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Melanoma classification on Dermoscopy images using Transfer learning with CNN architectures

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***Abstract*-Incidence rate of malignant melanoma has increased from the past two decades but the mortality that comes with it has stabilized. Early detection of melanoma was critical in the past as we do not have effective therapies and detection methodologies. State of the art classifiers based on CNNs are proved efficient to classify images of skin cancer more better than dermatologists and has provided more effective lifesavingdiagnosis, as now a days skin cancers can be detected in early stages. In this paper we will talk about classification of skin cancer using convolutional neural networks and transfer learning. We looked out for papers in Google scholar, PubMed, Google Scholar, ResearchGate, Web of Science databases for original research papers and review papers. The papers that has sufficient reports with proofs has been taken into consideration.**

***Keywords:*-Machine Learning, Deep Learning, Skin lesion Classification**

I.INTRODUCTION

There are 5.4 million new cases of skin cancer in USA every year. Skin cancer is a frequent type of cancer, with more danger. According to a recent study in the young adults skin cancer incidence has increased faster than any other cancer[1].In traditional Machine Learning technique, a domain expert needs to identify the applied features and make them more clearly visible to leaning algorithm to work, in order to reduce the complexity.Deep Learning algorithm, is a subfield of Machine Learning, works on artificial neural networks, which are algorithms inspired by the structure and function of the brain. The most danger form of cancer is melanoma cancer. Detection of melanoma at early stages is important for the survival of the patient [2,3,4].

There are three main types of cancer cells. They are squamous, Basal, and Melanocytes. Melanocytes are the most dangerous cells when compared to the other two types of cells. It again is classified into Melanocytic cells and non-melanocytic cells.The classification between malignant and benign melanoma is difficult, and it confuses dermatologists, and make them misclassify. Malignant Melanoma is the fifth most common cancer in men and women [14]. Although they only represent 5% of the total cancer cases in Unites States. But 75% of the deaths related to skin cancer. Previous works in computer aided classification lacked capability of generalizing like medical practitioners due to lack of sufficient data like dermoscopy classification[12,14,15].Dermoscopy images are the images that are obtained via specialized instruments and historical images are obtained via microscopy.

Images taken like photography have different factors like zoom, angle, and light on the picture and these variations can make them quite challenging. [6,7]. This variation factors can be mitigated by using datasets that contain images and training the CNN using these images to be able to classify images. These images need to be segmented and extracted before being able to classify them. We don't need to segment images; CNN will be trained to segment and classify images for both photographic and dermoscopic images. By using this technique, the rate of cure would reach over 90%.

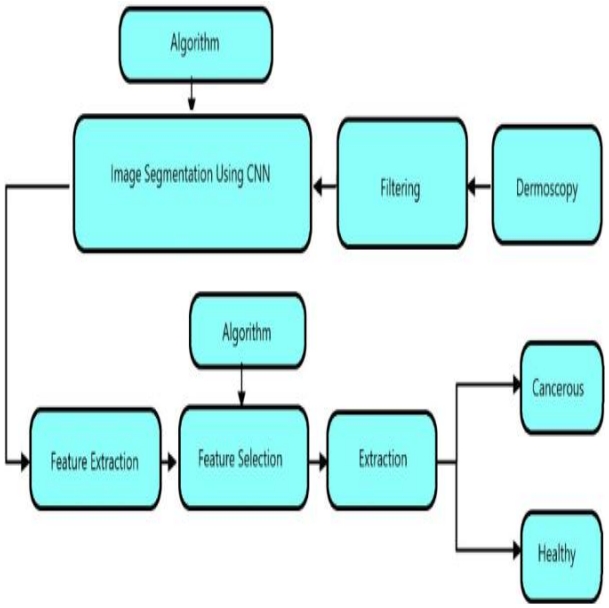

Fig 1. Flow diagram of steps in classifying a skin lesion using CNN.

This accuracy can be achieved by using dermoscopy images. Dermoscopy images is a noninvasive imaging technique for skin, which will be able to capture illuminated and magnified images of skin lesion to increase clarity of image and spots. So by removing unnecessary reflections on the images the visual effect of

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skin on a deeper level can be visible. Due to difference in skin texture, color, and shape and location segmentation which is a first step would become difficult. Second thing that is a problem for us would be the similarity between melanoma and non-melanoma images. And the third one would be other environmental conditions like hair, veins etc.

II. CONVOLUTIONAL NEURAL NETWORKS

CNNs are a kind of Artificial Neural Networks which were proven to be very powerful in image recognition and classification [9]. Each Artificial Neural Network has multiple areas. The three areas of ANN are input layer which takes the input, a hidden layer that is being trained on the images that are fed into input, and the output layer which produces the output [10]. Hidden layer extracts and segments the images. By using different kernels.

This convolutional process has three important features. It shares weights to the next layer to decrease the parameter number.

- It has learning connection locally.
- Invariance according to position of object.
- The accuracy of a CNN can be achieved by using some measures like accuracy, sensitivity, specificity and precision [8].

To calculate these values following equations are used:

$$\text{Accuracy} = \frac{t_p + t_n}{t_p + f_p + f_n + t_n}$$

$$\text{Sensitivity(TPR)} = \frac{t_p}{t_p + f_n}$$

$$\text{Specificity(TNR)} = \frac{t_n}{f_p + t_n}$$

$$\text{Precision(PPV)} = \frac{t_p}{t_p + f_p}$$

Where,

- **True negative (tn):** negative class is correctly predicted by the classifier model.
- **True positive (tp):** positive class is correctly predicted by the classifier model.
- **False negative (fn):** negative class is incorrectly predicted by the classifier model.
- **False positive (fp):** positive class is incorrectly predicted by the classifier model.

The CNN has two levels of training, one is feed forward level of training and another one is backpropagation level. IN the feed forward level, by using dot multiplication the image is injected into the network with the parameters of the neuron. After that the output of the network is evaluated.

III. CLASSIFICATION BASED ON TRANSFER LEARNING

In Transfer learning the knowledge of an existing machine that is already trained is applied to a different CNN but which is trying to solve a related problem. A neural network will try to detect edges in the first layers, shapes in the middle layer, and other features in the next layers. But using transfer learning the early and middle layers are used and we only retain the latter layers. It helps leverage the labeled data of the task it was initially trained on.

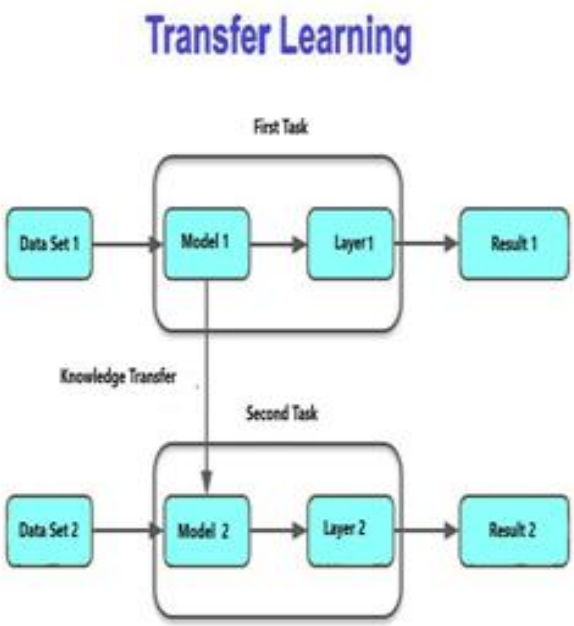

Fig 2. Transfer Learning model.

Author in this paper used transfer AlexNet using transfer learning. One of the approaches they used is classification layer and replaced it with SoftMax layer., and they fine-tuned the weight of architecture, and used augmenting data set by fixed random rotation angle. Softmax layer is bale to classify color image lesions that are segmented into nevus, and melanoma.The data set they sued contains 2000 from ISIC images and 374 of them are melanoma. 1372 are nevus images. Thye took another set from IS& quest and has 206 images, out of which 87 images are nevus and 119 are melanoma. The accuracy they obtained using AlexNet is 95.91% for the data set from ISIC, and 97.70% from the data set IS& Quest.

Author in this paper [11] applied deep learning to clinical images. To increase the accuracy of the system they segmented the skin lesions in a step before classification

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and they used correlation for illumination.The images were then applied to CNN layers for feature extraction and classification. The accuracy they obtained using this approach is 81%.

Another author used plain images that are photographed [12]. The features were extracted using Probabilistic Neural Network (PNN), in order to decide the color of the skin, and they achieved a classification rate of 76.2%.

[13] Used a CNN LightNet pre trained model to achieve better accuracy using transfer learning. Melanoma images classification was employed with a modest number of parameters using the CNN. The dataset from ISCI 2016 was used for this classification. Prior to classification dataset was not segmented or cropped. Then the above specified method was evaluated for sensitivity, accuracy, and classification in comparison to state-of-art using CNN architecture that employ lower number of parameters. They achieved an accuracy 0.816 for the proposed solution, and specificity of 0.980 with number of model parameters as 221890.

[14] Research is based on classification of images whether if its benign or malignant. Their dataset is taken from ISIC consists of 2437 images for training, and they used 660 test images and 200 images for validation purposes. They used Inception-v3 and ResNet-101 deep learning models for classification and achieved an accuracy rate of 84.09% and 87.42% with ResNet-101 and Inception-V3 architecture, respectively.

[15] Classification of skin lesion of melanoma Versus nevi or lentigines using dermatoscopic images was done by authors in this research using VGGNet. They compared different techniques of learnings, pretrained CNN using transfer learning and frozen layers versus a CNN trained from scratch. They also compared the above mentioned with a CNN using transfer learning and fine tuning of the weights. All of these CNNs were tested using images from ISCI 2016 challenge dataset, and a total number of 379 images were taken into consideration. By and fine tuning CNN with the weighting parameters got an accuracy of 81.33%.

Another author introduced a special architecture of CNN [16]. This CNN has multiple parts in which each part takes the same image at variety of resolutions. At the end the output layer combines outputs of multiple resolutions into single layer. This CNN identifies interactions with in different image resolutions and the weight parameters are optimized by end to end learning. The accuracy achieved by this algorithm is 79.5% using the data set from Dermofit image library.

Lopez et al [18] used VGGNetwhere using dermoscopicimages, classification of melanoma versus nevi or lentigines was addressed. In this paper the author compared the accuracy of classification of a CNN trained from scratch and a CNN with transfer learning and frozen layers, and also they compared a CNN with fine tuning and transfer learning using weighting parameters. All these configurations are tested based on 379 images from ISBI 2016 challenge dataset, and the CNN that is fine tuned with weights and used transferred learning achieved high accuracy of 81.33%.

Author [13] has used the data from HAM10000 dataset. They used a total number of 10015 images from training and validation. 80% of the images were used to train and 20% of them were used for validation purposes. They trained different CNN models DenseNet201, ResNet152, InceptionV4. They trained these models using the images from ImageNet.6705 images of the total images were melanocytic nevus some images are melanoma and other.

For melanocytic nevus they achieved a confusion matrix of 0.96 with DenseNet201, ResNet, InceptionV4, and a confusion matrix of 0.86, 0.94,0.82 with DenseNet201, ResNet, InceptionV4 respectively. And for melanoma they achieved a confusion matrix of 0.73,0.76,0.65 with DenseNet201, ResNet152, Inception V4 respectively, and as we can see there is an improvement in the confusion matrix which is about 2%.

[25] This author used a CNN and trained it using 4867 images from a dataset obtained from university of Tsukuba Hospital. A total number of 1842 patients are diagnosed with skin cancer from 2003 to 2016. Among these 1842 images 14 were malignant and benign. They performed this test to compare against thirteen dermatologists and nine dermatology trainees. They achieved an accuracy of 76.5% and 89.5% specificity and a sensitivity of 96.3%.

IV. CONCLUSION

From the reviews that we did on research papers, CNN was best to classify a skin lesion far better than dermatologists.AN among the different CNN architectures that are used by different research papers, in 2012 AlexNet was the winner among the other architectures in large scale visual Recognition Competition In 2015 it was, AlexNet, GoogleNet, ResNet and VGGNet [16,22,23].

Thus using CNNs for skin lesion classification was helpful but it has some drawbacks too! A study [32] reported that in the dermoscopic images the presence of blue ink had led to negative impact on accuracy. Also rotation and translation of the image were also important otherwise it lead to performance and accuracy issues. And another issue would be how the images are taken, whether we used a phone or dslr, cameras, each one gives different results.

So researchers should consider all these factors when they are testing CNNs for skin lesion classification. Also

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alarge database needs to be taken into consideration while testing these CNNs. But overall using=g CNNs for skin lesion classification gives better results ,avoiding human made mistakes.

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