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Skin Cancer Classification Using Convolutional Neural Networks

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Abstract: There is a necessary need for early detection of skin cancer and can prevent further spread in some cases of skin cancers, such as melanoma and focal cell carcinoma. Anyhow there are several factors that have bad impacts on the detection accuracy. In Recent times, the use of image processing and machine vision in the field of healthcare and medical applications is increasing at a greater phase. In this paper, weare using the Convolution neural networks to detect and classify the class of cancer based on historical data of clinical images using CNN.Some of our objectives through this research are ,to build a CNN model to detect skin cancer with an accuracy of >80% ,to keep the false negativity rate in the prediction to below 10%, to reach the precision of above 80% and do visualization on our Data. Simulation results show that the proposed method has superiority towards the other compared methods.

keywords: Skin cancer diagnosis, Deep learning, Convolutional neural networks [Standard CNN],Skin cancer, Artificial neural networks.

I. INTRODUCTION

The skin is considered as the one of the most broad organs in human's body which controls our body temperature and also protects the body from high temperature and light. It is also used to store the fat and the water. Skin cancer also occurs when skin cells occur when skills are damaged ,for example,by overexposure to ultraviolet (UV) [13]. Skin cancer is increasing rapidly at a greater phase in countries like canada ,USA and Australia[14][15].One of the most important problems of skin in the body is its infection risk to skin cancer. Skin cancer begins from the cells which are the main components that build up the skin, the skin cells grow and at the same time they divide to form new cells. Every day as the skincells grow older, they die and new cells are formed and will occupy their place. Sometimes this systematic process may fail. New cells are formed when the skin might not need them, and old cells might die when there is no need . These forms of extra cells generate a mass of tissue called a tumor.

Out of all the classes of skin cancers, melanoma is the most widely observed and harmful type of cancer and also accounts for more number of fatalities. The causes for melanoma are unknown till date but there are several factors like inheritance from parents and uv radiation are a part of causing this cancer.Though the probability of healing from this disease is high ,it is still considered as a serious issue due to its widespread factor.Melanoma generally starts affecting our body through the lymphatic system and also at times through the circulatory system and flows up to the distant points of the body. Research says that if we are able to identify this cancer at an early stage then it might help to reduce the probability of death,but it is a sad fact that evenby specialists ,it is a tough job to detect melanoma at an early stage . Hence using a procedure which can automate the diagnosis process will be helpful and thereby also reduces manual errors .In the past few years it is evident from various researches that the usage of computer vision techniques and digital image processing is highly appreciable and also the usage is exponentially increasing in the fields like healthcare,and many others.So using this processes can improve the speed of diagnosis and also there by decrease manual errors.

In the Recent years a special method which is part of Artificial Intelligence has been widely used in the fields like computer vision,digital image processing and image classification techniques and is called Artificial Neural Network (ANN) Artificial Neural networks are inspired by the baron of human which contains of several neural layers and perceptrons. Convolutional neural networks (CNNs) [1][2] are an extension to artificial neural networks which are giving appreciable results even for general and complex tasks like image processing and classification and object detection. The method efficiency was testified toward 21 board-certified dermatologists on biopsy-proven clinical images. In consideration of high and effective performance of the CNNs [3], they are used in a lot of applications in different parts of medical imaging techniques which includes lesion classification, MR images fusion, breast cancer and tumor diagnosis, and panoptic analysis.

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For the explained methodologies based on CNN [4], the images areinitially divided into several small super pixels and next theoperator is applied to each and every super pixel. Taking the reference form the aforementioned literature, it is decided that the use of CNN models increases the effectiveness of the diagnosis system. The next sections of the paper as follows in Section II the concept of Convolution neural networks explained. section III represents the mathematicalimplementation of CNN. Section IV is about our data set regarding our implementation. Section V about data preprocessing and image augmentation Section VI includesthe CNN model implementation in TensorFlow on our data and the visualization is done in Section VII, about theauthors and the paper is concluded in Section VIII. Finally, the References that help us to complete this Research.

II. CONVOLUTION NEURAL NETWORKS

The Convolutional Neural Networks (CNN) are an extension to the existing neural network.CNN is proposed by Yann LeCun, et al [6] .Convolution neural networks are preferred over fully connected feedforward neural layers in digital image applications due to sparks connectivity and weight sharing features of image pixels. CNN can also be tuned for various mathematical learning methods like back propagation ,learning algorithms and regularization techniques. Convolutional neural networks contain three main sections i.e,convolution layer,pooling layer and followed by a fully connected layer. In consideration of the high performance of the artificial neural networks, they areknown to be optimal solutions of many highly difficult problems like image segmentation and computer vision. A negative fact about these networks is that the multilayer perceptron models and other networks which use gradient descent learning algorithms and several other optimization algorithms for reducing the error rate between the achievedoutput from the network and the desired output , the solutionmight generally stick in the local optimum which might result in not giving the best global solution. CNN is very efficient for solving complex problems [12]. In CNN, the Convolution layer maintains a number of weights which are reduced by pooling layers to give output from the convolution layer and reduces the input size ratio of the layer . After the convolution layer, the outputs coming fromthe pooling layer are utilized and fed into the fully connected layers. An essential section of CNN is the Convolutional layer which consists of a variety of weights for different applications like image segmentation and multiple 2D matrices.

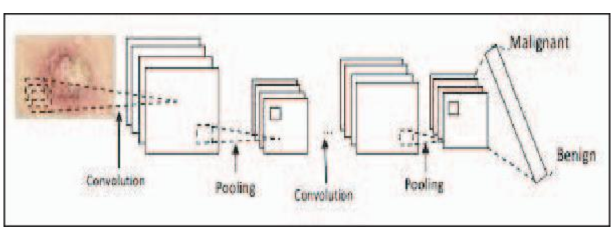

Fig. 2.1 A simple skin cancer detection using ordinary CNN

III. WORKFLOW

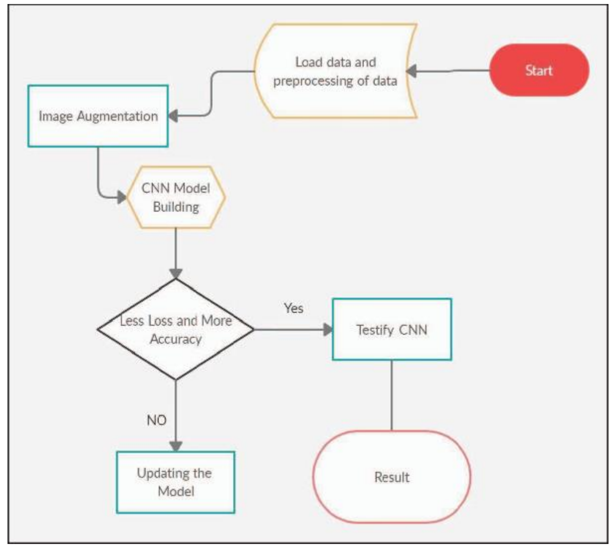

Fig. 3.1 Workflow overview. (Figure 3.1 depicts workflow and steps of our implementation to reach the objective.)

IV. DATASET

TABLE 4.1 HAM10000 metadataset

lesion_id	image_id	dx	dx_type	age	sex	localization
HAM_0000118	ISIC_0027419	bkl	histo	80	male	scalp
HAM_0000118	ISIC_0025030	bkl	histo	80	male	scalp
HAM_0002730	ISIC_0026769	bkl	histo	80	male	scalp
HAM_0002730	ISIC_0025661	bkl	histo	80	male	scalp
HAM_0001466	ISIC_0031633	bkl	histo	75	male	ear

table .4.1 HAM10000 MetaDataset overview

The important idea of the learning algorithm is to obtain weighted matrices for getting efficient features for the problem.The backpropagation method uses the chain rule forobtaining and minimizing the magnitude of the error in thenetwork.At each layer we use an activation function for scaling .In general we use activation function for scaling .In general we use activation functions like Relu andsigmoid .Relu also known as rectified linear unit is an activation function which take the max of the input to the function and 0 .Sigmoid is an activation function which scales and clamps the output between the range of 0 and 1.Ourdataset(HAM10000), a collection of different types of images of skin samples. The test images were also usedin different studies.

Training of deep neural networks for building automated ml models for the skin cancer classification and diagnosis of skin samples is objected to bythe small size and lack of diversity and effective information with the available dataset. In order to overcome this problem Harvard data verse released the HAM10000 ("Human Against Machine with 10000 training images") dataset. They collected a large number of skin samples from different areas, acquired and have been put in various senses.. The finalized dataset consists of 10015 skin images which are generally used for training deep learning algorithms and can be used in various computer vision applications. Dataset includes a set collection of all important skin cancer categories in: Actinic keratoses and i basal cell carcinoma (bcc) followed by , benign keratosis-like lesions like keratosis, (bkl), followed by dermatofibroma (df), followed by melanoma (mel), melanocytic nevi (nv) and lastly vascular lesions (angiomas, angiokeratomas, pyogenic granulomas and hemorrhage, vasc).

Out of the all samples a range of 50% of them have been confirmed through histopathology and the truth for the remaining samples is under examination. The dataset consists of lesions with multiple images, which can be identified by the lesion id -column within the HAM10000 dataset. An Overview of various classes in Image Dataset is depicted below in Fig. 4.2. Also, some statistics in the data are visualized and depicted in the form of charts and graphs in the below given Fig 4.3, Fig

4.4 and Fig 4.5

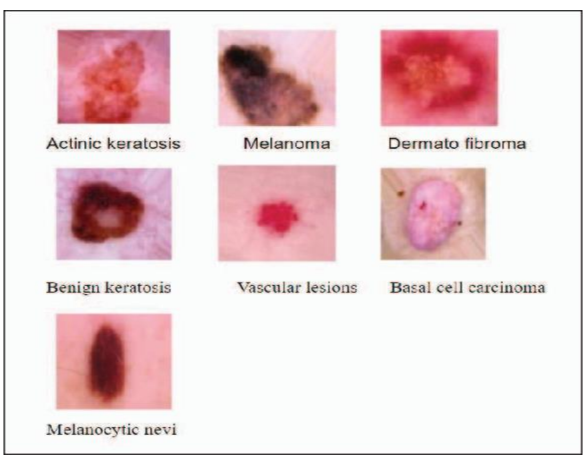

Fig. 4.2 Image Dataset (Sample images of various classes of cancer present in the HAM10000 dataset.)

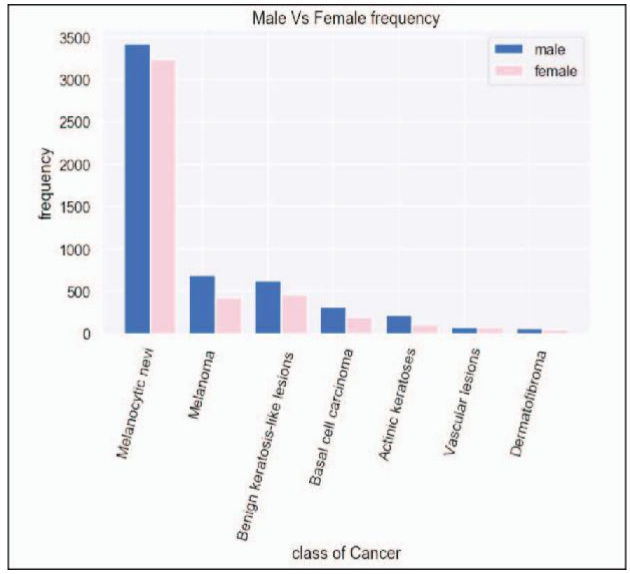

Fig 4.3 Male Vs Female frequency

As depicted in figure 4.3 it can be inferred from the data that in almost all classes and categories of skin cancer frequency of male count is relatively higher than female frequency.)

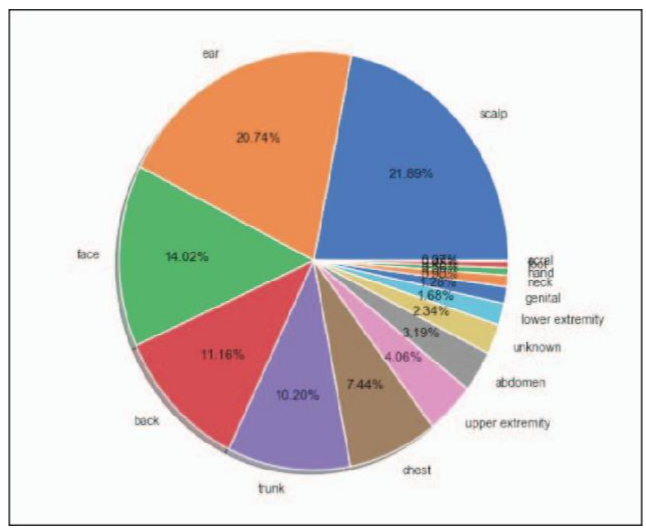

Fig 4.4 Distribution of Skin cancer frequency over various localizations.

As depicted in figure 4.4, it can be inferred from the data that most of the skin cancer diseases occur at the localization of ear face, trunk, scalp, chest, and visualized the same in the form of a pie chart.

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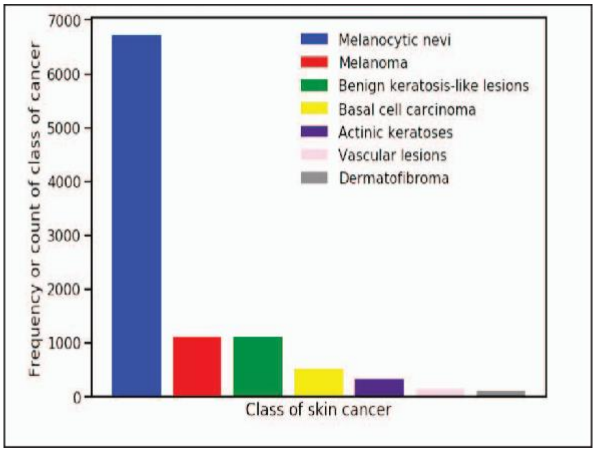

Fig 4.5. Frequency of each label in the dataset (As depicted in figure 4.5, the HAM10000 dataset consists of nearly 10015 images of which nearly 6700 images belong to the same class)

V. DATA PREPROCESSING AND IMAGE AUGMENTATION

The HAM10000 dataset is actually a large collection of multiple sources which consists of dermatoscopic images of pigmented skin lesions. Also, the test images were used in this paper in order to study and compare the different methods and effectiveness of the model. The dataset actually consists of totally 10015 colored images and most of the images are of resolution 600 x450.

As we see in the above table, the dataset totally consists of 10015 images of which 6705 images belong to the same label (Melanocytic nevi). So, it's an imbalanced dataset. In order to overcome this we made a comparison between multiple models to conclude the better of two. One with augmented images (for each image class in the dataset, we augmented nearly 3000 images and tried to maintain nearly equal frequency of all images and all reduced the data for Melanocytic nevi +(in order to maintain the balance). while training.

Also, we made a comparison without image augmentation. In which the model is trained with only the original images. The images were randomly moved and shifted within a range of 0.2(relative-range) horizontally and vertically. rotation range was 90 degrees. Also, random horizontal shifts were made to random images. All the

images are resized to 75x100. All the images are normalized (1./255) in order to increase the efficiency of the model.

A. Padding

We can find that the center pixels in an image are more used and appear a larger number of times ., when we do the convolution product using the vertical-edge filter.And the pixels in the corner edges of the image appear less number of times when compared to the`

In order to overcome this problem, we could add a image with zeros and p denotes the number of elements thatare added on each side of the image.

B. Stride

Stride denotes and indicates the step size that should be taken in the convolutional product. A large stride value might result in lowering the size of the output and vice-versa.

C. Convolution

After defining stride and the padding we can now further proceed and see how the convolutional product between a vector and a filter takes place.The convolution product on a 2D matrix is nothing but a sum of the product with each and every element in the vector and the corresponding element in the filter, we will now mathematically define the convolution product on a volume.An image is formally represented in the form of a vector of pixel intensity values with the following dimensions.

dimensions(img)=(n_h, n_w,n_d)n_h=the size of the height
n_w=the size of the width
n_d=the no of channels.

1. Colored images generally consist of three channels whichare red, green, blue also known as RGB channel image, where nd=3.While we convolve the filters on the input we want each pixel to be centered in the filter ,so because ofthis reason in practical we keep the filter as a odd dimensional square matrix

When we implement the convolutional product between the image and filter, the filter/kernel f and image must have the same depth or same number of channels in this way we convolve a variety of filters to each channel. Thus, the dimension of the filter is: dim(filter)=(f,f,n_d).

Eq.(2) denotes /describes the dimensions of the filter tobe convolved on the image.
The convolution of the filter over the image is shown below.
Mathematically denoting, for a given image and filter.

$$Conv(I,f)_{x,y} = \sum \sum \sum f_{(a,b,c)} I_{(x+a-1,y+b-1,c)}$$

center. and which leads us to lose the information in the corner and the edges.

Eq.(3) explains the convolution operation i.e, when a filter is placed and convolved on a part of the image each pixel inthe image is multiplied with its corresponding element in thefilter and summed up.

$$\left([\frac{n_h+2p-f}{} +1],[\frac{n_w+2p-f}{} +1], n\right);s>0$$

Eq.(4) explains the calculation of resulting

dimensionality after applying a convolution with filter f/kernel k on image I.

D. Pooling

In order to reduce the dimensionality of the image we use a pooling layer which decreases the images features through summarizing the information. This pooling operation is carried out through each and every channel and it ensures to affect the dimensions (nh, nw) only and keeps nd as the same previously. Given an image, we slide a kernel over the image following a certain stride value ,with no parameters to learn and we apply a function on the selected elements. We denote the pool size as p. We have:

dimension(pooling(img))=

$$\left(\left[\frac{n_h+2p-f}{s}+1\right],\left[\frac{n_w+2p-f}{s}+1\right], n_c\right);s>0 \qquad (5)$$

Eq.(5) explains the calculation of resulting dimensionality after applying a convolution with filter f/kernel k on image I.

E. Model Architecture

The CNN model used here for classification of skin cancer consists of a total of 16 layers. The images in the dataset consists of three channels R, G, B and hence nd=3as denoted in [eqn 1.0] , each of dimension 75x100. The image is then fed to a convolution layer with 16 filters each of kernel size 3x3 and activation function is relu(activation function is used to pass the output of the previous layer as a function to the input of the next layer).The image is passed to this layer for the first two convolutions. After the first two convolutions A max pooling layer is introduced with no parameters and passed through the image. This process is repeated with four more convolution layers and max pooling layers with different no of filters, filters and activation functions. After the convolutional layers the resulting vector is flattened and then passed to several fully connected layer networks.

Finally, since it is a classification the output should be in the form of probabilities i.e, in the range between 0 and 1, Hence activation function for the final layer would be sigmoid function which clamps the input to the range between 0 and 1. As the outputs should be in the form of probabilities, therefore the sum of all the probabilities should sum to 1. Hence all the outputs are normalized using a function called SoftMax. SoftMax function normalizes all the outputs in the final layer and sums to 1. There are 7 units in the output layer as there are 7 classes of skin cancer in the dataset and each represents the probabilities of prediction of that specific class. Then element aiin the final layer is normalized as follows:

$$a_i = \frac{e^{a_i}}{\sum_{i=1}^{7} e^{a_i}} \qquad (6)$$

VI. IMPLEMENTATION RESULTS

We Implemented multiple models and methodologies ofall those we found some of the results better and accurate of those we want to mention the results of three models. Wegot the better results using CNN trained with augmented images and model contains (7 convolutional layers and 4max pooling layers and 5 fully connected layers with trainable parameters of 440k nearly) and the data generated for training is nearly 23000 images.

We Initially implemented with another and different architecture of the model which consists of only original images and 6 convolutional layers and 8 fully connected layers. We then trained a model which consists of only a fully connected layer network. We finally obtained the best result of all the comparisons after training the model with augmented images and with architecture consisting of 17 layers (8 convolutional layers and 5 max-pooling layers and 4 fully connected layers).

TABLE 6.1 Training and testing statistics

Training accuracy	83.11% approximately
Testing accuracy (with original HAM10000 dataset	83.04%
Precision	0.818642
Recall	0.80509
Fscore	0.82797

Fig 6.1 (The above figure depicts the training and testing statistics)

The predictions result for the model are visualized below in the form of confusion matrices and charts (Fig 6.2, Fig 6.3 and Fig 6.4)

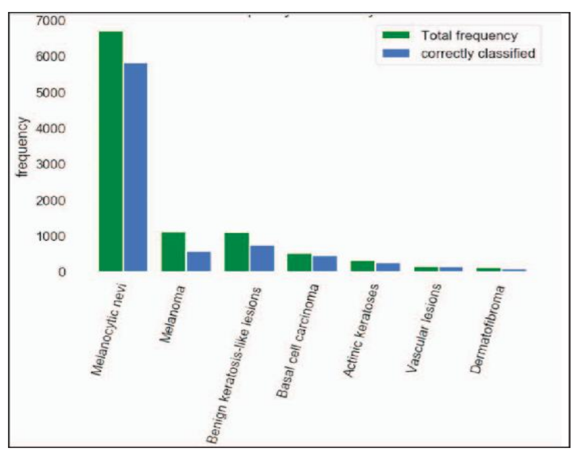

Fig 6.2 Analysis of predictions by model (As depicted in figure 6.2, the ratio of correctly classified and total classified)

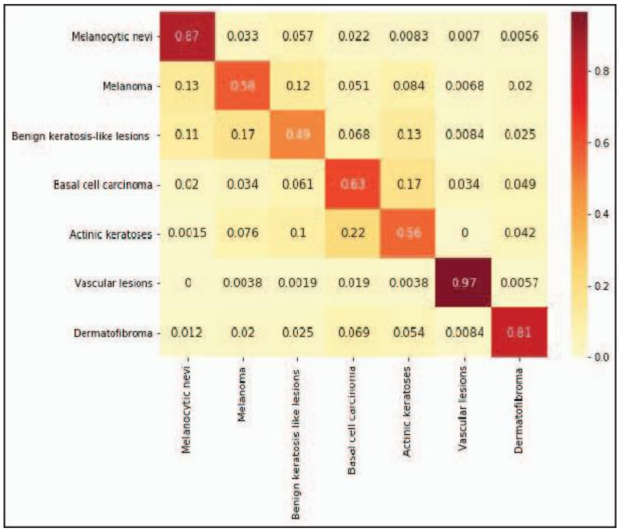

Fig 6.3. Training results with augmented images.(As shown in figure 6.3 aninference can be made from the confusion matrix that the model accuracy isquite high .)

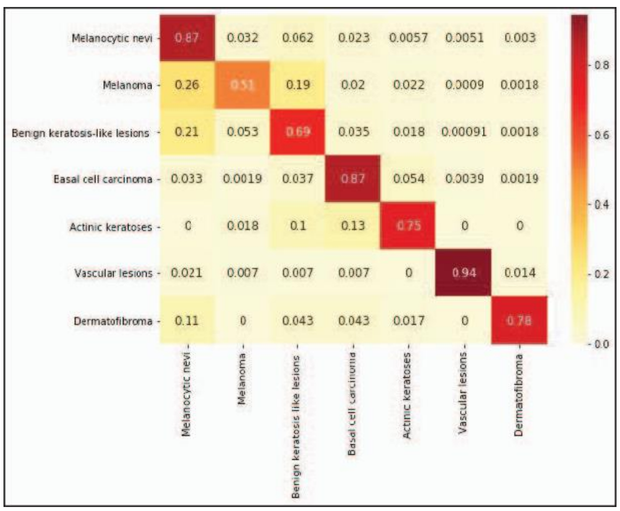

Fig 6.4 Testing results with original HAM10000 dataset

The model is also tested with the original images of the dataset and theresults are shown in figure 6.4.

CONCLUSION

To summarise and conclude the workflow and the research,after surveying multiple research papers and methodologies we tried to use and appreciate the purpose of neural networks in detection or classification of skin cancer comparing multiple architectures and methodologies. We achieved an accuracy of more than 80% with the HAM10000 dataset. We also tested the same with randomly generated augmented images and achieved nearly the same accuracy and precision. The performance indexes here are Accuracy, fscore, Precision, Recall. Final results showed that using the Standard CNN method gives the best achievement for the Skin cancer diagnosis.

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