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MEDICAL IMAGE ANALYSIS USING DEEP CONVOLUTIONAL NEURAL NETWORKS: ARCHITECTURE AND ITS APPLICATIONS

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Abstract

Medical image analysis is that the science of analyzing or resolution medical issues mistreatment totally different image analysis techniques for emotional and economical extraction of data. Deep learning may be a breakthrough in machine learning techniques that has flooded the sector of pattern recognition and computer vision analysis by providing progressive results. Deep learning provides totally different machine learning algorithms that model high level knowledge abstractions and don't believe handcrafted options. Recently, deep learning strategies utilizing deep convolutional neural networks are applied to medical image analysis providing promising results. This paper presents a review and applications of the progressive convolutional neural network based mostly techniques used for medical image analysis.

Keywords: CNN, Convolutional Neural Networks, Medical Image Analysis, Deep learning

I INTRODUCTION

Deep learning (DL) is wide utilized in analysis domains like computer vision, linguistic communication process and speech analysis. This methodology is suited notably to areas wherever great deal of knowledge has to be analyzed and human like intelligence is needed. The employment of deep learning as a machine learning and pattern recognition tool is additionally turning into a crucial facet within the field of medical image analysis and is obvious from the recent special issue on this subject [1]. The key purpose of this special issue is to analyze the initial impact of deep learning in medical imaging domain. Massachusetts Institute of Technology technological review, deep learning is among the highest 10 breakthroughs of 2013 [2].

The use of the normal machine learning strategies, like support vector strategies (SVMs), in medical image classification, began way back. However, these strategies have the subsequent disadvantages: the performance is way from the sensible commonplace, and also the developing of them is kind of slow in recent years. Also, the feature extracting and choice area unit long and vary in step with completely different objects [3]. The deep neural networks (DNN), particularly the convolutional neural networks (CNNs), area unit wide employed in dynamical image classification tasks and have achieved important performance since 2012 [4].

II LITERATURE REVIEW

De Vos, B.D et al. used CNN computerized axial tomography (CT) Anatomical localization; the results indicate that 3D localization of anatomical regions is feasible with second pictures [5].

Dou, Q.; Yu, L.; bird genus et al. developed AN rule for CNN MRI machine-controlled segmentation; liver, heart and nice vessels segmentation; it had been all over that this approach has nice potential for clinical applications [6].

Chen, X.; Xu et al. used CNN MRI neoplasm grading; a 3-layered CNN contains a eighteen performance improvement over to the baseline neural network. [8]

Pan, Y.; Huang et al. CNN anatomical structure pictures eye disease detection; the experiments were performed on SCES and ORIGA datasets; more, it had been noted that this approach is also nice for eye disease detection [7].

Dubrovina, A et al. CNN MRI Alzheimer’s illness prediction; the accuracy of this approach is way superior compared to second strategies [9]

Payan, A.; Montana, et al. developed CNN diagnostic procedure Automatic breast tissue classification; the pectoral muscles were detected with high accuracy (0.83) whereas tit detection had lower accuracy (0.56) [10].

Acharya, used U.R et al. CNN graphical record Automatic detection of heart muscle infarction; average accuracy was ninety three.53% with noise and ninety five.22% while not noise [11].

Mehta, et al. developed R CNN CT machine-controlled segmentation of human brain structures [12].

Medical imaging has become indispensable for the detection or identification of diseases, particularly for the identification of cancers combined with a diagnostic test, and bit by bit become a crucial basis for preciseness drugs [13,14]. Currently, imaging techniques for medical applications square measure primarily supported X-rays, X-radiation (CT), resonance imaging (MRI), antilepton emission pictorial representation (PET) and ultrasound [15].

III CONVOLUTIONAL NEURAL NETWORKS

CNN or the convolutional neural network (CNN) may be a category of deep learning neural networks.

Convolutional Neural Networks (CNNs) leverage abstraction data, and that they area unit so likeminded for classifying pictures. These networks use an advert hoc design galvanized by biological information taken from physiological experiments performed on the cortical region. In neural networks, Convolutional neural network (ConvNets or CNNs) is one among the most classes to try and do pictures recognition, pictures classifications. Objects detections, recognition faces etc., area unit a number of the area unites wherever CNNs are wide used.

There are two main components to a CNN:

- A convolution tool that splits the varied options of the image for analysis
- A totally connected layer that uses the output of the convolution layer to predict the most effective description for the image.

IV ARCHITECTURE OVERVIEW

CNN design is galvanized by the organization and practicality of the visual area and designed to mimic the property pattern of neurons at intervals the human brain.

The neurons at intervals a CNN square measure split into a three-dimensional structure, with every set of neurons analyzing little region or feature of the image. In different words, every cluster of neurons makes a specialty of characteristic one a part of the image. CNNs use the predictions from the layers to supply a final output that presents a vector of likelihood scores to represent the chance that a particular feature belongs to an explicit category.

A CNN consists of many forms of layers:

A. Convolutional layer - creates a feature map to predict the category chances for every feature by applying a filter that scans the entire image, few pixels at a time.

B. Pooling layer (down sampling) - scales down the number data of data of knowledge} the convolutional layer generated for every feature and maintains the foremost essential information (the method of the convolutional and pooling layers typically repeats many times).

C. Fully connected input layer - “flattens” the outputs generated by previous layers to show them into one vector that may be used as associate degree input for subsequent layer.

D. Fully connected layer - applies weights over the input generate by the feature associate degree lysis to predict a correct label.

Fully connected output layer generates the ultimate chances to see a category for the image.

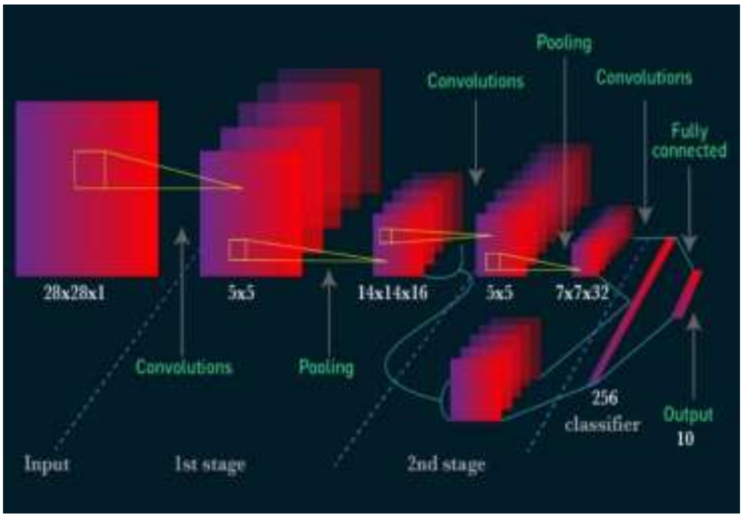

Fig 1 Architecture of CNN

4.1 Forward Propagation:

Recall that every somatic cell within the network receives its input from all neurons within the previous layer via connected channels. This input could be a weighted add of all the weights at every of those connections, increased by the previous layer's output vector [16]. This weighted add is passed to associate degree Activation operate, which ends up within the output for a specific somatic cell and therefore the input for future layer. This forward propagation happens for every layer till knowledge reaches the Output layer - wherever the amount of neurons corresponds to the amount of categories that square measure being foreseen.

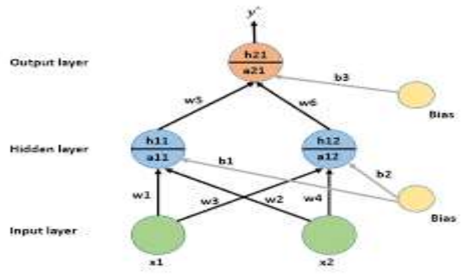

Fig 2 Forward propagation

4.2 Backpropagation:

Neural networks decide to increase the worth of the output node consistent with the proper category. this can be done through backpropagation. In backpropagation, the spinoff (i.e. gradients) of the loss operate with relation to every hidden layer's weights square measure wont to increase the worth of the proper output node. Gradient descent seeks to attenuate the general loss that's being calculated for the network's predictions.

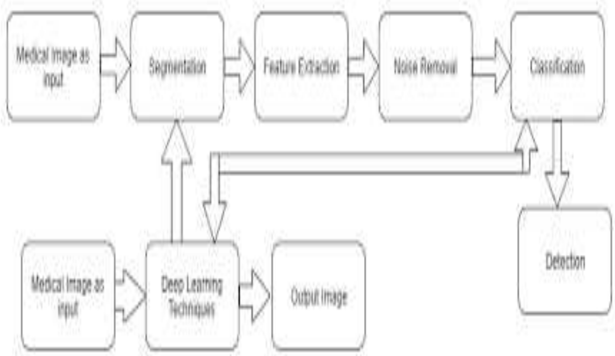

Fig 3 CNN in Medical Analysis

V MEDICAL IMAGE ANALYSIS

Medical imaging includes those processes that give visual data of the shape. The aim of medical imaging is to assist radiologists and clinicians to form the diagnostic and treatment method additional economical. Medical imaging may be a predominant a part of identification and treatment of diseases and represent totally different imaging modalities like X-raying (CT), resonance imaging (MRI), antilepton emission imaging (PET), ultrasound, X-ray and hybrid modalities. These modalities play a significant role within the detection of anatomical and purposeful data concerning totally different body organs for identification still as analysis [17].

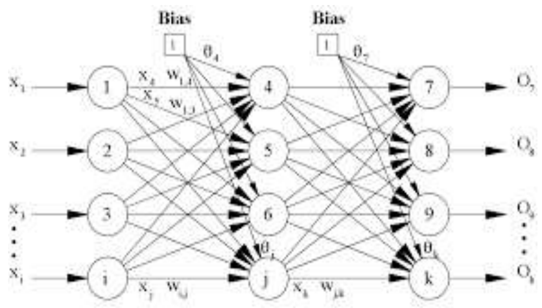

Fig 4 Back propagation

5.1 Medical image classification

Medical image classification involves decisive and distribution labels to medical pictures from a set set. The task involves the extraction of options from the image, and distribution labels victimization the extracted options. Let I denote a picture product of pixels and c1,c2,…,crc1,c2,…,cr denote the labels. for every constituent x, a feature vector ζζ, consisting of values f(xi)f(xi) is extracted from the neighborhood N(x) victimization (1), wherever xi∈N(x)xi∈N(x) for i=0,1,…,ki=0,1,…,k.

ζ=(f(x0),f(x1),…,f(xk))ζ=(f(x0),f(x1),…,f(xk)) [18]

A label from the list of labels c1,c2,…,crc1,c2,…,cr is appointed to the image supported ζζ.

5.2 Medical image segmentation

Medical image segmentation helps in image understanding, feature extraction and recognition, and quantitative assessment of lesions or alternative abnormalities. It provides valuable info for the analysis of pathologies, and afterwards helps in identification and treatment coming up with. the target of segmentation is to divide a picture into regions that have sturdy correlations. Segmentation involves dividing the image I into a finite set of regions R1,R1,…,RSR1,R1,…,RS as expressed in [19].

I=∪i=1sRi, Ri∩Rj=∅ and i≠j.I=∪i=1sRi, Ri∩Rj=∅ and i≠j. [19]

5.3 Medical image localization

Automatic localization of pathology in pictures is sort of a very important step towards automatic acquisition designing and post imaging analysis tasks, like segmentation and useful analysis. Localization involves predicting the thing in a picture, drawing a bounding box round the object and labeling the thing.

The localization perform f(I) on a picture I computes c, lx, ly, lw,lhc, lx, ly, lw,lh, that represent severally, category label, center of mass x and y coordinates, and also the proportion of the bounding box with regard to breadth and height of the image as expressed in [20].

f(I)=(c,lx,ly,lw,lh).f(I)=(c,lx,ly,lw,l) [21]

5.4 Medical image detection

Image detection aims at the classification and also the localization of regions of interest by drawing bounding boxes around multiple regions of interest and labeling them. This helps in determinant the precise locations of various organs and their orientation. Let I be a picture with n objects or regions of interest. Then detection perform D(I) computes ci, xi, yi, wi,hici, xi, yi, wi,hi and these ar severally the category label, centre of mass x and y coordinates, proportion of the bounding box with regard to breadth and height of the image I as given within the [22]

∪i=1nci,xi,yi,wi,hi=D(I).∪i=1nci,xi,yi,wi,hi=D(I). [22]

Segmentation could be a method of dividing a picture into multiple non-overlapping regions supported a particular criterion i.e., set of pixels or some intrinsic options like color, distinction and texture [23]. The attention-grabbing property of segmentation is that it reduces search space in a picture i.e., by dividing original image into 2 categories like object or background. The key facet of image segmentation is to represent the image in a very pregnant kind such it is often handily used and analyzed. Generally, segmentation is helpful in image process primarily based applications like life science [24,25], contour detection [26], object matching [27] and visual perception [28]. In literature, many image segmentation algorithms are projected, that area unit supported thresholding [29], region growing [30], cluster [31], edge detection [32], active contour models [33], graph cut [34] and mean shift [35]. In recent studies, segmentation has been applied on differing kinds of pictures [36-38] for applications like satellite pictures [39,40], tomographic maps [41] and medical pictures [42,43].

VI CNN APPLICATIONS IN MEDICAL IMAGE CLASSIFICATION

6.1 Breast tumors

Breast cancer is the most common cancer that affects women across the world. It can be detected by the analysis of mammographs. Two radiologists independently reading the same mammogram has been advocated to overcome any misjudgment.

6.2 Heart diseases

Electrocardiogram (ECG) is used for the assessment of the electrical activity of the heart to detect anomalies in the heart.

6. 3 Eye diseases

Initial training time can be reduced by Gaussian initialization, and overfitting can be avoided by weighted class weights. This was proposed for classifying diabetic retinopathy (DR) in fundus images. The performance was compared with SVM and other methods that required feature extraction prior to classification. The method achieved 95%95% specificity but less sensitivity of 30%30%. The trained CNN did a quick diagnosis and gave an immediate response to the patient during screening.

Author	Application	Method	Dataset	Accuracy
J. Ma [43]	Thyroid Nodule Diagnosis	Pre-Trained Convolutional Neural Network	Ultrasound Images	~83%
W. Sun [44]	Breast Cancer Diagnosis	Convolutional Neural Network using semi supervised learning	Mammographic Images with ROIs	82.43%
H. Pratt [45]	Diabetic Retinopathy	Convolutional Neural Network	Kaggle Dataset	75%

Fig 5 CNN Applications in Medical

VII CONCLUSION

In this paper, an elaborate study of the deep learning techniques and its application in the sector of medical image analysis is bestowed. It may be all over that convolutional neural network based mostly deep learning ways area unit finding larger acceptableness all told sub-fields of medical image analysis together with classification, detection, and segmentation. The recent success indicates that these deep learning techniques would greatly profit the advancement of medical image analysis.

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