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Skin Cancer Classification using Deep Learning Models

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Abstract: In recent years, researches proved that Melanoma is the deadliest form of skin cancer. In the early stages, it can be treated successfully with surgery alone and survival rates are high. A large number of methods for Melanoma classification has been proposed to deal with this problem, but although they did not find better ways to create the final solution. Thus, our aim is to go further and explore the classic models in order to handle the Melanoma classification problem based on modified VGG16 and modified InceptionV3. The conducted experiments revealed the effectiveness of our proposed method based on modified VGG16 with 73.33% of accuracy, when compared to other state-of-the-art methods on the same data sets, in terms of finding optimal and effective solutions and improving the objective function.

1 INTRODUCTION

Melanoma is the most unsafe form of skin cancer. It begins in the melanocytes (color- producing cells plant in the surface subcaste of the skin). In the utmost of cases, it's caused by ultraviolet radiation from sun or tanning beds which produce mutations (inheritable blights) that take the skin cells to expand fleetly and form nasty excrescences (l. Argenziano, et al., 2000).

Melanoma causes 55 500 cancer deaths annually which is 0.7 of all cancer deaths. The prevalence and mortality rates of carcinoma differ from one country to another due to the variation of ethnical and ethnical groups (Schadendorf et al., 2018). Nasty carcinoma is presumptive to come one of the most common nasty excrescences in the future, with yet a ten times advanced prevalence rate (Tadeusiewicz et al., 2010).

Visual examination of the suspicious skin area is generally adopted by dermatologist as a first step for the diagnosis of a malignant lesion. In fact, an accurate diagnosis is essential because of the resemblances of some lesion types. Furthermore, the diagnostic accuracy correlates strongly with the professional experience of the physician (Tadeusiewicz et al., 2010).

On the other hand, without any further technical support, dermatologists have a 65% to 80% accuracy rate in melanoma diagnosis. In suspicious cases, dermatologists explore and use dermatoscopic images as a complementary support of the visual inspection. In fact, the combination of both visual inspection and dermatoscopic images eventually results in an absolute melanoma detection accuracy of 75%-84% by dermatologists (Brinker et al., 2018)

Currently, artificial intelligence (AI) has come an aptitude to face these problems. Several deep-literacy infrastructures like reccurent neural networks (RNN), convolutional neural networks (CNN), deep neural networks (DNN), long short term memory (LSTM) are proposed in literature to descry cancer cell. These models are also successfully performed in classifying skin cancer.

Several CNN architectures, like ResNet, Inception and Xception, as well as VGG16, are proposed in literature and specially designed for image classification. Numerous researchers have developed methods based on deep learning to classify and identify skin cancer (Le et al., 2020; Garg et al., 2019; Guan et al., 2019; Nugroho et al., 2019; Pacheco et al., 2019).

In this work, we propose a modified InceptionV3 model for the classification of skin cancer. We propose also a modified VGG16 model which classifies skin cancer with a better accuracy value

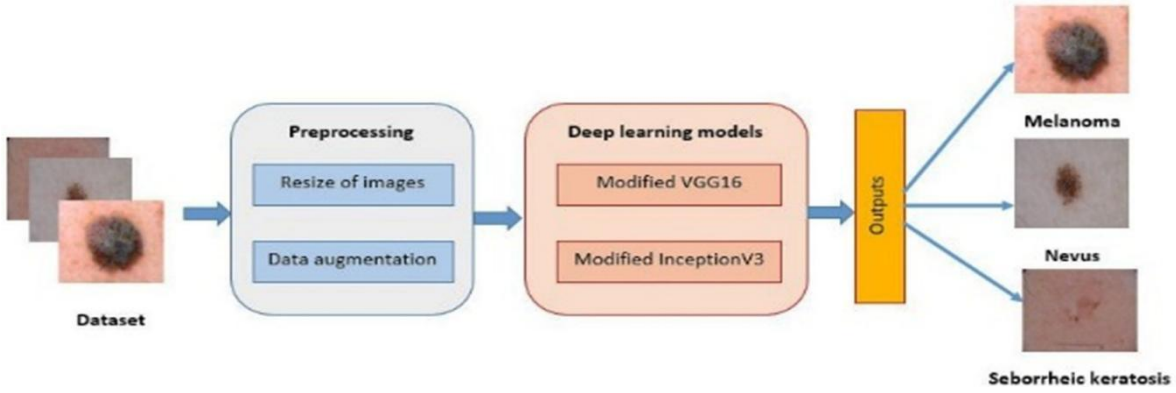

Figure 1: Flowchart of the proposed method for skin cancer classification using *modified VGG16* model.

compared to the state of the art.

The rest of the paper is organised as follows: Section 2 details materials and proposed method. Section 3 represents results and discussion. Section 4 concludes this paper.

2 MATERIAL AND PROPOSED METHOD

In this section, we will present the dataset used in this research work and present our proposed method for skin cancer classification.

2.1 Dataset Description

The used dataset in this present work contains three classes: melanoma, nevus and seborrheic keratosis. More details about this datasets are given below:

- **2000 training images** (https://s3-us-west-1.amazonaws.com/udacity-dlnfd/datasets/skin-cancer/train.zip)
  - melanoma images: 374
  - nevus images: 1372
  - seborrheic keratosis images: 254
- **150 validation images** (https://s3-us-west-1.amazonaws.com/udacity-dlnfd/datasets/skin-cancer/valid.zip)
- **600 testing images** (https://s3-us-west-1.amazonaws.com/udacity-dlnfd/datasets/skin-cancer/test.zip)

2.2 Proposed Method

Figure 1 presents Flowchart of the proposed method. A preprocessing stage is firstly applied on input image. The preprocessing involves resizing all images and increasing the number of images from both classes *melanoma* and *seborrheic keratosis*. Then we test the modified VGG16 model and apply our modified InceptionV3 model.

2.2.1 Data Augmentation

We used data augmentation techniques to artificially boost the amount of our training data because our data collection is rather small. The increase in data is an often-applied DL method that generates the required number of samples. It also improves network efficiency for a small database by optimizing it. Shifting, Rotation, flipping, transformation, and zooming are all examples of traditional data augmentation procedures. We used "*Keras Image Data Generator*" to apply image augmentations during training in this investigation.

As shown in section 2.1, the number of images of class '*Nevus*' is 1372. In order to balance the number of images for all three considered classes, we applied the data augmentation technique to augment the size of both classes '*Melanoma*' and '*seborrheic keratosis*'.

In this work, we choose a vertical flip, a horizontal flip and a 45-degree rotation for data augmentation. As a result, we got 1372 images for each class.

2.2.2 Skin Cancer Classification using Modified VGG16 Model

Figure 2 shows the flowchart of the proposed method for the classification of skin cancer using the VGG16 model. In this paper, modified VGG16 begin by five blocks, the first two blocks include two convolutional layers with a Relu activation function and Max Pooling followed by three blocks. Each block enclose three convolutional layers with a Relu activation function and Max Pooling. An adaptative Avg

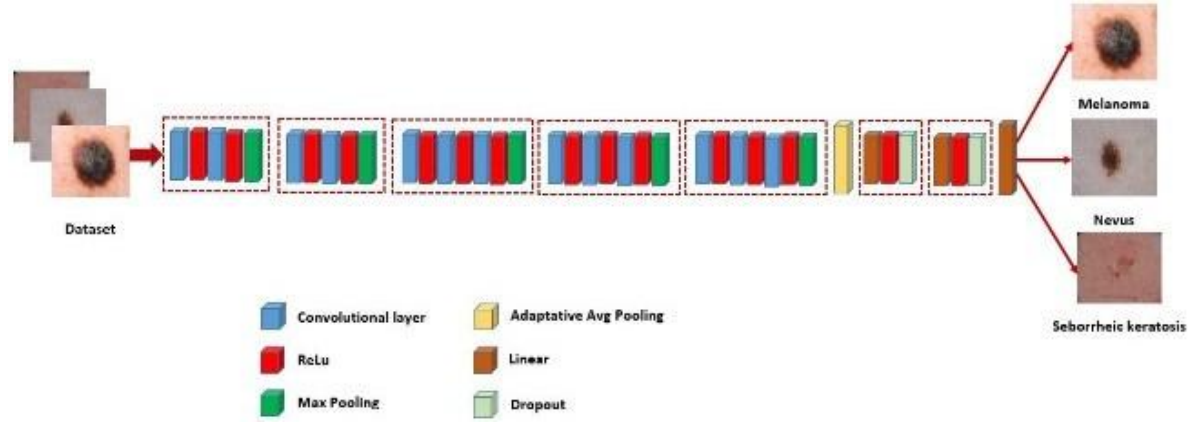

Figure 2: Flowchart of the modified VGG16 for skin cancer classification.

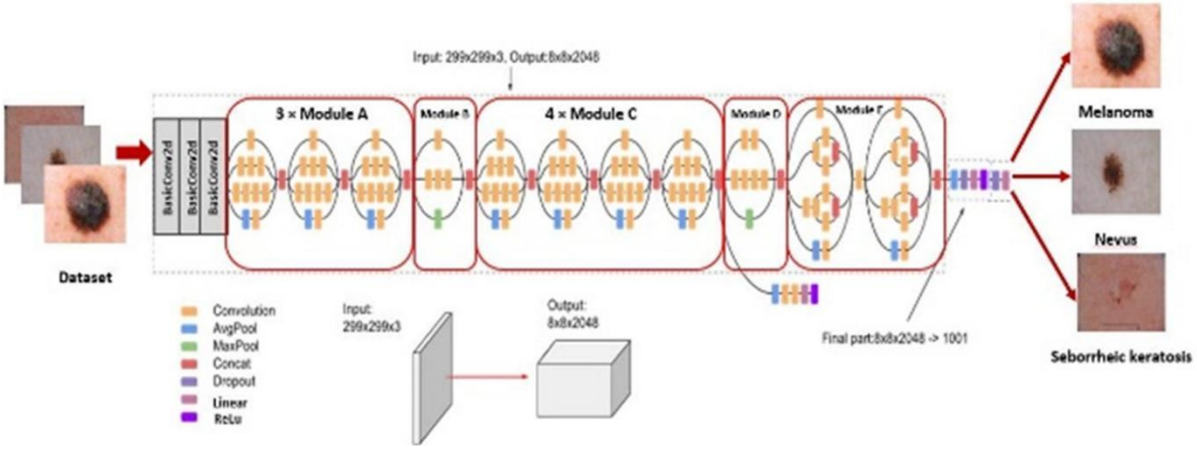

Figure 3: Flowchart of the modified InceptionV3 for skin cancer classification.

Pooling and two blocks follow these blocks. Each block contains linear layer, ReLu activation function, and Dropout Layer. Finally, a linear layer is used to predict the class of images.

We fine-tuned this model by 10 epochs. The Adaptive Moment Estimation known as "Adam optimizer" is used to optimize the loss function. The adopted model is trained by a cross-entropy loss function.

2.2.3 Skin Cancer Classification using Modified InceptionV3 Model

Figure 3 shows the modified method for the classification of skin cancer using the InceptionV3 model. InceptionV3 is a commonly used image classification model that has demonstrated more than 78.1% accuracy on the ImageNet dataset. The model itself is made up of basic symmetric and asymmetric components including convolutions, average pooling, maximum pooling, concatenations, drops, and fully connected layers. Batch normalization is widely used in the model and applied to activation inputs. The loss is calculated via SoftMax. Our Modified InceptionV3 begins by three blocks of BasicConv2d. Each block includes a convolutional layer and a batch normalization step followed by 3 Modules A, module B, 4 modules C, module D, and 2 modules E followed by Avg Pooling, Dropout, Linear layer, ReLu, Dropout layer and Linear layer.

3 RESULTS AND DISCUSSION

In this section, we present and discuss the obtained classification results when both proposed models are used. Accuracy, precision, recall and F1-score metrics are considered for performance evaluation of proposed classifiers. These mentioned metrics are respectively computed according to the following

equations for both *modified VGG16* and *modified InceptionV3* models.

$$accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

$$precision = \frac{TP}{Tp+FP} \quad (2)$$

$$recall = \frac{TP}{FN+TP} \quad (3)$$

$$F1 - score = 2 * \frac{precision*recall}{precision+recall} \quad (4)$$

where TP, TN, FP and FN are respectively the True Positive, True Negative, False Positive and False Negative.

Both *modified VGG16* and *modified InceptionV3* algorithms assess the classification performance. We achieved two experiments using the same described dataset. We conducted the first classification experiment considering all *melanoma*, *nevus* and *Seborrheic keratosis* classes. The second classification experiment is executed considering only two classes: *benign* and *malignant* classes.

3.1 Classification Results: Three Classes

In this section, we present the obtained classification results when the three classes are considered. Table 1 presents the average accuracy results of all considered classes for both *modified VGG16* and *modified InceptionV3* models.

Table 1: Classification accuracy.

	Accuracy
Modified VGG16	73.33%
Modified InceptionV3	42.00%

Table 2 details the accuracy results obtained with three considered classes for both *modified VGG16* and *modified InceptionV3* models.

Table 2: Classification accuracy for three classes.

	Modified VGG16	**Modified InceptionV3**
melanoma	50%	33%
nevus	54%	84%
Seborrheic keratosis	47%	24%

From tables 1, we can observe that *modified VGG16* model performs better than the *modified InceptionV3* model. In fact, the average accuracy value obtained with *modified VGG16* model is better (73.33%) than those obtained with *modified InceptionV3* model (only 42%).

Table 2 showed that both proposed methods present good classification performances for '*Nevus*' class with a superiority for *modified InceptionV3* model. In fact, this class achieves an accuracy value of 54% with *modified VGG16* and 84% with *modified InceptionV3*. However, classification performances using both proposed methods are significantly decreased for *'Seborrheic keratosis'* class. In this case, accuracy values are only limited to 47% and 24% for *modified VGG16* and *modified InceptionV3* models respectively.

3.2 Classification Results: Two Classes

In this section, we present the obtained classification results when the two *benign* and *malignant* classes are considered. Figure 4 shows the confusion matrix and the ROC curves for both *Modified VGG16* model.

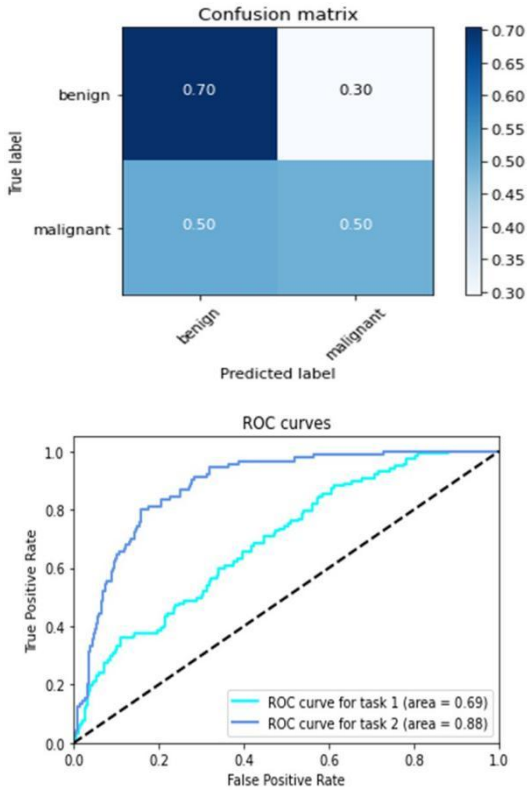

Figure 4: Confusion matrix and ROC curve for modified VGG16 model.

Figure 5 shows the confusion matrix and the ROC curves for both *Modified InceptionV3* model.

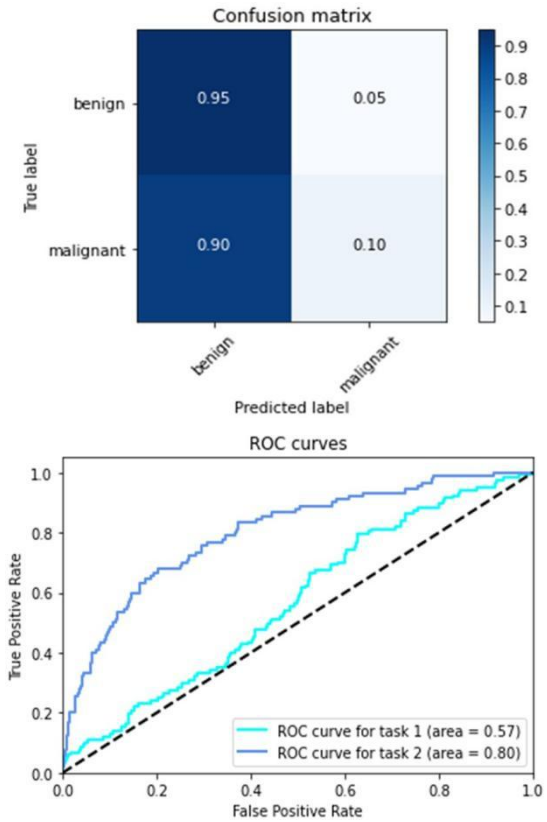

Figure 5: Confusion matrix and ROC curve for *modified InceptionV3* model.

Table 3 reports the average results for recall, precision and F1-score metrics computed using both proposed *VGG16* and *InceptionV3* models.

Table 3: Classification performances for Malignant and Benign classes.

	Modified VGG16	**Modified InceptionV3**
Recall	51.35%	58.33%
Precision	95.00%	70.00%
F1-score	66.66%	63.63%

The binary classification of Malignant and Benign classes also show that the proposed method based on the *VGG16* model achieves better performances then the second proposed method based on *InceptionV3* model. In fact, considering the proposed *VGG16* model, recall, precision and F1-score values are respectively equal to 51.35%, 95.00%, and 66.66%.

3.3 Discussion

The performances of the *modified VGG16* model are compared to three state of the art methods labelled as *KNN* (Daghrir et al., 2020), *SVM* (Daghrir et al., 2020) and *AlexNet* (Sasikala et al., 2020). Results are summarized in Table 4.

Table 4: Comparative study for binary classification.

Method	**Accuracy**
KNN (Daghrir et al., 2020)	57.3%
SVM (Daghrir et al., 2020)	71.8%
AlexNet (Sasikala et al., 2020)	65.3 %
Proposed method based on modified VGG16	**73.33%**

By comparing the accuracy values listed in Table 4 obtained for different considered methods, we can observe that our *modified VGG16* method performs better than *KNN*, *SVM*, and *AlexNet* methods. In fact, accuracy reached 73.33% with our proposed *VGG16* method. Although the accuracy is limited to 57.3%, the *KNN* method is able to hardly identify malignant skin lesions since it is sensitive to outliers.

On the other hand, the *SVM* method performs better than the *KNN* and *AlexNet* methods due to its adaptability and efficiency. In fact, accuracy is equal to 71.8% with *SVM* method, but it is limited to only 57.3% and 65.3% with *KNN* and *AlexNet* methods respectively. Although AlexNet achieved quiet performance, the *SVM* is still considered a more robust and powerful tool for identifying skin cancer.

4 CONCLUSIONS

In this work, we proposed two modified models for skin cancer classification: *modified VGG16* and *modified InceptionV3* models. The application of the data augmentation showed that the reduction of the data imbalance can be useful to improve classification performance, but careful tuning is required, for example, to make the data perfectly balanced training does not necessarily result in a better model.

Performances are evaluated using different metrics like accuracy, precision, recall and F1-score. Two experiments are conducted. In the first experiment, we considered *melanoma*, *nevus* and *Seborrheic keratosis* classes, but in the second one, only *benign* and *malignant* classes are considered. Results of first experiment showed that the *modified VGG16* is a reliable multiple classifier and performs better than modified *InceptionV3* model. For second experiment, compared to state of the art considered methods, results showed that better accuracy values are obtained for binary classification using *modified VGG16 model.*

It is clear that our proposed method given better results compared to different others recent methods. However, there is a need to improve its performances in our future work. In fact, merging or concatenating deep learning models could improve the classification results.

REFERENCES

Brinker, T.S., Hekler, A., Utikal, J., Grabe, N., Schadendorf, D., Klode, J., Berking, C., Steeb, T., Enk, A., & von Kalle, C., Skin Cancer Classification Using Convolutional Neural Networks: Systematic Review *J Med Internet Res*. 2018 Oct; 20(10): e11936

Daghrir, J., Tlig, L., Bouchouicha, M., Sayadi, M. Melanoma skin cancer detection using deep learning and classical machine learning techniques: A hybrid approach. *International Conference on Advanced Technologies for Signal and Image Processing*, Sep 2020.

Garg, R., Maheshwari, S., & Shukla, A. (2019). Decision support system for detection and classification of skin cancer using CNN. arXiv preprint arXiv:1912.03798.

Guan, Q., Wang, Y., Ping, B., Li, D., Du, J., Qin, Y., et al. (2019). Deep convolutional neural network VGG-16 model for differential diagnosing of papillary thyroid carcinomas in cytological images: a pilot study. Journal of Cancer, 10(20), 4876.

Argenziano, G., Soyer H. P., De Giorgio, V., et al. Interactive Atlas of Dermoscopy Milano, Italy: Edra Medical Publishing and New Media; 2000.

Le, D. N., Le, H. X., Ngo, L. T., & Ngo, H. T. (2020). Transfer learning with classweighted and focal loss function for automatic skin cancer classification. arXiv preprint arXiv:2009.05977.

Nugroho, A. A., Slamet, I., & Sugiyanto (2019). Skins cancer identification system of HAMl0000 skin cancer dataset using convolutional neural network. AIP Conference Proceedings, 2202, Article 020039.

Pacheco, A. G., & Krohling, R. A. (2019). Recent advances in deep learning applied to skin cancer detection. arXiv preprint arXiv:1912.03280.

Sasikala, S., Arun Kumar, S., Shivappriya, S.N. and Priyadharshini, T. (2020). Towards Improving Skin Cancer Detection Using Transfer Learning. *Biosc. Biotech. Res. Comm*. Special Issue Vol 13 No 11 (2020) Pp-55-60.

Schadendorf, D., Alexander CJ van Akkooi, Carola Berking, Klaus G Griewank, Ralf Gutzmer, Axel Hauschild, Andreas Stang, Alexander Roesch, and Selma Ugurel. Melanoma. *The Lancet*, 392(10151):971– 984, 2018.

Tadeusiewicz, R. (2010). Place and role of intelligent systems in computer science. *Computer Methods in Materials Scienc*e;10(4), pp.193-206,2010.