Classification of Skin Lesions by using Extended Incremental Convolutional Neural Network

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***Abstract*—Order of skin sores in different dangerous sort assumes a pivotal job in diagnosing different, neighborhood and quality related, ailments in the field of therapeutic science. Grouping of these sores in a few carcinogenic sorts i.e Melanoma(MEL), Melanomic Neves(NV), Basal Cell Carcinoma(BCC), Actinic Keratosis(AKIEC), Benign Keratosis(BKL), Dermatofibroma(DF) and Vascular Lesion(VASC) gives some understanding about the infection. Skin malignancy is the most deadly kind of malignancy however in the event that these infections are recognized in beginning times, at that point patients can have a high recurrence of recuperation. A few ways to deal with programmed arrangement have been investigated by numerous creators, utilizing different systems and methodologies however this paper proposed an extended version of novel Incremental methodology for Convolution Neural Network on dermoscopy pictures for characterization of skin sores in different skin malignant growths. This is a summed up methodology subsequently can be executed in different calculations for accomplishing higher exactness. Worldwide Skin Imaging Collaboration (ISIC) 2018 test dataset is utilized in this paper. The methodology utilized in this paper yields an accuracy of more than 95%.**

***Index Terms*—Dermoscopy image,Incremental Convolutional Neural Network(ICNN), Extended Incremental Convolutional Neural Network(ICNN), Lesion classification, Skin lesions**

I. INTRODUCTION

Skin disease is the uncontrolled development of anomalous skin cells. Skin diseases like basal cell carcinoma, and squamous cell carcinoma, melanoma - regularly start to change your skin. Skin malignancy can be relieved if it's found and treated early. Skin malignancy essentially grows on sun uncovered places like legs, arms, etc. Skin malignant growth influences individuals of all skin tones, incorporating those with darker compositions. At the point when melanoma happens in individuals with dim skin tones, it's bound to happen in zones not regularly presented to the sun, for example, the palms of the hands and bottoms of the feet.

The rest of the paper is organized as follows. Section 2 of paper constitute of Description of Dataset, Section 3 contains Convolutional Neural Network Fundamentals, Section 4 is Incremental learning approach for CNN, Section 5 is Architecture of CNN proposed model, Section 6 is Experimental Results and Section 7 is Conclusion.

II. DATASET DESCRIPTION

[9]The information is in dermoscopic sore pictures in JPEG design. All sore pictures are named utilizing the plan ISIC.jpg, where is a 7-digit one of a kind identifier. EXIF labels in the pictures have been expelled; any remaining EXIF labels ought not be depended upon to give precise metadata. The sore pictures originate from the HAM10000 Dataset, and were procured with an assortment of dermatoscope types, from every single anatomic site(barring mucosa and nails), from a recorded example of patients displayed for skin malignancy screening, from a few unique establishments. Pictures were gathered with endorsement of the Ethics Review Committee of University of Queensland(Protocol-No. 2017001223) and Medical University of Vienna(Protocol-No. 1804/2017).

The Ground Truth is single CSV record(comma-isolated esteem) document of binary classifications for every one of the 7 illness states, demonstrating the conclusion of each info injury picture.

1) MEL: Melanoma diagnosis confidence
2) NV: Melanocytic nevus diagnosis confidence
3) BCC: Basal cell carcinoma diagnosis confidence
4) AKIEC: Actinic keratosis / Bowens disease(intraepithelial carcinoma) diagnosis confidence
5) BKL: Benign keratosis(solar lentigo / seborrheic keratosis / lichen planus-like keratosis) diagnosis confidence
6) DF: Dermatofibroma diagnosis confidence
7) VASC: Vascular lesion diagnosis confidence

III. CONVOLUTIONAL NEURAL NETWORK-FUNDAMENTALS

[1], [2], [3], [7], [8] A Convolutional Neural Network(CNN) is included at least one convolutional layers(frequently with a sub-sampling step) and afterward pursued by at least one fully connected layers as in a standard multilayer neural system. The engineering of a CNN is intended to exploit the 2D structure of an info picture(or other 2D information, for example, a discourse flag). Another advantage of CNN 's is that they are simpler to prepare and have numerous less parameters than completely associated systems with a similar number of concealed units.

A. Convolutional Layer

Each neuron in the first layer is associated with a region of the input neurons. The region could be big or small. That region is called a local receptive field for that neuron. Then we slide the local receptive field over by stride length to the right to connect to a second neuron and goes doing, building up the first layer. Here the same weights and bias for each of the neurons are used. It means each neuron has shared weights an biases. So it can be inferred that all the neurons in the first layer detect the same feature. But at different places in the images. For example, the weights and bias are adjusted such that they can detect an edge in its field. This weights and biases can be used at other places in an image to detect edges. An advantage is it drastically reduces the total number of parameters. It means it reduces the processing time and use of resources.[12], [7]

$$(t) = (x \times w)(t) \tag{1}$$

B. Pooling Layer

CNNs also contain pooling layers. These layers usually used immediately after convolutional layers but not necessary. A pooling layer takes each feature map as input and outputs the reduced feature map. Condensed feature map means the dimension of the convolutional layer is reduced. As an example max-pooling, avg-pooling, etc. For instance, if the input layer is an NN layer then pooling layer yields output as $N/k \times N/k$ layer, here $k \times k$ is the size of pooling layer.

C. Normalization Layer

We usually normalize the layers by adjusting and scaling the activations i.e when we have features from 0 to 1 and some from 1 to 100, we should normalize them between some range say 0 to 1 to accelerate training. This technique drastically increases the training speed because this technique eliminates many outliers. Batch normalization provides some liberty to layers i.e by allowing each layer to learn by itself a little bit more independently of other layers.

D. Dropout Layers

The dropouts are specifically used for preventing the overfitting problem. In this technique, neurons are randomly removed during the training. Parameter p is used to control the dropouts. It means it determines to remove the neuron probability. These layers are used during training only.

E. Fully Connected Layers

The final layer in the CNN network is a fully- connected layer. Pooling layer is connected to every output layer by a fully connected layer. This fully-connected architecture is the same as in multilayer perceptrons.

IV. Extended Incremental approach

We proposed this technique for the complex, biased, etc. dataset. i.e images in dataset are differed by less probability distribution(fewer variations). If this type of condition persists in dataset then simple CNN can'table to detect it. If we tried to use simple CNN model then this model cant able to generalize the result properly and efficiently. But in Incremental training approach, CNN can able to classify biased, complex dataset properly and efficiently.

Steps for implementing Extended Incremental approach for CNN[7]:

1) We isolate the dataset into its individual class.

Algorithm 1: Incremental CNN Learning

Input: feature set α,
$L_i \in \alpha$, $L_i \in [\text{feature}]^{n*d}$ $\forall$i= $\in numberofclasses$,
$\xi \in variation\ function, \gamma \in variation\ value.$
Output: Weight Matrix $W^{\eta * \kappa}$.
$\tau \in \phi, \mu \in \phi.$
while $\alpha \neq \phi$ **do**
    if $L_i = \phi$ **then**
        return W*;*
    else
        $\tau \subset L_i \ldots \xi(\tau) \geq \gamma;$
        $\mu \in \mu + \tau;$
        W=$Train\_CNN(\mu)$;
        $\tau = \phi;$

TABLE I
Comparison table of Simple and Incremental CNN.

Approach	Accuracy	Loss
Simple CNN	64.6%	1.24
Incremental CNN	90.26%	0.35
Extended Incremental CNN	95.6%	0.35

2) By observation, we select the random number of images of all classes which showing large variation i.e they are easily classified. The intuition behind choosing high variant images is due to high variation in dataset CNN can classify them easily.
3) In the wake of choosing begin the preparation of model
4) Where to quit preparing - If we got pinnacle point i.e the condition where variety inexactness and misfortune is immaterial then this condition is known as an immersion point and here we need to quit preparing.
5) Presently change dataset by including some more pictures of all class arbitrarily(do not expel the past pictures simply continue including new pictures from the dataset with every addition) which having less variety than past pictures. Also, go to stage 3.
6) Proceed with this system until complete dataset get depleted.
7) As we draw nearer to increasingly complex dataset consider little augmentation on the grounds that as multifaceted nature builds misfortune expands precision diminishes so by utilizing the little group estimate we prompted the correct preparing of the model.

As seen in the Table I Simple CNN model yields only 64.6% accuracy and incremental model yields 90.26% of accuracy but extended incremental model yields 95.6% of accuracy.

Figure 1 shows how training accuracy and testing accuracy varies. The training accuracy increases regularly but testing accuracy varies it shows some random trend in its variation. The training accuracy is less than testing accuracy it is due to fewer data in the first increment. As we started adding fewer variant data the testing accuracy increases.

As shown in Figure 2 we trained model in Second Increment

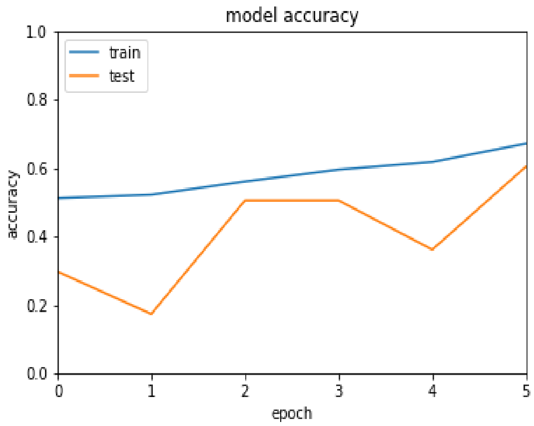

Fig. 1. Accuracy of Model in First Increment

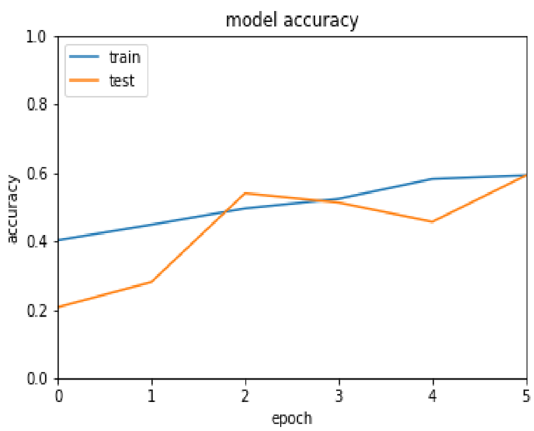

Fig. 2. Accuracy of Model in Second Increment

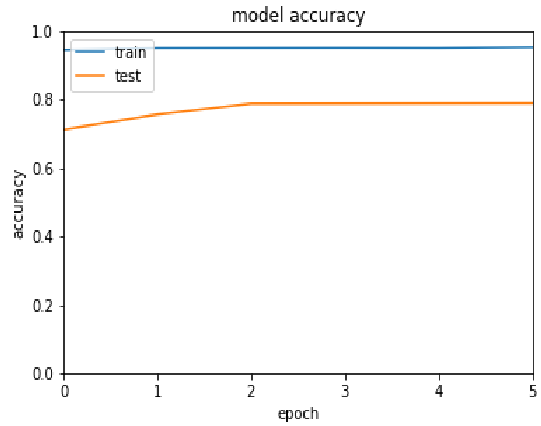

Fig. 3. Accuracy of Model in Third Increment

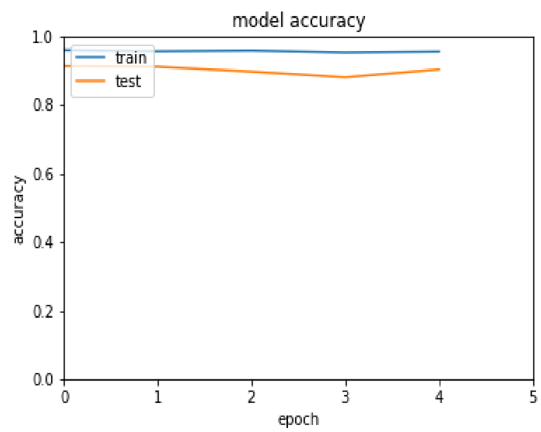

Fig. 4. Accuracy of Model in Fourth Increment

i.e with added fewer variant data to First Increment. As it is shown the training accuracy and testing accuracy in increased than in First Increment. The difference between training and testing accuracy also reduced. As we go on Increments the accuracy start increasing and loss starts decreasing. The accuracy is directly proportional to the number of Increments.

$$Accuracy \propto NumberIncrements \qquad (2)$$

Figure 3 shows Third Increment where the model gets trained but cant able to generalize it properly. This problem can be solved by increasing data or moving to further Increment. The Second Increment consists of large variant images. As we move further in Increments we have to fed most complex images dataset to model so for achieving the best accuracy for most complex dataset add very few images in previous increments. Figure 4 shows training of most complex images in the dataset. It can be seen that the training and testing accuracy is nearly the same.

Figure 5 shows the training and testing accuracy of final model. It can be seen that variation of both accuracy is negligible which is stopping condition.

V. Convolutional Neural Network- Proposed Architecture

[7], [9], [10], [11] The model type that we will be using is 'Sequential'. Sequential is the easiest way to build a model in Keras. It allows you to build a model layer by layer. We use the 'add' function to add layers to our Model. Our layers are Conv2D layers. These are convolution layers that will deal with our input images, which are seen as 2-dimensional matrices. First two consecutive Convolutional layer of kernels size 16 is followed by Max Pooling layer of size 3 is followed by Batch Normalization layer. Second two consecutive Convolutional layer of kernels size 32 is followed by Max Pooling layer of size 3 is followed by Batch Normalization layer and Dropout layer of size 0.25. Last two consecutive Convolutional layer of kernels size 64 is followed by Max Pooling layer of size 3 is followed by Batch Normalization layer. The number of filters can be changed according to need. This paper uses totally 6 Conv2D layers. Kernel size is the size of the filter matrix for our convolution. So a kernel size

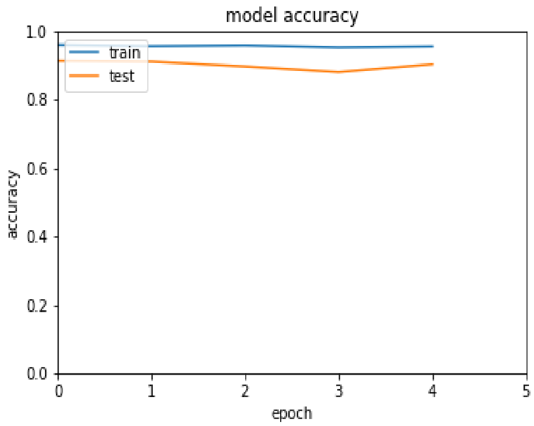

Fig. 5. Accuracy of Final Model

of 3 means we will have a 3x3 filter matrix. Activation is the activation function for the layer. The activation function we will be using for Conv2D layers is the ReLU or Rectified Linear Activation. This activation function has been proven to work well in neural networks. The Max pooling Layer is used. In between the Conv2D layers and the dense layer, there is a Flatten layer. Flatten serves as a connection between the convolution and dense layers. Dense is the layer type we will use in for our output layer. Dense is a standard layer type that is used in many cases for neural networks. Here we have three dense layers having a filter size of 64 and 128. The first dense layer is followed by Drop out of size 0.25 and second Dense layer is followed by Drop out the layer of size 0.5. We will have 10 nodes in our output layer, one for each possible outcome(0 to 9). The activation is softmax. Softmax makes the output sum up to 1 so the output can be interpreted as probabilities. The model will then make its prediction based on which option has the highest probability. We use to drop out between Fully Connected layer to avoid overfitting.

A. Prepossessing

Before feeding data to Convolutional Neural Network we have provided some preprocessing it includes image resizing, data cleaning, etc. To prepare images for the training of Convolutional Neural Network each of training images was resized to 300*300 form 600*400

B. Implementation

There three types of data set available in ISIC 2018 challenge first one is Training dataset, second is Teasing dataset and the third one is validation dataset. There also a Ground truth also called as labels.

The implementation is based on the technique of Incremental learning for the same probability distribution. For the first instance, we have a select small volume of data having large variations for training. We trained the model up to a maximum extent of accuracy i.e up to the peak where accuracy variation is low and accuracy value is large. The weight matrix of this instance is saved for future use. For the Second instance using the same model but for fewer variant data we tried to train the model by making modifications in the model. As soon as we reached the same condition in the first instance we stopped and save the weights. And continue this Step by Step Learning until our dataset gets exhausted. This technique helped our model to classify more complex dataset efficiently. This technique works efficiently if the dataset is biased. This technique drops the loss vigorously.

VI. Experimental Result

The motivation behind this work is this is the latest dataset on skin cancer i.e release in 2018 and this dataset contains lesions of 7 type of skin cancers. This algorithm has the highest accuracy on this dataset as compared to ISIC2017 dataset which is released in 2017[5]. Comparison of both results is depicted in Table III.

This method is implemented in Python 3. During the implementation, we need a platform of Intel Xeon and Titan X GPU with 64GB RAM. The performance is calculated by a confusion matrix. Firstly input is preprocessed and the classification is carried out the deep convolutional neural network. The System can efficiently classify seven types of skin lesions. The convolutional layer acts as a feature extractor.

Table II shows a comparison of precision, recall, f1-score, and support. Here support means a number of images taken for a tasting of the individual class. Class 0 and Class 4 has lower precision compared to the other Classes because there is a large variation in class. Their Symmetry, Border, Color are so variant that the human eye cannot predict it properly. All these the parameter varies randomly so the convolutional neural cant able to predict it. Other than Class 0 and Class 4 all are predicted accurately. The overall precision of the network is more than 89%.

We find TP, TN, FP, FN which refer to true positive, true negative, false positive, false negative at the pixel level respectively. Using the above terms Precision, Recall and F1-Score are evaluated as follows.

$$precision = \frac{TP}{TP + FP} \tag{3}$$

$$recall = \frac{TP}{TP + FN} \tag{4}$$

$$f1 - score = \frac{precision * recall}{precision - recall} \tag{5}$$

Top 5 result of ISIC 2017 competition combined with result of proposed algorithm is mentioned above in Table III.

Figure 6 and Figure 7 show the sample of classified and miss-classified images from dataset. As it can be inferred from Figure 7 the variation in miss-classified images are more and even they cannot be detected properly by the human eye. The variation shown by these miss-classified images on the basis of symmetry, border, color is extremely random. Figure **??** shows the confusion matrix of the proposed model. It is the comparison between the predicted label and true label.

TABLE II
COMPARISON OF PRECISION, RECALL, F1-SCORE FOR INDIVIDUAL CLASS
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Classes	precision	recall	f1-score	support
Class 0	0.72	0.73	0.72	215
Class 1	0.95	0.92	0.94	1303
Class 2	0.95	0.82	0.88	108
Class 3	0.89	0.86	0.87	64
Class 4	0.70	0.88	0.78	257
Class 5	1.00	0.92	0.96	24
Class 6	1.00	0.96	0.81	32
avg/total	0.89	0.88	0.89	2003

TABLE III
COMPARISON OF RESULTS OF SKIN LESIONS CLASSIFICATION ON ISIC 2017 AND ISIC 2018.

Method	Accuracy	Precision
[6] CSUJT	0.816	0.748
[6] MPG-UCIIIM1	0.849	0.747
[6] RECOD Titans	0.883	0.752
[6] USYD-BMIT	0.888	0.732
[6] IHPC-NSC	0.873	0.665
[6]Incremental CNN	0.9026	0.89
Extended Incremental CNN	**0.966**	**0.89**

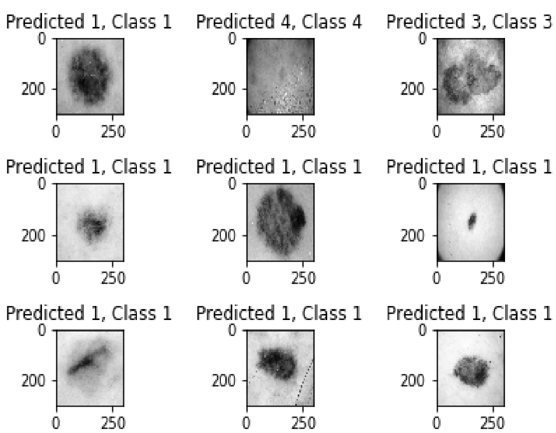

Fig. 6. Correctly Classified class samples

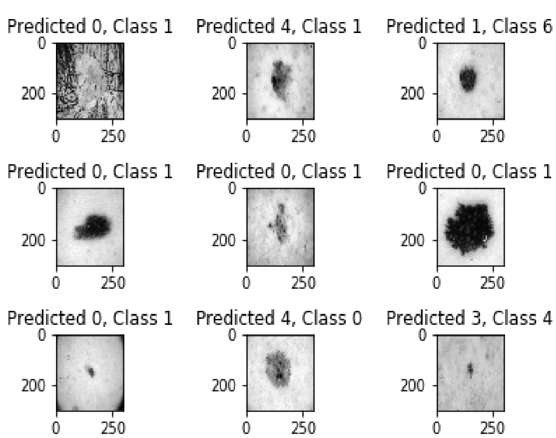

Fig. 7. Miss-Classified class samples

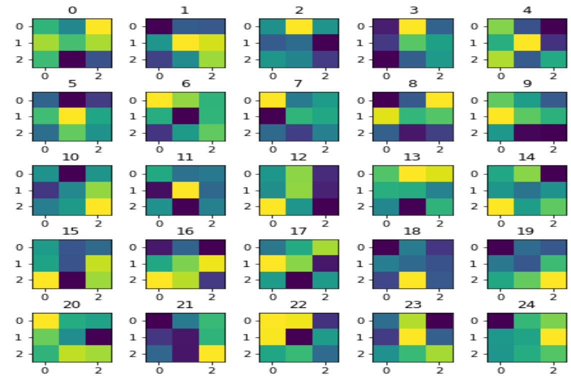

Fig. 8. Filters of last convolutional layer

As the confusion matrix representing the count of classified and miss-classified images. The diagonal of the confusion matrix is representing the correctly classified images and non-diagonal values represent the miss-classified images. The model correctly classified 153, 1201, 89, 55, 227, 22, 22 of respective class. As class 1 has the highest number of samples so it is shown in white to represent the test dataset contains a large number of class 1 images. The example images and their representation after convolutional layer are shown in Figure 9.

Figure 8 shows the image of the filter of the last convolutional layer. It looks like most of these have encoded some type of direction or color. Lighter blocks are indicating the smaller weight, as a result, feature map responds less to these input pixels. Darker blocks are indicating the larger weight, as a result, feature map responds more to these input pixels. Figure 9 shows how the feature is extracted in a convolutional neural network. These are some sample images of output after each convolutional layer of the trained model. As it can be seen that it get more complex and deeper as we move deeper and deeper in the network.

VII. CONCLUSION

In this paper, we proposed an Incremental approach for a convolutional neural network for cancerous image classification. In this paper, we have analyzed how the incremental model is useful when there is the most complex dataset. We compare the incremental approach with a simple approach and hence concluded that the incremental approach gives a better result. Further, we are aiming to increase the model accuracy by using some diverse methods in combination with the incremental approach.

REFERENCES

[1] Mane, Deepak & Kulkarni, U.V.: Visualizing and Understanding Customized Convolutional Neural Network for Recognition of Handwritten Marathi Numerals. Procedia Computer Science. 132. 1123-1137. 10.1016/j.procs.2018.05.027,(2018).

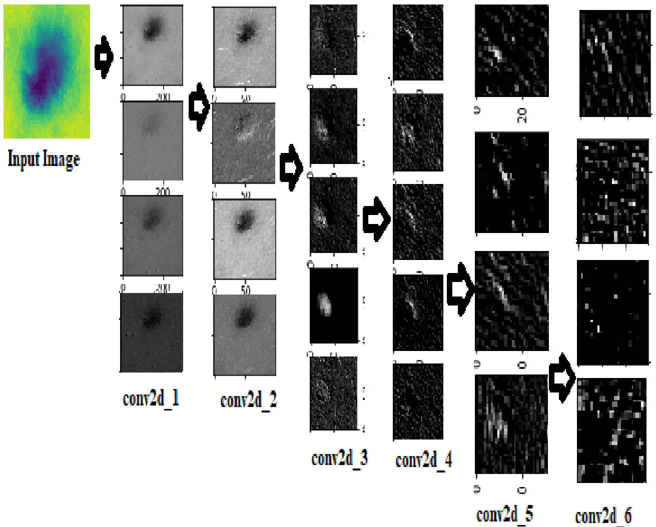

Fig. 9. Sample Image with its Six activation's.

[2] Tianmei Guo, Jiwen Dong, Henjian Li, Yunxing Gao :Simple convolutional neural network on image classification,pp 721-123,(2017).10.1109/ICBDA.2017.8078730

[3] Thu Thao, Le & Hong Quang, Nguyen, Automatic skin lesion analysis towards melanoma detection. 106-111. 10.1109/IESYS.2017.8233570,pp 106-107,(2017).

[4] Codella, Noel & Gutman, David & Celebi, M. Emre Helba, Brian & Marchetti, Michael & Dusza, Stephen & Kalloo, Aadi & Liopyris, Konstantinos & Mishra, Nabin Kumar & Kittler, Harald & Halpern, Allan : Skin Lesion Analysis Toward Melanoma Detection: A Challenge at the 2017 International Symposium on Biomedical Imaging (ISBI), Hosted by the International Skin Imaging Collaboration (ISIC), pp 168-171,(2017).

[5] Matt Berseth. : ISIC 2017Skin Lesion Analysis Towards Melanoma Detection. : A Challenge at the 2017 International Symposium on Biomedical Imaging (ISBI), Hosted by the International Skin Imaging Collaboration (ISIC) https://arxiv.org/pdf/1703.00523.pdf

[6] Yuexiang Li and Linlin Shen : Skin Lesion Analysis towards Melanoma Detection Using Deep Learning Network: A Challenge at the 2017 International Symposium on Biomedical Imaging (ISBI), Hosted by the International Skin Imaging Collaboration (ISIC) https://arxiv.org/pdf/1703.00577.pdf

[7] Chopade Ankit, in press: Seven Class Classification of Skin Lesions by using Incremental Convolutional Neural Network in Python. Accepted for publication in Conference of ICAEEC-2019 on 31 MAY-1 JUNE 2019.

[8] J Liu, PC Cosman, BD Rao : Robust Linear Regression via Regularization, IEEE Transactions on Signal Processing 66 (3), 698-713

[9] ISIC 2018: Skin Lesion Analysis Towards Melanoma Detection, https://challenge2018.isic-archive.com/. Last accessed 12 Dec 2018

[10] Introduction to CNN with keras, https://www.kaggle.com/amarjeet007/visualize-cnn-with-keras. Last accessed 12 Dec 2018

[11] Understanding of Convolutional Neural Network (CNN)Deep Learning, https://www.medium.com. Last accessed 12 Dec 2018

[12] Chapter 9- Convolutional Networks https://www.deeplearningbook.org/contents/convnets.html. Last accessed 15 Dec 2018