Project Report on Detection of Skin Lesions Using Convolutional Neural Networks

A Project Report/Synopsis submitted in partial fulfilment of the requirements for the award of
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Submitted By
Punit, Gurdaman Singh, Agampreet Kaur Walia
(Roll No: CO17348, CO17323, CO17307)
Under the supervision of
Dr. Varun Gupta

CHANDIGARH COLLEGE OF ENGINEERING AND TECHNOLOGY

(DEGREE WING)

Government Institute under Chandigarh (UT) Administration, Affiliated to Punjab University, Chandigarh

Sector-26 Chandigarh PIN-160019

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CANDIDATE'S DECLARATION

I hereby declare that the work presented in this report entitled Skin Lesions detection using CNN in fulfilment of the requirement for the award of the degree Bachelor of Engineering in Computer Science & Engineering, submitted in CSE Department, Chandigarh College of Engineering & Technology (Degree wing) affiliated to Punjab University, Chandigarh, is an authentic record of my/our own work carried out during my degree under the guidance of Dr. Varun Gupta. The work reported in this has not been submitted by me for award of any other degree or diploma.

Date: March, 2021

SKIN LESIONS DETECTION USING CNN

I. ABSTRACT

Given the success of Deep Convolutional Neural Network in Computer Vision tasks such as image classification, object detection, etc., DCNN has been applied to many other fields and lays path for new research domains. Recently, by transfer learning, Esteva et al proposed in "Dermatologist – level classification of Skin Cancer with Deep Neural Networks" that "CNN achieves performance on par with all tested experts, demonstrating an artificial intelligence capable of classifying skin cancer with a level of competence comparable to dermatologists". Inspired by the work, in this project, I attempt to fine-tune deep convolution neural networks that have succeeded with ImageNet dataset for classifying 7 types of skin lesion using HAM10000, a dataset containing 10000 dermatoscopic images. Fine-tuning the top layers was performed with VGG16, Inception V3, Inception ResNet V2 and Dense Net 201. VGG16 and Inception V3 give very similar results on the test set, 79.64% and 79.94% respectively. Inception ResNet V2 performed 3% better, and Dense Net 201 gives even the best single result for fine-tuning top layers with accuracy of 83.93%. Fine-tuning the whole model was performed with Inception V3 and Dense Net 201. After 20 epochs, while Inception V3 performed a little bit better with validation set, Dense Net 201 gives the best single result for test set with accuracy up to 87.725%. The results of experiments verify the intuition that features learned by pretrained models and the architectures of the DCNNs help learning features for a completely different domain dataset, here is the skin lesions dermatoscopic images dataset. Given the computational time and the test accuracy of fine-tuning the top layers and fine-tuning the whole model, for this particular dataset, I find that it's better to fine-tune the whole pretrained model with fewer epochs and less computational time and achieve better accuracy.

Keywords: Skin lesions, CNN, Inception ResNet, DenseNet

II. INTRODUCTION

Deep Learning method employs multiple processing layers to learn hierarchical representation of data. It offers a way to harness a large amount of data with few hands feature engineering. Deep Learning method has made impressive advances and evolvement in Computer Vision in recent years, starting from AlexNet in 2012.

What is a skin lesion? A skin lesion is any change in the normal character of your skin. A skin lesion may occur on any part of your body and cover a tiny or large area. Skin lesions can be singular or multiple, confined to one specific area of your body or distributed widely. Skin lesions include rash, cysts, pus-filled sacs, blisters, swelling, discolorations, bumps, hardening, or any other change in or on your skin. Skin lesions may result from a wide range of causes, as harmless as a small scrape or as serious as skin cancer. There are many common causes of skin lesions. For example, injury can cause a bruise, scrape or cut. Teenagers may have skin lesions from acne, while aging may bring freckles, moles and discoloration. A number of infectious diseases cause rashes, and allergic reactions may be accompanied by itchy hives or rashes. Skin changes can also occur with chronic conditions, such as diabetes or autoimmune disorders. Skin lesions, such as boils and carbuncles, may also be caused by local infections of the skin or hair follicles. Skin cancer and precancerous changes in the skin are more serious causes of skin lesions. These lesions most commonly appear on areas of your body that have been exposed to sun, including your face, arms and hands. Because skin lesions can arise from numerous conditions, which may be harmless or serious, contact your health care provider if you have a new skin lesion that causes you concern or lasts for more than a day or two, or if your child has a skin lesion. Skin lesions are usually mild, but in some cases, they can be a sign of a serious condition. There are many common causes of skin lesions. For example, injury can cause a bruise, scrape or cut. Teenagers may have skin lesions from acne, while aging may bring freckles, moles and discoloration. A number of infectious diseases cause rashes, and allergic reactions may be accompanied by itchy hives or rashes. Skin changes can also occur with chronic conditions, such as diabetes or autoimmune disorders. Skin lesions, such as boils and carbuncles, may also be caused by local infections of the skin or hair follicles.

Skin cancer and precancerous changes in the skin are more serious causes of skin lesions. These lesions most commonly appear on areas of your body that have been exposed to sun, including your face, arms and hands. Skin lesions may accompany other symptoms, which vary depending on the underlying disease, disorder or condition. Symptoms that frequently affect the skin may also involve other body systems.

What is CNN? A **Convolutional Neural Network (ConvNet/CNN)** is a Deep Learning algorithm which can take in an input image, assign importance (learnable weights and biases) to various aspects/objects in the image and be able to differentiate one from the other. The pre-processing required in a ConvNet is much lower as compared to other classification algorithms. While in primitive methods filters are hand-engineered, with enough training, ConvNets have the ability to learn these filters/characteristics. The architecture of a ConvNet is analogous to that of the connectivity pattern of Neurons in the Human Brain and was inspired by the organization of the Visual Cortex. Individual neurons respond to stimuli only in a restricted region of the visual field known as the Receptive Field. A collection of such fields overlaps to cover the entire visual area.

Convolutional neural networks are composed of multiple layers of artificial neurons. Artificial neurons, a rough imitation of their biological counterparts, are mathematical functions that calculate the weighted sum of multiple inputs and outputs an activation value. The behavior of each neuron is defined by its weights. When fed with the pixel values, the artificial neurons of a CNN pick out various visual features. When you input an image into a ConvNet, each of its layers generates several activation maps. Activation maps highlight the relevant features of the image. Each of the neurons takes a patch of pixels as input, multiplies their color values by its weights, sums them up, and runs them through the activation function.

The first (or bottom) layer of the CNN usually detects basic features such as horizontal, vertical, and diagonal edges. The output of the first layer is fed as input of the next layer, which extracts more complex features, such as corners and combinations of edges. As you move deeper into the convolutional neural network, the layers start detecting higher-level features such as objects, faces, and more.

The special characteristics of Deep CNN is that the first layers usually learn very general and "low-level" features of images, while the very last layers of the network learn the semantics and high-level features. Hence, with fine-tuning, Deep Convolutional Neural Networks trained on for image classification task on one dataset can be reused for others image classification task with different dataset. Consequently, fine-tuning has been used widely in Computer Vision research. By fine-tuning InceptionV3, Esteva et al proposed in "Dermatologist – level classification of Skin Cancer with Deep Neural Networks" that "CNN achieves performance on par with all tested experts, demonstrating an artificial intelligence capable of classifying skin cancer with a level of competence comparable to dermatologists". Esteva et al were using their own obtained dermatologist – labelled dataset consisting of 129,450 clinical images, including 3374 dermoscopy images. This whole dataset includes 2032 skin diseases, belonging to nine skin diseases partitions. By fine-tuning InceptionV3 on this dataset, Esteva et al got up to 66% accuracy classification on nine classes. In this project, I used HAM10000 dataset obtained by ViDIR Group, Department of Dermatology, Medical University of Vienna. Dermatoscopy is a widely used diagnostic technique that improves the diagnosis of benign and malignant pigmented skin lesions in comparison to examination with the unaided eye. The HAM10000 dataset contains 10015 dermatoscopic images collected over a period of 20 year from two different sites, the Department of Dermatology at the Medical University of Vienna, Austria and the skin cancer practice of Cliff Rosendahl in Queensland, Australia. The dataset includes a representative collection of important diagnostic categories in the realm of pigmented lesions: Actinic keratoses and intraepithelial carcinoma / Bowen's disease, basal cell carcinoma, benign keratosis- like lesions (solar lentigines / seborrheic keratoses and lichen-planus like keratoses), dermatofibroma, melanoma, melanocytic nevi and vascular lesions (angiomas, angiokeratomas, pyogenic granulomas and hemorrhage). Works of this project are as follow:

- Fine tune DCNNs for 7 types of skin lesions for 10000 dermaoscopic images.
- Compare performance of DCNNs: VGG16, Inception ResNet V2, Inception V3, Dense Net
  201. Each DCNNs are fine-tuned from the top layers. Fine-tuning the all layers are performed with Inception V3, Dense Net 201.
- Create an ensemble of Inception V3 and Dense Net 201 with all layers fine-tune.

III. RELATED WORK

The performance of skin lesion segmentation and classification truly depends upon the selection of most discriminant features [7, 8]. A good segmentation method traces the precise boundaries, whereas the complex background makes the segmentation process difficult—which directly effects the extracted features. In machine learning community, deep convolutional neural networks (DCNN) performed up to the mark, even on complex and large datasets. The DCNN widely used in medical imaging such as skin lesion recognition and brain tumor classification [9]. Features are extracted from different layers to handle a large number of data and variation between them. Saptarshi et al. [10] extracted texture and morphological features that are later selected through SVM recursive feature elimination (SVM-RFE) approach. Codella et al. [11] fused hand-coded features (LBP) with the deep learning descriptors for melanoma classification. The introduced method reported sensitivity rate of 95% using ISBI 2016 dataset. Manu Goyal et al. [12] performed semantic segmentation using ISBI 2017 dataset. The partial transfer learning and full transfer learning is employed to solve the problem of data deficiency. They achieved similarity rate 81.9% on ISBI 2017 dataset along sensitivity rate 78.9%.

Sara et al. [13] described a melanoma detection technique which is worked on three steps including lesion enhancement, vignette correction, and artifacts removal. In their work, they used wavelet-based decomposition instead of pre- and post-processing approaches. The wavelet decomposition gives an improved performance on ISBI 2017 dataset. Mostafa et al. [14] introduced an encoder–decoder network by dilated residual systems for lesion segmentation using dermoscopy images. In the introduced approach, features are extracted through ResNet pre-trained model and employed NLL and EPE approach for features reduction instead of traditional reduction techniques. The ISBI 2016 and ISBI 2017 datasets are utilized for evaluation and achieved accuracy of 0.984 and 0.936, respectively. Adria et al. [15] utilized pre-trained VGG-19 for CNN features extraction. An augmentation is performed for data deficiency. The transfer learning is performed in the presented method for features mapping and achieved sensitivity rate of 78.66% on ISBI 2016 dataset.

Kawahara et al. [16] proved that the DCNN features could correctly classify the lesions without segmentation and the preprocessing problems such as artifacts or low contrast. The features are extracted through AlexNet, and Dermofit Image Library dataset is utilized for evaluation of a system which includes a total of 1300 dermoscopic images. The presented method gives an accuracy of 85.8%, which is good as compared to existing techniques.

Emre et al. [17] introduced a distinct color-based ML technique for lesion classification using dermoscopy images. The colors are divided into clusters by employing a *K*-means clustering approach, and late regression algorithm is trained for classification of lesions into benign and melanoma. The experiments are performed on Interactive Atlas of Dermoscopy (EDRA) dataset and achieved 72% classification accuracy. Chen et al. [18] implemented two major modules such as SegNet and ClsNet, simultaneously. ResNet 101 was used for features extraction and performed an evaluation on ISBI 2017 dataset. The results show significant performance as compared to the base model.

IV. METHODOLOGY

Explore the Dataset

This step involves exploring the data as well as preparing the data for training neural networks. Seven skin lesions in the dataset are: Melanocytic nevi, melanoma, Benign keratosis-like lesions, Basal cell carcinoma, Actinic keratoses, Vascular lesions, Dermatofibroma. While melanoma is extremely dangerous, and Basal cell carcinoma as well as Actinic keratoses can be cancerous, the rest are benign skin lesions. 8000 examples in the dataset are benign and 2000 examples are malignant. The dataset is also biased toward Melanocytic nevi, which has close to 7000 examples. Hence, in the worst-case scenario, our neural network model should get accuracy more than 60%. Figure 2 displays 5 samples for each skin lesion type. For non-experts, it's very hard to distinguish which type is which.

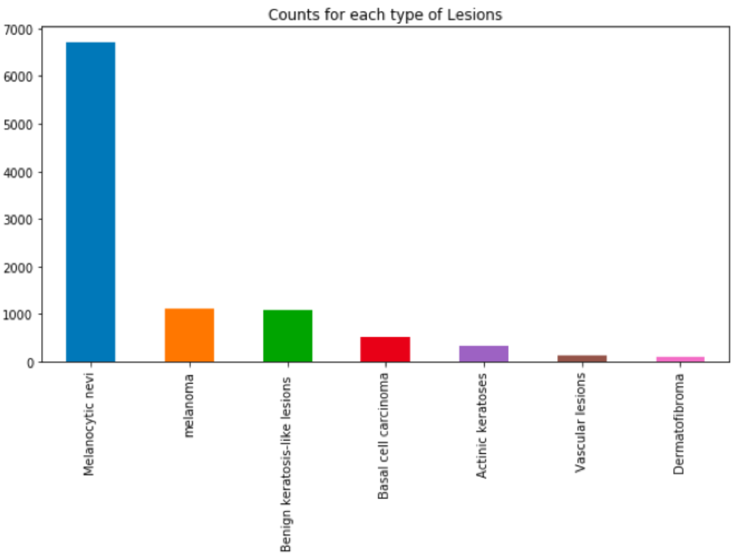


Figure 1. Count for each type of lesions

The original images are of size 450 x 600, which is too huge, so I resize the images to 64x64 RGB images for baseline model, and 192x256 for fine-tuning models. The dataset is normalized by dividing by 255 and is split into 7210 training examples, 1803 validation examples, and 1002 test examples.

1. Baseline Model

Before fine-tuning DCNNs, I build a small CNN to estimate the difficulty of classifying skin lesions. The architecture of the CNN is as follow:

- First: A convolutional layer with 16 kernels, each of size 3 and padding such that the size of the image is maintained.
- Second: A max pooling layer with window 2x2. The output is feature maps with spatial activation size reduced by a factor of 2.
- Third: A convolutional layer with 32 kernels, each of size 3 and padding to maintain the same size.
- Fourth: A max pooling layer with window 2x2. The output is feature maps with spatial activation size reduced by a factor of 2.
- Fifth: A convolutional layer with 64 kernels, each of size 3 and padding to maintain the same size.
- Sixth: A max pooling layer with window 2x2. The output is feature maps with spatial activation size reduced by a factor of 2.
- The architecture of this model is heuristically based. I follow the convention in famous DCNNs: using the smallest (3x3) convolutional layers; and double the number of filters in the output whenever the spatial activation size is halved to maintain roughly constant hidden dimensions. To train this model, data augmentation is employed. The intuition of this method is to transform the training dataset a bit in each epoch to produce variation and to guarantee that the model will never see the same image twice. Learning rate is initialized at 0.01 and Adam optimizer is used. Learning rate decay is also used so that the learning rate will halve whenever the validation accuracy plateaus for 3 epochs. Baseline model is trained for a total of 35 epochs

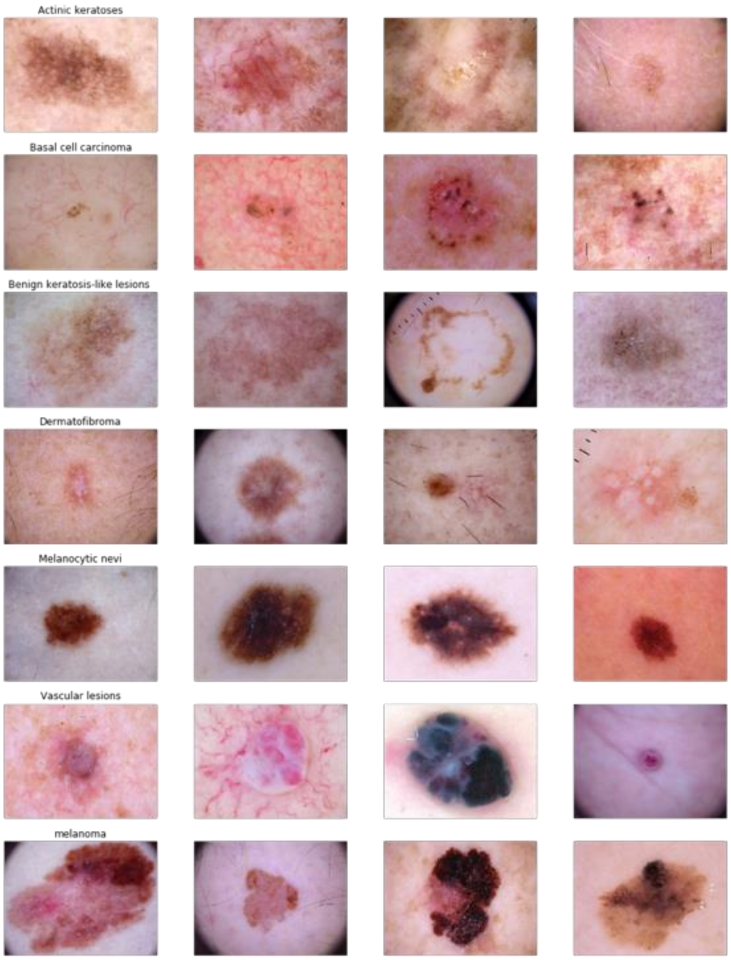


Figure 2: 5 samples for each type of skin lesion

2. VGG16

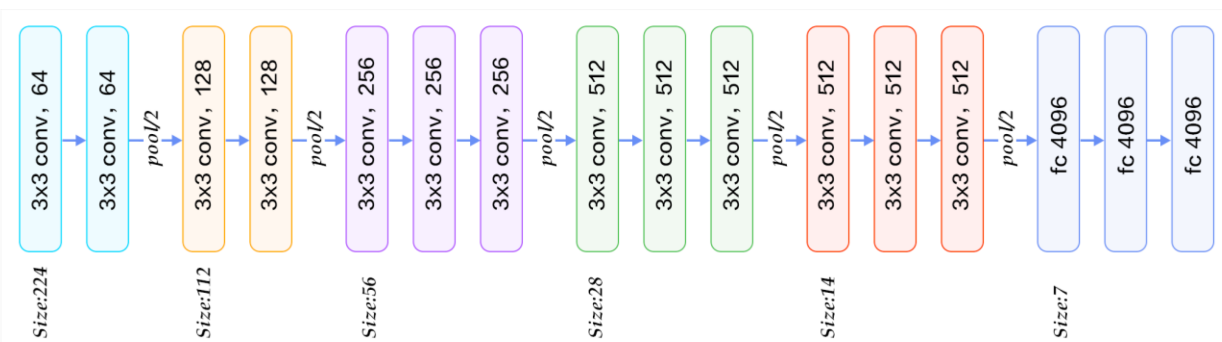
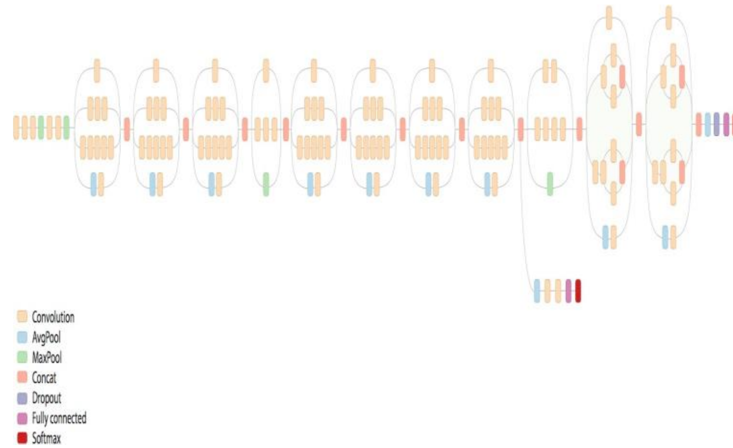


Figure 3: VGG16



Even though there are many DCNNs model achieving better result on ImageNet than VGG16, I choose to fine-tune VGG16 given its simplicity. Figure 3 is the schema for VGG16 D. The best performing VGG16 net is similar except that the third, fourth and fifth convolutional block has 4 convolutional layers. VGG16 has 0.901 accuracy for top-5 and 0.713 for top-1 on ImageNet.

To fine-tune VGG16, the top fully-connected layers are removed, and new fully-connected layers (consisting of: one global max pooling layers, one fully connected layer with 512 units, one dropout layer with 0.5 rate, one softmax activation layer for 7 types of skin lesions) for our classification tasks are added. First, freeze all layers in VGG16, and perform feature extraction for the newly added FC layers so that the weights for these layers aren't completely random and the gradient wouldn't be too large when we start fine-tuning. After 3 epochs of feature extraction, we unfreeze the final convolutional block of VGG16 and start fine-tune the model for 20 epochs. Throughout the training process, learning rate of
0.001 and Adam optimizer are used. The same data augmentation and learning rate decay strategy as in baseline model is used. VGG16 was fine-tuned for a total of 30 epochs

3. Inception

Inception V3 was the top performers on ImageNet with 0.937 accuracy for top-5 and 0.779 for top-1. The namesake of Inception v3 is the Inception modules it uses, which are basically mini models inside the bigger model. The inspiration comes from the idea that you need to decide as to what type of convolution you want to make at each layer: Do you want a 3×3? Or a 5×5? The idea is that you don't need to know ahead of time if it was better to do, for example, a 3×3 then a 5×5. Instead, just do all the convolutions and let the model pick what's best. Additionally, this architecture allows the model to recover both local feature via smaller convolutions and high abstracted features with larger convolutions. The larger convolutions are more computationally expensive, so [4] suggests first doing a 1×1 convolution reducing the dimensionality of its feature map, passing the resulting feature map through a ReLU, and then doing the larger convolution (in this case, 5×5 or 3×3). The 1×1 convolution is key because it will be used to reduce the dimensionality of its feature map.

Figure 4: Inception V3 with 11 inception blocks

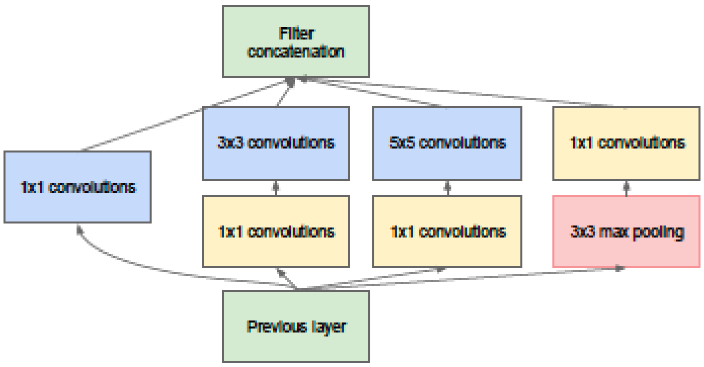


Figure 5: Inception Module

Given Inception V3 trained on ImageNet with 11 inception blocks, I performed 2 kinds of experiment: 1. fine-tuning Inception V3 from the last 2 inception blocks; 2. Fine-tune the whole pretrained model. The reason for this is the implementation of Batch Norm in Keras. The way Keras implemented Batch Norm is as follow. During training the network will always use the mini-batch statistics either the BN layer is frozen or not; also during inference it will use the previously learned statistics of the frozen BN layers. As a result, if we fine-tune the top layers, their weights will be adjusted to the mean/variance of the new dataset. Nevertheless, during inference they will receive data which are scaled differently because the mean/variance of the original ImageNet dataset will be used. Consequently, if I followed exactly what were did when fine-tuning VGG16 with InceptionV3, we will have very bad validation accuracy. This issue was discussed in https://github.com/keras-team/keras/pull/9965 and https://github.com/keras-team/keras/issues/9214. One temporary solution to this issue I can think of is to set all Batch Normalization layer to trainable, so during inference, batch norm layers will statistics of the mini-batch from our training set. I am not sure if this solution is complete, so I decide to fine-tune the all layers of Inception V3 as well as fine-tune the top 2 inception blocks with all batch normalization layers in the model set to trainable. This experiment last for 35 epochs. Fine-tuning the whole Inception V3 was 20 epochs.

Another variant of Inception that is top performer on ImageNet is Inception-ResNet. Inception- ResNet incorporates Residual connection, which is proved to be inherently necessary for training very deep convolutional models. VGG16 was used for fine-tuning Inception V3, Inception-ResNet V2. Top layers of Inception-ResNet V2 was fine-tuned for 30 epochs.

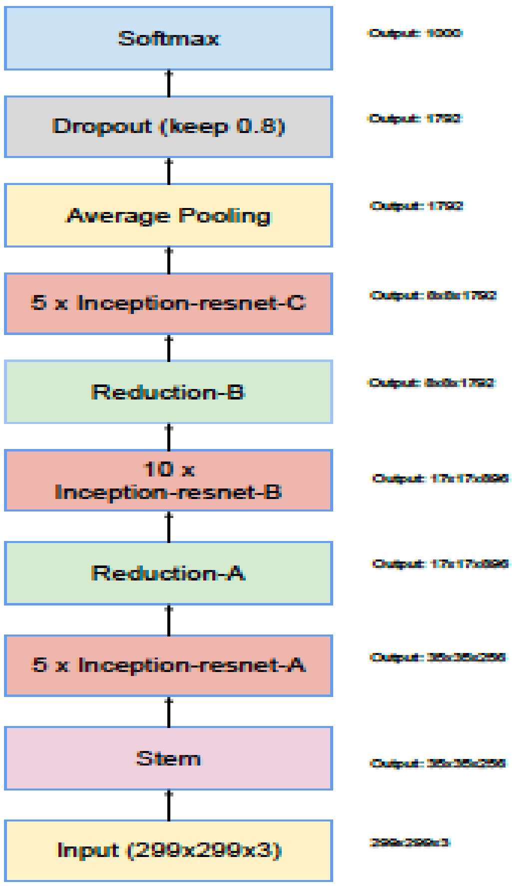


Figure 6: Inception-ResNet

4. Dense Net

Dense Net is a new DCNN architecture introduced that is one of

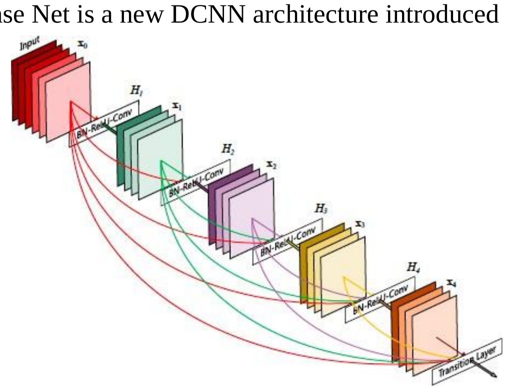


Figure 7: Inception-ResNet-C

the top performers on ImageNet, 0.936 top-1 and 0.773 top-5. The performance of Dense Net is competitive to Inception V3, but Dense Net has less parameters (approximately 20 million compare with approximate 23 million of Inception V3). Dense Net 201 has 4 dense blocks, Figure 8 displays the general architecture of a dense block. In a dense block, the l^{th} layer has l inputs, consisting of the feature-maps of all preceding convolutional blocks, and its own feature-maps are passed on to all subsequent layers $L - l$. Each layer reads the state from its preceding layers and writes to the subsequent layer. It changes the state but also passes on information that needs to be preserved.

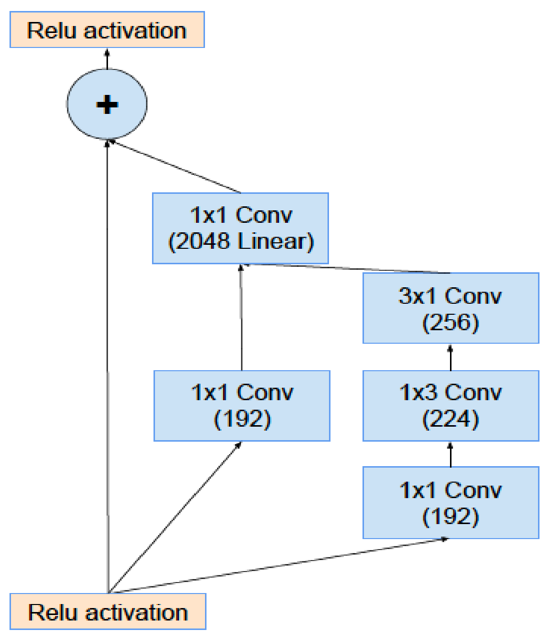


Figure 8: Dense block architecture

Dense Net architecture explicitly differentiates between information that is added to the network and information that is preserved by concatenating features instead of summing features as in ResNet.

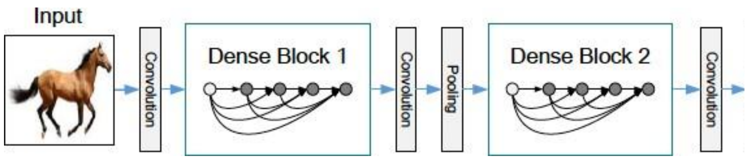


Figure 9: A Dense Net with 3 Dense Blocks

In a dense block, one layer generates feature maps through a composite function, consisting of three consecutive operations: batch normalization, ReLU, and a 3x3 convolution. Convolution and Pooling Layers in the between of each dense block is called together a transition layer. Dense Net 201 consists of 4 dense blocks, and I will perform 2 kind of experiments of this network: 1. Fine-tune on the last dense block (the last dense block has 32 layers); 2. Fine-tune on the whole network. The same training strategy as in previous sections is used to fine-tune Dense Net. Top layers of DenseNet 201 was fine-tuned for a total of 27 epochs, and the whole DenseNet 201 was fine-tuned for 20 epochs. When fine- tuning the whole model of Dense Net 201 and Inception V3, I let the weights to be initialized as the original weights from pretrained model on ImageNet.

IV. RESULTS AND ANALYSIS

Fine-tuning the top layers

Model	**Validation**	**Test**	**Test Loss**	**Depth**	**# Params**
aseline Model	77.48%	76.54%	0.646671	11 layers	2,124,839
VGG16	79.82%	79.64%	0.708	23 layers	14,980,935
Inception V3	79.935%	79.94%	0.7482	315 layers	22,855,463
Inception ResNet V2	80.82%	82.53%	0.6691	784 layers	55,127,271
nseNet 201	**85.8%**	**83.9%**	0.691	711 layers	19,309,127

Fine-tuning all layers

Model	**Validation**	**Test**	**Test Loss**
Inception V3	86.92%	86.826%	0.6241
DenseNet 201	86.696%	87.725%	0.5587
Ensemble (Inception V3 and	**88.8%**	**88.52%**	**0.41156**

Fine-tuning all layers give us better results than fine-tuning only the top layers, and the time needed for fine-tuning all layers are in fact lower than fine-tuning the top layers. The reason for this is that when fine-tuning all layers, I only performed for 20 epochs, but when fine-tuning the top layers, I perform for 30 epochs. If I only fine-tuned the top layers for less than 30 epochs, the results wouldn't be as good. This observation implies that fine-tuning the whole model not only gives better end result but also helps the model converge faster than fine-tuning the top layers only.

V. DISCUSSION AND FUTURE WORK

By the art of transfer learning and ensemble learning, I was able to create an ensemble of fine- tuned Inception V3 and DenseNet 201 and achieved 88.52% accuracy on test set and 88.8% on validation set for HAM10000. Through experiments, I also find that for this dataset, fine-tuning the whole model not only gives better end result but also helps the model converge faster than fine-tuning the top layers only. One serious problem observed during training is overfitting. All of my experiments overfit the training data for 10 – 13%. Many methods are used to minimize overfitting, but I wasn't able to narrow down the amount of overfit further. Future work in avoiding overfitting as well as on better training strategy will help the models to converge to better results.

VI. REFERENCE

[1] Esteva, A., Kuprel, B., Novoa, R., Ko, J., Swetter, S., Blau, H., and Thrun, S. (2017). *Dermatologist- level classification of skin cancer with deep neural networks*. Nature, 542(7639):115–118

[2] P. Tschandl, C. Rosendahl, and H. Kittler, *The HAM10000 dataset, a large collection of multi-source dermatoscopic images of common pigmented skin lesions*, Sci. Data, vol. 5, p. 180161, 2018
(download: https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/DBW86T)

[3] K. Simonyan and A. Zisserman. *Very deep convolutional networks for large-scale image recognition.*
In ICLR, 2015.

[4] Szegedy, C., Liu, W., Jia, Y., Sermanet, P., Reed, S., Anguelov, D., Erhan, D., Vanhoucke, V., and Rabinovich,A. *Going deeper with convolutions*. CoRR, abs/1409.4842, 2014.

[5] G. Huang, Z. Liu, K. Q. Weinberger, and L. Maaten. *Densely connected convolutional networks*. In CVPR, 2017

[6] Kieffer, B., Babaie, M., Kalra, S. & Tizhoosh, H. *Convolutional neural networks for histopathology image classification:Training vs. using pre-trained networks*. arXiv preprint arXiv:1710.05726 (2017)

[7] Khan MA, Akram T, Sharif M, Saba T, Javed K, Lali IU et al (2019) Construction of saliency map and hybrid set of features for efficient segmentation and classification of skin lesion. Microsc Res Tech 82:741–763

[8] Afza F, Khan MA, Sharif M, Rehman A (2019) Microscopic skin laceration segmentation and classification: a framework of statistical normal distribution and optimal feature selection. Microsc Res Tech. https://doi.org/10.1002/jemt.23301

[9] Khan MA, Javed MY, Sharif M, Saba T, Rehman A (2019) Multi-model deep neural network-based features extraction and optimal selection approach for skin lesion classification. In: 2019 international conference on computer and information sciences (ICCIS), pp 1–7

[10] Chatterjee S, Dey D, Munshi S (2018) Optimal selection of features using wavelet fractal descriptors and automatic correlation bias reduction for classifying skin lesions. Biomed Signal Process Control 40:252–262

[11] Codella NC, Nguyen Q-B, Pankanti S, Gutman D, Helba B, Halpern A et al (2017) Deep learning ensembles for melanoma recognition in dermoscopy images. IBM J Res Dev 61:5:1–5:15

[12] Goyal M, Yap MH (2017) Multi-class semantic segmentation of skin lesions via fully convolutional networks. Preprint arXiv:1711.10449

[13] Ross-Howe S, Tizhoosh H (2018) The effects of image pre- and post-processing, wavelet decomposition, and local binary patterns on U-nets for skin lesion segmentation. Preprint arXiv:1805.05239

[14] Sarker M, Kamal M, Rashwan HA, Banu SF, Saleh A, Singh VK et al (2018) SLSDeep: skin lesion segmentation based on dilated residual and pyramid pooling networks. Preprint arXiv:1805.10241

[15] Lopez AR, Giro-i-Nieto X, Burdick J, Marques O (2017) Skin lesion classification from dermoscopic images using deep learning techniques. In: 2017 13th IASTED international conference on biomedical engineering (BioMed), pp 49–54

[16] Kawahara J, BenTaieb A, Hamarneh G (2016) Deep features to classify skin lesions.

[17] In: 2016 IEEE 13th international symposium on biomedical imaging (ISBI), pp 1397–1400

[18] Celebi ME, Zornberg A (2014) Automated quantification of clinically significant colors in dermoscopy images and its application to skin lesion classification. IEEE Syst J 8:980–984