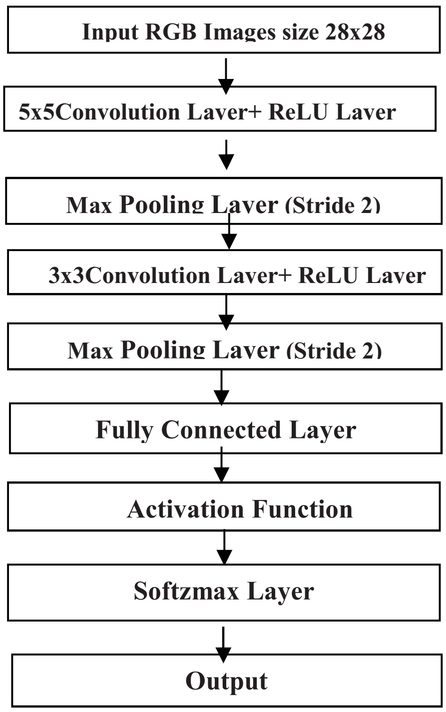

Fig.4. CNN architecture for one Convolution Layers

C. *CNN for Three Convolutional Layer*

The Fig 5 shows three convolutional layer CNN algorithm architecture. In this algorithm architecture three convolution, three max pooling and one fully connected layer are used. Fig 8 shows the training progress plot of the CNN with10 epochs, training time is 3 minutes and 44 sec. The plot shows one part of validation accuracy and second part shows the loss (accuracy/mini batch) of the data. This architecture first used convolution layer of filter size 7x7 and channel size is 8 with the same padding , 2x2 and max pooling layer with (Stride2).Then applied convolution layer of filter size 5x5 and channel size is 16 with the same padding , 2x2 and max pooling layer with (Stride2).Again applied convolution layer of filter size 3x3 and channel size is 32 with the same padding , 2x2 and max pooling layer with (Stride2) and fully connected layer and obtained classification accuracy 98.89 after training the CNN network.

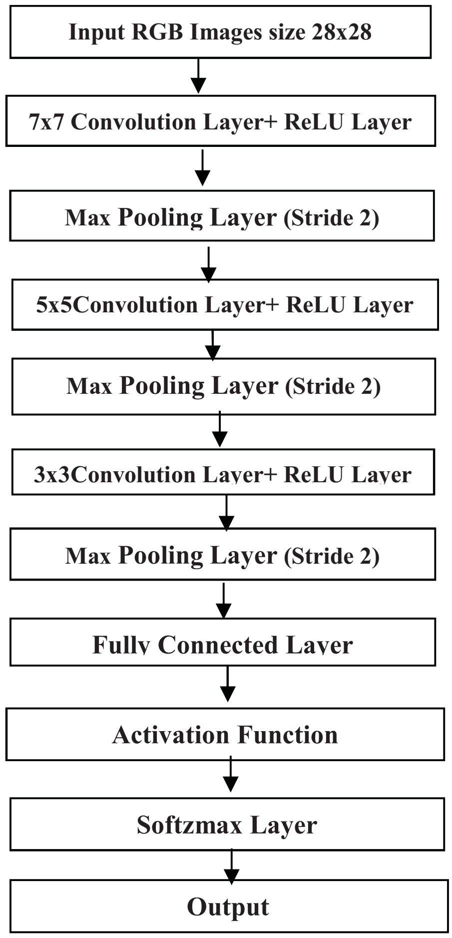

Fig. 5. CNN architecture for three Convolution Layer

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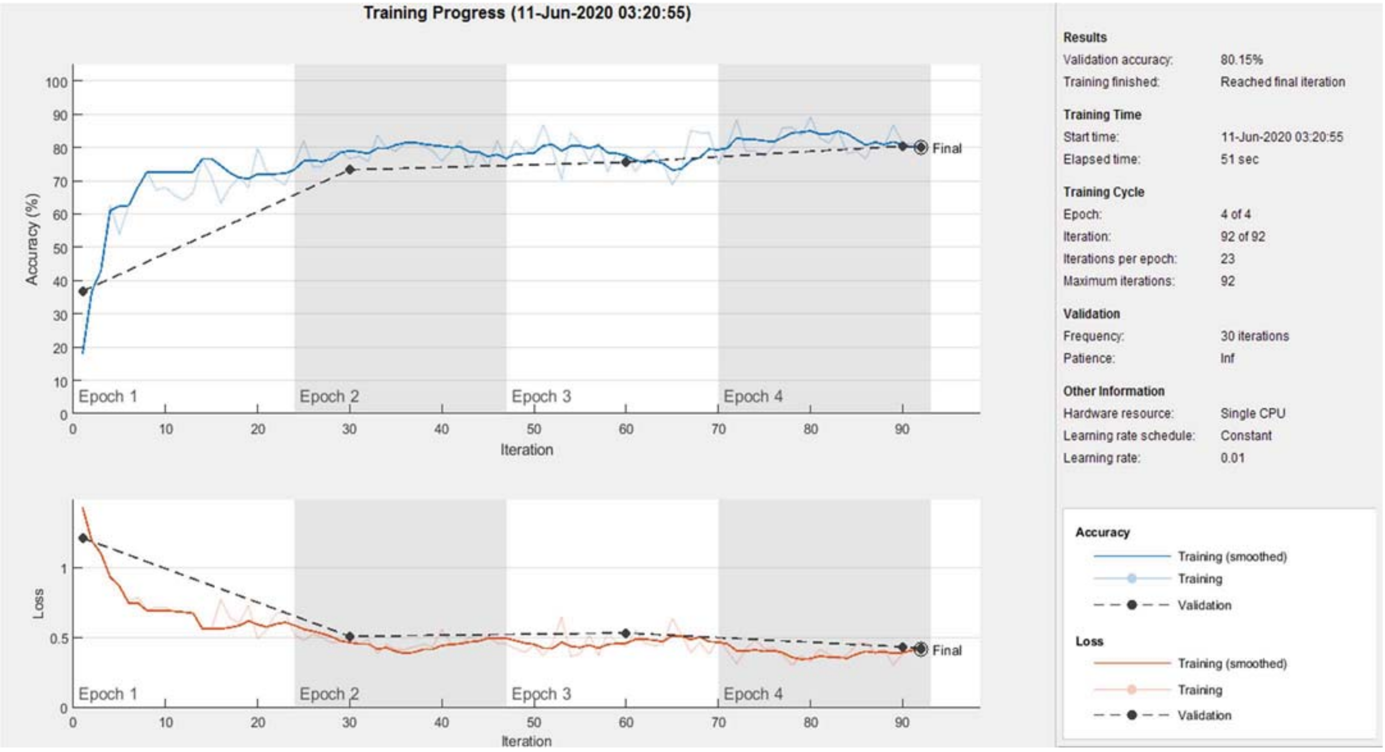

Fig. 6. Validation accuracy for one convolution layer

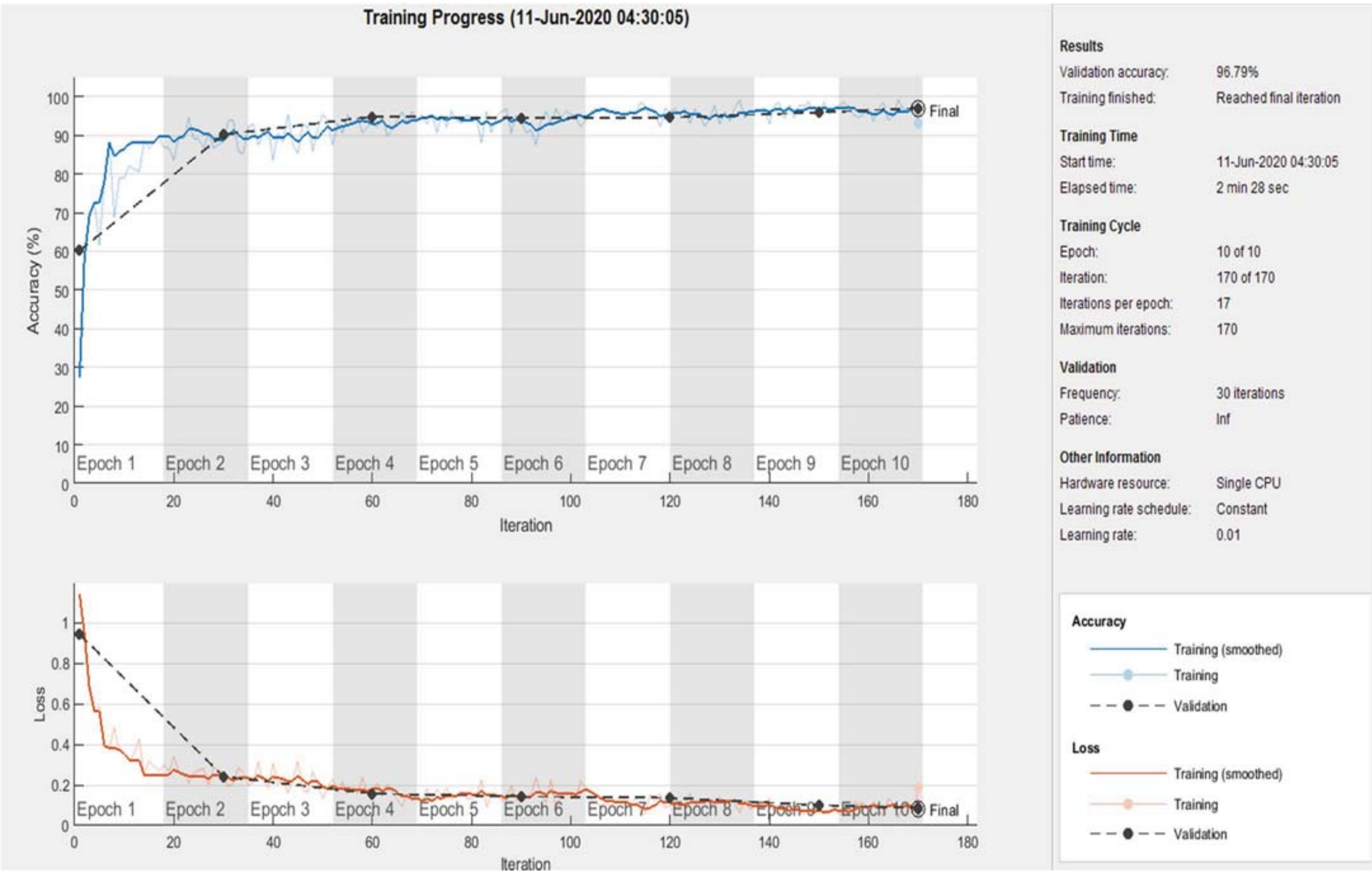

Fig.7. Validation accuracy for two convolution layer

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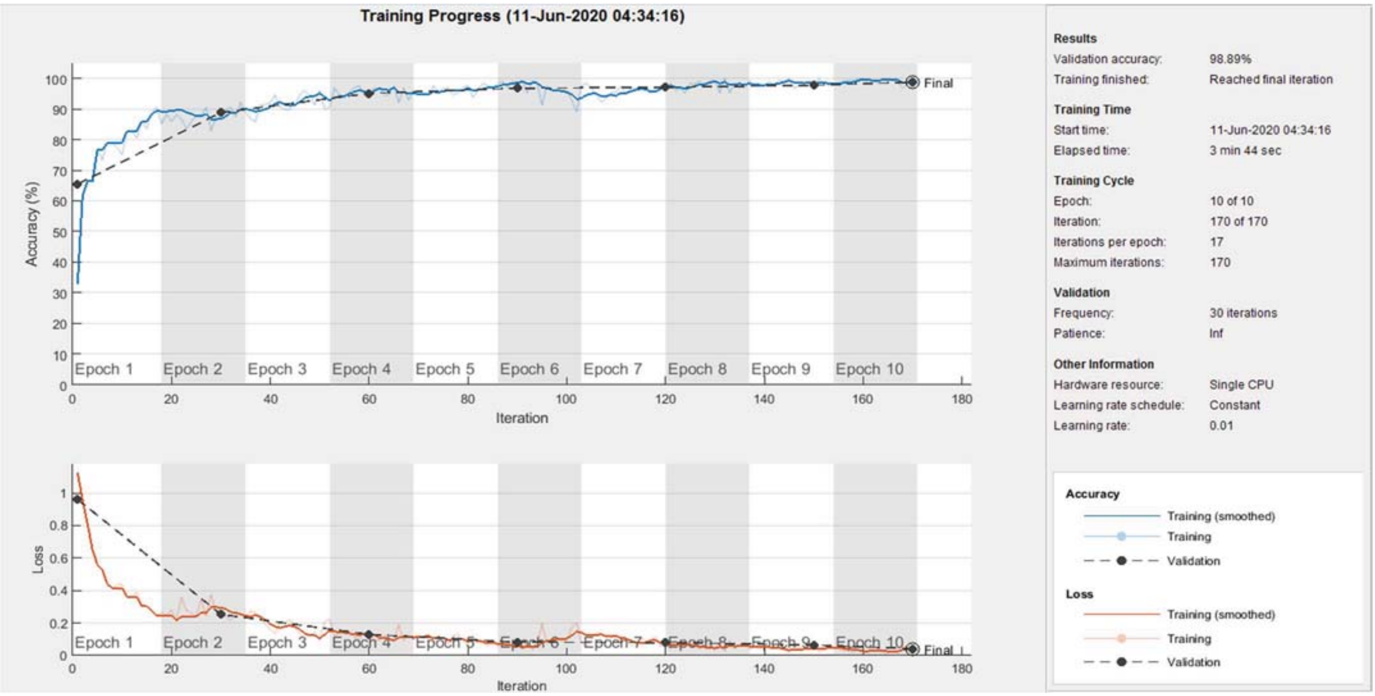


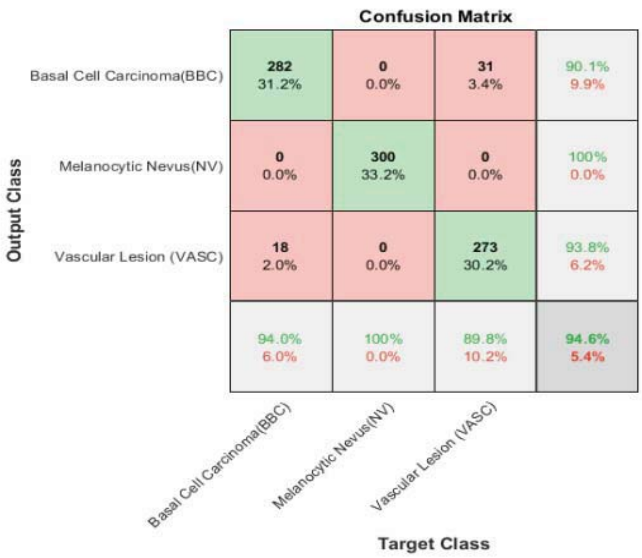
Fig.8. Validation accuracy for three convolution layer

V. EVALUATION

The following tables show the number of images, number of epochs, and accuracy of the training CNN network for validation and the training time of CNN network with respect to number of epochs and layers. Table 1 contains same number of images for each process and same number of epochs (4). The computational time of CNN network for different layers. For each process there is a confusion matrix which shows in Fig 9, 10, 11. Table 2 contains the same number of images for each process and same number of epochs (6) and computational time. Table 3 contains the same number of images for each process and same number of epochs (10). The training time varying when increase the layers of CNN architecture and increase the number of epochs. So it is seeing for all tables that the computational time of CNN increase when increase the number of layers and number of epochs.

TABLE I. DIFFERENT LAYERS ACCURACY AND COMPUTIONAL TIME

No of Images	No of Layers	Epochs	Accuracy	Computational Time
1050	1	4	94.58	1 min 21 sec
1050	2	4	94.25	54 sec
1050	3	4	92.59	38 sec



(a)

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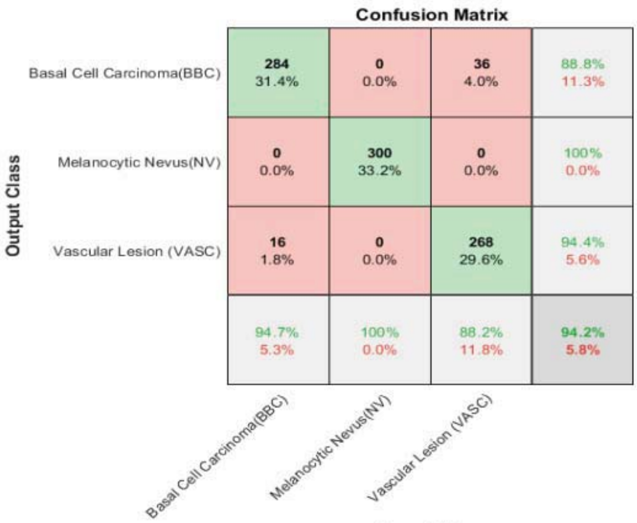
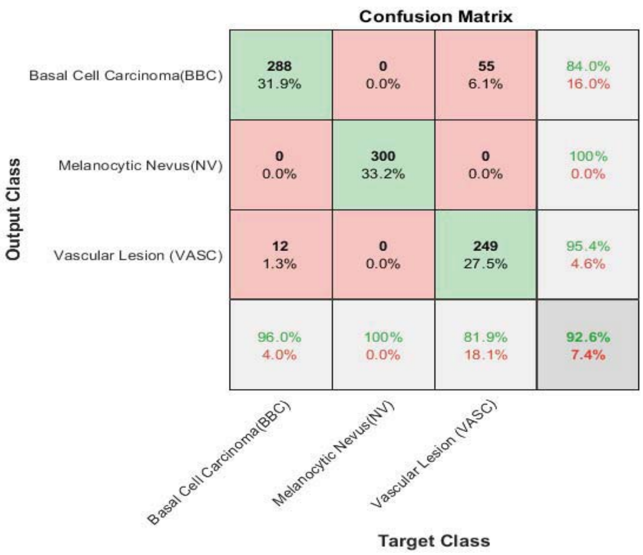


(b)

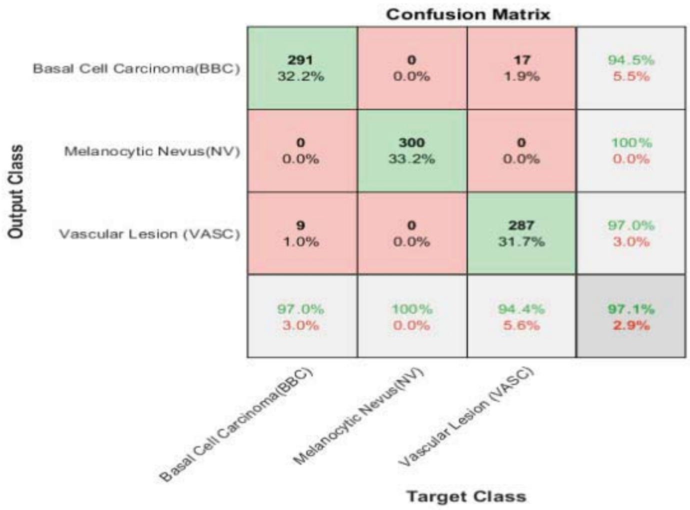


(c)

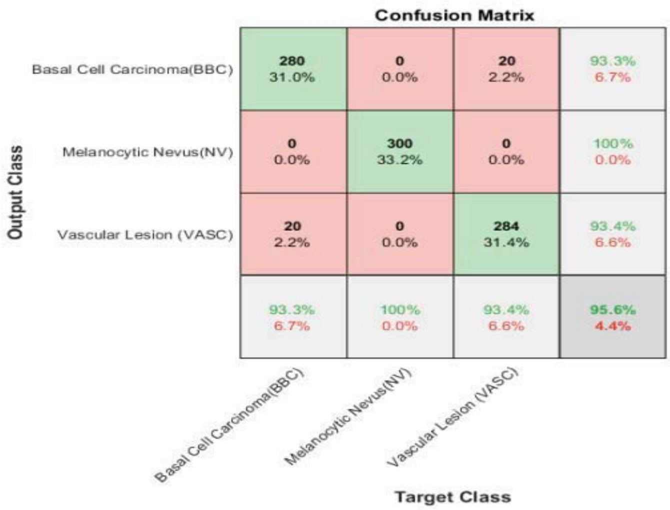
Fig. 9 (a,b and c). Confusion Matrixs of different layers wirh same epoch

TABLE II. DIFFERENT LAYERS ACCURACY AND COMPUTIONAL TIME OF CNN

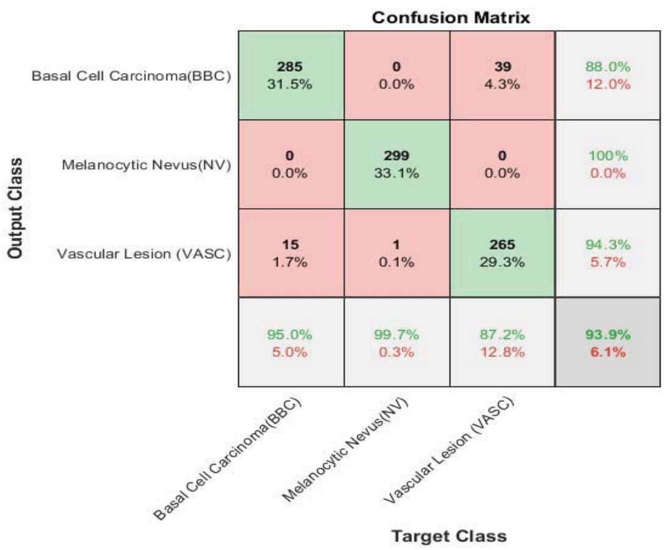
No of Images	Layers	Epochs	Accuracy	Training Time
1050	1	6	97.12	2 min 7 sec
1050	2	6	95.58	1 min 30 sec
1050	3	6	93.92	32 sec



(a)



(b)



(c)

Fig. 10 (a,b and c). Confusion Matrixs of different layers wirh same epoch

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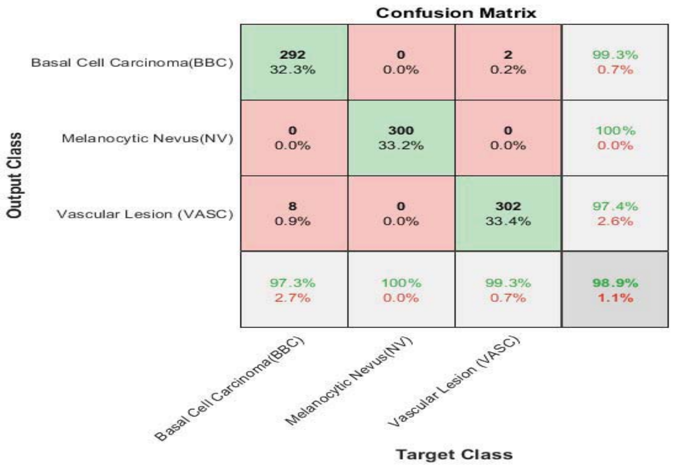
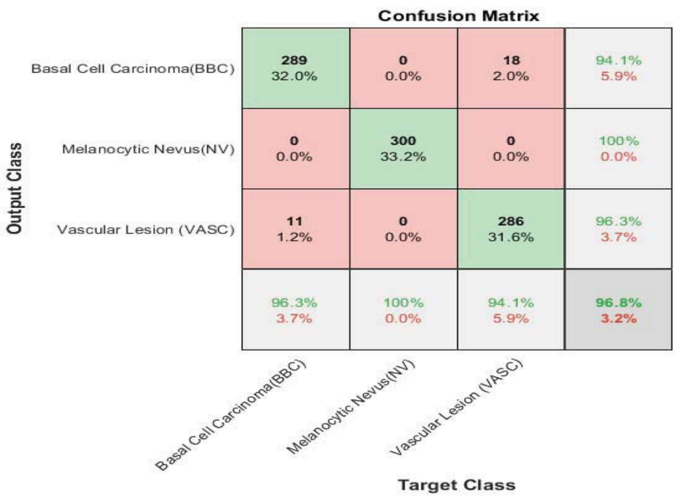
TABLE III. DIFFERENT LAYERS ACCURACY AND COMPUTIONAL TIME OF CNN

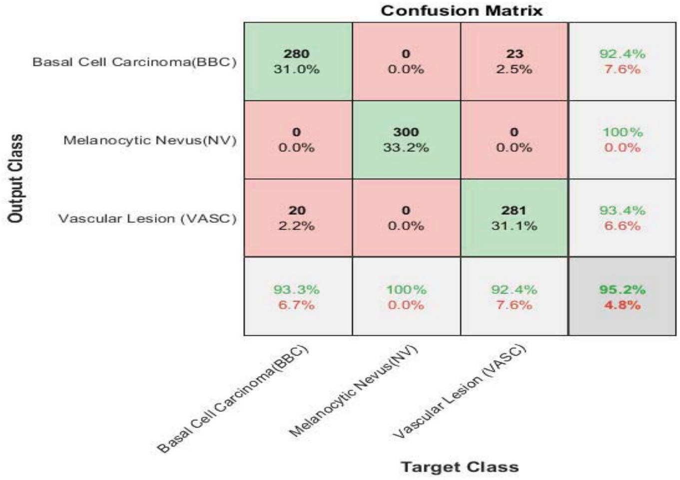
Number of Images	Layers	Epochs	Accuracy	Training Time
1050	1	10	98.89	3 min 44 sec
1050	2	10	95.79	2 min 29 sec
1050	3	10	95.24	32 sec



(a)



(b)



(c)

Fig. 11 (a,b and c). Confusion Matrixs of different layers wirh same epoch

Table IV shows the comparison of the current work with previous work with respect to the number of images and number of classes which carried in last decade.

TABLE IV. COMPARISON PROPOSED WORK WITH PREVIOUS ONE

Years	Authors	class	Accuracy		
2020	CNN (Proposed work)	3	98.89		
2020	CNN [23]	3	90%	81%	84%
2019	SSD-Mobilenet model [24]	2	99%	100%	
2019	incorporate background knowledge [25]	1	80.39%.		
2019	CNNs [26]	2	83.83%	97.55%	
2018	[27]	1	98.33%,		2018
2018	CNN [28]	3	82.26%	88.82%	90.40%
2017	CNN [19]	2		69.4%	72.1%
2017	CNNs [29]	3	90.96%	97.00%	97.60%
2017	multi-scale CNN[30]	1	0.903		
2016	automated computer-aided model CNN ([31]	1	11%		
2016	CNN[32])	1	81.8%		
2016	VGG-16 CNN[33]	1	78%		
2011	KNN[34]	1	66.7%		
2011	KNN [35])	3	73.47%	80.6%	86.73%

CONCLUSION AND FUTURE RESEARCH DIRECTION

To it is concluded from all the results if studied and work carefully that the performance of the digital applications for skin cancer improves in many ways while using the convolutional neural network algorithms. This current work 98.89% classification accuracy was achieved with a convolutional neural network architecture using three convolution layers. While used the convolutional neural network architecture using three convolution layers got the accuracy result better than used the two or one convolution layers. The most important thing is processing time of CNN network training. It is noted the

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computational time increase when increase the number of layer and number of epochs of CNN network. So it is need high processor to decrease the computational time for each process.

In the future, convolutional neural network algorithms for skin cancer disease would help in medical field to avoid the conventional lab tests. Moreover, without testing kits or without the use of x-rays machine skin cancer disease would be automatically detected and classify using the convolutional neural network algorithm embedded in digital device.

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