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Automatic Processing of Chest X-Raysto Identify Tuberculosis

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Abstract. In recent years, Artificial Intelligence has become a helpful tool for medical diagnosis. Through techniques such as deep learning, relevant information on medical images is obtained that helps to characterize and detect pathologies, such as tuberculosis; one of the ten most common deaths in the world. A method of automatic classification for chest radiographs to identify tuberculosis is proposed. The convolutionalbase of a convolutional neural network with 16 hidden layers is used: VGG16, which extracts the most relevant characteristics to enter later a classification system. The proposed model obtained 97% accuracy under the evaluation methods: training/test set and cross validation, the efficiency of the reported classification scenario represent a computer assisted diagnosis for the detection and medical images of tuberculosis.Since the results are competitive with those reported in state of the art,it can be applied to different pathologies of chest X-rays.

Keywords: Tuberculosis, chest X-rays, pathologies of chest, VGG16 architecture.

1 Introduction

According to the World Health Organization (WHO), tuberculosis (TB) is in theten death leading causes in the world. This disease is caused by mycobacterium tuberculosis, which usually affects the lungs as well as other parts of the body.TB has a high mortality rate of around 50%, without treatment. Mexico in 2019 had between 23, 000 and 37, 000 new cases of TB, with a rate of 23 cases per100, 000 inhabitants, primarily young adults. Recently, it continues to representa significant problem and according to reported figures, an excess in the number of expected cases has occurred in recent years, mainly in young adults of both sexes; the rate is estimated

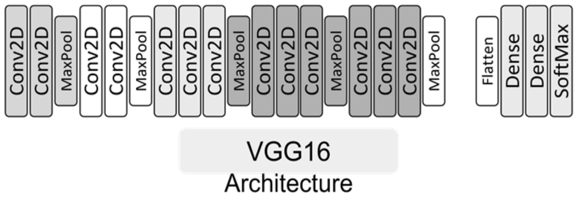

Fig. 1. Convolutional base (before flatten) of the neural network used to obtain themost important characteristics of chest radiographs to identify tuberculosis.

at 51.7 cases per 100, 000 inhabitants. The most used diagnosis to detect tuberculosis is through chest X-rays [1].

Artificial Intelligence (IA) currently encompasses a wide variety of subfields,such as deep learning, which attempts to model high level abstractions in data using computational architectures that support multiple and iterative nonlinear transformations of data expressed in matrix or tensor form. Therefore, automatic learning represents an emerging area in computer assisted diagnosis to detect, through imaging, different pathologies [2].

In the present study, a convolutional neural network (CNN) is implemented, which corresponds to receptive fields in a very similar way to neurons in the primary visual cortex of a biological brain. This type of network is very effective for artificial vision tasks, such as image classification and segmentation, since its application is carried out in two dimensional matrices [3]. The VGG16 is a CNN architecture [4]. Its name comes from the developer team Visual Geometry Group, in Oxford University, and the number of preprocessing layers it contains (16 processing layers) as illustratedin Fig. 1.

The model only requires a specific preprocessing that consists of subtracting from each pixel the average RGB value, calculated in the training set. During model training, the input to the first convolution layer is an RGB image of size 224 x 224. For all convolution layers (Conv2D), the convolution kernel is of size 3×3: the smallest dimension to capture the notions top, bottom, left/right and center. This was a model specificity at the time of publication [5]. Until VGG16, many models were geared towards higher dimensional convolution kernels (size 11 or size 5, for example).

Remember that the objective of these layers is tofilter the image, keeping only the discriminating information, such as atypical geometric shapes. These convolution layers are accompanied by Max Pooling layers, each 2×2 in size, to reduce the size of the filters during training. At the output of the convolution and pooling layers, we have 3 layers of fully connectedneurons. The first two are composed of 4096 neurons and the last one of 1000 neurons with a softmax activation function to determine the image class [6]. Asit can see, the architecture is clear and easy to understand, which is also a strongpoint of this model.

2 Methodology

A data set from the Montgomery County Tuberculosis Screening Program was used. This set contains 138 frontal chest radiographs manually labeled by expertsin the field,

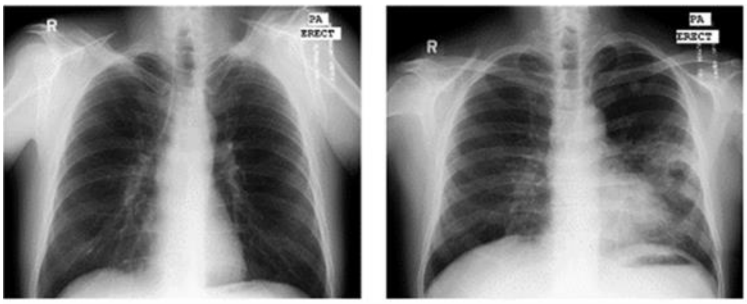

Fig. 2. Sample from the Montgomery dataset reported in the Kaggle repository with138 chest radiographs divided into (left) normal and (right) tuberculosis.

of which 80 are normal cases and 58 are cases with manifestations ofTB. In Fig. 2 is shown the two class types of the data set used in the proposed methodology. Thoracic images require preprocessing before entering the VGG16 architecture, this step is important, since the neural network needs to extract features from the structure images themselves. Preprocessing consists of resizingall X-ray images to 224×224 pixels.

The VGG16 architecture was used as a feature extractor through its convolutional base, to obtain a feature vector. Subsequently, the vector entered two classification scenarios: cross validation (CV) with 10 and 20 folds for the original training set, respectively; and training/test set providing 80% of the data set for training and 20% for testing the scenario.

For both classification scenarios, three classifiers were used: Support Vector Machine (SVM), Naïve Bayes (NB), and Centroid Based Classifier (CBC), since these classifiers have reported strong and competitive values in the literature, in other words, the three are widely usedin state of the art. To quantify the behavior of the proposed methodology, the accuracy and precision evaluation metrics were used, based on the confusion matrix, which permits identifying true or false predictions. Fig. 3 illustrates the proposed model.

The input to cov1 layer is of fixed size 224 x 224 RGB image. The imageis passed through a stack of convolutional (conv.) layers, where the filters were used with a very small receptive field: 3×3 (which is the smallest size to capture the notion of left/right, up/down, center). In one of the configurations, it also utilizes 1×1 convolution filter, which can be seen as a linear transformation of the input channels (followed by non-linearity).

The convolution stride is fixed to1 pixel; the spatial padding of conv. layer input is such that the spatial resolution is preserved after convolution, i.e. the padding is 1-pixel for 3×3 conv. layers.

Spatial pooling is carried out by five max pooling layers, which follow some of the conv. layers (not all the conv. layers are followed by max pooling). Max-poolingis performed over a 2×2-pixel window, with stride 2 [7].

Three Fully Connected (FC) layers follow a stack of convolutional layers (which has a different depth in different architectures): the first two have 4096 channels each, the third performs 1000-way ILSVRC (ImageNet Large-Scale Visual Recognition

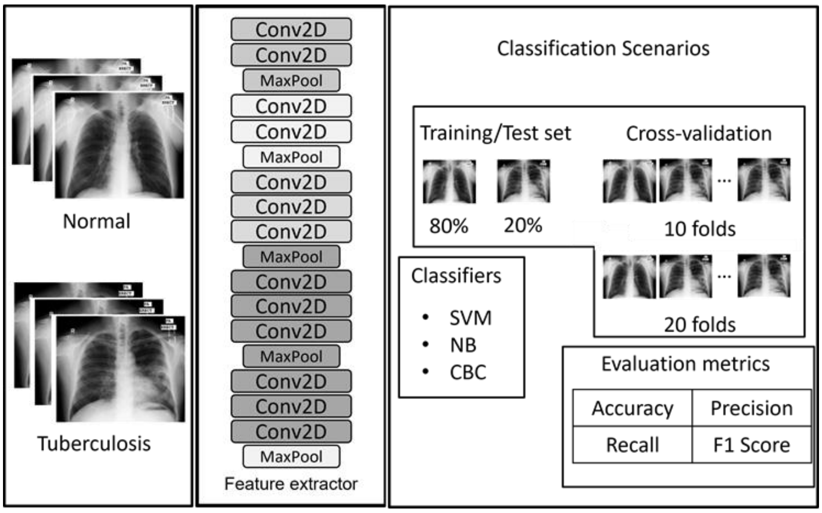

Fig. 3. Automatic processing model of chest radiographs to identify tuberculosis.

Table 1. Training/Test set classification scenario results.

Train/Test set			
Evaluation metrics	SVM	NB	CBC
Accuracy	0.96	0.86	0.86
Precision	**0.97**	0.87	0.87
Recall	0.96	0.84	0.84
F1 Score	0.96	0.85	0.85

Table 2. Results of the cross-validation classification scenario.

Train/Test set				
Folds	Evaluation metrics	SVM	NB	CBC
10	Accuracy	0.82	0.75	0.72
	Precision	**0.86**	0.78	0.74
	Recall	0.82	0.74	0.72
	F1 Score	0.81	0.73	0.71
20	Accuracy	0.86	0.76	0.74
	Precision	**0.89**	0.77	0.76
	Recall	0.85	0.75	0.73
	F1 Score	0.85	0.73	0.72

Challenge) classification and thus contains 1000 channels (one for each class). The final layer is the soft max layer. The configuration of the fully connected layers is the same in all networks.

All hidden layers are equipped with the rectification (ReLU) non-linearity. Itis also noted that none of the networks (except for one) contain Local Response Normalisation (LRN), such normalization does not improve the performance on the ILSVRC dataset, but leads to increased memory consumption and computation time. The VGG is a popular computer vision algorithm that is often usedusing transfer learning to avoid having to retrain it and solve similar problemsthat the VGG has already been trained on.

There are many other algorithms ofthe same type as VGG like ResNet or Xception available in the Keras library [8].

3 Results

In the training/test set scenario, the best results are obtained with the SVM classifier, reaching 97% accuracy. The results are shown in Table 1. The columns show the classifiers with the respective evaluation metrics. Table 2 shows the results for the CV method, comparing the fold increase, obtaining the best resultsin the SVM classifier using 20 folds, with 89% accuracy.

4 Conclusion

The proposed model of automatic classification of chest radiographs to detect tuberculosis obtained 97% accuracy. The value obtained is due to the improvement of the characteristics of chest radiographs, using a convolutional neural network (CNN) from the Visual Geometry Group (VGG16). The reported modelis competitive with the state of the art, as well as a support tool in the medical diagnosis of tuberculosis.

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