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Classification of Skin Lesions using CNN

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Abstract. Various computational methodologies can be found in the specialized literature, with different applications, among which the classification of skin lesions in dermoscopic images stands out in this work. Although the initial analysis of skin lesions was performed using a set of visual rules known as the ABCDE rule (Asymmetry, Borders, Lesion Color, Diameter, and Evolution), the performance of this visual analysis is influenced by factors such as lighting variation during image capture, the presence of artifacts that cause noise, and the specialist's eye strain during image analysis. A mistaken initial analysis can delay the development of an adequate treatment plan, affecting the effectiveness of this treatment. In the task of computational recognition of elements in an image, the Convolutional Neural Network (CNN) stands out. In this context, this work presents the results of the application of CNN ResNet for the identification of melanomas. To carry out this work, TensorFlow and a database with 9144 images were used. The results were promising, reaching approximately 75% accuracy.

Keywords: Convolutional Neural Networks, Skin Lesion Classification, Image Classification.

1 Introduction

Among all cancers that affect humans, the most common is skin cancer. According to the Federal Government's official health website, skin cancer commonly occurs in people over 40 years of age. In younger people or even in children this type of tumor is considered rare. The cancer anomaly proliferates from the moment the cells multiply in an uncontrolled way, reaching stages that allow classifying these skin lesions into melanoma and non-melanoma. Another important fact is that the percentage of cases of non-melanoma skin cancer already registered in Brazil reaches 30% of malignant tumor cases, of which 3% correspond to the melanoma type. This type (melanoma) is the most aggressive and if not treated early, it can lead to metastasis, which is the spread of the disease to other organs and, consequently, increasing the risk of death of the patient. In the world, melanoma is also responsible for the majority of cancer deaths [1][2].

The non-melanoma type of cancer has a higher probability of survival, that is, the clearest chance of cure, as long as it is detected and treated early. Two types stand out in the non-melanoma class: basal cell carcinoma and squamous cell carcinoma. Basal cell carcinoma has a developing nodule in the form of a wound. This type of injury is common in records in the country. Meanwhile, squamous cell carcinoma refers to the appearance combined with an already exposed wound or even a burn, but in both cases, they are called in the form of a wound [1].

The diagnosis of skin cancer is made by the dermatologist, and this early diagnosis is important for the patient's survival. For a superficial analysis, it is convenient to use the ABCDE rule (Asymmetry, Borders, Lesion Color, Diameter, and Evolution), in which each character represents, respectively, the asymmetry, the irregularity of the borders, the color, the lesion diameter, and the evolution. of the injury. The letter A presents a symmetrical shape the lesion is considered benign, otherwise, it is malignant. In the same way that the letter B has regular borders, it is of the benign type, otherwise, it will be malignant. As with the letter C, the color being defined with a shade is considered a benign tumor, on the other hand, with the diversification of colors it will be considered malignant. The diameter is represented by the letter D, in turn, occupying a space smaller than 6 mm (millimeters) is considered a benign tumor, otherwise, it is called a malignant tumor. Finally, the letter E is related to the rapid evolution that may occur in terms of shape, appearance, color, and even thickness. The anomaly can be studied using a dermoscopy which, in turn, is directly responsible for images of the skin, that is, photographs are taken of the superficial layers of the epidermis. However, the biopsy is a clinical method that is present in these cases. Therefore, an incision of a small part of the skin is made and soon afterward it is submitted to the laboratory for confirmation of the medical report [3][1][4].

Because of these existing methodologies, it is still possible that some failure in the diagnosis occurs, this is confirmed today where there are clinical centers with few resources and for this reason, there is a need to create a software product that is capable of minimizing errors in diagnosis. doctor and using artificial intelligence it will be feasible to build a predictive algorithm with dermoscopic images. This is responsible for analyzing patterns in the images that link characteristics that are related to skin cancer [3].

The advancement of areas of research and development related to health and technologies is evident. Artificial Intelligence (AI), specifically in the area of Machine Learning (ML) and Digital Image Processing (DIP), can contribute to assisting dermatologists in the diagnosis of this type of cancer. In the task of recognizing elements in an image, the Convolutional Neural Network (CNN) has great prominence. CNN is inspired by multilayered Artificial Neural Networks with perceptron neurons. The objective of CNN is to extract features from the images automatically, using convolutional filters defined from the weights of the neurons in the network [5]. Therefore, in this work, the results of the application of CNN for the identification of skin lesions are presented. TensorFlow and a base with 9144 images were used. The training was carried out with 80% of the data and the rest was used for validation. The standardization of the size of the images, using padding, filling the contour of the images with black, until they reached the dimension of 128 by 128 pixels. We chose to use the average function as a pooling and dropout strategy by 20%. The learning rate used was 0.000001 with the Softmax function to normalize the outputs. The results were promising, reaching 75% accuracy. Some related works are presented below.

2 Related Works

To encourage the use of machine learning for the automated diagnosis of skin lesions, the authors of a 2018 paper released a dataset with about 10,000 dermoscopic images. Considering the diversity of image storage, different techniques were used to extract and catalog the files. To define the diagnoses was used from the consensus of experts to the results of biopsies [6].

In the work by Maron et al. [7] a comparison between diagnoses from a CNN and 112 dermatologists from 13 German hospitals was presented. The authors used 11,444 dermoscopic images of skin lesions and a set of 300 biopsy-verified images in comparison with dermatologists. The CNN model surpassed the dermatology ones, reaching 91.3% and 98.8% of accuracy, against 74.4% and 56.5% of the dermatologists in the experiments performed. Despite several technologies currently being evaluated and employed for the detection of skin cancer (infrared imaging, laser spectroscopy, convolutional neural networks), the cost of equipment, and training is still a commonly faced problem [8].

The authors of another work used the Weka 3.8.1 tool to build and evaluate the Artificial Neural Networks (ANN) and Vector Support Machine classifier models. The training was performed with a base of 200 examples, 14 attributes (including the class attribute), and 3 classes. The AutoWeka 2.6.1 package was also used, allowing to obtain an accuracy of 95.5% for an ANN model [3].

3 Methodology

A Convolutional Neural Network (CNN) was implemented using the Python language. The implemented algorithm uses the Tensorflow library and a base with 9144 images[6], with 80% of the images used for training and 20% for validation. The standardization of the size of the images was performed, using padding, filling the contour of the images with black until they reached the dimension of 128 by 128 pixels. We chose to use the average function as a pooling and dropout strategy by 20%. The learning rate used was 0.000001 with the Softmax function to normalize the outputs. The EfficientNetB0, EfficientNetB7, InceptionResNetV2, InceptionV3, ResNet50V2, ResNet101V2, ResNet152V2, VGG16 and VGG19 architectures were tested.

4 Results

In the graph of Figure 1, it is possible to verify the results of the training carried out with 50 epochs for the models obtained with the EfficientNetB0, EfficientNetB7, InceptionResNetV2, InceptionV3, ResNet50V2, ResNet101V2, ResNet152V2, VGG16 and VGG19 architectures.

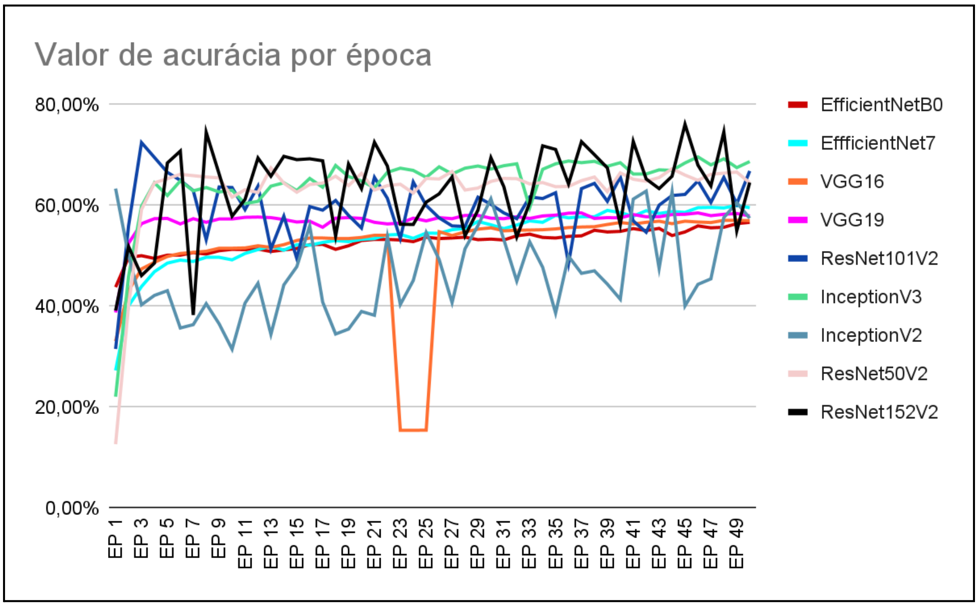

Figure 1. Comparison between architectures with 50 epoch training.

The Resnet152V2, Resnet101V2, InceptionV3 and ResNet50V2 models obtained the best accuracies in the training stage, as can be seen in the graph of Figure 2, obtaining 74.56%, 72.48%, 69.64% and 67.45%, respectively.

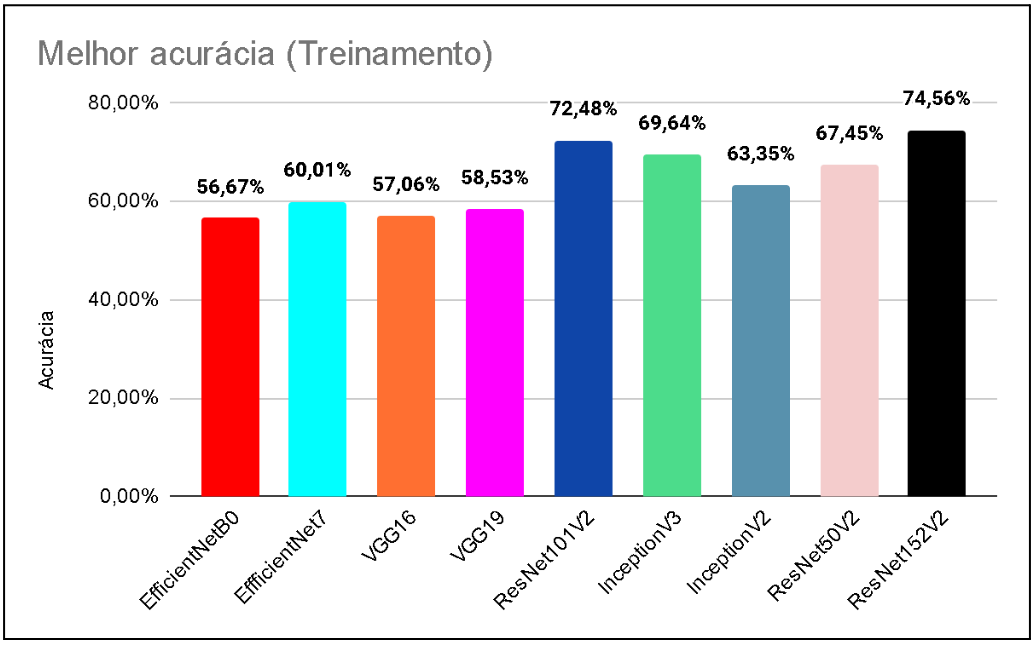

Figure 2. Better model accuracies in the training stage.

Still in Figure 2, it can be seen that the worst accuracy results in the training stage were with the EfficientNetB0 (56.67%), VGG16 (57.06%), VGG19 (58.53%) and EfficientNetB7 (60, 01%).

In the graph of Figure 3, it is possible to observe the percentage of accuracy with the validation data of each model. It can be seen that the Resnet101V2 algorithm obtained the best result, reaching approximately 70% accuracy (68.48%). Resnet152V2, which obtained better training results (Figures 1 and 2), in this case, presented accuracy below other models, reaching 62.66%. The worst accuracy results in the validation stage were with the EfficientNetB0 (55.00%), VGG16 (56.45%), EfficientNetB7 (58.81%), VGG19 (60.21%) architectures.

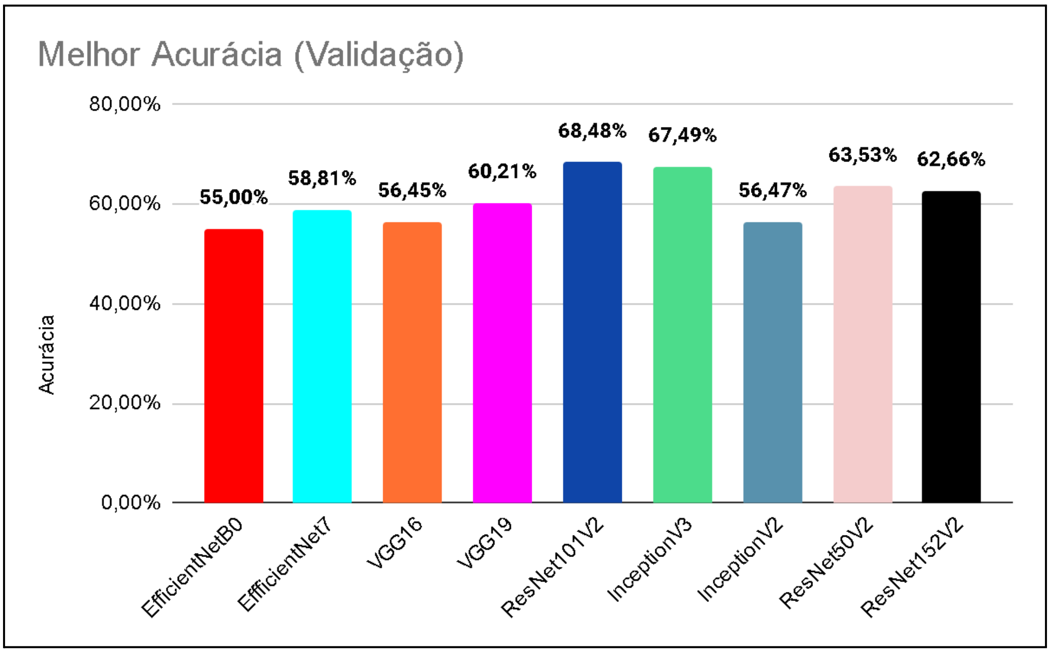

Figure 3. Better model accuracies in the validation stage.

5 Final considerations

In this work, the accuracy results of different architectures of CNNs for the classification of images of skin lesions were presented. The architectures with the best accuracy results were the models obtained with the architectures ResNet101V2 (72.48% in training and 68.48% in validation), InceptionV3 (69.64% in training and 67.49 in validation), and ResNet151V2 (74 .56% in training and 62.66% in validation). It is hoped that the results presented can contribute to the construction of tools that help dermatologists in the diagnosis of skin lesions.

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