A Comparison of Neural Network Approaches for Melanoma Classification

Maria Frasca, Michele Nappi, Michele Risi
Genoveffa Tortora and Alessia Auriemma Citarella

Problem

Melanoma is the deadliest form of skin cancer and it is diagnosed mainly visually, starting from initial clinical screening and followed by dermoscopic analysis, biopsy and histopathological examination. A dermatologist's recognition of melanoma may be subject to errors and may take some time to diagnose it.

Is it possible to create a diagnostic assistance system for melanoma detection?

Context

- Melanoma is a tumor, often very aggressive, which originates in the skin or, more rarely, in the eyes or mucous membranes [1]. It is originated when a genetic error occurs in melanocytes, located in the basal part of the epidermis.
- It is responsible only for 4% of all cancers occurred in human skin, but it is accountable for 75% of deaths caused by skin cancers [2].
- The manual inspection from dermoscopy images made by dermatologists is usually time-consuming, may be subject to errors and it is a subjective analysis [3].
- To identify skin lesions, dermatologists adopt the "ABCDE Rule" (A = asymmetry, B = edges, C = color, D = size, E = evolution) [4].

Contributions

- A process mainly based on the adoption of deep learning models (2D Convolutional Neural Network, Residual Neural Network, Self-Organizing Map Neural Network) for the classification of melanoma. Our aim is *i)* to compare the results of the adopted techniques in order to select the best effective neural network for the recognition and classification of melanoma, and *ii)* to evaluate the impact of the pre-processing phase on the final classification.
- Use of a dataset consisting of biomedical data of 10.015 dermatoscopic images divided into 7 target classes, as Actinic keratoses and intraepithelial carcinoma/Bowen's disease (akiec), basal cell carcinoma (bcc), benign keratosis like lesions (solarlentigines/seborrheic keratoses and lichen planus like keratoses, bkl), dermatofibroma (df), melanoma (mel), melanocytic nevi (nv) and vascular lesions (angiomas, angiokeratomas, pyogenic granulomas and haemorrhage, vasc).

References

[1] N. Razmjooy *et al.* "A computer-aided diagnosis system for malignant melanomas." Neural Computing and Applications 23.7-8 (2013): 2059-2071.

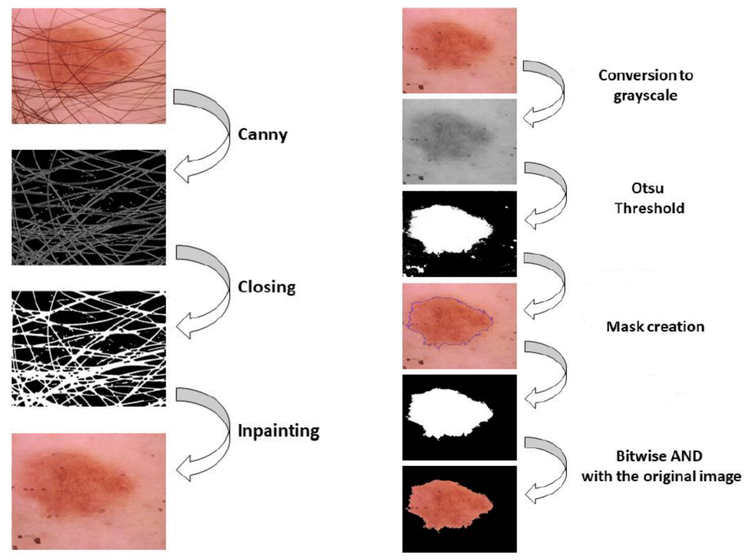
[2] C. Lu *et al.* "Automated segmentation of the melanocytes in skin histopathological images." IEEE Journal of Biomedical and Health Informatics, 17.2 (2013): 284-296.

[3] C. N. Vasconcelos, and B. N. Vasconcelos. "Convolutional neural network committees for melanoma classification with classical and expert knowledge based image transforms data augmentation." arXiv preprint arXiv:1702.07025 (2017).

[4] R. J. Friedman *et al.* "Malignant melanoma in the 1990s: The continued importance of earlydetection and the role of physician examination and self- examination of theskin." CA: A Cancer Journal for Clinicians, 41.4 (1991): 201–226.

The Analysis Process

Step 1 - Image Pre-processing and Data Augmentation. Given the large number of classes, the problem has been binarized, making all the labels other than *"mel"*, equal to *"not mel"*. This transformation returned an unbalanced dataset ad to mitigate this problem, after the phase of image processing has been carried out we defined and implemented a *Data Augmentation* process through concatenated operations composed of horizontal and vertical flips, rotations of *+180, +90 and -90 degrees*, each original image of melanoma has been used to generate seven distinct images.

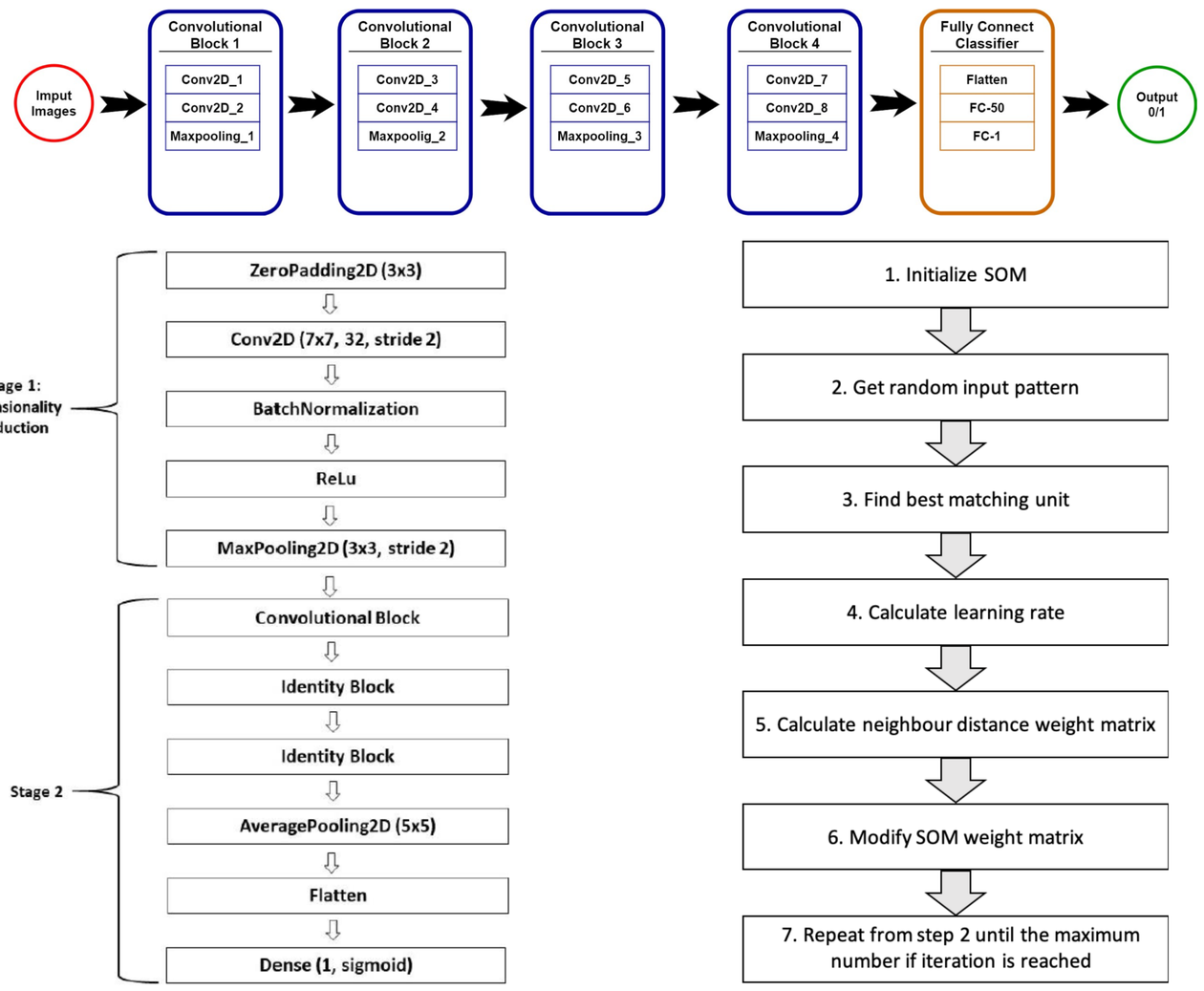


Concerning the *Pre-Processing*, there are three main steps to automatically extract a lesion in a dermoscopic image. These steps strongly depend on the clinical features of a lesion. The operations that have been performed are:

- ***Hair removal:*** hair occlusion in dermoscopy images affects the diagnostic operation of the skin lesion.
- ***Lesion segmentation:*** its primary purpose is to select specific objects or regions in an image.
- ***Clinical feature segmentation:*** a local segmentation of the image is performed by highlighting the clinical features of a lesion such as the texture, shape and color.

Step 2 - Deep Neural Network Classification. Deep Learning can be useful in the study and classification of skin cancer. In particular, images were classified by the following deep neural networks:

- ***2D-Convolutional Neural Network (2D CNN)***: it was trained through 100 epochs, batch size of 50 and by using the Adam optimizer. The neural network was composed with 4 convolutional blocks and one last fully connected block for the classification. The training set, test set and validation set have been set by considering the percentages 80%, 20% of the initial dataset, and 20% of the training set, respectively.
- ***Residual Neural Network (ResNet)***: it was trained with 100 epochs, batch size equal to 32, we used Adam optimizer with learning rate equal to 0.001 and clipnorm equal to 1, and binary cross-entropy as loss function.
- ***Self-Organizing Map Neural Network (SOM)***: The number of neurons used to configure the grid was 20x20. The initial learning rate used was 0.5 while the final rate was 0.01. The training was carried out using a number of supervised/unsupervised iterations both equal to 2000.



Results

- ResNet obtained better accuracy results (i.e., ***81,5%***); 2D CNN (***74,1%***) suffered of a generally problem of gradient cancellation, whose descent, given by the minimization of the error function, is reduced exponentially through the backpropagation of the previous layers (in the ResNet this did not occur due to residual learning); the main limitation for SOM (***69%*** for accuracy) was the static nature of the size and topological structure of the output grid.
- With respect to the process carried out without image pre-processing, we obtained an improvement of ***2,2%*** for the accuracy (2D CNN and SOM), and ***2,5%*** for ResNet.