Melanoma Prediction in Dermoscopy Images

Ajinkya Kanse[1], Dr. M. S. Panse[2]
[1]Student of Master of Technology, [2]Professor
[1]Electronics Engineering,
[2]Department of Electrical Engineering
[1,2]Veermata Jijabai Technological Institute, Mumbai, India,
E-mail: [1]ajinkyakanse18@gmail.com, [2]mspanse@el.vjti.ac.in

Abstract

One of the fast-growing skin cancers is melanoma. Early detection and diagnosis of melanoma are critical to the fight against cancer. An automated system is proposed that can facilitate the diagnosis. This paper presents an approach for classifying skin lesions as malignant or benign and is implemented using a machine learning model like ResNet. The method used consists of a sequential combination of the ResNet model as the base network and a custom block.

Keywords: *ML (Machine Learning), Skin cancer, malignant, benign.*

1. Introduction

Melanoma skin cancer is rapidly increasing skin cancers and accounts for almost 75% of skin cancer deaths [1]. Early diagnosis is of great importance for treating this disease, as it is treatable easily at early stages [1]. Cutaneous melanoma is the most dangerous skin tumor that causes 90% of skin cancer mortality [8]. One of the techniques used in the examination is dermoscopy. It is a non-invasive technique and provides a high-quality visual perception of skin lesions. For the early detection of melanoma, dermoscopy is an effective tool and assists in a detailed inspection.

Distinguishing between melanoma and non-melanoma skin lesions is gaining attraction recently. Traditional image processing techniques help in diagnosis to a certain extent. More accurate classification is possible using machine learning.

For effective classification, a machine learning model (neural network) can be used. The method proposed by Zhen Yu *et al.* a [1] uses the ResNet deep neural network. It acts as a feature extractor, gaining information from the training images. Following the feature extractor is the fisher encoding strategy, which is used to aggregate the deep features for a more discriminative and robust representation [1]. In the end, an SVM classifier with a Chi-squared kernel is used for the classification task [1].

The method proposed by Lequan *et al.* [4] uses a two-stage approach. In the first stage, segmentation is performed. To segment skin lesions a convolutional deep network is used [4]. It contains multi-scale functions for correct segmentation [4]. To categorize skin lesions as malignant and benign a very deep residual network is used based on the result of the previous step [4].

Overall, this paper tries to classify the skin lesion images as malignant or benign using the ResNet model as a base network and a custom block. The dataset used in this paper is Skin Cancer: Malignant vs. Benign, which is publicly accessible on Kaggle.

2. Methodology

The proposed CNN model consists of the ResNet-50 model as the base network. As mentioned earlier, it consists of a custom block. The block consists of layers such as the global average pooling layer, dropout layer, dense layer, and output layer. The output layer is the dense layer with the number of nodes corresponding to the output classes. In this case, the number of output classes is two, malignant and benign. So there are two nodes at the output.

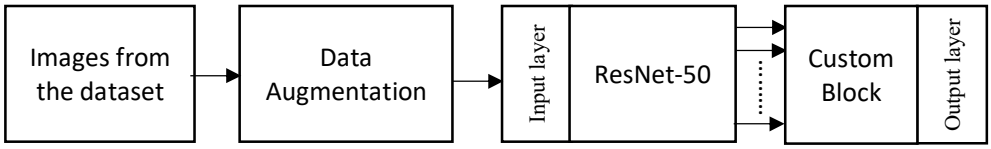

Figure 1. Block diagram

The dataset used in the experiments is the Skin Cancer: Malignant vs. Benign dataset [12]. The dataset is accessible to all on Kaggle. The dataset includes standard-size images, 224 x 224 pixels. Resize is the only processing performed on the dataset images. The data augmentation is performed on the images before the images are feed into the model. It is a process that involves generating more images virtually if the dataset contains fewer images. It also contributes to the reduction of overfitting to some extent. There is also a provision for saving the augmented images to the local disc. The size of the image used for training and testing is 512 x 512 pixels. The dataset images are illustrated in figure 2.

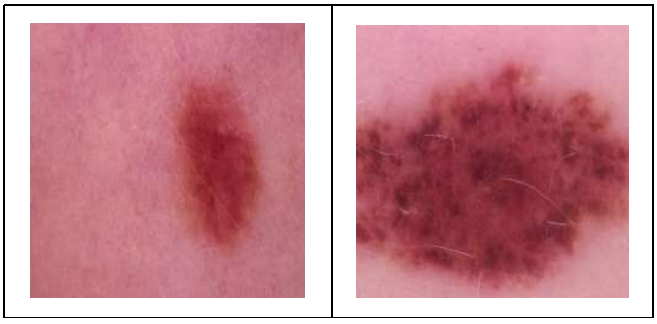

Figure 2. Images form the dataset [12]

Once the images are augmented, the images are fed into the model. In this case, ResNet-50 is used as a base network. The model is performing well in the ImageNet classification task [6]. As a result of its lower error rate, the ResNet model is preferred [6]. The input layer is also part of the base network. It has the dimension of 512 x 512 x 3, where three indicate that the images are color images. The base network followed by the custom block form the entire neural network as shown in Figure 1. The output layer uses softmax as the activation function. Adam optimizer is used with the default learner rate of 0.001. The loss function used is categorical crossentropy.

3. Results

This section provides information on the outcomes of the experiments. The testing of the model is carried on the test dataset. Results are as follows:

Table 1. Results of the model 1

Parameters	Values
Precision	85.45 %
Recall	85.72 %
F1-Score	85.28 %
Accuracy	85.30 %

The model used for the results achieved in Table 1 is the combination of the base network connected to the custom block. The transfer learning method is used. The results are calculated using test data. The accuracy score of the model is 85.30%.

Table 2. Results of the model 2

Parameters	Values
Precision	87.16 %
Recall	87.44 %
F1-Score	87.22 %
Accuracy	87.27 %

The model used is the same as the one used for obtaining the results in Table 1. The difference is that it has been fine-tuned. This model performs better than the first because all the parameters of the model are updated. It obtains a test accuracy score of 87.27 %. In the above case, it is possible to achieve better performance by using the different training techniques and introducing various parameters while training the model.

4. Conclusion

In the experimental work above, we seek the best ResNet model, using transfer learning or fine-tuning. The best model obtained is using 20 epochs for training is ResNet50 connected to the custom block using the fine-tuning method. In this case, the model is all effective and produces good results while using a 25% dropout. The accuracy of the model can be enhanced by using the segmentation method or the various optimizers.

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