# An Efficient Classification of Benign and Malignant Tumors Implementing Various Deep Convolutional Neural Networks

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**Abstract— Every year, doctors diagnose skin cancer in around 3 million Americans or more. Now it is one of the most common types of cancer. If skin cancer is detected early, it can easily be treated with topical medications. So this results, skin cancer is responsible for less than 1% of all cancer deaths. There are two forms found in skin cancer observation, and those are benign and malignant. So the early detection of skin cancer is necessary to prevent any severe condition for the patient. Its diagnosis is crucial if not detected in the early stage [1]. The paper aims to detect benign and malignant forms of skin cancer using dermoscopic images, applying deep convolutional neural networks in an efficient approach. We use three various pre-trained deep learning models, namely as VGG19, ResNet50 and EfficientNetB0 to enable the most efficient model to detect skin cancer conditions. Here we describe how the models work for detecting images and which one detects most efficiently.**

**Keywords-** Skin cancer, deep convolutional neural network, benign, malignant, deep learning techniques

## I. INTRODUCTION

Cancer is one of the most common and deadly diseases in these years. The death rate in cancer is much higher than in other types of health conditions. Many researchers have accumulated the result that Asian people are getting more affected by cancer disease. One of the conventional cancers is skin cancer. It is increasing dramatically in recent years due to many reasons, including excessive exposure to ultraviolet radiation [1].

Meanwhile, a significant death rate, early detection of skin cancer can reduce the risk of death and curable in most cases [2]. Differentiate accurate diagnosing of benign and malignant skin lesions are essential to treat appropriately to the patients [3]. In the last 5-year survival rate of malignant melanoma is 98% when detected and treated early [4].

Microscopic images can attain by standard cameras or mobile devices, which can assist dermatologists in diagnosing the disease. Significantly better pictures are gained by dermoscopic tools, which are very important to determine different lesion types [3]. Thus computer-based skin cancer detection is very efficient for non-specialized users because only dermatologists can classify the skin tumors from other skin oriented diseases [5]. The use of dermoscopic images enhances the diagnostic accuracy of skin lesions by 49% [6].

Deep convolutional neural networks(CNNs) can classify more accurately since then by its object-oriented algorithmic power for detecting images. Convolutional Neural Networks (CNNs) is a subdomain of Deep Learning, which concludes tremendous success on Machine Learning and computer vision[7]. Previously computerized methods have used for detection such as neural networks. However, one of the common hurdles of implementing these methods has limited to the accessibility of quality dermoscopic images of various classes of skin diseases. In the past, research has mainly concentrated on melanocytic lesion detection, which is a single class of the disease [8]. CNN models such as VGG, GoogLeNet, and ResNet have performed better in image recognition and classification in ImageNet Large Scale Visual Recognition Challenge (ILSVRC) in 2012 [9].

In this paper, we compared various deep convolutional neural network models such as VGGNet19 [10], ResNet50 [11], and EfficientNetB0 [12] implementing against a publicly available dataset (ISIC Archive Dataset [13]). Deep learning's primary challenge to train large amounts of data for medical tasks, which we can ease by recycling knowledge from models trained on different tasks in a scheme, and it is called transfer learning [14]. The training of a deep classifier on biomedical images such as dermoscopic images can improve by the use of pre-trained models trained in a massive set of natural images [15]. So we applied pre-trained models to increase the overall classification accuracy. In order to abate the limitations of our training dataset, we considered doing rotation, resizing, and flipping images to increase samples of the dataset.

In the later parts of this paper, we oriented as follows. The methodology explained in detail containing the dataset, image processing, classification details of our experimental models, and classification performance of each model (section II). The last part of this paper concludes the experimental results and conclusion (Section III and IV respectively).

## II. METHODOLOGY

Figure 1 is the block diagram of the overall workflow of our research work. Raw images has been collected from Processed Skin Cancer pictures of The International Skin Imaging Collaboration (ISIC) Archive. Then the images have been shaped to fit the algorithm. After that, the classification algorithms VGG19, ResNet50 and EfficientNetB0 are implemented and the perform ace is measured based on the Accuracy, Precision, Recall and f1-scores.

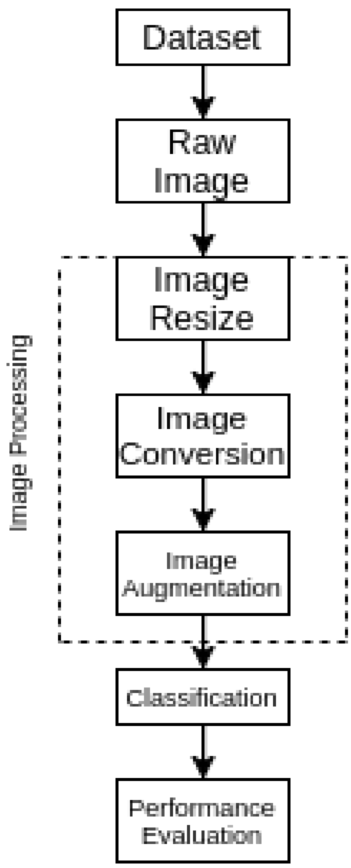


Figure 1: Block diagram of the classification workflow

**A) Dataset:** This research work will be using Processed Skin Cancer pictures of the ISIC Archive dataset. Dataset has two types of tumor Benign and Malignant.

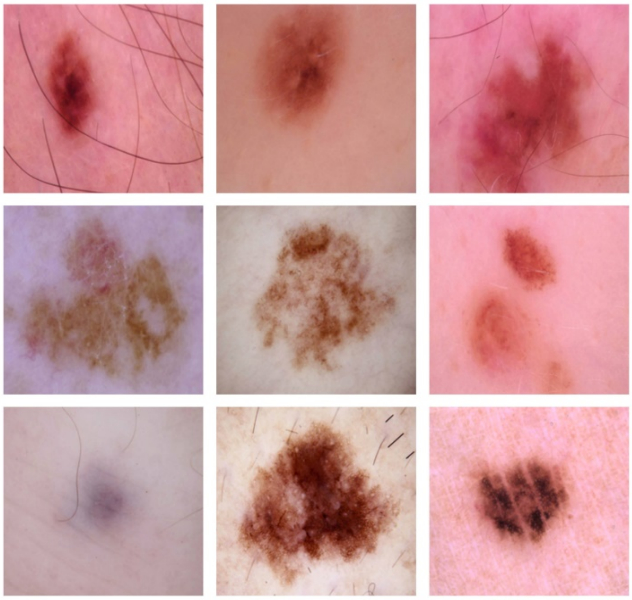

Figure 2: Some of the sample dataset of Benign tumors

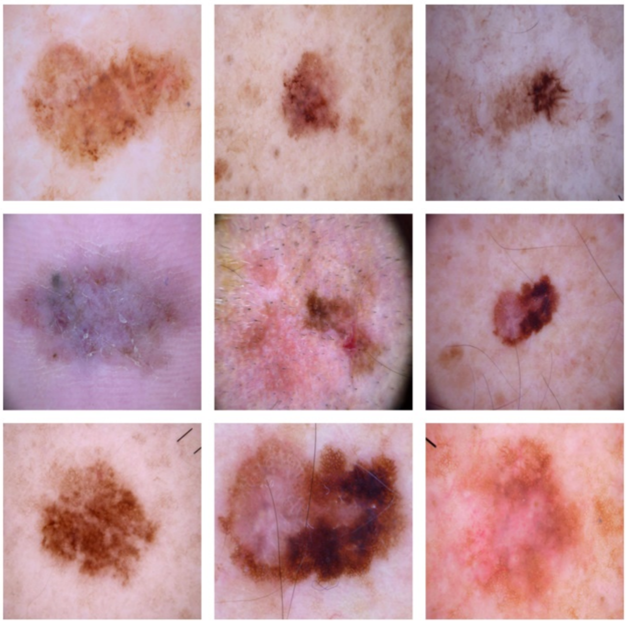

Figure 3: Some of the sample dataset of Malignant tumors.

In the dataset, 2637 pictures (224x244) of the two types of moles are provided for training where 1440 images are Benign and rest of them are Malignant. Furthermore, 660 number of images were used to train the algorithms which includes 360 pictures of Benign and remaining images are Malignant.

**B) Image Processing:**

a. **Image Resize:** A Deep Convolutional Neural Network required an image input of 224-by-224 for classification. A resizing operation has been applied to pertinent images to the network input. These images resized to 224x224 for a consistent dimension to the input of the network.

b. **Image Conversion:** Some of the images are not in 3-channel input images. We need to convert to a standard 3-channel input image for the network to function accordingly. All gray scale images are converted to RGB images for 3- channel input.

c. **Image Augmentation:** Image augmentation is a process where we can create artificial data from our training data by multiple processing, such as random rotation, shift, flips in different angles, shear, zoom, and noise invariance. Image augmentation is required to build a robust image classifier using less amount of training data so that it can increase the overall performance of the network.

**C) Classification:** Convolutional Neural Networks (CNNs) is one of the promising algorithms of Deep Learning to detect images. Convolutional Neural Networks are state of the art models for Image Classification, Segmentation. It is also said to be Deep Convolutional Neural Networks. Like other Neural Networks, it has several layers, such as the input layer, multiple hidden layers and the output layer. In between multiple hidden layers, often there are some pooling layers, which performs subsampling on the input data to decline the training loss. A convolutional layer has a set of linear filters, which can learn its weight from training data [15]. For the segmentation of an image by CNN, it assigns a class label to each pixel [16]. These filters learn patterns across the whole image. A convolutional neural network has three steps of neural layers, such as Convolution, Pooling, and Fully-Connected. When an image passes through the input layer, the convolutional layers establish a convolution on the input image. Each convolutional layer connects to the previous convolutional layer. It enables CNN to use the full 2D structure of the input data so that CNN results in better image recognition. Here an underlying CNN architecture, as shown in Figure 4.

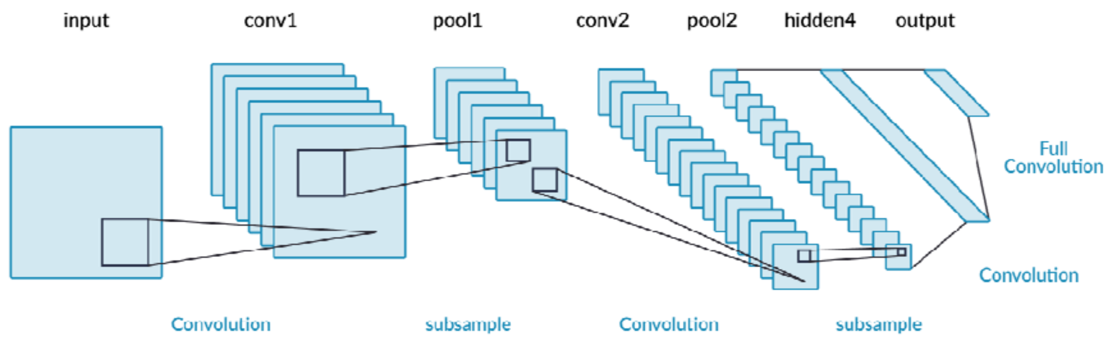


Figure 4: Convolutional Neural Network Architecture

Transfer learning is used in most of the cases in deep learning because it enables training the deep neural network with relatively less amount of data [14]. In our used dataset, the weight of different layers is initialized for the proposed network using VGG19, ResNet50, and EfficientNetB0 pre-trained models, which combines better results overall.

**CNN Models:**

a) **Visual geometry group (VGG)**:VGG-19 is a convolutional model, which has a broad spectrum of success in image classification. 2 researchers develop it from the University of Oxford [10]. Its architecture combines tiny convolutional filters (3x3), which archives tremendous improvement on existing configurations that can pull off by pushing the depth of layers up to 16-19 [10]. The convolution stride is fixed to 1 pixel, and the padding is also 1 fixed for (3x3) ConvNet. Spatial pooling has five max-pooling layers and Max-pooling is performed over a 2x2 pixel window [10]. The final output layer is the soft-max layer, which evaluates the desired output. An architecture of VGG-19 is shown in Figure 5.

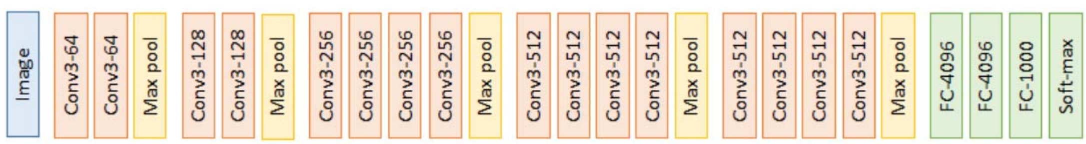


Figure 5: VGG19 Architecture

b) **Residual Network (ResNet50):** Microsoft research team developed ResNet in 2015. It has a depth of 152 layers and 8 times deeper than VGG-19, having less computational complexity. Residual net ensembles only have a 3.57% error on the ImageNet test set, which is lower than other models [11]. The residual addresses the problem of training a really deep architecture by introducing identity skip connection so the layers can copy their input to the next layer [11]. Here a building block of ResNet shown in Figure 6.

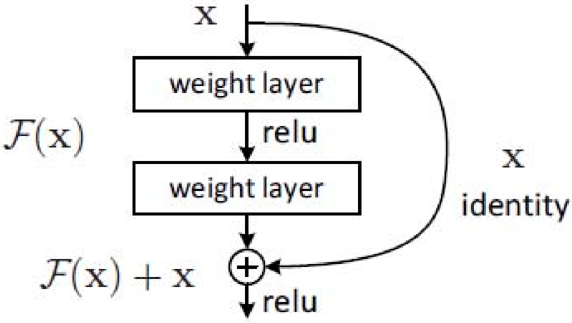


Figure 6: The building block of ResNet [11]

c) **EfficientNetB0:** EfficientNetB0 is a model where we scale up or down other existing models to achieve much better accuracy and efficiency than previous ConvNets [12]. There are so many ways to scale up ConvNets as (ResNet200) or scale down (ResNet18) by adjusting network layers [12]. Compound scaling combines the network width, depth, and resolution in a uniform approach [12]. This model does not change the layer operation in the baseline network while scaling [12]. In our experiment, EfficientNetB0 shows enormous results than other models. Here, we show model scaling in Figure 7.

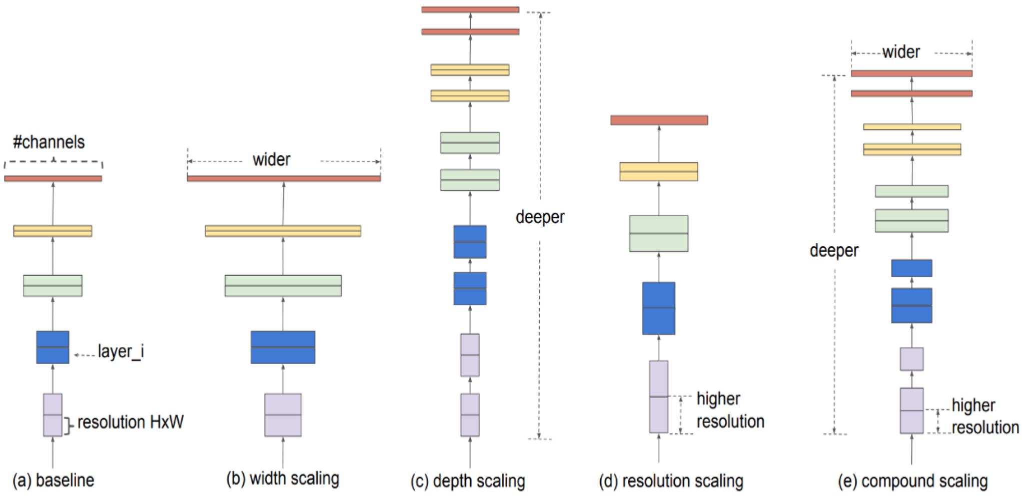


Figure 7: Model Scaling (EfficientNet) [12]

**D) Performace Measure:** There are some model performance measure parameters that we use to evaluate the performance, such as:

**i. Accuracy:** Accuracy determines how accurate the model is.

$$\text{Accuracy} = \frac{TP+TN}{TP + FN + FP + TN} \qquad (1)$$

**ii. Precision:** It discovers how correctly the system identified the tumor in terms of True Negative and False Positive.

$$\text{Precision} = \frac{TN}{FP+TN} \qquad (2)$$

**iii. Recall:** Recall is the ability of the classifier to find the positive samples.

$$\text{Recall} = \frac{TP}{TP+FN} \qquad (3)$$

**iv. F1 Score:** F1 score determines the balance between precision and recall.

$$F1 = 2 \times \frac{Precision - Recall}{Precision + Recall} \qquad (4)$$

## III. RESULTS

Table 1 & 2 along with Fig 8 - 10 represents the overall performance of our model. In our model we can see that we used VGG19, ResNet50, EfficientNetB0 for classifying the cancer cells. We splitted the dataset in two segment of 70% and 30% for training and testing purposes. All three algorithms has input shape of 224X224X3 and 25 epochs. For optimizing the Adam optimizer has been used.

Table no 1: MODEL EVALUATION: TRAINING DATASET

| ***Algorithms*** | ***Accuracy*** | ***Precision*** | ***Recall*** | ***f1-Score*** |
|---|---|---|---|---|
| **VGG19** | 0.8444 | 0.8851 | 0.8187 | 0.8506 |
| **ResNet50** | 0.9429 | 0.9479 | 0.9211 | 0.9178 |
| **EfficientNetB0** | 0.9867 | 0.9831 | 0.9855 | 0.9817 |

Table no 1: MODEL EVALUATION: TEST DATASET

| ***Algorithms*** | ***Val-Precision*** | ***Val- Recall*** | ***Val- f1-Score*** |
|---|---|---|---|
| **VGG19** | 0.8705 | 0.8353 | 0.8525 |
| **ResNet50** | 0.8655 | 0.8869 | 0.8761 |
| **EfficientNetB0** | 0.9160 | 0.9288 | 0.9127 |

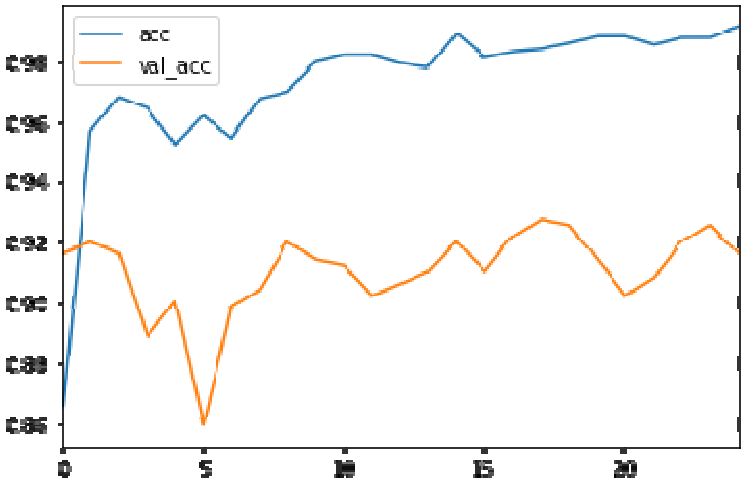


Figure 8. Accuracy and Val Accuracy of EfficiantNetB0

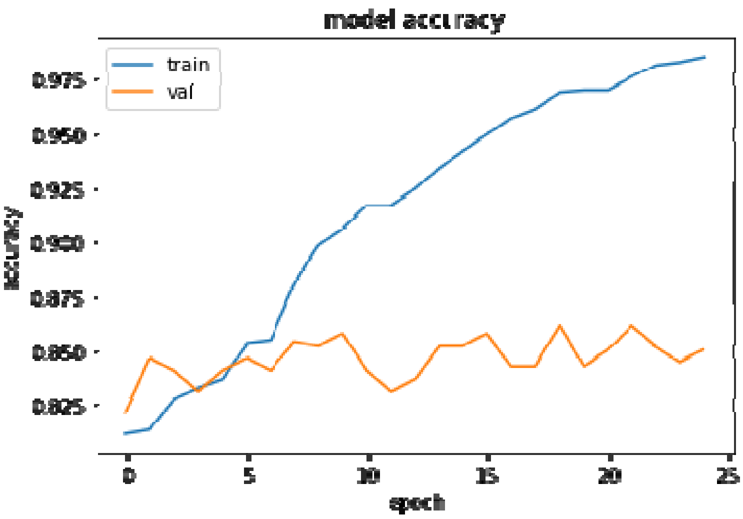


Figure 9. Accuracy and Val Accuracy of ResNet50

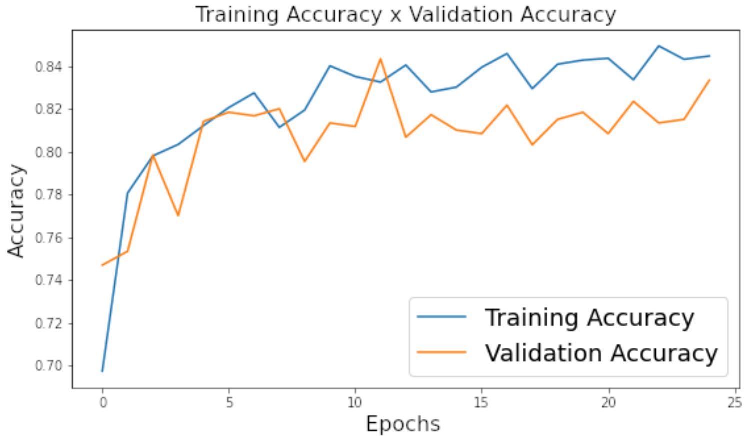


Figure 10. Accuracy and Val Accuracy of VGG19

The results shows that EfficientNetB0 has 98.67% of Accuracy among the three algorithms on the training dataset. Rest of the two VGG19 and ResNet50 showed accuracy of 94.29% and 84.44% accordingly. Moreover, EfficientNetB0 accorded Precision of 98.32% and VGG19, ResNet50 accorded 94.11% and 88.51%. In addition to that, the three algorithms provided Recall score of 98.55%, 94.79% and 81.87% accordingly.

## IV. CONCLUSION

In this paper, we have proposed a computerized automated method for benign and malignant tumor classification. Specifically, we have demonstrated that pre-trained deep learning models, trained for natural image classification can also be significant for dermoscopic image classification. But, fusing the in-depth features from various layers of a single network or various pre-trained CNNs is shown to lead to better classification performance. Here we use various CNN models as follows: VGG-19, ResNet50 and EfficientNetB0. Where pre-trained EfficientNetB0 executed better performance of 98.67% accuracy in classification among other models such as VGG-19 and ResNet50 have 94.29% and 84.44% accuracy respectively.

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