Detection and Classification of Dental Caries in X-ray Images Using Deep Neural Networks

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***Abstract*—Dental caries, also known as dental cavities, is the most widespread pathology in the world. Up to a very recent period, almost all individuals had the experience of this pathology at least once in their life. Early detection of dental caries can help in a sharp decrease in the dental disease rate. Thanks to the growing accessibility to medical imaging, the clinical applications now have better impact on patient care. Recently, there has been interest in the application of machine learning strategies for classification and analysis of image data. In this paper, we propose a new method to detect and identify dental caries using X-ray images as dataset and deep neural network as technique. This technique is based on stacked sparse auto-encoder and a softmax classifier. Those techniques, sparse auto-encoder and softmax, are used to train a deep neural network. The novelty here is to apply deep neural network to diagnosis of dental caries. This approach was tested on a real dataset and has demonstrated a good performance of detection.**

Keywords-dental X-ray; classification; Deep Neural Networks; Stacked sparse auto-encoder; Softmax.

I. INTRODUCTION

The radiographs are essential to establish a good diagnosis and identify several problems that are impossible to visualize otherwise.

In orthodontics, dental radiography that is used frequently is the panoramic shot which offers a good "overview" of the teeth and jaws and provides the essential information for screening and diagnosis of several conditions and problems which can be detected at an early age.

Dental caries is an infectious disease. The enamel of the tooth is the first affected. A cavity forms in the tooth and then the decay spreads in depth. If the cavity is not treated, the hole expands and decay can affect the dentin (layer under the enamel) [1]. Pain is beginning to be felt, especially with the hot, cold or sweet things. Decay can affect the pulp of the tooth. We then speak about a toothache. Finally, a dental abscess may appear when the bacteria attack the periodontal ligament, the bone or the gum.

Cavities are very frequent. More than nine out of ten people would have had, at least one, tooth decay. In France, more than a third of 6 year-old children and more than half of 12 year-old children have been affected by this infection. In Canada, 57 percent of children aged between 6 and 12 years have had at least one tooth decay [2].

Dental radiography is an important element in the oral health follow up. It comes in addition to the visual examination done by the dentist. The x-ray allows dentist to "see" what is happening inside of the teeth and bones, thanks to x-rays of low intensity which can cross these structures. The types of radiography most common used by the dentist are: the retro-alveolar, the bite-wing, the panoramic radiograph [3].

The machine learning is defined as the ability to make an agent learn how to take a decision on the basis of observations [4]. In the biomedical context, the action of this agent is reflected by additional information to assist the dentists in making his decision. The patient management is found assigned to several steps, either at the level of diagnosis, of the treatment choice, or also in the surgical intervention. In the framework of this paper, the agent under focus has a role to classify biomedical images by machine learning with the intention of discovering clinically pertinent pathology patterns. These classification operations are based on decision-making tool. However, the inter patients variability poses many challenges for the traditional classification algorithms. These have for the most part been configured and parameterized on small data sets or on a very specific cohort.

During the last decade, the representations learning, a sub-domain of the machine learning, has experienced a huge comeback particularly in the computer vision domain. These representations algorithms have especially allowed crossing a significant step with regards to the objects recognition [7] and to speech recognition [8]. In machine learning, the model of Artificial Neural Networks (ANN) is a valuable tool. Although the ANN, was invented close to sixty years ago, it still remains an area of active research. Recently, with the deep learning, ANN has in fact allowed to dramatic improvements in many applications fields such as the computer vision. The increasing amount of available data and the computing power have made it easier to train high capacity models such as deep learning. However, the inherent difficulties involved in training such models, as an example the local minima, still have an important impact. The deep learning thus aims to find solutions through adding some regularization or improving the optimization. Unsupervised pre-training or dropout are examples of such solutions.

Our contribution is as follows: we propose a system of detection and classification of dental caries in X-ray images using deep neural network. This system can be very useful for dentists to classify dental X-ray images into tooth decay or normal tooth images. A stacked sparse auto-encoder and a softmax classifier [8] are used in our deep neural network.

This paper will be structured as follows: Section 2 presents the recent work. In Section 3, we will describe our methodology and demonstrate how to train and classify tooth images with deep neural networks with a stacked sparse auto-encoder and a softmax classifier. In Section 4, we will give some results of testing experiments. Finally, Section 5 concludes this paper.

II. Related work

Primarily, the detection of dental caries has been a visual process, principally based on visual-tactile examination and radiographic examination [1]. In the recent literature, several techniques have been developed for the detection of dental caries. Kositbowornchai et al. [9] developed a neural network to detect artificial dental caries using images from a charged coupled device (CCD) camera and intra-oral digital radiography. The main disadvantage of this method is that the evaluation of the system was done using teeth with artificial carries, which are completely different from naturally affected ones. Saravanan et al. [10] developed a new method to detect dental caries in its early stage using histogram and power spectral analysis. In this method, the detection of tooth cavities is done based on the region of concentration of pixels with regard to the histogram and based on the magnitude values with regard to the spectrum. The main drawback of this study is that this method depends only on the intensity of pixels. Berdouses et al. [11] developed a computer-aided automated methodology for the detection and classification of occlusal caries from photographic color images. This method is based on the segmentation of photographic color images.

Even though there are many methods for caries detection in early stage, it is still necessary to develop accurate carries detection method to help dentist.

The problem of the classical approach of forms recognition is that it is very difficult to build a good characteristics extractor and that it must be readjusted for each new application. The deep learning is a class of methods whose principles are known since the end of 1980s, but whose use was really generalized since approximately 2012.

One of the perspectives of the techniques of deep learning is the replacement of work which still is relatively laborious by algorithmic models of supervised learning, non-supervised (i.e., not requiring specific knowledge of the problem studied) or by techniques of extraction of hierarchical characteristics.

The idea is very simple: the training system consists of a series of modules, each one represent a processing step. Each module can be trained, with adjustable parameters similar to the weight of the linear classifiers. The system is trained end-to-end: to each example, all the parameters of all the modules are adjusted to approximate the output produced by the system of the desired output. The deep qualifying term comes from the arrangement of these modules in successive layers [12].

To be able to train the system in this way, it must be known in which direction and how much to adjust each parameter of each module. For this, it is necessary to calculate a gradient. The calculation of this gradient is done by the method of back-propagation, practised since mid-1980s. A deep architecture can be viewed as a multilayer network of simple elements, similar to the linear classifiers, inter-connected by training weight. This is what is called a neural network multi-layers.

The advantage of deep architectures stems from their capacity to learn to represent the world in a hierarchical manner. As all layers can be trained, no need to build a characteristics extractor by hand. The training will do it [13]. In addition, the first layers extract some simple characteristics and after that the following layers will combine to form more and more complex concepts.

III. Methodology

In this section, we will describe and motivate how to train and classify tooth images with deep neural networks with multiple hidden layers. Multiple hidden layers neural networks can be very useful in solving classification problems with complex data, such as images. Each layer can learn features at a different level of abstraction. We will use, in our deep neural, stacked sparse auto-encoders for features extraction and a softmax layer to classify the teeth images.

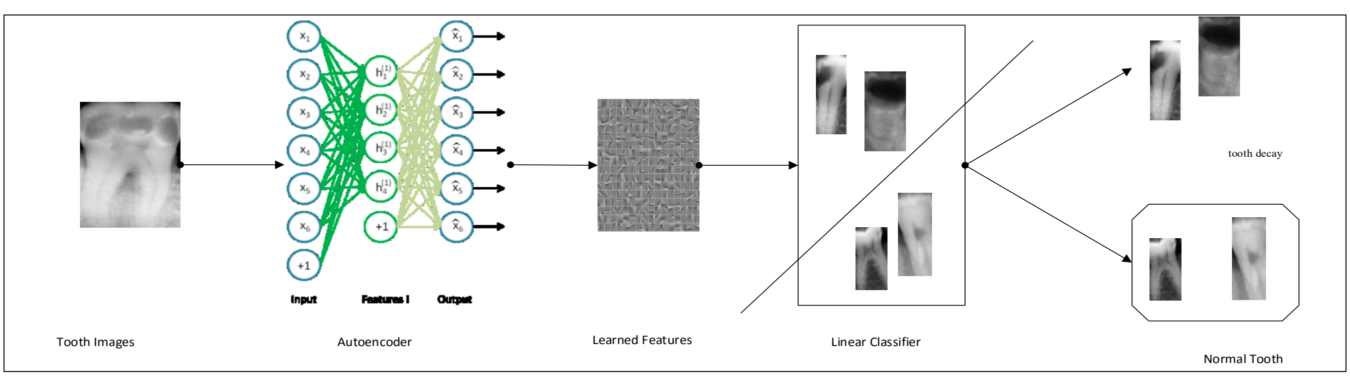

Figure 1. Shematization of our deep neural networks architecture

A. *Stacked Sparse Auto-Encoder*

A stacked auto-encoder is a neural network consisting of multiple layers of sparse auto-encoders in which the outputs of each layer is wired to the inputs of the successive layer [14].

In our work, we choose to use stacked sparse auto-encoder (SSAE) in our deep neural network. The size of tooth image is 64-by-64 pixels. The SSAE is trained, in an unsupervised fashion, in order to extract hidden features.

We begin by the training of the first auto-encoder without use of labels. The size of the input vector in the training data of the first auto-encoder is 4096 nodes. It will be minimized into 300 nodes in the first hidden layer. In the second step, we train another auto-encoder using data as the encoding of the inputs data provided by the previous auto-encoder. In this step, also, we decrease the size of the hidden representation to 150, so that the encoder in the second auto-encoder learns an even smaller representation of the input data. We repeat this step according to the number of the desired layers.

This method trains the parameters of each layer individually while freezing parameters for the remainder of the model. To produce better results, after this phase of training is complete, fine-tuning using back-propagation can be used to improve the results by tuning the parameters of all layers at the same time.

B. *Softmax layer*

The softmax classifier (SMC) is important in the field of machine learning because it can map a vector to a probability of a given output in binary classification. Softmax classifier is a supervised model which uses a logistic regression defined as:

$$h_\theta = \frac{1}{1+\exp(-\theta^T x)}$$

Where θ represents a vector of weight, and x is a vector of input values learned by the previous SSAE.

In the softmax function, we suppose that the labels were binary: y(i) ∈ {0,1}. We used this classifier to distinguish between decayed teeth and normal teeth. The SMC's parameter θ was trained to minimize the cost function. The output of this classifier, as we can see in Fig. 1, is two classes: decayed teeth or normal teeth.

As we can see in Fig. 3, our diagram of the stacked network is formed by the encoders from three auto-encoders and the softmax layer.

IV. EXPERIMENTAL RESULTS AND DISCUSSION

In this section we report the results of testing experiments we carried out to evaluate our deep neural network to classify dental X-ray images. The data set of images was collected from many dentists.

The aim of this work is to classify dental X-ray images into decayed or normal teeth images. So, we have used 1/3 of images for training each class and the rest of other images in the dataset were used for the classification test [14].

The size of input images is 64-by-64 pixels which is an entry vector having as dimension 4096. The images have been adjusted in such way that the value of the pixels is between 0 and 1. For each image, there are two possible labels, corresponding to decayed or normal teeth images.

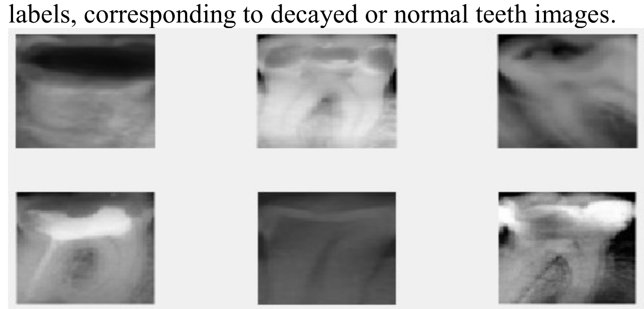

Figure 2. Some Dental X-ray images of our data set

As we can see in Fig. 2, we can view some of the images after loading the training data.

For this experience, all considered networks have a hidden layer containing 3 units and a layer of output. The structure of the different auto-encoders, as we can see in Fig. 3, is chosen in a consistent manner. Each experience has been repeated 20 times, with 500 iterations for the training and 400 iterations for the final learning.

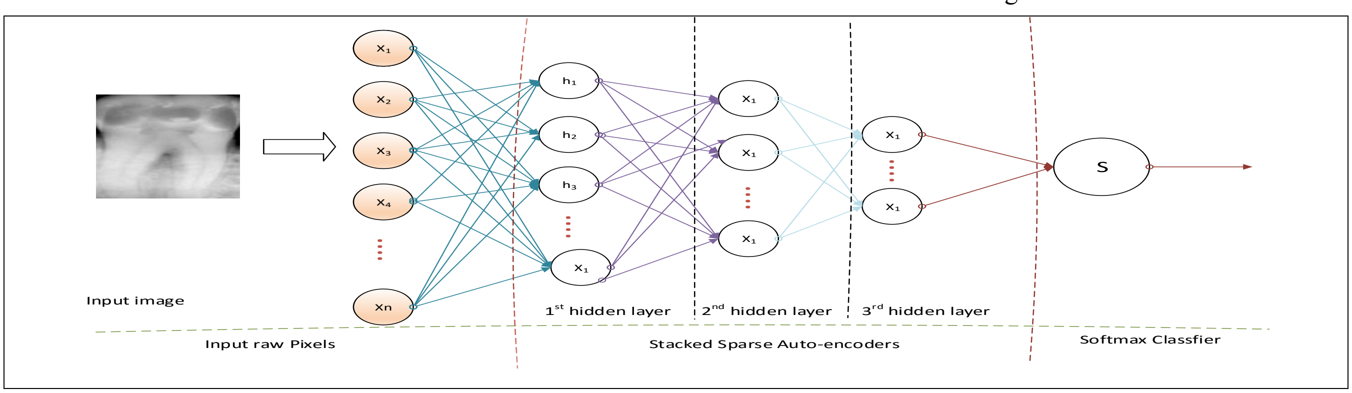

Figure 3. Shematization of stacked auto-encoder and a softmax classfier is to classify dental X-ray images into tooth decay or normal tooth images

To measure the quality of our classification system, we perform the result by the confusion matrix (Table 1). The classification test of our deep neural networks shows very good performance with a rate that reaches 97%.

TABLE I. QUALITATIVE RESULT OF OUR CLASSIFICATION APPROACH

Accuracy *97%*		**Target Class**		
		Tooth Decay	***Normal Tooth***	***Class precision***
Output class	***Tooth Decay***	48 %	1%	98%
	Normal Tooth	2%	49%	96.1%
	Class recall	96%	98%	

In this Table, 48% of all tooth images are correctly classified as decayed teeth. Similarly, 49% cases are correctly classified as normal teeth. 1% of all images are incorrectly classified as decayed teeth. Similarly, 2% of all data are incorrectly classified as normal teeth. Out of teeth decay predictions, 98% are correct, and for the normal teeth predictions, 96.1% are correct. For all teeth decay cases, 96% are correctly predicted as decayed teeth. For all normal teeth cases, 98% are correctly classified. Overall, 97% of the predictions are correct.

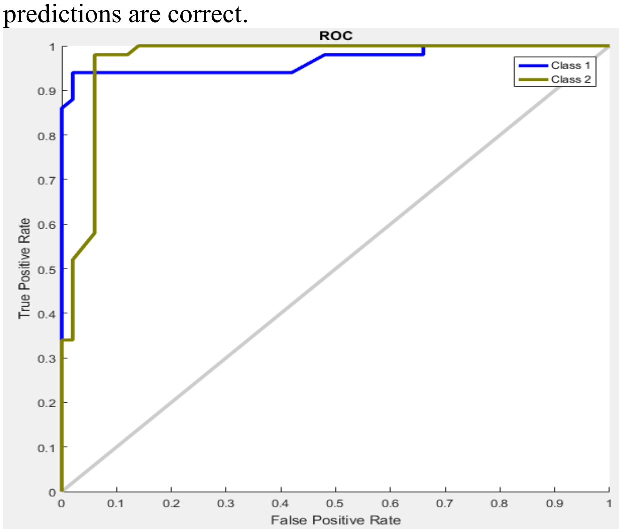

Figure 4. ROC Curve

Fig. 4 illustrates the performance of our classifier model by showing the TPR (True Positive Rate) against the FPR (False Positive Rate) for different threshold values.

V. CONCLUSION

In this paper, a deep neural network using Stacked Sparse Auto-encoder framework is presented for classification of dental X-ray images. The aim of this work is to classify dental X-ray images into decayed or normal teeth images.

In this work, we have used stacked sparse auto-encoder containing three hidden layers and a softmax classifier.

The conclusion we can draw from our experiments is: in comparison with the classic approach to random initialization of the network weight, this method promotes a convergence of the network to a better local minimum as well in classification with regression. This method gives a good result, as approved in Table 1. However, the accuracy and reliability of our results can be improved using a larger dental database.

The implementation of training strategies on really deep structures with several hidden layers is a future extension of this work.

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