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DIAGNOSIS IN MEDICINE USING DEEP LEARNING ALGORITHMS

Deepak Pandey[1], Gunjan Sharma[2], Kundan Shwetha[3]

Biomedical Engineering, Vidyalankar Institute of Technology, Mumbai[1,2,3]

Abstract: Image segmentation, identification and disease analysis has become very difficult, due to human made mistakes. With evolution of Deep learning techniques this automated process has become efficient in analyzing an object or image and identifying it, without mistakes, based on the learning from hundreds or thousands of images. Now a days deep learning has been used in variety aspects of medicine like MRI scanning, Skin cancer classification, Brain tumor detection etc., In this paper we will talk about what is deep learning, how it works, and how the opportunities involved with using deep learning in image analysis and classification has evolved

I INTRODUCTION

From the past few decade image segmentation, and identification of lesions or organs from medical images such as MRI images or CT or raw images taken form phone or DSLR, has become a challenging task in medical image analysis. Deep learning is a machine learning technique. It trains a computer with several hundreds of images, and it will have input and output layers, image will be processed through these layers and it will be predicted. The main inspiration behind deep learning is the way human brain works. Deep learning is a subfield of machine learning, which works on artificial neural networks, and these are the algorithms inspired by the structure and function of the brain. When you train a artificial neuron using multiple images, by learning linear and on linear interactions, the model will correctly recognize the image we need to identify. So here we don't need human intervention to successfully perform the job of image identification.

II CONVOLUTIONAL NEURAL NETWORKS

In the image recognition and classification areas CNNs which are kind of Artificial Neural Networks are proved immensely powerful [1]. ANN will have three layers, input layer, hidden layer, and output layer. Image as an input is fed to the input layer, and hidden layer is used to train the network based on the images, so that when we want to recognize the target image based on the trained images it will give output through output layer. CNNs comprise of two components, one is hidden layer which will extract the features and the other layer which will do the classification [2]. The input node is given information in numerical form. Each node is given a number and the information is used as an activation value. Higher the number, greater the activation.

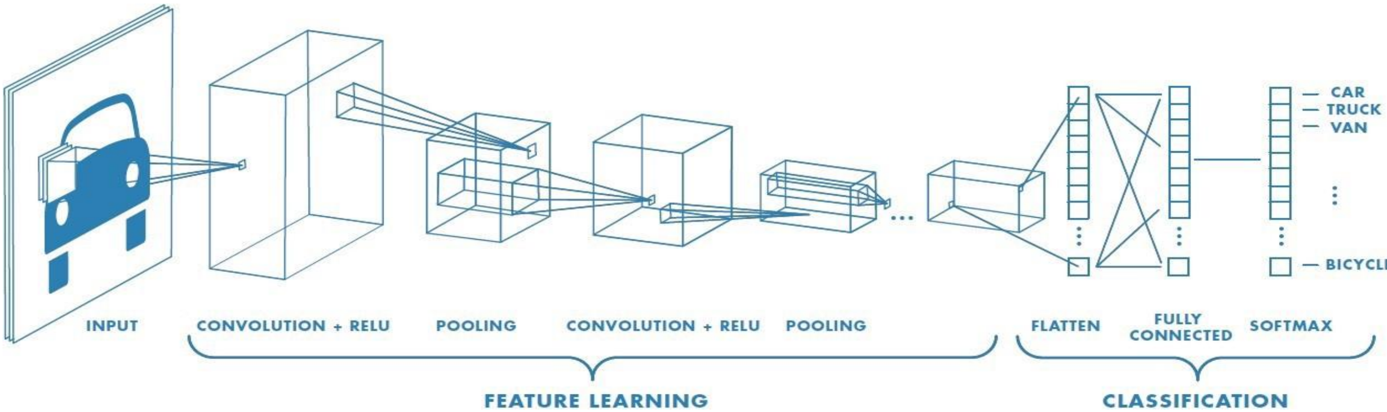


Image 1: Layers of a CNN (Convolutional Neural Network)

The activation value is passed to next Node based on weights or called connection strength. Each Node will modify the transfer function based on the activation value it receives, then sums the activation value, and next it applies an activation function. Activation function is applied to this neuron and the based on that it will understand if it must pass along the signal or not [3].ANNs learn by weights , and by adjusting the weights ANN will decide on what extend ANN pass the signal. Whoever is training the ANN they are the one who decides on adjusting the weights. And this activation process continues until it reaches output node, and the output node produces the output in a way we understand it. There are two ways you can get any program do what you need, one is hard programmed approach where you tell it what exactly you want it to do, other is neural network where you train it based on several inputs and tell it what you want for outputs, and then it will learn on its base don previous learning when a new image is fed.

III CONCEPTS OF DEEP LEARNING:

Weighted sum: Either features from a training set or output from another neuron could be an input for another neuron. There is a unique weight attached with each connection between two neurons. If you want to move from one neuron to another you have to apply the weight. The neuron for each synapse that is incoming apply activation function to sum the weighed inputs, and it passes the result to all the next neurons. So, for a neuron the input is the sum of weights from all the previous neurons output.

Activation Function:

The output of that node is defined by the activation function of a node. Activation Function translates input signals to output signals. So, by selecting proper activation functions better feature extraction is achieved [4,5,6]. Some of the activation functions are represented by *g*.

Softmax: The output of Softmax, is usually used in the last layer which is considered as a probability distribution over the categories.

Softplus: Softplus represents smooth approximation of ReLU, which is one of variants of ReLU.

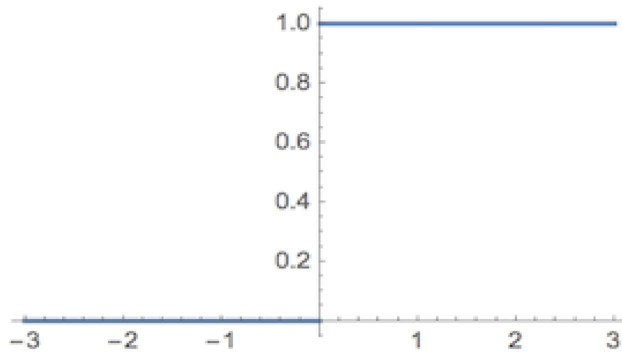
$$g(a) = \log(1+e^{a})$$

Rectified linear unit (ReLU): Superior Performance is shown by this activation function in many cases,and gradient diffusion problem can be solved by ReLU [7,8]. Some of the most popular deep learning activation functions are [5,9,10,11].

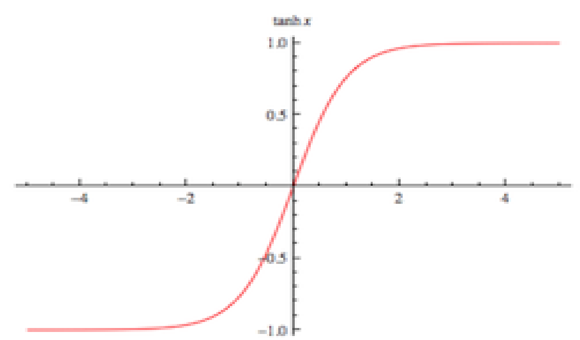
$$g(a) = \max(0, a)$$

Maxout: In this function the weight matrix is a three-dimensional array, and the third array corresponds to the connection of neighboring layers [12].

Threshold Function: This function passes 0, if the sum of the values of the inputs reaches a certain threshold. It will pass 1 it the sum value is more than 0. This is like a step function as shown in the below image. It is a yes or no function and is straight forward.



Hyperbolic Tangent Function: The value of this function goes below 0 also, from -1 to 1. Even though this not like brain functionality, this process gives better results while training neural networks. when there is a strong negative input which may keep the output at 0, this might mess with the learning process so sometimes neural networks get struck. These are the some of the concepts behind deep learning mechanism, and how neural networks are trained using these principles and functions.



How Deep learning Evolved and Helped in Medical Field

CNNs are extensively being used in medical field for segmentation, classification, and identification of various diseases, like knee cartilage segmentation[15], MR brain image segmentation[14], Brain tumor segmentation[13], Skin cancer classification[16], classification of Histopathology [17], lesion detection of Mammography[18], breast cancer detection[19], retinal disease identification[20], and many more. We reviewed some research papers, on Deep Learning techniques used in medicine for different diagnosis.

Liu et al [21] dida research to create an algorithm to segment brain, they used datasets from T1w. and images contain architecture of four sections input section, convolution section, fully connected section, and the last classification section. They validated their algorithm and approach on data from the Multimodal Brain Tumor Image Segmentation challenge, and the input images used are of 240 patients from the hospital in Texas. Performance of segmentation was evaluated through DSI. It is defined as measure of overlap between the A and B contours divided by their total mean area. The study showed a DSI value of 0.75 in the tumor core.DSI is define by the following formula

$$DSI=2|A\cap B|/|A|+|B|$$

In head and neck the image segmentation is a time-consuming process and is also a difficult process in radiotherapy. The normal anatomy of the site can be significantly affected by large primary or node lesions. In head and neck cancer patients CNN is used to speed up and also improve organs at risk delineation. [22], author has used 50 patients for neck and head radiotherapy and used a CNN which has convolutional layer of repeating blocks, normalization layer, rectified linear unit, dropout layer and pooling unit. They observed results similar to that of using a CNN in segmenting spinal cord, larynx, mandible etc., A similar strategy has been proposed by [25] who used the existing CNN which is 3D to detect and segment brains for patients who are undergoing stereotactic treatments. Authors focused on the performance while combining multimodal MRI, and by adding virtual patients to increase the total number of patients and the ability to use advanced segmentation to distinguish between vital and necrotic parts of metastates. The quantification of detection has been evaluated by sensitivity.

$$\textbf{Sensitivity}=\textbf{TPmet}/(\textbf{TPmet}+\textbf{FNmet})$$

Next one is lung segmentation. With the use of semi-automatic tools segmentation of thoracic showed good performance, with a DSI value of 0.9. [23] tested a model which is composed of10-layer CNN with sharp mask and evaluated its performance against definitions that are manual of the aorta, body, trachea in 30 CT scans of patients who are affected by lung cancer. The best performance is achieved by sharpmask with a DSI value of 0.65 to 0.9.

Next one is abdomen segmentation. Due to significant anatomical variability even the use of DL techniques by using auto segmented software has hampered the results of segmentation in the abdomen.[24] was the ones to attempt pv segmentation for the first time, using CNN. Automated DL based segmentation has achieved a DSI of 0.7 to 0.83, compared to manual benchmarks.

Next one to discuss about is Pelvis segmentation. For the pelvic segmentation several auto strategies has been implemented, and the development of efficient DL technique improve the current state of art [27].

[26] and colleagues proposed an algorithm which has 9 layers CNN for advanced rectal cancer lesions on T2 and DWI MRI images. They got a DSI of 0.7 and an AUC of 0.99compared to manual algorithms.

IV CONCLUSION:

In this paper we have provided information on what is deep learning, how it has evolved in medicine. We also focused on well know training algorithms and architectures. We looked at how it has evolved in oncology, how it is helpful in various sectors of medicine. For Skin cancer classification the image lesions can easily be identified with CNNs and it is predicted that by 2021 there will be lot of people around 6billion people using phone to diagnose their skin cancer [28].There is tremendous opportunity for using current algorithms and further exploring optimizable methods. However there are some challenges too, if we can overcome these challenges we can best use of deep learning.

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