MAT JOURNALS
Journal of Image Processing and Artificial Intelligence
Volume 4 Issue 1

Skin Cancer Detection using Deep Neural Networks

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Abstract
Cancer is the most dangerous and stubborn disease known to mankind. It accounts for the most deaths caused by any disease. However, if detected early this medical condition is not very difficult to defeat. Tumors which are cancerous grow very rapidly and spread into different parts of the body and this process continues until that tumor spreads in the entire body and ultimately our organs stop functioning. If any tumor is developed in any part of our body it requires immediate medical attention to verify that the tumor is malignant(cancerous) or Benign(non-cancerous). Until now if any tumor has to be tested for malignancy a sample of tumor should be extracted out and then tested in the laboratory. But using the computational logic of Deep Neural Networks we can predict that the tumor is malignant or Benign by only a photograph of that tumor. If cancer is detected in early stage chances are very high that it can be cured completely. In this work, we detect Melanoma(Skin cancer) in tumors by processing images of those tumors.

Keyword: *neural network, Melanoma, Vgg16, ResNet50*

INTRODUCTION
Our system addresses Part 3, Lesion Classification of the ISIC 2017 challenge. Our algorithm uses neural networks to distinguish between malignant(cancerous) and Benign(non-cancerous) tumors. We have used ISIC 2017 challenge dataset to achieve our objective we used deep convolutional networks like Vgg16, Inception, ResNet50.

CLASSIFICATION
In order to use the images to train our neural network, each image should be of same size irrespective of their dimension. Therefore each image was cropped so that all the images in the dataset can be of the same size and resized to 224 pixels by 224 pixels. In order to increase the number of training images, every original image was rotated 80 and 240 degrees before resizing, resulting in a total number of 6000 images.

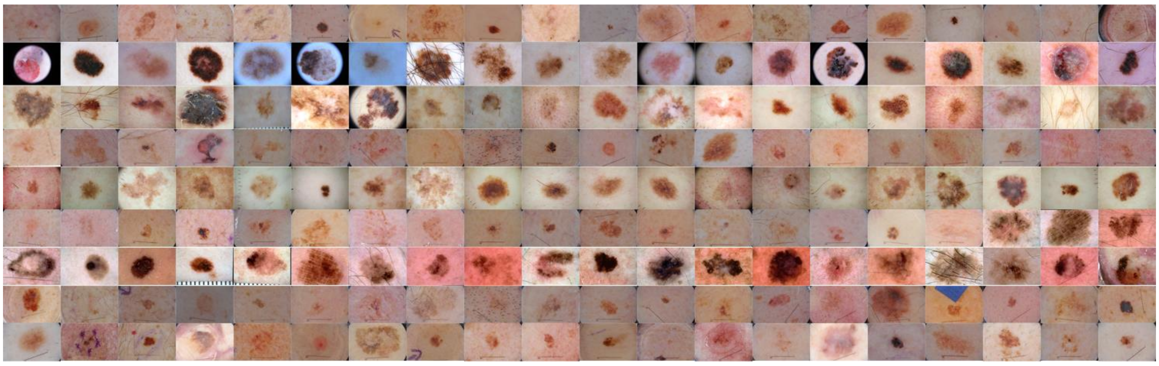

Fig 1: *Sample Malignant(Melanoma) Tumors*

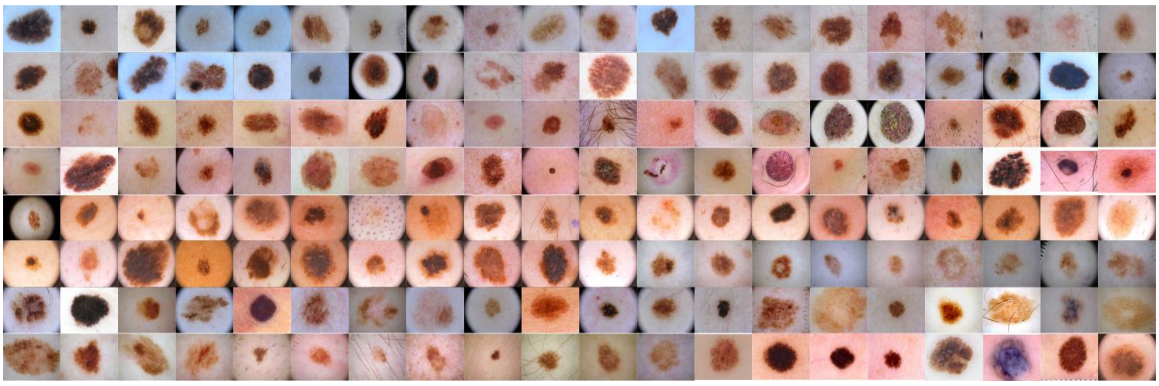

***Fig 2:** Sample Benign Tumors*

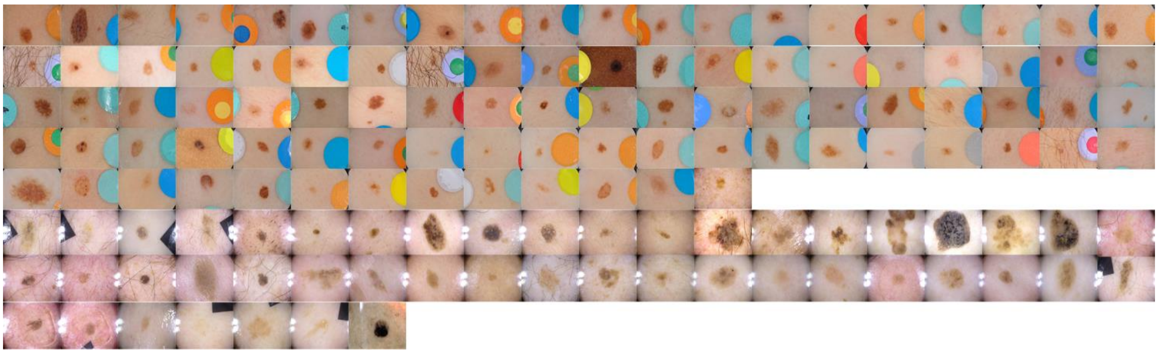

***Fig 3:** Tumors with colored mark and Bright Light*

There are some images which consist of a coloured mark and also some with a bright light pattern, therefore they were cropped manually so that our model only learn features of the tumor, not the coloured mark or bright light pattern.

Model Architecture

In this system, we used 3 different deep convolutional neural networks which trained on ImageNet dataset for classifying 1000 classes. Using this 3 ConvNets we performed transfer learning. We only trained fully connected layers of this network which is Vgg16, Inception, ResNet50.

This network operated on an input image of 224 by 224 pixels and produced a probability distribution over the labels. Each of the training images was randomly cropped to 224 by 224 before presenting to the model. Dropout was used on the fully connected layers and rectified linear units were used for all non-linearities.

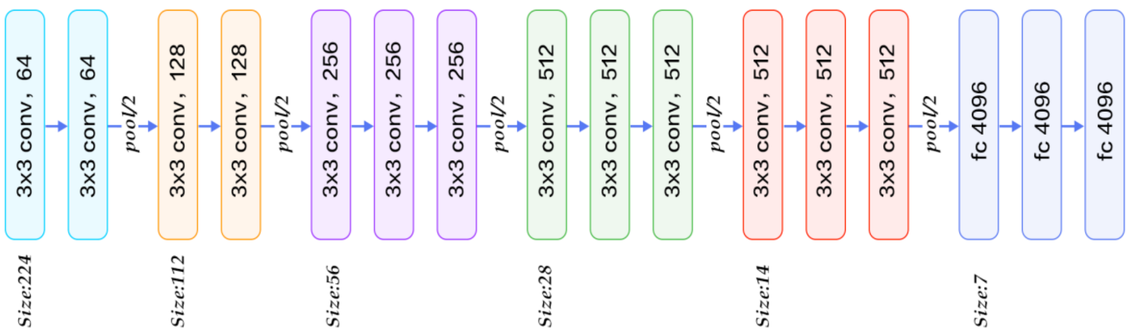

***Fig 4:** Vgg16 ConvNet*

VGG16: This is first major deep neural network presented by Oxford Visual Geometry Group which contains 16 layers. In this 13 convolutional layers and 3 fully connected layers are used. This network originally trained on around 1.2Millions of images for classifying them into 1000 categories.

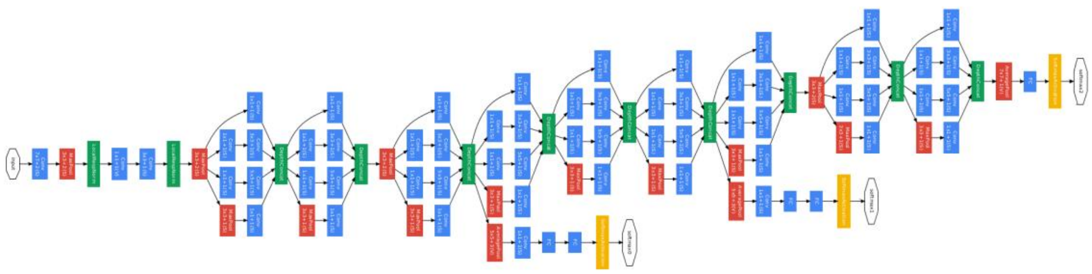

Fig 5: *Inception ConvNet*

Inception: Inception network was introduced by Google in 2014 ImageNet competition and was again trained on 1.2Millions of images on 1000 categories. In this network 22 layers are used in which 21 convolutional layers and 1 fully connected layer. This was little complex architecture compared to Vgg16 with different layer connecting one layer. As stacking layer one layer above does not provide accuracy after certain layers.

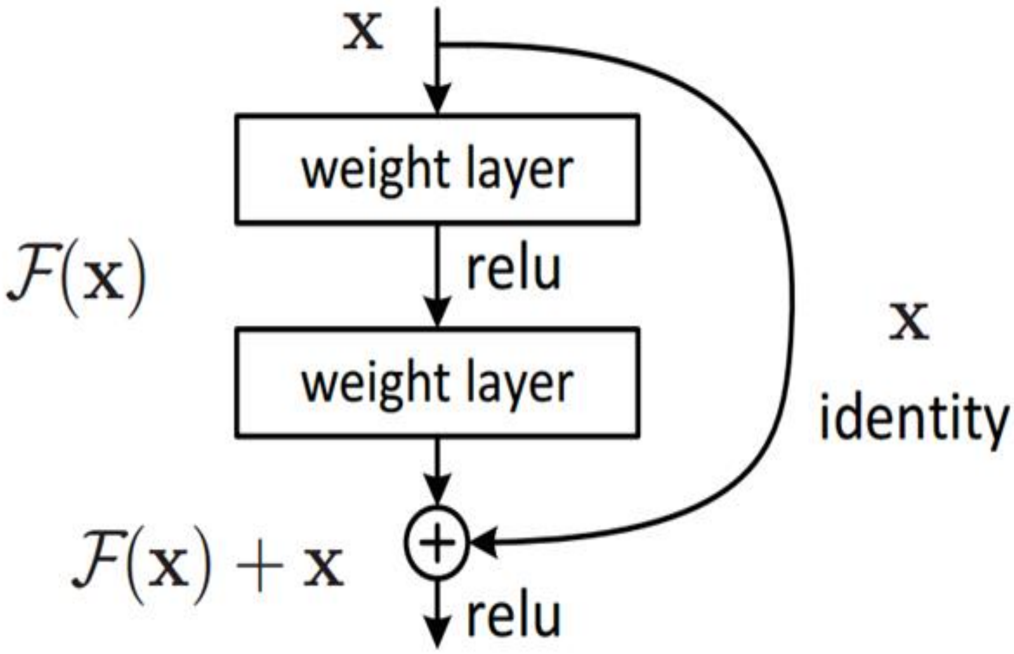

Fig 6: *ResNet50 ConvNet*

ResNet50: ResNet network was introduced by Microsoft in 2015 ImageNet competition and was again trained on 1.2Millions of images on 1000 categories. In our work, we used ResNet50 which contains 50 layers, 49 convolutional layers and 1 fully connected layer. This network used ResNet block for training very deep neural network which always a problem in case updating loss.

Training

The network was trained using the Adam, RMSProp, Eve optimization algorithm. The learning rate was initialized to 1e-3 and techniques like Cyclical Learning Rates for training neural network was used for adjusting learning rates. Mini batches of size 50 were used, each class represented an equal number of times.

Cross-validation was used to train the model. As the mini batches were selected, an additional set of data augmentation was applied to the image at runtime. These data augmentation included the following:

- Flipping
- Shear Range
- Width shift
- Rotation
- Height Shift
- Zoom

Training continued for a total of 210 epochs after each epoch the accuracy was measured on the validation set and recorded. After the 210 epochs completed, the model selected for each set of fold corresponded to the iteration that maximized the accuracy as computed on the validation data set.

Performing training in Vgg16 we froze the first 13 layers of the convolutional neural network which already gain good amount knowledge from different categories of ImageNet and updated values of only fully connected layers. While training this network we passed all images through network saved them as numpy array as it reduces the training time significantly. But when we introduced data augmentation in it every time image is different we have to pass every image through a complete neural network.

This same above technique we introduced while training for Inception and ResNet50.

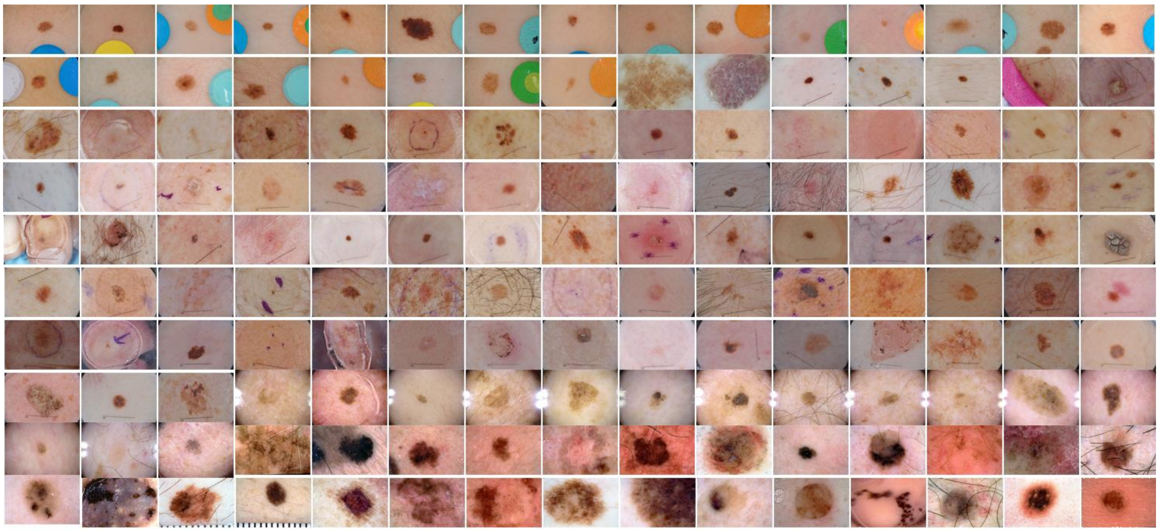

Fig 7: *All validation images*

RESULTS

To score the validation and test submission sets, the best model from each of the K training folds was used. The probability of each model was used to generate average probability score for each image.

The validation accuracy we got is 83.86% on Vgg16, 85.31% on Inception and 86.02% on ResNet.

CONCLUSION

We have trained our model using Vgg16, Inception and ResNet50 neural network architecture.

In training, we have provided 2 categories of images one with Malignant (Melanoma-Skin cancer) tumors and other with benign tumors. After training, we tested our model with random images of tumor and an accuracy of 83.86%-86.02% was recorded in classifying that it is malignant or benign. By using neural network our model can classify Malignant(cancerous) and benign(non-cancerous) tumors with an accuracy of 86.02%. Since cancer, if detected early can be cured completely. This technology can be used to detect cancer when a tumor is developed at early stage and precautions can be taken accordingly.

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