FPGA based diagnostic system for Malignant Melanoma dermatoscopy image recognition

A.K. Ulyankin[1], O.O. Myakinin[1]

[1]Samara National Research University, Moskovskoe Shosse 34, Samara, Russia, 443086

Abstract. The use of Deep Learning (DL) and Convolution Neural Network (CNN) combined with Digital Image Processing (DIP) techniques could improve the diagnostics and make it more accurate. This project proposes an approach of Malignant Melanoma detection through the use of NN and DIP, training the neural network with a large number of dermatoscopic images previously verified by biopsy (histology). Moreover, an optimization of the processing time of DIP algorithms and CNN weights through FPGA (Field-Programmable Gate Array) has been discussed. It is necessary for a lower power consumption and portability, as well as to create an embedded system that will be able to assist in making the medical diagnosis of melanoma on its early stages.

1. Introduction

This project consists of three major parts, an image capturing device, a computer and the DE10-nano board. For better quality of image, firstly high-quality lenses are used to acquire precise pictures of the nevus. Those pictures are sent to be processed and analyzed. After being sent by a mobile device, the image is received by a PC. That is used to control data flow to the FPGA, when the FPGA is available for processing it, then the image is sent to FPGA. [1].

After that the system must extract descriptors, which capable of retrieving the same characteristics used by oncologists, such as symmetry and color, respectively. In next step, these descriptors are sent to a neural network, also implemented on the FPGA fabric, for analysis and the chance of that signal being a melanoma is outputted.

2. Analysis

The FPGA makes possible to obtain a greater processing speed and lower power consumption, thus being possible to realize the analysis of a large number of images in reduced time, while requiring lower power consumption, compared to applications designed for general purpose processors. Moreover, to further improve our design, the circuit on FPGA was implemented by using fixed-point arithmetic. All these characteristics made possible to have a portable and efficient solution to assist healthcare professionals in the diagnosis of melanoma.

The image processing routines are executed on the FPGA fabric and are composed of multiple steps.

2.1. Segmentation

The first operation to be performed is segmentation. A binary mask is created and used to compute the descriptors. The mask defines the region of nevus.

$$\mathbf{C}^k = \begin{bmatrix} c_{00}^k & \cdots & c_{0j}^k & \cdots & c_{0M}^k \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ c_{i0}^k & \cdots & c_{ij}^k & \cdots & c_{iM}^k \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ c_{N0}^k & \cdots & c_{Nj}^k & \cdots & c_{NM}^k \end{bmatrix}. \quad (1)$$

$$\mathbf{P}^k = \begin{bmatrix} p_{00}^k & \cdots & p_{0j}^k & \cdots & p_{0M}^k \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ p_{i0}^k & \cdots & p_{ij}^k & \cdots & p_{iM}^k \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ p_{N0}^k & \cdots & p_{Nj}^k & \cdots & p_{NM}^k \end{bmatrix}, \quad (2)$$

$$p_{ij}^k = \begin{cases} 1 & \text{se } c_{ij}^k \geq a \\ 0 & \text{se } c_{ij}^k < a \end{cases}. \quad (3)$$

Being $\boldsymbol{C^k}$ the grayscale image, $\boldsymbol{P^k}$ the thresholded image (mask) and a threshold/

2.2. Symmetry analysis

$$d_0^k = \left| \sum_{\substack{i=0 \\ i<c_x}}^{N-1} \sum_{j=0}^{M-1} p_{ij}^k - \sum_{\substack{i=0 \\ i\geq c_x^k}}^{N-1} \sum_{j=0}^{M-1} p_{ij}^k \right| \quad (4)$$

$$d_1^k = \left| \sum_{i=0}^{N-1} \sum_{\substack{j=0 \\ j<c_y}}^{M-1} p_{ij}^k - \sum_{i=0}^{N-1} \sum_{\substack{j=0 \\ j\geq c_y^k}}^{M-1} p_{ij}^k \right| \quad (5)$$

Where the values C_x^k and C_y^k are the centers of mass on each of the x and y-axis. Which are computed by finding the contour of our interest area and calculating its moment, for each axis. Resulting in two descriptors, d0 and d1.One of the important parameters of classification is the nevus symmetry.

2.3. Color analysis

In addition, other important parameters are the mean and variance in each color channel, that states if the mole to be analyzed has uniform colors, resulting in six descriptors d3 to d8.

$$d_3^k = \frac{1}{L} \sum_{i=0}^{N-1} \sum_{j=0}^{M-1} \mathrm{R}\left(v_{ij}^k\right) \times p_{ij}^k \quad (6)$$

$$d_4^k = \frac{1}{L} \sum_{i=0}^{N-1} \sum_{j=0}^{M-1} \left(\mathrm{R}\left(v_{ij}^k\right) - d_3^k\right)^2 \times p_{ij}^k \quad (7)$$

$$d_5^k = \frac{1}{L} \sum_{i=0}^{N-1} \sum_{j=0}^{M-1} \mathrm{G}\left(v_{ij}^k\right) \times p_{ij}^k, \quad (8)$$

$$d_6^k = \frac{1}{L} \sum_{i=0}^{N-1} \sum_{j=0}^{M-1} \left(\mathrm{G}\left(v_{ij}^k\right) - d_5^k\right)^2 \times p_{ij}^k, \quad (9)$$

$$d_7^k = \frac{1}{L} \sum_{i=0}^{N-1} \sum_{j=0}^{M-1} \mathrm{B}\left(v_{ij}^k\right) \times p_{ij}^k, \quad (10)$$

$$d_8^k = \frac{1}{L}\sum_{i=0}^{N-1}\sum_{j=0}^{M-1}\left(\mathrm{B}\left(v_{ij}^k\right) - d_7^k\right)^2 \times p_{ij}^k. \tag{11}$$

Being L, the number of pixels equal to 1 in the binarized matrix, R(), G(), B(), functions that selects the red, green and blue channel, respectively, of the pixel V_{ij}

2.4. Diameter Calculation

The diameter of the nevus is computed through the use of the contour points from the binarized image. Using these points, a circle of minimum area, that has all the contour points inside is computed. The diameter of the circle is then our 9th descriptor d8.

2.5. Data analysis (FPGA)

If the system has all the descriptors it is needed to analyze them, for that a machine learning algorithm will be used, the type of Multi-Layer Perceptron (MLP). This algorithm is composed of multiple basic units called neurons, as depicted in the following picture.

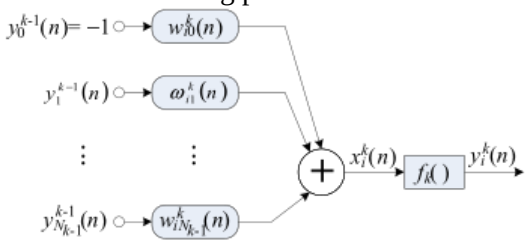

Figure 1. The Multi-Layer Perceptron.

Each neuron is a complex unit that sums all its inputs and a bias and passes through an activation function. These activation functions were implemented by using state-of-the-art techniques, to efficiently compute the mathematical functions and requiring a minimal number of slices for memory.
The neurons are then aggregated in layers. In which each layer in a network is fully connected with all other neurons in the past layer.
In this application, a MLP with 3 layers and 36 neurons were used.

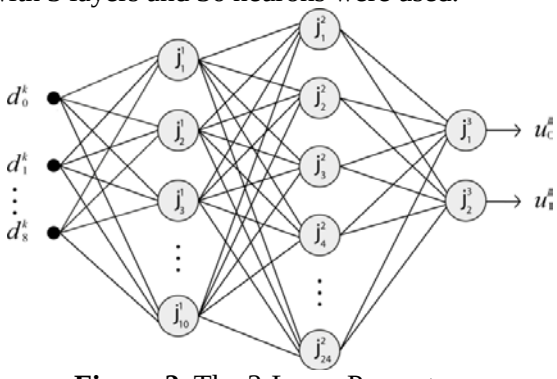

Figure 2. The 3-Layer Perceptron.

Where, u0 and u1 are the outputs corresponding to being melanoma or not, respectively, and dkj is the j-th descriptor at the instant k. The network was trained using the backpropagation algorithm, before being inserted in FPGA.
In the image below we have a high level visualization of the system implemented in FPGA. The three entries are referring to the image, the entries referring to R, G and B channels. And two outputs indicate whether or not the analyzed image has melanoma.
Within this block, we have two subsystems, one with the implementation of digital image processing (DIP) for the extraction of the descriptors and the other with the machine learning. In the figure below we can visualize these blocks.

The block of DIP was implemented in FPGA as shown below. In this block we have three system inputs for the R, G and B channels of the image and nine outputs, with nine descriptors extracted from the image. Inside we have subsystems that are responsible for transforming the image from RGB to grayscale, for generating the nevus mask, for applying the mask to the RGB image, for calculating the average in three RGB channels, for calculating the variance in three RGB channels, for calculating the diameter and calculation of the symmetry in the x and y axes.
The block of Artificial Neural Network was implemented in FPGA as stated on your design block diagram shown below. In this block we have nine entries referring to the descriptors extracted from the image by the DIP subsystem and two outputs, which are the outputs of the FPGA referring to the classification of the image. Inside we have multiple subsystems that represent neurons, in each block of neuron we have two subsystems, one with the implementation of the linear combination and another - with the activation function.

3. Results and Conclusion

Following the implementation of the DIP routines, the network was also implemented using fixed-point format for numerical representation. Moreover, although the network was trained on software and the weights computed using single-precision floating-point format, there was no perceivable accuracy loss of the implementation on FPGA. The result of Malignant Melanoma detection is 90% correct in the test dataset chosen.

4. References

[1] ADDI PROJECT: PH2Database [Electronic resource]. – Access mode: https://www.fc.up.pt /addi/ph2%20database.html.