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A Study and Analysis of Content based medical image retrieval for DICOM Images using Deep Convolutional Neural Network

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***Abstract*- Content based medical image retrieval (CBMIR) system is an effective way of supplementing the diagnosis, treatment for various diseases and it is also an efficient management tool for handling large amount of data. The important issue in content-based medical image retrieval is a semantic gap. This research study focused on reducing the semantic gap between low level feature such as visual information captured by the device and high-level semantic concepts are perceived visual information by human vision system. Among several techniques, machine learning techniques are used earlier as actively investigated as a possible direction to bridge the semantic gap for a long term. To provide an effective medical image classification and retrieval service, the intelligent content based medical image retrieval with sematic system is required. So, the recent success of deep learning techniques overcomes the semantic gap problem. In the medical domain DICOM images plays a vital role and it is cursed with huge dimensionality. In this paper, CBMIR employed with deep learning techniques and it is discussed. The experimental data is very complex in nature and it contains the large set of training samples. The DCNN technique has been employed to classify the DICOM images and obtained the high accuracy.**

Keywords: DCNN, Deep learning, DICOM, CBMIR

1. INTRODUCTION

The recent escalating use of digital images in diverse application areas such as medicine, education, remote sensing, and entertainment has led to enormous image archives and repositories that require management and retrieval of effective image data. The medical images are stored in PACS (Picture Archive and Communication System) archives and the data is stored according to DICOM (Digital Imaging and Communication in Medicine standard). (Ashnil Kumar, Jinman Kim, Weidong Cai, Michael Fulham, and Dagan Feng 2013) Medical image data have been expanded rapidly in quantity, content, and dimension due to an enormous increase in the number of diverse clinical exams performed digitally and to the large range of image modalities available.DICOM image repositories present a challenging environment for query and search algorithms, due to the highly specialized nature of the images.Medical CBIR is an established field of study that is beginning to realize potential when applied to multidimensional and multimodality medical data. The content-based image retrieval systems for medical images are important to deliver a stable platform to catalogue, search, and retrieve images based on their content and practitioners to perform fast diagnosis through quantitative assessment of the visual information of various modalities.

CBMIR system strongly depends both on the availability of correct features for proper representation of semantic view of image and effectiveness of the used similarity measure. The CBMIRcharacteristics of potent are high retrieval accuracy and less computational complexity (Kranthikumar, Venugopal 2014). The CBMIR, which retrieves a subset of images that are visually similar to the query from large image database, is the focus of intensive research. It is provides the potential of having an efficient tool for disease diagnosis, by finding related pre diagnosed cases and it can be used for disease treatment planning and management (Fan Zhang, Weidongcai, Alexander G, Hauptmann 2016).

This paper organized as follows: Section 2 discuss about the deep learning, Section 3presents literature review, Section 4 describes the results and discussion and finally the paper concluded in section 5.

2. DEEP LEARNING

Deep Learning is a subfield of machine learning concerned with algorithms inspired by the structure and function of the brain called artificial neural networks. Deep learning methods aim at learning feature hierarchies with features from higher levels of the hierarchy formed by the composition of lower level features. (Xavier Glorot,YoshuaBengio 2010) This includes learning methods for a wide array of deep architectures, including neural networks with many hidden layers and graphical models with many levels of hidden variables, among others.

Deep learning uses supervised and unsupervised strategies to learn multi-level representations and features in hierarchical architectures for the tasks of classification and pattern recognition. This poses many challenging issues on data mining and information processing due to its characteristics of large volume, large variety, large velocity, and large veracity. The Various deep learning models have been developed in the past few years (QingchenZhanga, Laurence T. Yang, ZhikuiChenc, PengLic 2018). The most typical deep learning models include stacked auto-encoder (SAE), deep belief network (DBN), convolutional neural network (CNN) and recurrent neural network (RNN), which are also most widely used models. Most of the other deep learning models can be variants of these four deep architectures. This paper presents the study and analysis of content based medical image retrieval for DICOM images using Deep Convolutional Neural Network.

2.1 Convolutional Neural Network

The Convolutional neural network is the most widely used deep learning model in feature learning for large-scale image classification and recognition. (Yaniv Bar, IditDiamant, Lior Wolf , Hayit Greenspan 2015) CNN constitute a feed-forward family of deep networks, where intermediate layers receive as input the features generated by the former layer, and pass their outputs to the next layer. A convolutional neural network consists of three layers, i.e., convolutional layer, subsampling layer (pooling layer) and fully-connected layer. Figure 1 shows the convolutional neural network architecture in which convolution layer is the main building block of a convolutional neural network. The convolution layer comprises a set of independent filters. Each filter is independently convolved with the image feature.

A pooling layer is designed to down sample feature maps produced by the convolutional layers, which is often accomplished by finding local maxima in a neighbourhood. Also, pooling gives translational invariance and in the meanwhile, it reduces the number of neurons to be processed in upcoming layers and that to progressively reduce the spatial size of the representation to reduce the number of parameters and computation in the network (https://medium.com). Pooling layer operates on each feature map independently. The most common approach used in pooling is max pooling. In fully connected layers, each neuron has a denser connection as compared to the convolutional layers.

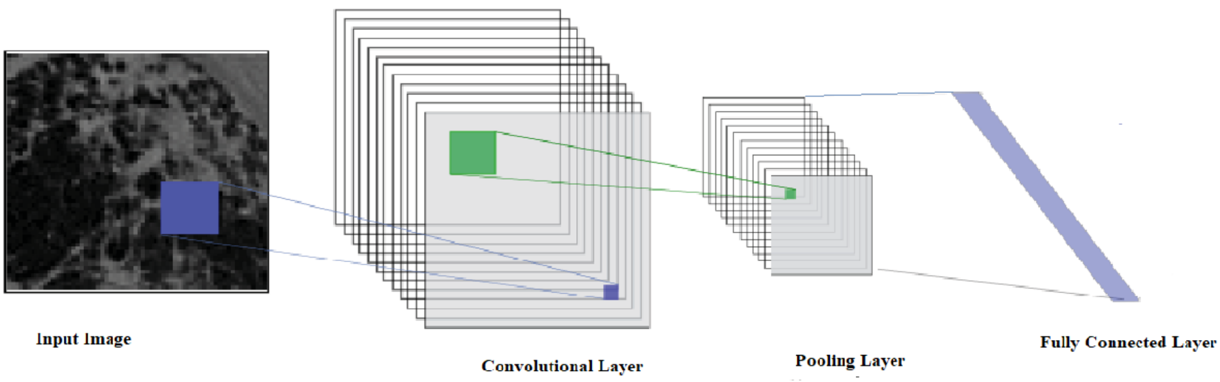

Figure 1. Architecture of Convolutional Neural Network

3. LITERATURE SURVEY

Adnan Qayyumetet al (Adnan Qayyum,Syed Muhammad Anwar, Muhammad Awais, Muhammad Majid 2017) proposed the framework of deep learning for CBMIR system by using deep Convolutional Neural Network (CNN) that is trained for classification of medical images. The dataset contains twenty-four classes with different modalities are used to train the network. The learned features from the trained model and the classification results are used to retrieve medical images. It achieved best results when the class-based predictions are used. An average classification accuracy of 99.77% and a mean average precision of 0.69 are accomplished for retrieval task. This proposed framework suitable to retrieve multimodal medical images.

Kumar et al (Kumar A, Kim J, Cai W, Fulham M, Feng D 2013) presented the state-of-the-art of medical CBIR studies that have been applied in the retrieval of 2D images, images with multiple dimensions, and multimodality images from repositories containing a diverse collection of medical data. They distinguished that CBIR systems have progressive from 2D image retrieval to multidimensional and multimodality image retrieval. There are still remain several challenges to tackle particularly, those that relate to retrieval imagining and interpretation, feature selection from multiple modalities, efficient image processing, development of retrieval algorithms and systems for clinical applications. Further research in the aforementioned domain should be pursued to produce CBIR frameworks that are practical, usable, and most importantly, have a positive impact on healthcare.

Wei Xiong et al (Wei Xiong, Bo Qiu, Qi Tian , ChangshengXu , SimHengOng , Kelvin Foong 2005) described a content-based medical image retrieval (CBMIR) framework using dynamically optimized features from multiple regions of medical images. These regional features, including structural and statistical properties of colour, texture and geometry, are extracted from multiple dominant regions segmented by applying Gaussian Mixture Modelling (GMM) and the Expectation Maximization (EM) algorithm to medical images. Over them, Principal Component Analysis (PCA) is utilized to construct query templates and to reduce feature dimensions for descriptive feature optimization. Applying this method used the medical imageCLEF 2004. The proposed framework achieved thebetter retrieval performance (MAP 0.4535) over the existing work.

Samuel Remediosa et al (Samuel Remediosa,b, Dzung L. Phamb , John A. Butmanc, and SnehashisRoyb 2014) developed a novel 3D deep convolutional neural network (CNN)- based method for MR image contrast classification. The proposed framework forCNN, automatically identifies the MR contrast of an input brain image volume. Explicitly, they are explored three classification problems: (1) identify T1-weighted (T1-w), T2-weighted (T2-w), and fluid-attenuated inversion recovery (FLAIR) contrasts, (2) identify pre vs.postcontrast T1, (3) identify pre vs post-contrast FLAIR. A total of 3418 image volumes attained from multiple sites and multiple scanners were used. To evaluate each task, the proposed framework model was trained on 2137 images and tested on the remaining 1281 images. The results showed that image volumes were correctly classified with 97.57% accuracy.

Tsochatzidis et al. (. Tsochatzidis, K. Zagoris, N. Arikidis, A. Karahaliou, L. Costaridou, and I. Pratikakis 2017) proposed the framework for content-based image retrieval (CBIR) and computer aided diagnosis (CADx). In essence, their model segmented a lesion on a query image, and compared to the segmented lesions in database, consisting of 400 Regions of interest derived from the Digital Database for Screening Mammography (DDSM). The basis of comparison was the Euclidean distances between the representation vectors of the query lesion and database lesions. The model then outputs both reference images and a likelihood of a lesion being benign or malignant. They reported that their combined CBIR and CADx method resulted in state of the art prediction accuracy of 81%. These examples highlight how the field of machine learning in medical image analysis is changing rapidly, and that there may still be numerous applications which have not been conceived of yet.

J. Cho, K. Lee et al. (J. Cho, K. Lee, E. Shin, G. Choy, and S. Do. 2015) presented the determining the optimum size of the training data set necessary to achieve high classification accuracy with low variance in medical image classification systems. The CNN with GoogLeNet was applied to classify axial Computed Tomography (CT) images into six anatomical classes such as brain, neck, shoulder, chest, abdomen, and pelvis. They are trained the CNN by six different sizes of training data set (5, 10 , 20 , 50 , 100, and 200) and then tested the resulting system with a total of 6000 CT images. The training images were achieved the 88-98% accuracy a test set of 6000 images. But the categorization into several body regions is not a realistic medical image analysis task. Being able to achieve classification with a small dataset is possibly due to the general intrinsic image homogeneity across different patients, as opposed to the near-infinite variety of natural images.

Akakin, H. et al (M. Anthimopoulos, S. Christodoulidis, L. Ebner, A. Christe, and S. Mougiakakou, 2016), presented the convolutional neural network based system for classification of Interstitial Lung Diseases (ILDs). Their dataset comprised of 7 classes, out of which 6 were ILD patterns and a healthy tissue class. They achieved a classification performance of 85.5% in characterizing lungs patterns.

4. RESULTS AND DISCUSSION

This Paper conducted an extensive survey on Content based medical image retrieval using DCNN for DICOM images. After careful investigation, the paper implemented the DCNN model for the experimental dataset which is collected from the publicly available medical image databases portal. The experimental DICOM image dataset contains 2200 images of 22 classes of Brain, lung, bladder, liver, kidney, head, leg...etc. with different modalities. Each class contain 100 images in DICOM format with different size. All images in the database were centre cropped using dimensions of 250 × 250 prior to training and convert to the gray scale image. The Meta data such as body part examined are extracted from all images for assigning the class label. The data from each class was divided randomly and 70% and 30% are considered images for training and testing data set respectively.

The DCNN model is constructed with six layers such as input layer, convolutional layer, pooling layer, stack2line layer, sigmoid and output layer. The model was trained using Stochastic Gradient Descent (SGD) with back propagation. It was optimized with a very low learning rate of 0.0001 with 6 epochs of SGD.The SGD is most commonly used algorithm for training neural networks and it is very competent in learning discriminative linear classifiers under a convex loss function like SVM or Logistic Regression. Finally, the softmax function is used for classification after trained DCNN network.

The table 1 shows the confusion matrix for medical image classification with eight different classes such as bladder, brain, breast, cervix, chest, colon, oesophagus and head. The confusion matrix delivers the correctly predicted classes from training samples. The test dataset contains fifty images per class.The predicted instances of actual class for test dataset are 50, 25, 50, 40, 39, 50, 50 and 49 respectively. The table 2 shows the performance metrics for each class.The fig 2 shows the performance evaluation of experimental dataset based on precision, recall and specificity values for each class. Finally the DCNN model is obtained the overall classificationaccuracy is 84% based on performance metrics.

Table 1. Confusion matrix for DICOM image classification

		Actual Class							
		Bladder	**Brain**	**Breast**	**Cervix**	**Chest**	**Colon**	**Esophagus**	**Head**
Predicted Class	**Bladder**	50.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	Brain	0.0	25.0	0.0	0.0	0.0	0.0	0.0	0.0
	Breast	0.0	1.0	50.0	0.0	0.0	0.0	0.0	0.0
	Cervix	0.0	0.0	0.0	40.0	0.0	0.0	0.0	0.0
	Chest	0.0	0.0	0.0	0.0	39.0	0.0	0.0	0.0
	Colon	0.0	0.0	0.0	0.0	0.0	50.0	0.0	0.0
	Esophagus	0.0	0.0	0.0	0.0	0.0	0.0	50.0	0.0
	Head	0.0	0.0	0.0	0.0	0.0	0.0	0.0	49.0

Table 2. Performance metrics

	Bladder	Brain	Breast	Cervix	Chest	Colon	Esophagus	Head
True Positive	50.00	25.00	50.00	32.00	39.00	50.00	50.00	49.00
False Positive	0.00	0.00	11.00	1.00	9.00	0.00	0.00	2.00
False Negative	0.00	25.00	0.00	16.00	8.00	0.00	0.00	1.00
True Negative	0.00	18.00	0.00	11.00	5.00	0.00	0.00	1.00

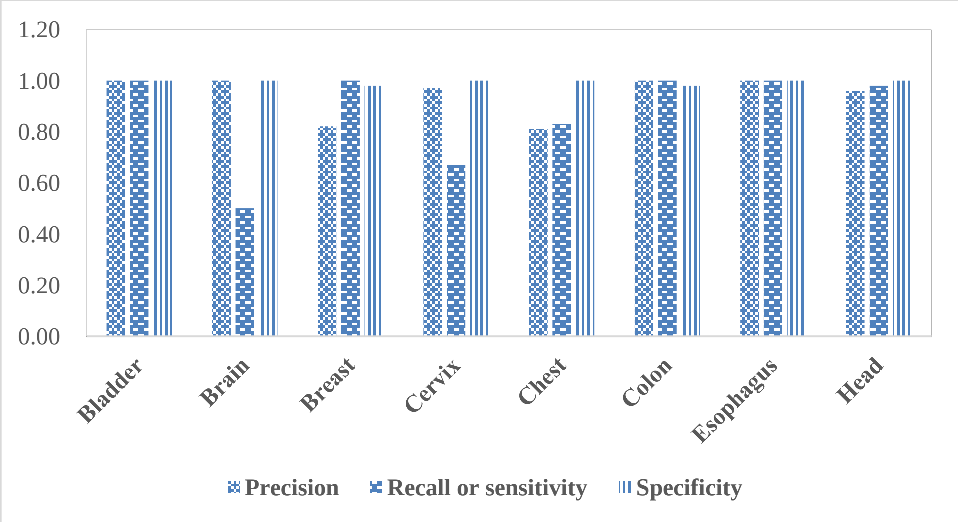

Figure 2. Performance Evaluation of 8 classes

5. CONCLUSION

In this paper, deep convolutional neural network is used for DICOM image classification. The DCNN is achieved the better accuracy for multimodality DICOM image classification using minimum network layers. In this DCNN model reduces the semantic gap by learning discriminative featuresdirectly from the images. The last fully connected layers of the network have been used to extract features for the retrieval task. The network was effectively trained for 22 classes of medical images with an average classification accuracy of 84%. Widely used metrics i.e., precision and recall were used to test the performance of classification. Thus deep learning technique is well suited for medical image classification. By adding more number of layers, it can achieve the high performance accuracy. Further, planned to improve the classification and retrieval accuracy by using larger dataset with different deep learning technique.

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