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Deep Neural Network for Covid-19 Pandemic Recognition Using CT Data

AMINE BEN SLAMA[1,*], HANENE SAHLI[2], ABDERRAZEK ZERAII[1], HEDI TRABELSI[1], LEILA BEN FARHAT[3], SALAM LABIDI[1] AND MOUNIR SAYADI[2]

[1]*Laboratory of Biophysics and Medical Technologies*
Higher Institute of Medical Technologies
University of Tunis El Manar
Tunis, 1006 Tunisia
[2]*Laboratory of Signal Image and Energy Mastery*
The National Higher School of Engineers of Tunis
University of Tunis
Tunis, 1008 Tunisia
[3]*Department of Radiology*
Monji Slim Hospital
La Marsa, 2070 Tunisia

Covid-19 pandemic detection is the key to health safety and coronavirus prevention. Due to the complex changes in CT scan treatment, it is difficult to identify the Covid-19 in the lung image. According to the latest clinical research, an automated fast framework is still required to resolve error prone problem from the pandemic assessment and Covid-19 patients screening during this critical control period. Computer aided methods can be very useful in this regard. They are suitable to estimate the infected lung boundary based on elliptical Hough transform with reduced time processing. In this paper, we propose to use a computerized approach to show that the deep neural network (DNN) is a distinctive method to classify Covid-19 pandemic. Experimental results on various lung CT scan images of different Covid-19 patients, demonstrate the effectiveness of the proposed methodology when compared to the manual scoring of pathological experts. According to the performance evaluation, we recorded more than 92% for accuracy of infection detected in ROI scoring over the truths provided by experienced radiologists. Comparative automatic studies are performed to demonstrate the suitability of the proposed technique over other advanced techniques from the literature.

Keywords: Covid-19 pandemic, CT data analysis, deep neural networks (DNN), classification scheme, convolutional neural network (CNN)

1. INTRODUCTION

The coronavirus disease (Covid-19) causes severe respiratory symptoms. This syndrome is associated with high level of emergency admission and mortality [1]. Covid-19 surprised the world with its fast spread, and potential deep impact on the lives of billions of people and low economic perspective. Until now, there are approximately more than 213 countries confirmed with over than 48,129,210 confirmed cases (88,613 with critical condition) and 1,224,506 deaths, with a mortality rate of 3%.

This new virus is an infectious, contagious disease with various clinical signs, where the diagnosis is made by pathologists using visual inspection of reverse transcription pol-

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ymerase chain reaction (RT-PCR) sample [2]. This test is consequential. But it is error prone and notably time consuming. RT-PCR has been reported to suffer from high false positive rates. The effectiveness of this approach is highly dependent on the pathologist's attention and experience. Advances in computer technology now make computer-assisted diagnosis a possibility. Automated analysis of lung CT scan images does not replace the pathologist, but it may assist him or her to get consistent, objective and rapid diagnoses due to its high sensitivity [3]. From December 2019 until now, millions of people die due to Covid-19 infection. Therefore, automatic schemes focused on lung CT images with either artificial intelligence techniques can potentially make a significant contribution to health care [4-6]. The most important aim of these computerized methods is to identify the different infected region in lung CT image. Afterward, the detection of progression disease score is highlighted in order to give quantitative and accurate measures in the Covid-19 diagnosis process. Fig. 1 sets some light on the key steps of the proposed methodology.

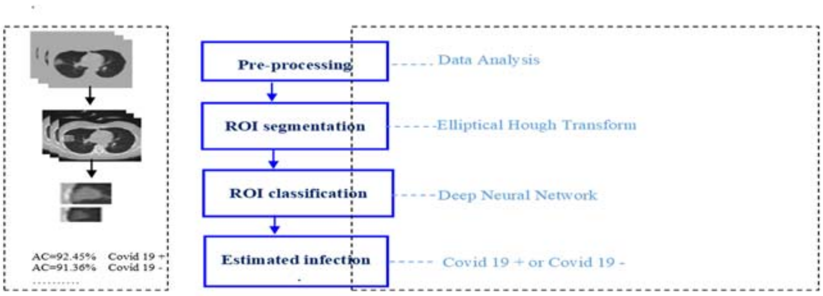


Fig. 1. Flowchart of the proposed system.

Multiple works [7-9] were interested to an automatic recognition of lung from CT images. The enhancement process itself does not increase the pertinent information existing in the data; it simply emphasizes some specified image characteristics. Until now, multiple analysis methods [10] applied to CT scan which admits insufficient parameters to provide different lesion assessment. Therefore, as yet many methods have been suggested to solve this issue. Several works [11-13] were based on segmentation approaches as an intermediate preprocessing step for valuable characteristics extracting that improve the diagnostic system.

Further segmentation approaches are developed such as the absolute fuzzy connectedness with gradient focused affinity to level sets [14]. However, the iterative relative fuzzy connectedness method turned out to be efficient considering precision and accuracy terms. It is proved to be usefulness in segmentation task [15] considering the intensity gradation in MRI and CT images in several applications for instance: Multiple Sclerosis [16], artery-vein separation [17], brain tumor segmentation [18, 19]. Different segmentation techniques were expanded for the CT region detection [20] by the use of active contour techniques [21], Hough transform models, machine learning [23], deformable models, morphological operators. In this paper, the specific process defy well-respected is 2D lung CT image segmentation based on elliptical Hough transform for automatic anomalous region recognition.

Fields within the biomedical analysis are proposed in the literature which can reliably overcome the overlapping difficulty and sort out the incorporated disease in clinical signal and image data set. An accurate deep classifier is the most significant component of any computer aided diagnostic scheme that is developed to assist specialists in disease prognosis. Computer aided design systems (CAD) are considered to support radiologists in the process of visually screening disorder. The use of a precise CAD scheme for early recognition could absolutely facilitate medical therapy. The deep learning system is a relatively new field in machine learning. This method automatically generates multilevel models with categorized representations of the input data. For classification schemes, these representations are more resistant to the irrelevant variations (*e.g.* artifacts) that are often present in the input dataset. The deep belief network (DBN) model is a deep learning system that has increased in attractiveness as an effective implementation of a proficient learning technique. This latter stacks simpler model; known as restricted Boltzmann machines (RBMs). The included unsupervised learning presents a multilevel structure layer-by-layer, automatically extracting increasingly more abstract representations from the layers. After this process, the DBN can then be used to adjust the weights between adjacent layers of a combined (DBN-DNN). DBN-DNN mostly avoids the gradient problem that can occur when training a standard neural network (without pre-initialization). The pre-training method also improves model performance by enhancing the model and generalization avoiding overfitting. The majority of the proposed methods expose many enhancements in the first stages of automatic diagnostic process by detecting the region of interest (ROI) and then extracting significant characteristics of pathologies. In this study, deep neural network is used to diagnose the Covid-19 pandemic.

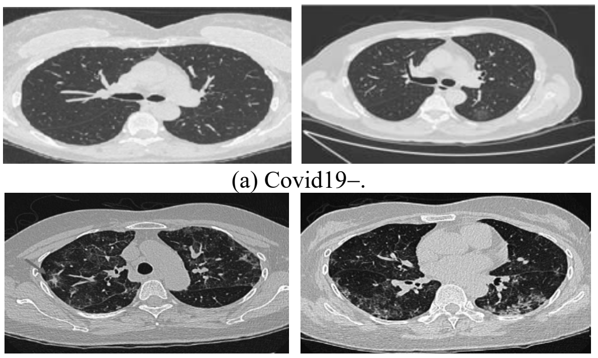
The contributions of this work are two folds. First, an automated segmentation strategy is developed based on an elliptical Hough transform algorithm (EHT). The resulting lung regions are obtained by the estimation of the deviation angle between the major and minor axis of ROI. This technique can be well-suited for CT image segmentation. Then, we introduce a classification approach using the deep neural network to recognize the studied CT database by dividing into two categories: Covid19− (healthy topics) and Covid19+ (anomalous topics). This method is especially beneficiary for detecting the disease progression.

This paper is organized as follows: Section 2 describes the proposed computer aided methods. In Section 3, experimental results and discussions of the entire proposed approach are reported using lung CT scan. Conclusions are provided in Section 4.

2. MATERIAL AND METHODS

In this work, from Github website information's, we have taken out all computerized tomography dataset. All registered cases are obtained at the first affiliated hospital of Zhejiang university in the period from January 19 to February 14, 2020 [3]. Each Covid19+ topics were confirmed with Reverse transcription polymerase chain reaction (RT-PCR) technique.

Indeed, RT-PCR is a laboratory method that combines reverse transcription of RNA into DNA (in this background appointed finished DNA or cDNA) and amplification of specific DNA targets employing polymerase chain reaction (PCR). CT samples were used in this contribution involving 152 Covid19+ and 43 Covid19− samples. The used sets contain sequence respecting 256 grey levels and 1206*1263 pixels for each image. Fig. 2 shows quantitative examples of lung CT scan image of two categories (Covid19+, Covid 19−). The segmentation process was tested with images from our database. All tacky images that have misplaced border, marked attenuations and positioning outside the ROI have been abandoned.



(a) Covid19−.

(b) Covid19+.

Fig. 2. Lung CT scan examples of four patients.

2.1 Description of the Proposed Method

The proposed computerized method for Covid19 recognition consists mainly of two steps:

(A) Detection of Covid19− infected cases

The first step amounts to construct a binary image for the estimation of infected and diseased region. The gray scale value of detected region was computed by the average value of ROI-pixels. The threshold was manually selected from one ROI for each participant. Lung abnormalities can be characterized by elliptic geometry. The projected algorithm starts by obtaining a rough assessment of the curve via threshold segmentation. The first class presents the infected region and the second is the background. Consequently, we propose to detect approximately the ROI using the ellipse contour initialized by the thresholding step for extracting different region from Lung CT image.

(B) Classification of Covid19− infected cases

By the use of Elliptical Hough Transform (EHT), the lung regions (ROI) are steered by the training network with their desired outputs. Once the training process is completed, the structure and synaptic weights of the network are safeguarded to be ready for the validation processing of CT images.

2.2 Lung Boundary Extraction Based Elliptical Hough Transform

The main aim of the automatic segmentation scheme is the boundary extraction of the lung region from the remainder background. In this study, the proposed lung border extraction is focused on elliptical Hough transform procedure (EHT). Here, we report that the elliptic detection of infected region can successfully characterize the pathology compared to healthy subject.

2.3 Lung Region Classification using DBN-DNN

Recurrent neural networks (RNNs), deep neural networks (DNNs) and convolutional neural networks (CNNs) present some training methods among the deep learning approaches. The DNN technique contains two-dimensional hidden layer linked to the upper layer from the network architecture (the weight also). Convolutional layers, pooling layers, fully connected layers and normalization layers are the hidden layers of the DNN model. DNN classifier gives better results by using the training backpropagation algorithm (conjugate gradient training method). The application of DNN method is highlighted in order to classify lung regions using CT images. Until now, this classifier is commonly applied for different medical applications. For the categorization of Covid19 abnormality cases, pertinent characteristic from detected ROI have been chosen in essence to aid pathologists in their diagnosis. We can notice that the segmentation results are accomplished for the training network input. The training and the test phases are finished in DNN classification procedure. The training set contains 91 Covid19+ and 26 Covid19− and the network test is completed with 61 Covid19− and 17 Covid19+. In this work, the DBN-DNN method is performed to separate subjects into two classes: Covid19+ and Covid19− (1 × (2 output classes)). In this work, we used the tangent sigmoid transfer function for all neurons. In view of the resemblance of lung distinctiveness, the DNN system is explored based on the feature number in the training input to get the most effective illustration of the data. Focused on lung feature vectors, the deep learning network is implemented. For deciding on the optimum DBN-DNN structure, a cross-validation strategy is realized. Each experiment includes five folds for the training and one for the validation. We explain that the five-fold cross-validation experiments are dealt for the selection of the optimal hidden nodes number. As shown in Fig. 3, the proposed DNN classifier was trained pursuant the chosen hyperparameters.

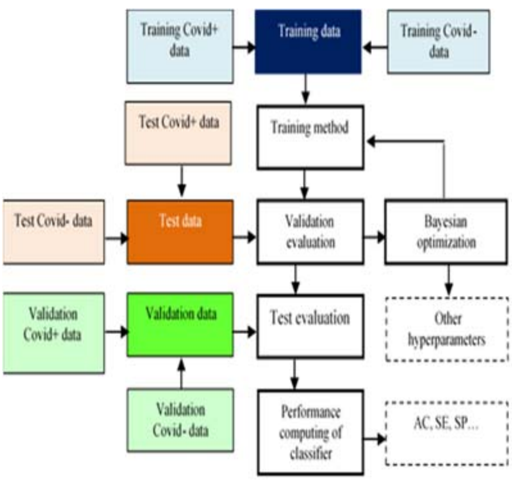


Fig. 3. The proposed optimization processes.

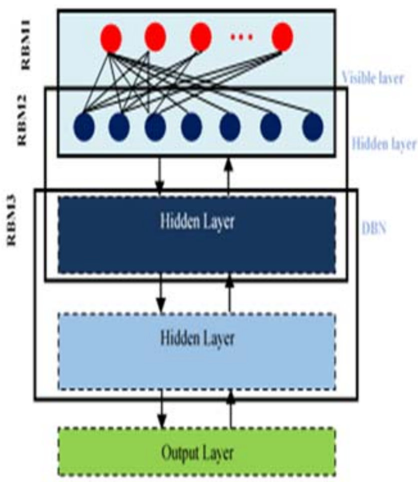


Fig. 4. The structure of the DBN classifier.

2.3.1 DBN classifier construction and training DBN with RBMs

The DBN architecture is organized into the following four main parts: three RBMs and an output layer; as exposed in Fig. 4. First, an unsupervised system is educated for the DBN training. Second, the combination of the DBN classifier and the output layer form the DNN input. In a supervised system, we obtain the DBN and we train the DNN with the backpropagation algorithm.

2.3.2 RBM training process

RBM is random neural network architecture. Two principal layers are: the input layer (visible layer) and the hidden layer; as shown in Fig. 5. The nodes are completely connected flanked by two layers. Nevertheless, no connection is made in the same layer. On the other hand, a bipartite structure is constituted. The bottom layer includes visible nodes (v) and the top layer restrains hidden nodes (h). The symmetric interaction terms between the visible and the hidden nodes are exposed by the matrix W.

The energy function of the joint configuration can be defined by:

$$E(v,h;\theta) = -\sum_{ij} W_{ij} v_{ij} h_j - \sum b_i v_i - \sum a_j h_j. \tag{1}$$

Where $\theta = \{W, a, b\}$ represents the model parameters, a_i is the bias of visible unit i, and b_j is the bias of hidden unit j.

The joint probability distribution of a certain configuration is obtained by the Boltzmann distribution:

$$P_\theta(v,h) = \frac{1}{Z(\theta)} \exp(-E(v,h;\theta)). \tag{2}$$

Where $Z(\theta)$ is the normalization constant.

If $v = (v_1, v_2, \ldots, v_i, \ldots)$ is an input vector to the visible layer, the binary state h_j of the hidden unit j is set to 1 with the probability as follows:

$$P(h_j = 1 | v) = sigmoid(\sum_i W_{ij} v_i + a_j). \tag{3}$$

With the states of the hidden units, the binary state v_i of visible unit i is set to 1 with the probability below:

$$P(v_i = 1 | h) = sigmoid(\sum_j W_{ij} h_j + b_i). \tag{4}$$

RBM strategy is often trained depending on the following phases: (1) the states of the visible units are set according to the training data; (2) Computing the binary states of the hidden nodes; (3) After establishing the states of all the hidden units, the states of all visible units are defined; (4) The gradients of W are assessed by the contrastive divergence method. The gradient descent algorithm is performed to reveal the parameters W, a, b.

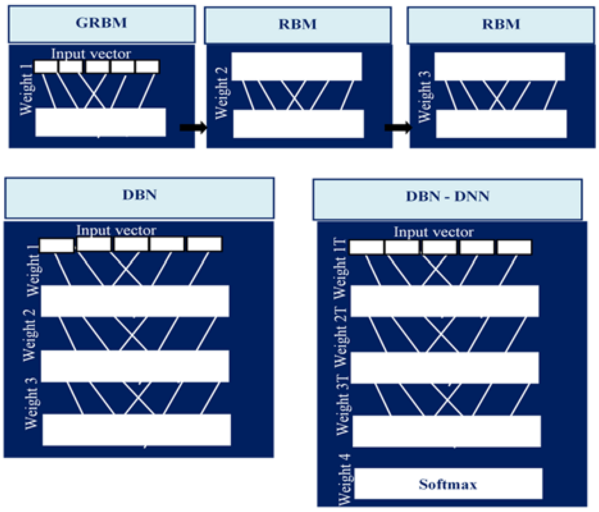


Fig. 5. Training restricted Boltzmann machine (RBM).

3. RESULTS AND DISCUSSIONS

3.1 Results of Lung ROI Detection

In this part, the lung ROI detection results are demonstrated based on the elliptical Hough transform. In Fig. 6, we illustrate the fixed ellipse that corresponds to the central, established by the CT image. The major and minor axes of the lung region are obtained after outer-to-outer measures event, in support of a given ellipse.

3.2 Results of Covid-19 Classification

Fig. 6 reveals the EHT model applied in different CT image. In order to illustrate performance of our method in lung infection detection on the CT database, we choose 6 images representing different patient affected by Covid-19. The final lesion contours using the proposed algorithm are used as an input for the DBN-DNN training set.

To exemplify the performance of the proposed process, various computer-aided-methods (DBN-DNN and CNN systems) are as well tested. From the cross-validation results highlighted in Table 1, it is comprehensible that the DBN-DNN method is more robust than the CNN classifier in terms of validation error rate (less than 8%).

Table 1. Validation error rates (%) of the DNN and CNN classifiers using the five-fold cross-validation technique tested on the training CT images dataset (mean values±standard deviation).

Classifier	Fold 1	Fold 2	Fold 3	Fold 4	Fold 5
CNN	11.2±1.5	12.6±2.1	10.5±1.2	13.6±2.2	11.8±1.7
DBN-DNN	8.6±0.9	9.8±1.3	7.5±0.6	6.4±0.8	7.9±0.7

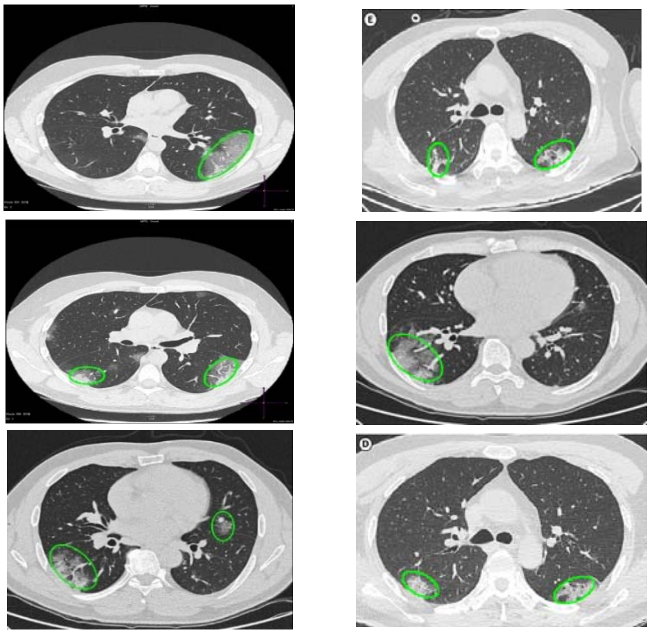


Fig. 6. Lung ROI detection results using frames from two patients affected by Covid19. The fixed ellipse introduces the ROI used to train the deep classification process.

In order to acquire truthful evaluation of the proposed classification approach of Covid19 abnormality, the performance of the proposed classifier was compared with other deep learning process. Based on the convolutional neural network methods, a comparative study of the classification frameworks is introduced. The scaled conjugate gradient (SCG) learning function is employed for enhancing the convergence rate in the CNN structure. As revealed in Fig. 7, the 2D-CNN was utilized in the lung region extraction process. In this task, we can notice that the pooling operations were applied to decrease the data dimension, prevent overfitting and effectively get better the generalization problem. The target of the convolution layer was flattened to a 256-dimensional feature vector. After that, it converted into a 16-dimensional feature vector using a full connection network. Concerning the location attention network, the relative distance value from edge was primary normalized to the same order of magnitude and secondly concatenated to this full connection network. Subsequently, three two connection layers were ensued to come out the ending classification result (Covid19+ or Covid19–) demonstrated with an accuracy rate.

For getting a quantitatively specific comparison of the proposed strategies, we have drawn the receiver operating characteristic curves (ROC) to validate the obtained classification results [21, 22]. Fig. 8 presents the ROC curve to approve the experimental classification results. This common method consists of the area under the ROC curve computing. The value of this area is between 0 and 1. When the area value is 1, it corresponds to an ideal classifier. In this framework, the area under curves is equal to 0.89 and 0.757 for DNN and CNN respectively.

Other used evaluation criteria measures are highlighted in the classification stage; exposed by the following equations:

$$AC = \frac{TP + TN}{TP + FN + TN + FP} \tag{5}$$

$$SE = \frac{TP}{FN + TP} \tag{6}$$

$$SP = \frac{TN}{TN + FP} \tag{7}$$

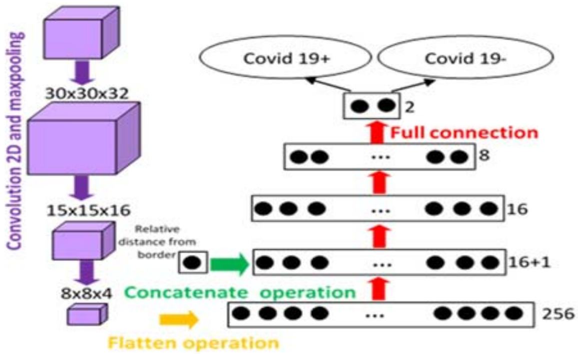


Fig. 7. The structure of the CNN classifier.

TP and TN exhibit the true positive and true negative numbers, and FP and FN present the false positive and false negative numbers, respectively. The proposed approach supplies significant results (AC, SE, and SP) with mean average of 92.04%, 92.65% and 93.18% respectively. (See Fig. 9) Compared to the quantification results by experts, we establish the high accuracy of proposed classification method on the Lung CT database. The proposed scheme was able to detect the infected lung region with an interesting correctness result in the whole images. The proposed CT images analysis method can constantly be used to support doctors by providing a second opinion in their diagnosis of Covid-19 pandemic progress.

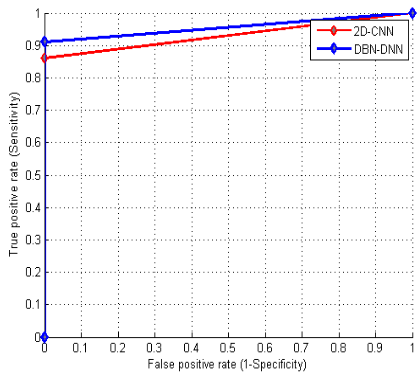


Fig. 8. The performance of the DBN-DNN.

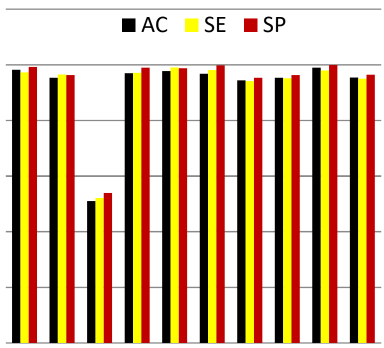


Fig. 9. The resulting AC, SE and SP.

4. CONCLUSIONS

This paper introduces an automatic method to enhance the diagnosis of Covid-19 pandemic by tracking infected region in CT images. Elliptical Hough transform model for ROI lung detection combined with DBN-DNN classifier is proposed for lung area classification and then Covid-19 development analysis. The deep neural network is designed using textural feature in order to determine data categories: Covid19+ and Covid19− for following CT image evaluation. Experimental results demonstrate that the proposed method is highly efficient when compared to the 2D-CNN approach. A multiclass categorization can be applied in the going work by separating subjects into different categories through increasing necessarily the abnormal datasets. Also, other types of features may be applied in order to improve the classification process. The proposed strategy frequently supports a hard groundwork for computer-assisted anomalies evaluation system of an expert premature diagnosis.

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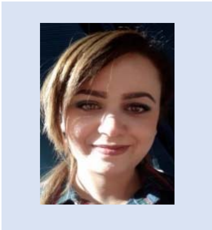
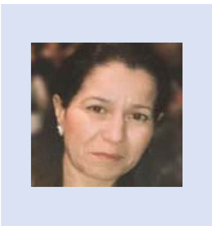
Amine Ben Slama received a Ph.D. degree in Biophysics and Medical Imging and member of research group in Laboratory of Biophysics and Medical Technologies at ISTMT – University of Tunis El Manar. His research interests include image and signal processing, classification and intelligent data processing for parotid gland tumor and vestibular disorder discrimination.



Hanene Sahli received a Ph.D. degree in Science and Technology-Electrical Engineering, from the University of Tunis, ENSIT. She is a member of the research group in Signal Image and Energy Mastery laboratory (SIME) at the same university. Her research interests include machine learning methods, biomedical video and image analysis and biomedical signal processing.

Abderrazek Zeraii was born in Tunis in 1990 (Tunisia). He is a Ph.D. student in Biophysics and Medical Imaging and member of research group in Laboratory of Biophysics and Medical Technologies Tunis. His research interests include MRI imaging and signal processing, neuroimaging tools for post stroke prediction.

Hedi Trabelsi born in 1975 in Tunis (Tunisia), he received the B.Sc. degree in Biophysics from the faculty of Sciences of Tunis. He is currently a Professor at the Higher Institute of Medical Technologies of Tunisia University of Tunis El Manar. His research interests are focused on diffuse optical tomography and physics simulation.



Leila Ben Farhat born in 1971 in Tunis (Tunisia), she received a Doctorate degree in Medicine from the Faculty of Medicine of Tunis, she is currently a Professor and Head of the Fepartment of Radiology at Monji Slim Hospital, also she is a member of the European Society of Radiology (ESR). Her research interests are focused on brain tumor, cardiovascular diseases, abdominal and interventional Imaging.

Salam Labidi received her Ph.D. and started developing her research career by focusing on radiation protection. She is currently a Professor of Biophysics at Higher Institute of Medical Technology of Tunis, University of Tunis El Manar, Tunisia. She directs the research team "Radiation Protection and Biological Image" at Laboratory of Biophysics and Medical Technology, Tunis, Tunisia.

Mounir Sayadi born in 1970 in Tunis (Tunisia), he is currently a Professor at the National Superior School of Engineers of Tunis (ENSIT) and Head of the Laboratory of Signal Image and Energy Mastery SIME. His research interests are focused on adaptive signal processing and filtering, medical image and texture classification and segmentation.