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Melanoma Skin Cancer Detection using CNN AlexNet Architecture

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Abstract: ***Skin cancer is one of the most common cancer among humans especially in US. If it is detected and treated early before it effects to the lymph nodes it can be cured. It is very difficult for a physician to detect skin cancer with naked eyes just by examining the skin lesion because it looks very similar to any other normal mole and hence proves to be fatal. Melanoma is a type of skin cancer that has vaster death rate than any other type of skin cancers. Melanoma skin cancer develops from the pigment containing cells known as melanocytes as they start multiplying in an unusual way. This paper proposes a convolutional neural network (CNN) model using AlexNet architecture that classifies the skin lesion images into melanoma and non-melanoma skin cancers. Using this method 84% of validation accuracy and 70% of test accuracy is obtained.***
Keywords: CNN, Melanoma, AlexNet, ReLU, cost function

I. INTRODUCTION

Several forms of human cancers exist, skin cancer is the most common example of these cancers. There are two major skin cancer types, namely malignant melanoma and non-melanoma (basal cell, squamous cell, and Markel cell carcinomas, etc.) Most skin cancers are caused by ultraviolet light (UV) exposure. UV rays from sunlight or tanning beds can damage the DNA of your skin if you don't protect your skin. It cannot properly control the development of skin cells, leading to cancer, when the DNA is changed.

Melanoma is a rare and very aggressive form of melanocyte-forming skin cancer. These are the cells that make your so-called melanin pigment. This is the most dangerous form of skin cancer. These cancerous growths develop when unrepaired DNA damage to skin cells (most often caused by ultraviolet radiation from sunshine or tanning beds) triggers mutations (genetic defects) that lead the skin cells to multiply rapidly and form malignant tumors. But most skin cancers are nonmelanoma, which means the melanocytes are not involved. Basal cell and squamous cell skin cancers are the two most common of these. When caught early, they can almost always be healed. Yet melanoma will easily become a problem that is more difficult to treat if you don't detect it and treat it early. According to World Cancer Research Fund, Melanoma accounted for about 22% of diagnoses of skin cancer in 2018, and non-melanoma tumors accounted for about 78% of diagnoses of skin cancer. Melanoma is the 19th most common cancer in men and women, with nearly 300,000 new cases worldwide in 2018. Non-melanoma skin cancer is the 5th most commonly occurring cancer in men and women, with over 1 million diagnoses worldwide in 2018.

Computer analysis and image processing are the efficient tools that support quantitative medical diagnosis . It requires an appropriate segmentation algorithm that can effectively detect the pixels of skin melanoma in the information image. The pre-processing methods are used in determining various levels includes collection of skin lesion images, filtering of images using Dull Razor filtering for removing hairs and air bubbles in the image, converting to grey scale image, noise filtering, threshold-based segmentation of lesion images [1]. It requires an appropriate segmentation algorithm that can effectively detect the pixels of skin melanoma in the information image. For the detection of melanoma, particular analysis is applied on the skin lesion images according to a set of specific clinical characteristics. Then skin lesion is classified as either "potential melanoma" or "non-melanoma" [2]. Melanoma classification method based on convolutional neural network and is proposed for dermo scope imaging [3]. They introduced method called region average pooling, this makes feature extraction focus on the region of interest and the other technology Computer-assisted approach for Melanoma Skin Cancer detection using Image Processing algorithms. The input to the system is the skin lesion image and then by applying image processing techniques, it analyses lesion image to conclude about the presence of skin cancer. The Lesion Image analysis algorithums checks for the various Melanoma parameters like Asymmetry, Border, Colour, Diameter (ABCD) etc. by texture, size and shape analysis for image segmentation and feature stages[7]. In order to detect the melanoma various methods are illustrated to examine the computational steps to analyze cancer through the use of various types of images. Different kinds of frameworks proposed for detection of melanoma and their productivity[4]-[6].

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II. METHODOLOGY

A. *Proposed method*

1) *AlexNet Architecture:* In Deep Learning, a Convolutional Neural Network (CNN) is a class of deep neural networks, most commonly applied to analysing visual imagery. Convolutional Neural Networks are state of the art models for Image Classification, Segmentation, Object Detection and many other image processing tasks. AlexNet is an incredibly powerful model capable of achieving high accuracies on very challenging datasets. However, removing any of the convolutional layers will drastically degrade AlexNet's performance.

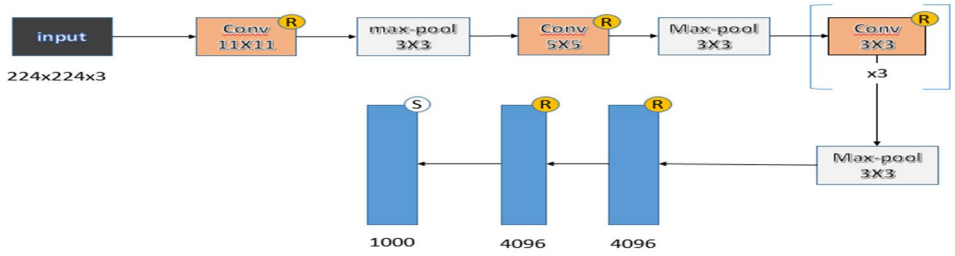


Fig. 1: Alexnet Architecture

Figure 1 illustrates the overall Alexnet architecture. With 60M parameters, AlexNet[8] has 8 layers - 5 convolutional and 3 fully-connected. First layer is convolution layer,input image size is 224x224x3 .Filter size is 11x11 in addition to 4 pixels is called stride . RELU layer applying an activation function such as the max (0, x) function, to product elementwise non-linearity. Any negative input given to the ReLU activation function turns the value into zero immediately. The following is the convolutional layer followed by the pooling layer. The pooling layer tries to reduce the dimensionality of each feature map while keeping important features, where pooling may be Sum, Max, Average, etc. AlexNet uses a max pooling layer. Second convolution layer has filter of size 5x5, followed by max pooling layer. The output of this layer is passed through three consecutive convolution layers, followed by max pooling layer. The output of these three convolutional layers are passed as input to number of 2 fully connected layers where each layer contains 4096 neurons. Last layer consists of sigmoid function. Sigmoid function is usually used in output layer of a binary classification, where result is either 0 or 1, as value for sigmoid function lies between 0 and 1 only so, result can be predicted easily to be **1** if value is greater than 0.5 and 0 otherwise.

2) *Optimizer and loss function:* The goal of machine learning and deep learning is to reduce the difference between the predicted output and the actual output. This is also called as a Cost function(C) or Loss function**.** As our goal is to minimize the cost function by finding the optimized value for weights. Gradient descent is an iterative machine learning optimization algorithm to reduce the cost function. This will help models to make accurate predictions. Here we use stochastic gradient descent. In stochastic gradient descent we use a single data point or example to calculate the gradient and update the weights with every iteration. We have used binary cross entropy loss function (BCE). BCE loss is used for the binary classification tasks. BCE Loss creates a criterion that measures the Binary Cross Entropy between the target and the output. If we use BCE Loss function, we need to have a sigmoid layer in our network.

3) *Design Methodology:* Design methodology contains design for training the model with the dataset of melanoma and non-melanoma skin lesion images obtain from Kaggle and testing the images using the trained model over the never seen before dataset. Training model is given in Figure 2 which contains blocks of defining data preprocessing, CNN architecture to train the model, optimizers and loss functions , setting call backs and training the model over this model with datasets and finally saving the model. Callbacks are set of functions to be applied at particular stage of the training. To get the insight of internal states and statistics of the model during the training.

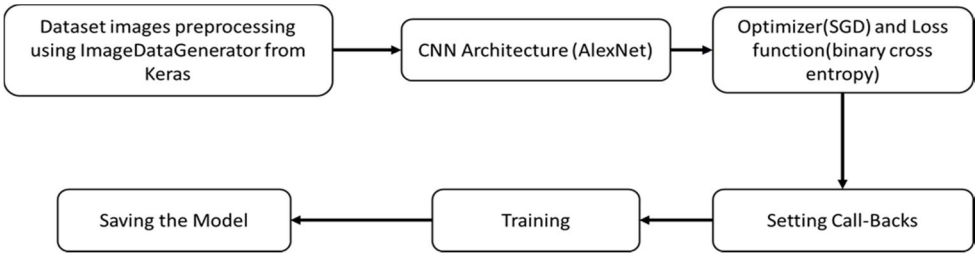


Fig 2 : Methodology of Training the Model

After the model is trained over the train data it has to be tested. This is done according to the Figure 3 methodology for testing the model.

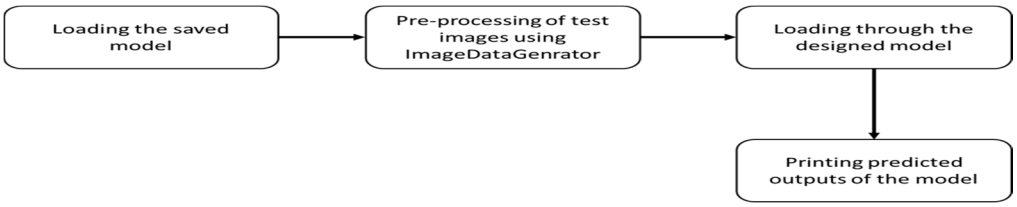


Fig 3: Methodology of Testing the Model

In this method the saved model is loaded and same preprocessing of test data is done according to the train dataset then loading the test images through the design model and printing of the model.

III. EXPERIMENTAL SETUP AND RESULTS

A. Experimental Setup

The CNN model for Melanoma skin cancer detection was done using AlexNet architecture which is mentioned above. The model is simulated using PyCharm which is an integrated development environment used in computer programming, specifically for the Python language. The main packages used for project interpreter Python 3.7 are Keras 2.3.1 which is an open-source neural-network library written in Python. It is capable of running on top of TensorFlow 2.1.0 which is a free and open-source software library for dataflow and differentiable programming across a range of tasks.

Model contains all the layers of AlexNet architecture including their Output shapes with filters used and the parameters of that layer. The parameters like biases and weights are Total params: 24,731,009, Trainable params: 24,731,009 and Non-trainable params: 0.

The model is trained using this architecture over a train data of 7113 Melanoma skin lesion images and 7111 Notmelanoma skin lesion images. It is validated using 1700 Melanoma and 1700 Non melanoma images which gave a maximum validation accuracy of 84% after checking for 500 epochs and steps_per_epoch=24.

The images are pre-processed using ImageDataGenerater from keras.preprocessing package. Optimizer used is Stochastic gradient descent with learning rate of 0.001 and loss function used is binary_crossentropy.

The designed model is given below:

Table 1 : Designed Model: "sequential_1"

Layer (type)	Output Shape	Param #
conv2d_1 (Conv2D)	(None, 57, 57, 96)	34944
activation_1 (Activation)	(None, 57, 57, 96)	0
max_pooling2d_1 (MaxPooling2	(None, 28, 28, 96)	0
conv2d_2 (Conv2D)	(None, 24, 24, 256)	614656
activation_2 (Activation)	(None, 24, 24, 256)	0
max_pooling2d_2 (MaxPooling2	(None, 11, 11, 256)	0
conv2d_3 (Conv2D)	(None, 9, 9, 384)	885120
activation_3 (Activation)	(None, 9, 9, 384)	0
conv2d_4 (Conv2D)	(None, 7, 7, 384)	1327488
activation_4 (Activation)	(None, 7, 7, 384)	0
conv2d_5 (Conv2D)	(None, 5, 5, 256)	884992
activation_5 (Activation)	(None, 5, 5, 256)	0
max_pooling2d_3 (MaxPooling2	(None, 2, 2, 256)	0
dropout_1 (Dropout)	(None, 2, 2, 256)	0
flatten_1 (Flatten)	(None, 1024)	0
dense_1 (Dense)	(None, 4096)	4198400
activation_6 (Activation)	(None, 4096)	0
dense_2 (Dense)	(None, 4096)	16781312
activation_7 (Activation)	(None, 4096)	0
dense_3 (Dense)	(None, 1)	4097
activation_8 (Activation)	(None, 1)	0

B. Experimental Results

Evaluation accuracy over never before seen images is: 70.00%

The test was conducted over a 20 never seen images which have predicted output as follows

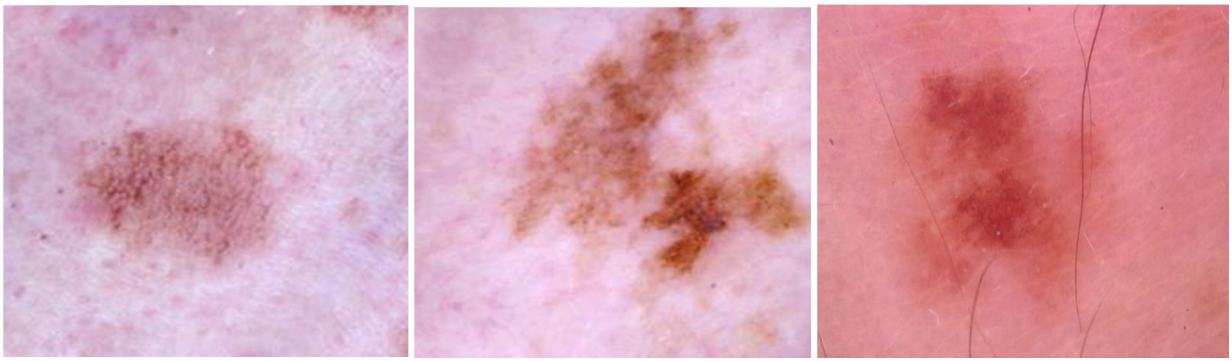
{'Melanoma': 0, 'NotMelanoma': 1}

Melanoma images: [[0.4395] [0.2876] [0.1757] [0.5927] [0.2678] [0.8008] [0.2146] [0.5443] [0.2035] [0.1872]]

NotMelanoma images: [[0.8923] [0.9037] [0.3816] [0.8829] [0.7551] [0.8916] [0.4973] [0.8157] [0.8874] [0.3172]]

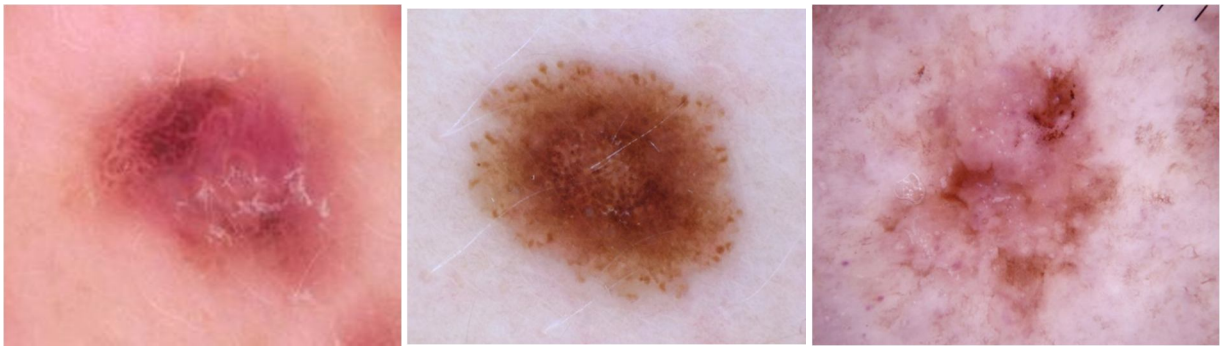
In melanoma images 7 out of 10 images were detected correctly and in Non melanoma images 7 out of 10 images were detected correctly.

Some of correctly detected images



Melanoma(i) Melanoma(ii) Nonmelanoma(iii)

Some of wrongly detected images



Melanoma(iv) Nonmelanoma(v) Nonmelanoma(vi)

Fig 5: Melanoma and Nonmelanoma Skin lesion images which are detected correctly and wrongly by the model desgined.

Figure 5 shows the image of skin lesion which are detected correctly and wrongly first two images are accurately detected with values less than 0.5 which is near to 0 which is labeled for Melanoma images, third image is also detected correctly by value greater than 0.5 which is near to 1 labelled for Non melanoma images. The iv v vi images are wrongly detected like for iv melanoma image it gave value greater than 0.5 which is near to 1 labelled for Non melanoma image. Likewise Non melanoma images v and vi images gave value less than 0.5 indicating Melanoma. So the over all accuracy we got is about 70% which has to be improved.

IV. CONCLUSION AND FUTUTRE WORK

Automated detection of Melanoma is a complex task. In this paper a basic CNN model is put forward to differentiate melanoma skin lesion images from non-melanoma images. Pre-processing, feature extraction and classification of data sets is done by 8 layered AlexNet architecture. Among 10 melanoma test images 7 were detected as melanoma images. Among 10 non melanoma images 7 were detected correctly. This demands a need to improve the model to give better and efficient accuracy and to reduce the loss percentage. Further to increase the accuracy and to reduce the loss percentage advanced architecture can be implemented to get a better accuracy and can be implemented for clinical trials. Also, an application can be developed which will be user friendly. This would also broaden the scope of learning more about neural networks.

V. ACKNOWLEDGMENT

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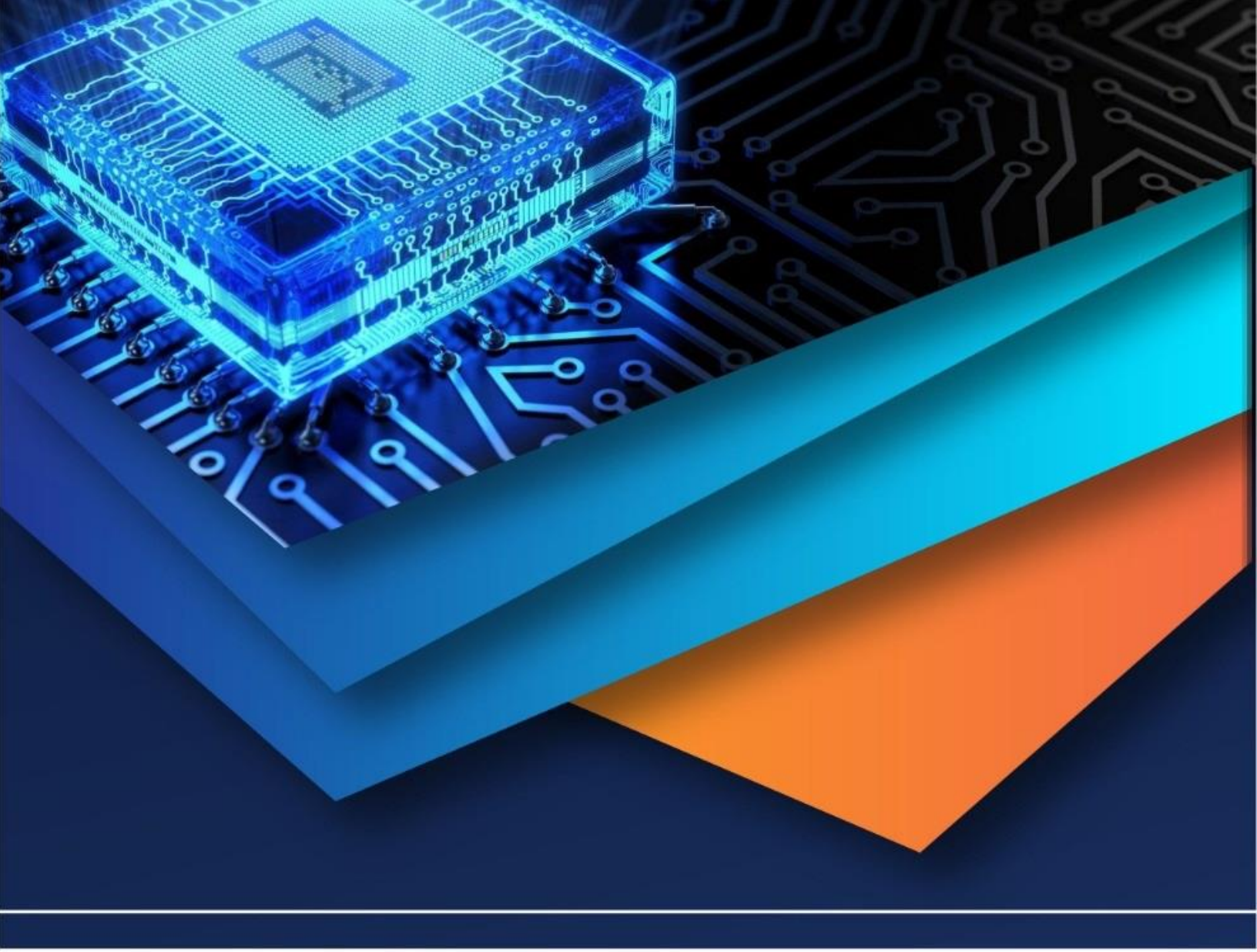

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