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Review of Applications of Deep Learning Methods for Classification of Bio Medical Images

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Abstract

Deep Learning methods for machine learning are applied in various domains. An attempt is made in this paper to explore possibility of applying deep learning methods for analyzing radiographs in general and intra oral periapical radiographs in particular. Machine learning is becoming a pervasive technology. Application domains of machine learning range from production line to health informatics. Researchers all over the world are working on inventing methods for intelligent data processing in all walks of life. Health informatics is a branch buzzing with machine learning methods for data processing. Radiographs are a form of data which is generated in abundance, in health industry. Intelligent processing of this data is requirement of the hour.

Keywords: *Deep Learning; Bio-Medical Images; Neural Network Architectures; Convolutional Neural Networks; Dental Radiographs*

Abbreviations

CNN: Convolutional Neural Networks; RBMs: Restricted Boltzmann Machines; DBNs: Deep Belief Networks; DNNs: Deep Neural Networks; RNNs: Recurrent Neural Networks; IOPA: Intra Oral Peri Apical

Introduction

Deep Learning methods for machine learning are applied in various domains. An attempt is made in this paper to explore possibility of applying deep learning methods for analyzing radiographs in general and intra oral periapical radiographs in particular.

Data processing techniques take a wider perspective, as now-a-days, data is in not only in numerical form but also in audio and image forms. Multimodality is characteristic of data today. Data analytics has found wide applications in health informatics in the last decade. Major form of data in health informatics is radiographic images. Deep learning is applied widely for image segmenting, image classification and image analysis.

Materials and Methods

Daniele Ravi., *et al.* [1] have comprehensively explored applications of deep learning in health informatics. They have mainly focused on key applications in the domains of (a) translational bioinformatics (b) medical imaging (c) pervasive sensing (d) medical informatics and (e) public health. They have used deep learning methods for analysis of health care related data. This is done by using neural networks with multiple hidden layers. More than two hidden layers is a minimum requirement of learning deep. Each new layer added, increases the level of abstraction thereby increasing precision in feature extraction. The deep learning architectures like (a) Convolutional Neural Networks (CNNs) (b) Restricted Boltzmann Machines (RBMs) (c) Deep Belief Networks (DBNs) (d) Deep Neural Networks (DNNs) (e) Recurrent Neural Networks (RNNs) and (f) deep Autoencoders, have domains of their own applications. In these architectures, neuron is stimulated by the input from interconnected neurons and an action potential is generated when the voltage exceeds the threshold level. These action potentials allow neurons to excite or inhibit other neurons. Through these networked neural activities, biological network can encode, process, and transmit information in the network. Each of the five domains, stated above, were explored for applications of deep learning to solve problem of data analysis. Six different architectures and their success rates for different application domains were discussed.

The performance of machine learning methods heavily depends on the choice of the form of data representation and choice of selected features. In reference [2], authors have shown that in traditional machine learning algorithms, much of efforts are put into the design of pre-processing pipelines and data transformations. Selecting appropriate features is important but labor-intensive. This highlights the weakness of current learning algorithms. Also the challenge remains in extracting and organizing the discriminative information from the data.

In the first step of the method proposed by Nasr-Esfahani., *et al.* [3] is pre-processing of input image in order to improve its quality by enhancing its contrast. The output of this stage is applied to a CNN for automatic segmentation of image into two regions e.g. vessels and background. The input image is analyzed patch by patch. A patch is defined by placing a window around each pixel of the image. These patches are formed by sliding a (33 × 33) window, with a stride size of 1, on the image of size (512 × 512). Each patch is fed into the CNN network as an input. The selected patches may have overlapping pixels. The output of CNN determines whether the central pixel of a patch is in a vessel region or not. Hence the trained CNN will be able to segment the image into two regions and extract vessels locations.

The CNN includes two convolutional layers with 50 feature maps. These convolutional layers have (6 × 6) and (3 × 3) kernel sizes which are followed by (2 × 2) and (4 × 4) max pooling layers respectively. At the end, the outputs from these four layers are fed into a two-layer fully connected network. Finally, this network has 500 neurons in the first layer and 2 neurons in its second layer. The 2 neurons in the final layer generate two probabilities for the central pixel of the patch, in the vessel region or in the background.

Muktabh Mayank Srivastava., *et al.* [4] obtained 3000 bitewing radiographs. All the radiographs were examined by dentists for existence of dental caries. Then, these were used as ground truth for both training as well as testing of CNN. 2500 radiographs were used for training system and 500 for testing. Input to the system is a 2-d image bitewing radiograph and output generated is a binary label (0 or 1) for each pixel. CNN developed for this task has 100+ layers.

In reference [5], the data bank for the conducted experiments was created with information collected from 3864 Brazilian preschool children with ages less than five years. Data collection was done through questionnaire containing 15 questions. This feature vector was used to review the four classification techniques, namely, (a) decision trees (b) MLP neural networks (c) kNN and (d) support vector machines. The simulations were carried out using the Weka Data-mining tool, which includes several pre-processing and classification methods. The performance measures used to compare the classifiers are (a) the classification error, and (b) the area under the ROC curve (AUC).

Authors in [6], proposed a method to detect and identify dental caries using X-ray images as dataset and deep neural network as a technique. In deep neural network, Stacked Sparse Auto-Encoders (SSAE) are used for features extraction and a softmax layer to classify the teeth images. The network has a hidden layer containing three SSAE units and a layer of output. Each sample has been repeated 20 times with 500 iterations for the training and 400 iterations for the final learning.

Five types of Tuberculosis (TB) lung CT images are used as datasets [7]. However, while classifying TB types through a software, some outliers do not fit in any of the above five types. Group 6 contains those outlier images. Distinguishable images are applied to perform training and the rest are used for testing, leading to an automated process, differentiating the five types of TB.

Reference [8] has developed a computer-aided triage system to mitigate the problem of unnecessarily long and delirious time-to-treatment. This problem is due to time constraints imposed on radiologists because of their massive workload. In this research work, more than 400,000 images have been expertly labelled as normal or non-normal. Convolution Neural Network is used to output (0 or 1), as a classification of normal and non-normal images. According to the levels of abnormality, further classification cannot be performed, as such, the problem is of strictly binary classification. Thus the classification problem is solved in the following three steps. (a) To develop a simple pre-processing pipeline using digital image processing techniques. (b) To create a pipeline to apply three different neural network architectures for classification. They are GoogLeNet, InceptionNet, and ResNet, and (c) To use neural network visualization techniques to understand what type of features are considered emphatically.

In reference [9], authors have developed a novel model for neural networks which works in attention-based task-driven visual processing manner. The model considers attention-based processing of a visual scene. The design is general enough to be applied to static images and videos. This recurrent neural network (RNN) processes the inputs sequentially. For the purpose of fixation, different locations within the image are processed one at a time. Information from these fixations is combined incrementally to build up a dynamic internal representation of the environment.

Authors of reference [10] have presented a network and training strategy that relies on the strong use of data augmentation. This is done to use the available annotated samples more efficiently. The CNN designed consists of a contracting path and an expansive path. The contracting path consists of the repeated application of two (3 x 3) convolutions followed by a Rectified Linear Unit (ReLU) and a (2 x 2) max pooling operation with stride 2 for down-sampling. At each down-sampling step, the numbers of feature channels are doubled.

Results and Discussion

Reference [1] has discussed four aspects to summarize potential issues associated with deep learning. (a) The entire deep learning model is often not interpretable. Most of the researchers use deep learning approaches as a black box without the possibility to explain why it provides good results. Therefore possibility to apply modifications in the case of misclassification is very rare. (b) For training a reliable and effective model, large sets of training data is required. Although data in health care domain is available in abundance, the form in which it is available is not always directly useful. A common problem that arises during the training of a deep learning architecture is overfitting, this is due to small data sets. (c) In many of the applications using deep learning tools, the raw data cannot be directly used as input. Therefore, pre-processing, normalization and change of input domain is often required before using the data for training. Finding the correct pre-processing method for the data and to choose the optimal set of hyper-parameters are also very challenging. (d) A small change in the input samples, creating infinitesimally small noise may lead to misclassification of samples. On the other hand, it is also possible to obtain meaningless synthetic samples which are strongly classified into classes wrongly.

In reference [2], authors have discussed broader domains in which deep learning is applied. The domains discussed are speech recognition, distributed representations and language processing, image analysis etc.

Authors in reference [3] have considered a dataset of 44 X-ray angiography images. The images in this dataset have the resolution of (512 × 512) and are grayscale. These images were segmented manually, by an expert. The preprocessing by multi-scale Top-Hat transform is done by using a disk shape structuring element with varying size from 3 to 19. each (512 × 512) input image is divided into 230,400 patches of size (35 × 35). For training of the network, 40,000 patches are extracted from each training image where half of the patches are selected from vessel regions and half of them from background regions. Thus, training of the CNN is done with 26 images and the total of 40000 × 26 input sample patches. The rest of the 18 images of the dataset are used as test samples.

Quantitative evaluation of the proposed method based on factors accuracy, sensitivity, specificity, positive predictive value (PPV), and negative predictive value (NPV) is performed. Method was 93.5% accurate. Sensitivity was 90% with 97% of specificity. The predictive indices of the method were PPV 96.7% and NPV 90.6%.

The precision, recall and F1-score of the system developed in reference [4] is compared with the diagnosis of three professionals. The developed system performed way ahead of dentists in both sensitivity in predicting caries as well as F1-score.

In reference [5] experiments were carried out aiming to analyze the performance for the different selected attributes. Feature vector was of 15 input variables, that is, without feature selection. In this experiment a better result was achieved with the MLP method, followed by the SVM (in terms of 10-fold cross-validation error). In terms of AUC, MLP have achieved better results, followed by kNN.

The aim of research work in reference [6] was to classify dental X-ray images into decayed or normal teeth images. 1/3 of images were used for training each class and the rest of the images in the dataset were used for the classification test. Results of the proposed system are discussed below. 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.

In reference [7], confusion matrix was created to test the accuracy of classification in 6 different classes. Overall 96% accuracy was observed within dataset of size 500.

GoogLeNet, is a NN of sufficient complexity, achieves significantly above random classification accuracy when distinguishing between normal and abnormal chest x-ray images as compared to other two networks. Network visualization demonstrates that macroscopic features are learned effectively by the model as observed by reference [8].

Authors in this paper [9] have built The Recurrent Attention Model (RAM). Designed model was evaluated on several image classification tasks as well as a simple game. Common design choices to all experiments performed were retina and location encodings, glimpse network, location network and core network. Image classification is done on basis of centered and non-centered digits.

In reference [10], the input data used in u-net is averaged over 7 rotated versions of the input image. With-out any further pre-processing or post-processing a warping error of 0.0003529 and a rand-error of 0.0382 is recorded. This performance is significantly better than the sliding-window convolutional network result where best submission had a warping error of 0.000420 and a rand error of 0.0504.

Conclusion

Researchers have worked analysing radiographic images with machine learning algorithms. Chest radiograph, bitewing radiographs, angiograms etc. were different types of medical images processed and analysed using machine learning tools. Machine learning tools like CNNs, RBMs, DBNs, DNNs, RNNs and deep Autoencoders are used by researchers. Some demerits of using this tools were discussed in [1]. Intra oral periapical radiographic images can be used as data images. Analysis of these images using deep learning algorithms like CNN can be carried out. Accuracy of diagnosis for detecting carious lesions can be improved over multi-layer perceptron networks.

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Conflict of Interest

Nothing to declare.

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