

Classification of skin cancer images using TensorFlow and inception v3

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Abstract

It is easy for a human eye to distinguish the images of similar appearance but classifying the images like that of cancer affected skin requires more expertise. And as the skin cancer cases are increasing globally, it requires more number of human experts. To overcome this problem, many people are working on constructing machine learning classifiers which can detect skin cancer automatically by classifying skin images. This paper concentrates on developing an approach for predicting skin cancer by classifying images using deep convolution neural network. The proposed work is tested on standard cancer dataset and obtained more than 85% accuracy.

Keywords: Classification; Deep Convolution Neural Network; Inception-V3; Machine Learning; Tensor Flow.

1. Introduction

1.1 Motivation

Today, almost every application in the world is directly or indirectly influenced by computer systems. Computers are used in diverse areas for various automated applications. In the diseases like cancer, identifying the disease at the early stage is very important for better treatment and cure. Today many people across the globe are suffering with skin diseases and number of skin cancer cases are more compared to any other types of cancer [1]. As all the skin cancers are not the deadly cancers, by looking at the skin images, it is required to predict whether it is deadly cancer or not. From all skin cancers, melanoma cases are present in just 5% of cases, but 75% of times, it may lead to death according to American Cancer Society [2, 3]. Detecting skin cancer by human doctors requires more expertise and knowledge and with increased number of skin cancer cases, it requires more number of experts who can correctly diagnose the disease. As it is difficult to get more number of human experts, today many researchers are working on developing machine learning algorithms to solve this problem. Automated detection of skin cancer is a challenging task [4] but by training the computer it can identify whether the skin is affected with deadly cancer or not. This paper proposes Deep learning approach to predict the cancer. The proposed work is implemented with Tensor Flow and Inception V3 models and tested on standard cancer dataset and obtained more than 85% accuracy.

1.2 Problem Definition

Skin cancer is the most common due to abnormal growth of skin cells. But this growth always may not be the symptom of deadly cancer. So, distinguishing correctly and proper treatment leads to

better cure of the disease. In this paper, deep convolutional neural network (DCNN) [5], a machine learning classification technique is used to classify the skin cancer images. As accuracy is the most important factor in this problem, by taking more number of images for training the network and by increasing the number of iterations, the DCNN accuracy can be enhanced. Tensor Flow is a large scale machine learning system developed by Google [6] and Inception V3 is Google's CNN architecture [7]. Here, the DCNN algorithm is implemented with Tensor Flow and Inception V3.

1.3 Terminology

1.3.1 Types of Skin Cancer

Skin cancer [8] affects people whose skin is highly exposed to the sun rays. Those who have lighter coloured skin have higher risk of cancer. There are two types of cancer. They are

Malignant Cancer In Fig.1 the cancer cells spread from one part of the body to the other there by even though, the cancer cells are removed from the initial affected part, it may raise from other parts. It is considered to be the deadly cancer. Sarcomas, Carcinomas [9] are the common varieties in this malignant cancer and melanoma though less in number is a serious type of cancer.

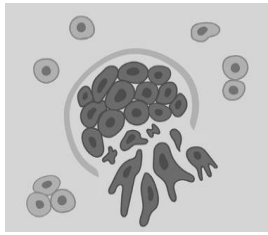


Fig. 1: Malign Cells

Benign Cancer In Fig.2 cells do not spread from one part of the body to the other part. It is called benign cancer. If the cancer cells are removed from initial place it will never come back again. It is regarded as normal cancer.

Most Common types of benign cancers are Adenomas, Meningioma's, Fibromas or fibroids, Papilloma's, lymphomas, Nevi, Myomas, Haemangioma, Neuromas, Osteochondromas [9].

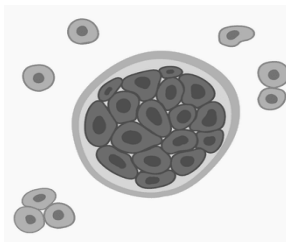


Fig. 2: Benign Cells

1.4 Transfer learning

Transfer learning is a machine learning technique [10] which is based on the concept of reusability.

Fig.3 describes the inception v3 model which processes convolution, pooling, softmax and fully connected operations.

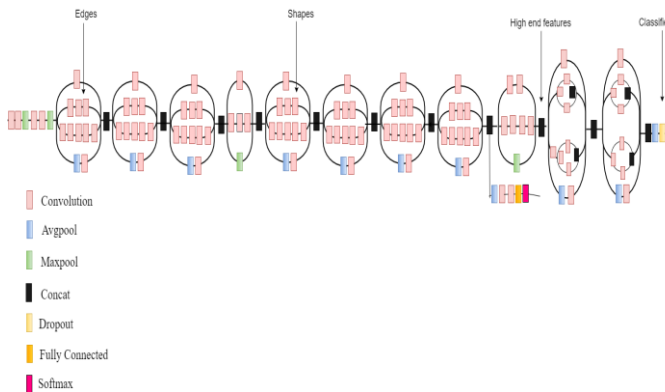


Fig. 3: Inception V3

Here a pre-trained neural network developed for one task can be used as the starting point of other. The image recognition model Inception-v3 contains two parts:

- Feature extraction part using convolutional neural network.
- Classification part using fully-connected and softmax layers.

The pre-trained Inception-v3 model succeeds in state-of-the-art accuracy for distinguishing universal things using 1000 classes, like "Zebra", "Computer", and "Dishes". The model extracts fea-

tures from input images in the first part and classifies them based on those features in the second part [11].

1.5 Tensor flow

Tensor Flow is an artificial neural network having more than three layers as in Fig.4. It has one input, one output and multiple hidden layers [12].

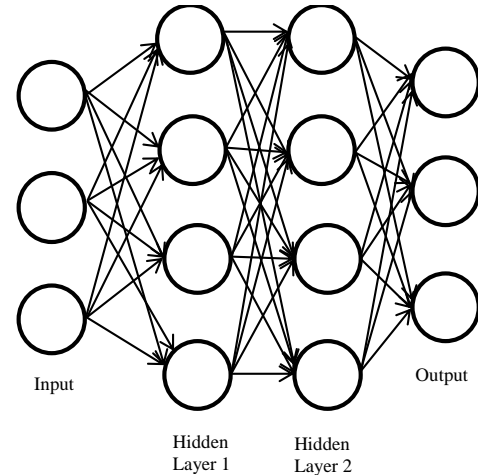


Fig. 4: Neural Network

It is a deep learning frame work developed by Google. It has control over every neuron (node) in the network and has libraries suitable for image processing. The weights of the neural network can be modified to achieve better performance [13].

2. Literature Survey

There are various techniques in image processing for image classification. Deep convolution neural network (DCNN) is a new approach for this problem. Researchers are using this technique recently in various classification problems. Deep learning models are used in many application areas of medicine [14, 15]. DCNN is used to classify the time series signals in [16]. Here the time series signals are first converted to 2D images using recurrence plots and then CNN is used for image recognition. Early detection saves the life of many patients in cancer diseases and the detection of skin lesions is proposed in [17]. The proposed methodology was tested on ISIC dataset and found to be accurate. Skin cancer cases are increasing day by day and presently they are more in number compared to any other type of cancer US. By following VGG16, VGG19 & Google Net models, deep convolution network was constructed and implemented on GPU architecture in [18]. The proposed approach obtained 73% accuracy. Classification of non-malignant lesions from malignant was done in [19]. The training approach used deep residual networks with transfer learning. As the early symptoms of Melanoma cancer and moles are almost similar, it is very hard to distinguish both. RBF Gaussian SVM approach is used for classification in [20]. Classification and detection of skin cancer using 2D Wavelet decomposition and multi-layer, radial basis neural networks is discussed in [21]. Usage of wavelet transforms and fuzzy logic for the skin cancer detection is discussed in [22]. Deeper models results in better skin cancer image classification [23]. Melanoma screening using segmentation before feature extraction is used in [24, 25].

3. Architecture

Fig.5 shows the step by step process of the proposed work model [26, 27]. The steps in the proposed classification model are as follows:

1. Perform convolution and pooling on the image recursively
2. Apply drop out and fully connected. Now the image must be classified according to the training class labels.

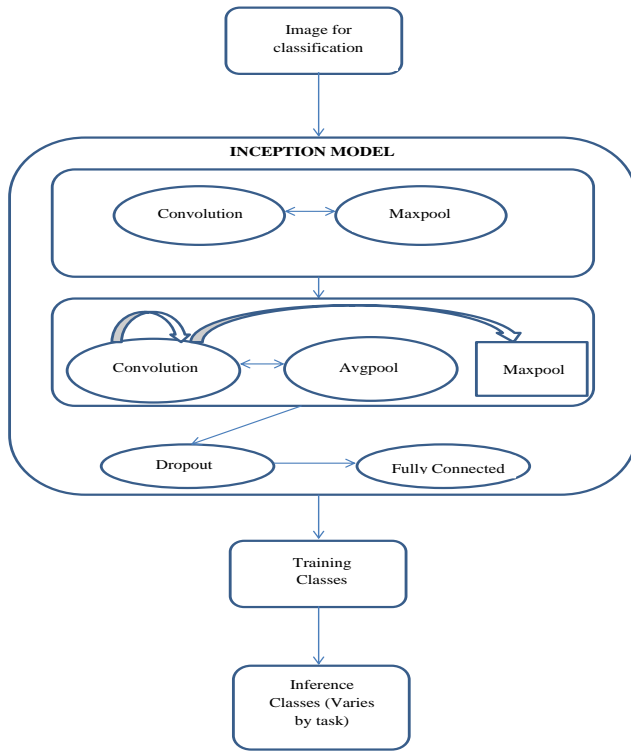


Fig. 5: Architecture of proposed work

Convolution is a step by step process; it extracts diverse features of the input. Each kernel is responsible for producing an output feature [12]. The lower level features of an image like edges, lines, and corners are exacted by lower layers and the higher-level features are extracted by higher layers. So, an input image with height h and width w and depth d ($h \times w \times d$), if it is convolved with M kernels, each kernel with height h_1 , width w_1 and depth d_1 ($h_1 \times w_1 \times d_1$), individually produces M features.

To make the features obtained from convolution robust against noise, pooling is applied. The resolution of features is reduced by pooling. Pooling can be done via max pooling or average pooling. Fig.6 depicts pooling.

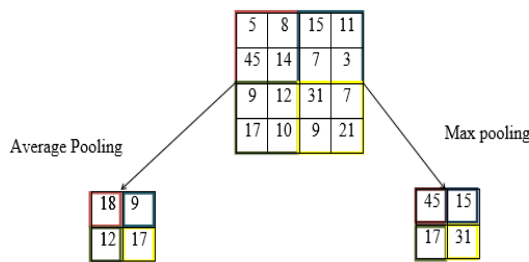


Fig. 6: Average Vs Max Pooling

A standard dataset from ISIC [28] having 13000 images was used for experimentation. The dataset contains two types of cancerous skin images and so they were divided into two folders benign and malignant. Fig.7 shows the dataset is divided into two folders.

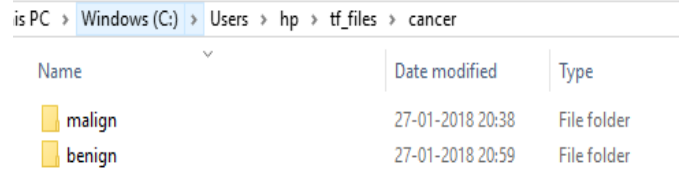


Fig. 7: Dataset Folders

In Fig.8 skin cancer image is taken as input and inception V3 is applied in which convolution, pooling, softmax and fully connected operations are performed. After performing these tasks, it is classified according to various training classes and finally it is labelled as malignant and benign cancer.

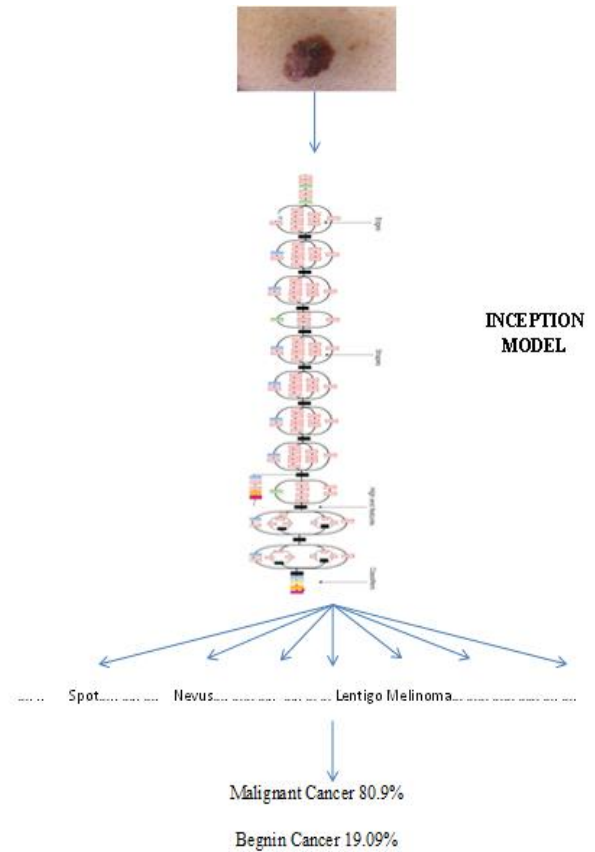


Fig. 8: Skin Cancer Image Classification

The steps in the classification using proposed work are as follows:

- Algorithm TFclassification {
- Step 1: Begin
 - Step 2: Build list of images // start training
 - Step 3: Give path for storing bottle neck values
 - Step 4: Provide inference to the images //to create bottle neck values
 - Step 5: Create a folder for all images of bottleneck values
 - Step 6: Create bottle neck values for every single image
 - Step 7: Create new softmax layers and fully connected layers // End of training
 - Step 8: Test the new image
 - Step 9: End

4. Experimental results

The experimental work is done by connecting docker to the virtual box. The neural network is trained to create bottleneck values. Fig.9 shows the generation of bottle neck values. Bottleneck values compress the features to fit in the available space.

```

ISC_000005.jpg_inception_v3.txt - Notepad
File Edit Format View Help
0.59869903,0.01941772,0.00408197,0.041433085,0.1481361,0.2878975,0.062063076,0.14336441,0.17448904,1.0866989,0.26
0.15915062,0.07869256,0.2428124,0.13715748,0.041201144,0.13416025,0.24218954,0.49090382,0.11478219,0.11240168,0.4
0.386,0.20826456,0.24216427,0.2986276,0.042863395,0.081876256,0.04454358,0.3727851,0.35750788,0.437534,0.04873768,0
0.5998636,0.05572871,0.14213803,0.017539047,0.07582663,0.06741581,0.2465441,0.4576961,0.50937843,0.26339516,0.257
0.058833353,0.32684907,0.35561353,0.51957865,0.049285404,0.1609073,0.0.0.0.3924774,0.20149831,0.0.0.0.06665495,0.150
0.14158301,0.4823318,0.2210299,0.99882644,0.4981131,0.08184368,0.11180212,0.021778539,0.5559225,0.0.0.0.024016054
94,0.35939866,0.010521285,0.0048679,0.6564458,0.045206536,0.18324727,0.23542625,0.0228876,0.5077435,0.17005646,0.
28628,0.47896472,0.34678406,0.26810184,0.04177554,0.11062724,0.44283837,0.40996927,0.0.0.0.14101897,0.34645328,0.27
997,0.25928882,0.290367,0.44636574,0.4437512,0.00655035,0.9708026,0.32337853,0.6154826,0.96587855,0.20298855,0.05
377637,0.26912177,0.24565233,0.113864124,0.693789,0.13655378,0.22042638,0.3521245,0.24951637,0.4086997,0.42636704
0.18518116,0.07071196,1.2034231,0.28778544,0.8357196,0.078944534,0.23706399,0.85095644,0.1699187,1.4150407,0.3415
962853,0.065331735,0.007857532,0.48764792,1.1030152,0.013795568,0.40359783,0.10441542,0.19696663,0.0400892,0.0148
4,0.0043279575,1.7216873,0.7495651,0.14808879,0.22138299,0.010267096,0.84980196,0.085929625,0.15696219,0.4966189,
2135,0.011204147,0.13905303,0.010722939,0.046378,0.023836855,0.041009784,0.1666094,0.75672144,0.084598534,0.01349
547,0.015460312,0.0.0.0.006995091,0.0013757134,0.0.0.0.007876453,0.08730004,0.0041746963,0.010079725,0.0033672138,0.0
9,0.000947519,0.012216659,0.04661597,0.70890075,0.032316938,0.08749625,0.25697553,0.108005136,0.447201,0.06041482
6807818,0.0037632738,0.001533173,0.008420608,0.018503306,0.8671831,0.52827317,0.272642,0.20614243,0.73600674,0.01
0.13064933,0.13725935,0.0.0.0.13625544,0.097136825,0.011836987,2.0052606,0.21504557,0.001960166,0.23205206,0.022109
073123,2.7088832,0.038261674,0.55674636,0.254772,0.111231625,0.0011224383,0.045137793,0.021338623,0.778714,0.0.0.
0051320074,0.23381107,2.167087,0.030862255,0.0076702563,0.03430823,0.057489816,0.10801639,0.19097767,0.007866765,
4,0.47800988,0.12092869,0.15835993,0.0.0.0.00021266006,0.7049006,0.006166461,0.3484623,2.3104901,0.8590067,0.285632
32315406,0.18606253,1.2296666,0.0902089,0.22846337,0.40239036,0.3738442,0.72851914,0.36211848,1.2671914,0.0132558

```

Fig.10: Fig.11 shows the generation of bottle neck values when the number of iterations is 10 and 100 respectively. It also indicates the accuracies.

```

MINGW64/c/Users/hp
VASIREDDY'S@LAPTOP-G2V514R0 MINGW64 ~
$ python tf_files/retrain.py --bottleneck_dir=tf_files/bottlenecks --how_many_training_steps=10 --model_dir=tf_f
ception --output_graph=tf_files/retrained_graph.pb --output_labels=tf_files/retrained_labels.txt --image_dir=tf_
ancer/
Not extracting or downloading files, model already present in disk
Model path: tf_files/inception/classify_image_graph_def.pb
INFO:tensorflow:Looking for images in 'benign'
INFO:tensorflow:Looking for images in 'malign'
2018-02-18 17:17:06.580009: I C:\tf_jenkins\home\workspace\rel-win\M\windows\PY\35\tensorflow\core\platform\cpu_
t this TensorFlow binary was not compiled to use: AVX AVX2
INFO:tensorflow:100 bottleneck files created.
INFO:tensorflow:200 bottleneck files created.
INFO:tensorflow:300 bottleneck files created.
INFO:tensorflow:400 bottleneck files created.
INFO:tensorflow:500 bottleneck files created.
INFO:tensorflow:600 bottleneck files created.
INFO:tensorflow:700 bottleneck files created.
INFO:tensorflow:800 bottleneck files created.
INFO:tensorflow:900 bottleneck files created.
INFO:tensorflow:1000 bottleneck files created.
INFO:tensorflow:1100 bottleneck files created.
INFO:tensorflow:1200 bottleneck files created.
INFO:tensorflow:1300 bottleneck files created.
INFO:tensorflow:1400 bottleneck files created.
INFO:tensorflow:2018-02-18 17:17:30.893362: Step 0: Train accuracy = 53.0%
INFO:tensorflow:2018-02-18 17:17:30.893866: Step 0: Cross entropy = 0.674133
INFO:tensorflow:2018-02-18 17:17:33.078573: Step 0: Validation accuracy = 45.0% (N=100)
INFO:tensorflow:2018-02-18 17:17:40.978371: Step 9: Train accuracy = 80.0%
INFO:tensorflow:2018-02-18 17:17:40.978371: Step 9: Cross entropy = 0.620208
INFO:tensorflow:2018-02-18 17:17:41.357713: Step 9: Validation accuracy = 76.0% (N=100)
INFO:tensorflow:Final test accuracy = 60.0% (N=140)

```

Fig. 10: Creation of bottle neck values for 10 Iterations

```

INFO:tensorflow:2018-02-20 20:33:37.377544: Step 50: Validation accuracy = 85.0% (N=100)
INFO:tensorflow:2018-02-20 20:33:38.709215: Step 60: Train accuracy = 80.0%
INFO:tensorflow:2018-02-20 20:33:38.709215: Step 60: Cross entropy = 0.485752
INFO:tensorflow:2018-02-20 20:33:38.840712: Step 60: Validation accuracy = 65.0% (N=100)
INFO:tensorflow:2018-02-20 20:33:40.160609: Step 70: Train accuracy = 80.0%
INFO:tensorflow:2018-02-20 20:33:40.160609: Step 70: Cross entropy = 0.508081
INFO:tensorflow:2018-02-20 20:33:40.296029: Step 70: Validation accuracy = 80.0% (N=100)
INFO:tensorflow:2018-02-20 20:33:41.606110: Step 80: Train accuracy = 74.0%
INFO:tensorflow:2018-02-20 20:33:41.607098: Step 80: Cross entropy = 0.521531
INFO:tensorflow:2018-02-20 20:33:41.738591: Step 80: Validation accuracy = 85.0% (N=100)
INFO:tensorflow:2018-02-20 20:33:43.045726: Step 90: Train accuracy = 76.0%
INFO:tensorflow:2018-02-20 20:33:43.046717: Step 90: Cross entropy = 0.518094
INFO:tensorflow:2018-02-20 20:33:43.180168: Step 90: Validation accuracy = 70.0% (N=100)
INFO:tensorflow:2018-02-20 20:33:44.385250: Step 99: Train accuracy = 79.0%
INFO:tensorflow:2018-02-20 20:33:44.385250: Step 99: Cross entropy = 0.499397
INFO:tensorflow:2018-02-20 20:33:44.516781: Step 99: Validation accuracy = 81.0% (N=100)
INFO:tensorflow:Final test accuracy = 87.1% (N=140)
INFO:tensorflow:Froze 2 variables.
Converted 2 variables to const ops.

```

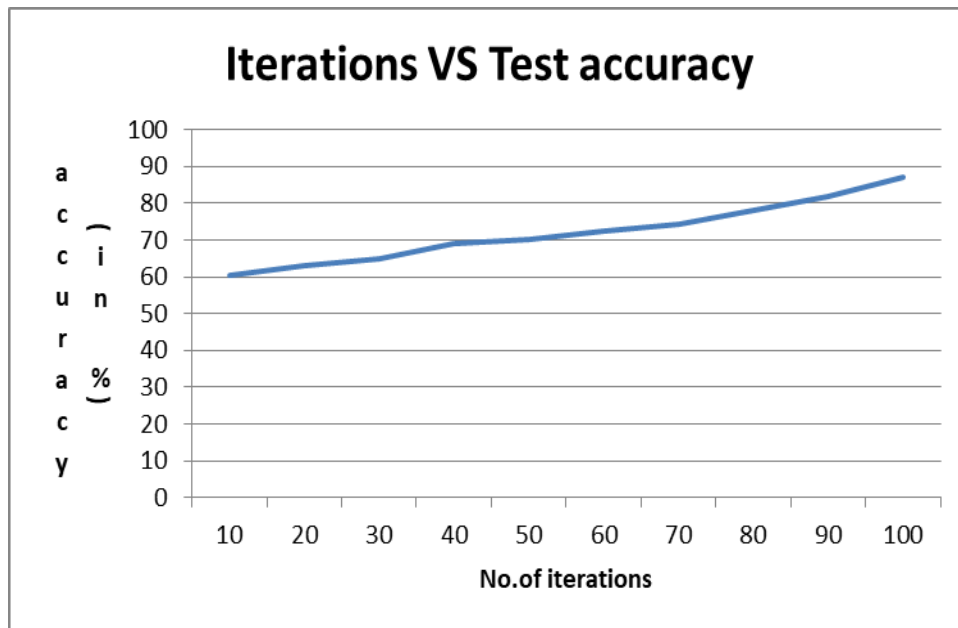
Fig. 11: Creation of bottle neck values for 100 Iterations

Fig.12 shows the test accuracy vs. no. of iterations graph. The graph shows that the test accuracies are increasing with the increase in number of iterations.

Fig.13 shows the result when a sample test image is taken. As the score of benign is high compared to malign, the test image classified as benign.

5. Conclusion

Image classification of skin cancer using DCNN with tensor flow and inception V3 models is implemented on CPU version. By using bottleneck values, good accuracy can be achieved even with CPU version. By increasing the number of iterations, the proposed approach got more than 85% accuracy.



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