

Advances In The Use Of Neural Networks To Process And Analyze Medical Image

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Abstract:

Images are the largest source of data, especially in the medical field, but it is sometimes difficult to detect all the information in them. Image processing, therefore, plays a major role in helping doctors and specialists detect lesions and diseases. With technological development, researchers began using artificial intelligence with sophisticated neurotic networks to process and analyze images. This has contributed to more accurate information, and there have been radical changes in the way doctors use x-rays and organic images. This research discussed how neural networks work and how they are used in image processing, and the most important technologies newly used in this field.

Key words: Convolutional neural network, Image Flattening, Fully Convolutional Network, Convolutional Residual Networks, image processing

Introduction. One of the most difficult challenges of analyzing medical images is to provide accurate information about the shape or size of a lesion or organ, usually by fragmenting the image, identifying pixels for organs or lesions, using certain techniques to process the image, and then extract information. Many researchers have proposed different automated division systems by applying available technologies that rely on traditional methods such as edge detection filters. Following the development of artificial intelligence, technologies using machine learning to process images have evolved. In this article, we try to shed light on the role of neural networks and machine learning in the treatment of medical images and what are the most important techniques used.

Materials & Method. Convolutional neural network (CNN) Twisted neural networks help to take advantage of spatial information and thus are well suited to classifying images, as they use a custom architecture inspired by biological data taken from physiological experiments on the visual cortex.

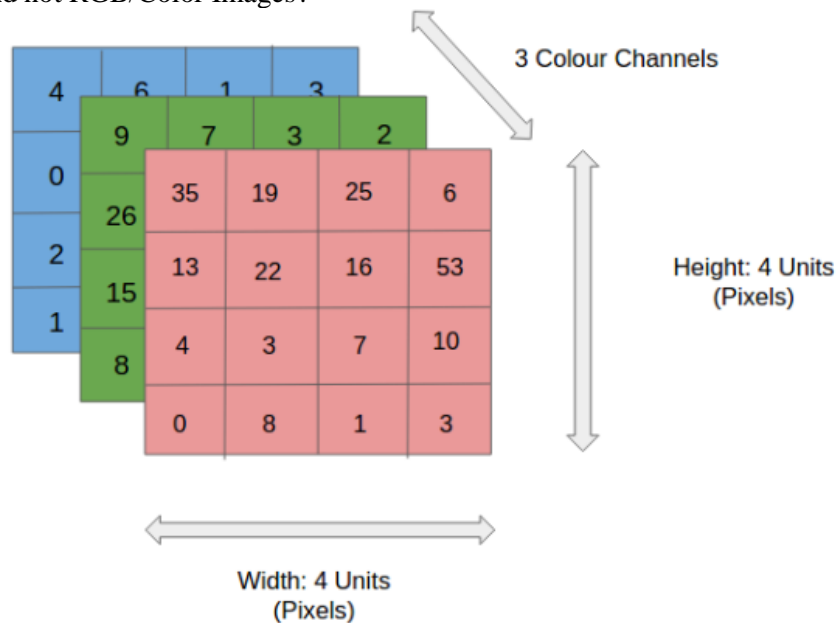
There are several methods by which CNN architecture can be used to apply it to the field of image processing, thus obtaining significant results.

If we think of CCN as a machine learning algorithm, it does the following: it takes the input image, then the significance (weights) is assigned to the various aspects / objects in the image and the result is that it is able to differentiate one from the other.

A CCN consists of:

- The input layer which is a grayscale image
- The output layer which is binary or multi-class labels
- The hidden layers, which consist of convolution layers, ReLU (rectified linear unit) layers, the pooling layers, and a fully connected neural network

Why grayscale and not RGB/Color Images?



Any color image has three channels, red, green and blue. There are several such color spaces like the grayscale, CMYK, HSV in which an image can exist.

The problem when dealing with images with multiple color channels is that we have vast amounts of data to work with, which makes the math laborious and difficult. On the other hand, the process becomes complex, as the neural network or any machine learning algorithm has to work with three different data (red, green, and blue values) to extract the features of the images and classify them into their appropriate categories. CNN's role is to reduce the images to a form that is manageable without losing essential features for good prediction. This is important when we need to make the algorithm visualizable for large data sets. Training data consists of gray gradient images, and these images will be an entry point to the twisting layer to extract features. The attention layer consists of one or more nucleuses in different weights, used to extract features from input images, to assume that we use Kernel (K) in size $3 \times 3 \times 1$, with the following weights:

If we move Kernel over the input image, we'll be able to calculate different pixels based on adjacent pixel values.

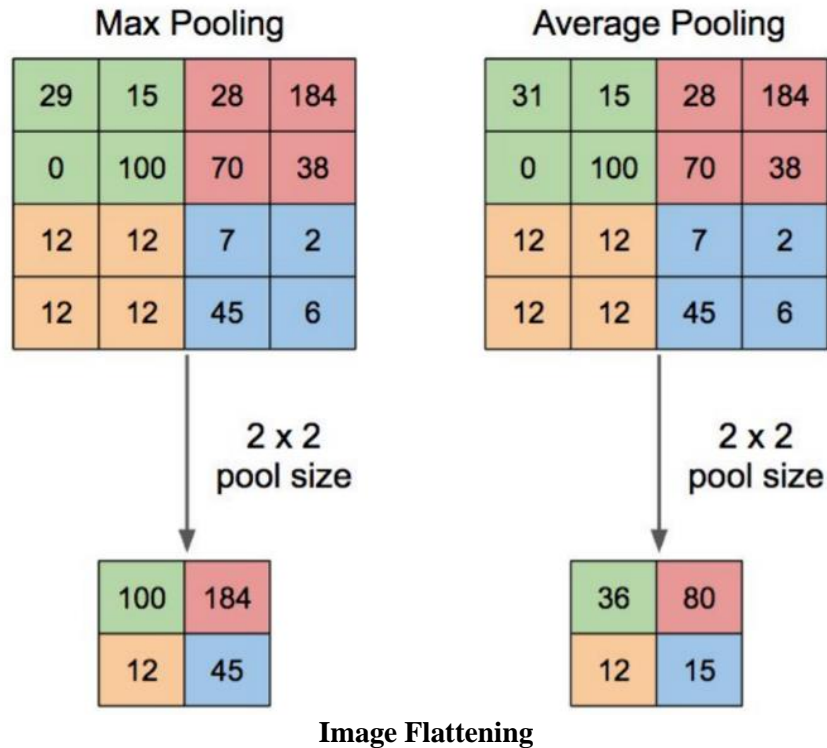
We need several repetitions to cover the whole picture. CNN learns the weights of these forces on its own. As a result of this process, we'll get a landmark map that basically detects image features instead of looking at the value of a pixel.

Image features such as edges and points of interest provide rich information about image content. This information is essential for many image analysis applications: recognition, matching, reconstruction, etc.

Pooling Layer

You take a set of samples to reduce the computational complexity required to process a large volume of data associated with a particular image.

There are two types of pooling, Max Pooling, which returns the maximum value from the portion of the image covered by the Pooling Kernel, and the Average Pooling that averages the values covered by a Pooling Kernel.



After the assembly process, we will need to convert the output into a scheduling structure that can be used by an artificial neurosonic network to perform the classification process. The number of layers and the number of neuron networks vary depending on the difference and complexity of the problem.

Why ReLU?

Linear function directly outputs input if positive otherwise, zero will be output. ReLU has become a default activation function for many neural networks because the model it uses is easier to train and performs better, whereas Leaky ReLU can be used to handle the problem of vanishing gradient. Some of the other activation functions include Leaky ReLU, Randomized Leaky ReLU, Parameterized ReLU Exponential Linear Units (ELU), Scaled Exponential Linear Units Tanh, hardtanh, softtanh, softsign, softmax, and softplus.

The use of machine learning and artificial intelligence has evolved in recent years and has many applications associated with medical image processing and disease diagnosis.

The possibility of applying classification techniques has been discovered SVM, kNN and PNN in two publicly available FNAB and gene microarray benchmark dataset for the characterization of benign and malignant tumours of the breast. To classify a data set for the purpose of classifying benign and malignant tumors in the breast. And achieved very high success rates?

These algorithms are applied to 7 sets of datasets and then performance is estimated by privacy, sensitivity, positive expected value, and predictive accuracy. Comparative analysis shows that bagged and boosted decision tree outperforms better than a single decision tree.

In order to overcome the drawbacks of local minima, improper learning rate and over fitting, extreme learning machine was focussed.

The approach used works on the GCM data set, lung and lymphoma, and

2D CNN

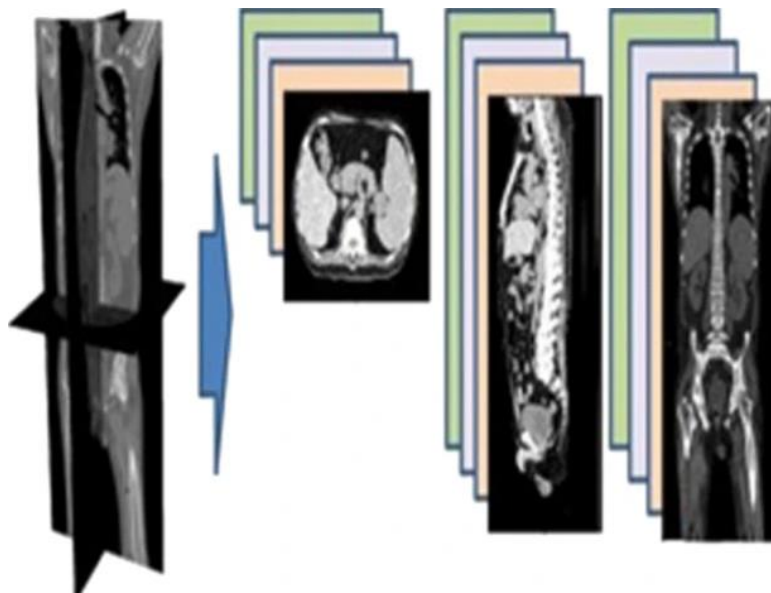
After discovering the features provided by CNN networks in terms of image classification and pattern recognition, D2 technology was adopted for image segmentation and processing. By performing the partition using the D2 input image and applying D2 filters.

In the study done by Zhang et al. (2016), multiple sources of information (T1, T2, and FA) in the form of 2D images are passed to the input layer of a CNN in various image channels (e.g., R, G, B) to investigate if the use of multi-modality images as input improves the segmentation outcomes. Their results have demonstrated better performance than those using a single modality input. In another experiment done by Bar et al. (2015), a transfer learning approach is taken into account and low-level features are borrowed from a pre-trained model on Imagenet. The high-level features are taken from PiCoDes and then all of these features are fused together.

2.5D CNN

This technique was adopted because D2.5 possesses more spatial information than one pixel and with less computational costs than D.3. It involves extracting three orthogonal D2 spots in XY, YZ, and XZ, respectively.

Here is an example of applying this idea to split knee cartilage. In this example, three separate twisted neural networks were defined, each of which was fed by a set of spots extracted from each orthogonal plane.



The relatively low number of training voxels (120,000) and satisfactory achievement of 0.8249 Dice coefficient proved that a triplaner CNN can provide a balance between performance and computational costs.

3D CNN

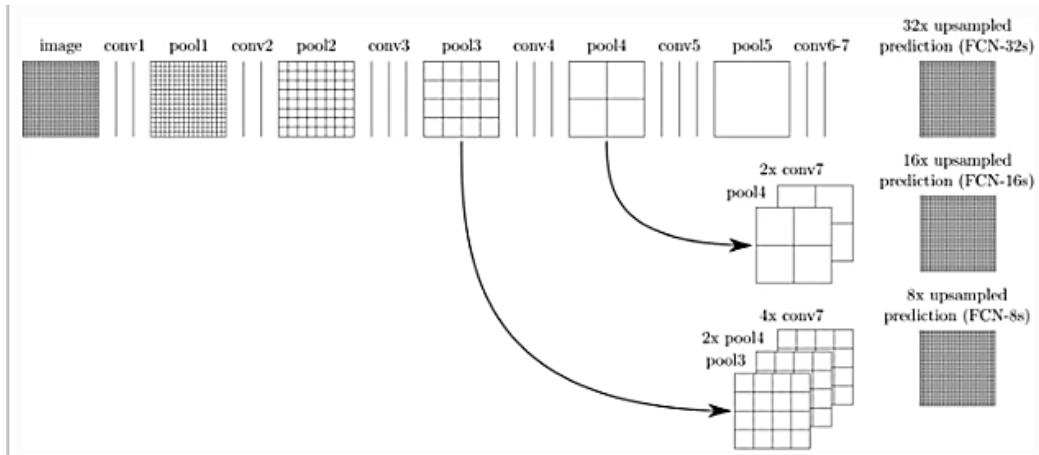
2.5D methods are still limited to 2D kernels, so they are not able to apply 3D filters.

3D CNN can be used to extract more powerful volume representation across the three axes (x, y,z). The 3D network is trained to predict the label of a central voxel according to the content of surrounding 3D patches. The idea of using 3D information for fragmentation was based on the availability of 3D medical imaging and the development of computers, with the aim of taking full advantage of the advantages of spatial information. The most important feature of volumetric images is that it provides comprehensive information in any direction rather than having a single view in 2D approaches.

One example of using this method is to divide the brain tumor from an arbitrary size. Using this method larger areas were processed around voxel which helped the entire system, and with the use of a smaller nucleus size of 3×3 we got better accuracy (an average Dice coefficient of 0.66) and less processing time (3 min for a 3D scan with four modalities) compared to the original design.

Fully Convolutional Network (FCN)

This network was developed where the last fully connected layer was replaced by a fully twisted layer. This helps to enhance predictability. And to achieve better results, high-resolution activation maps are integrated with overlapping outputs and then passed to convolutional layers for more accurate outputs.

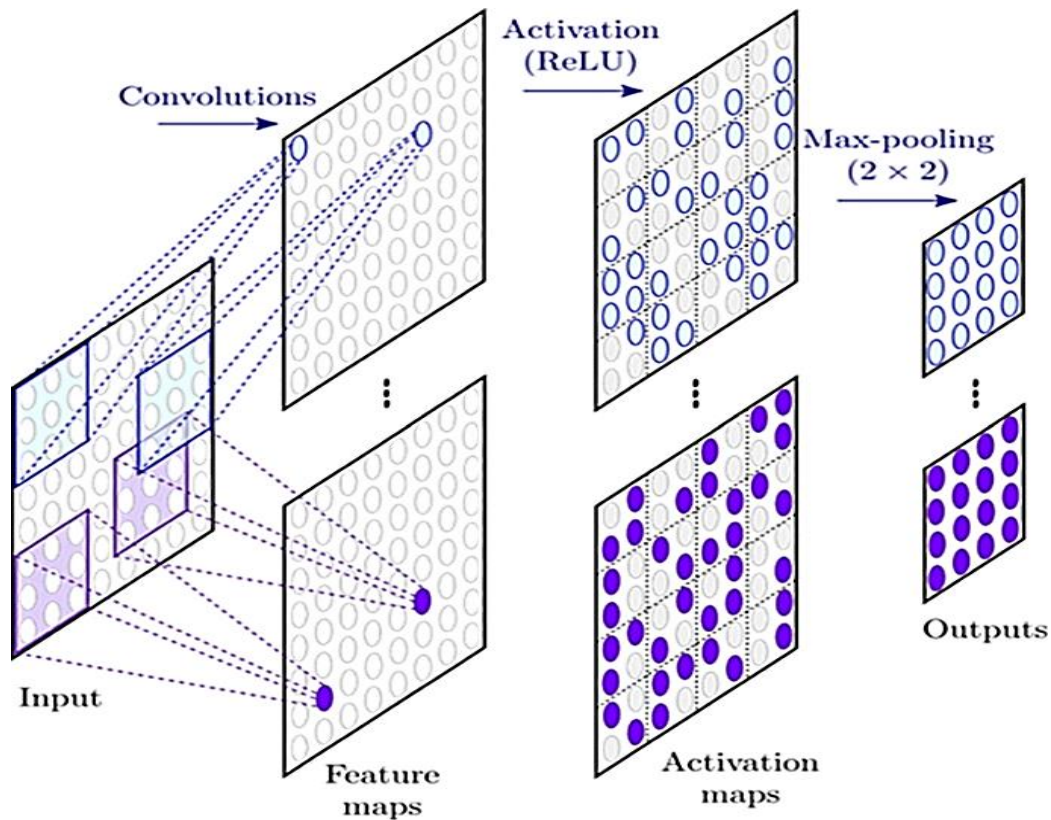


Convolutional Residual Networks (CRNs)

Although deeper networks have a greater ability to learn in theory, they suffer from problems such as progressive vanishing and dangerous degradation. This means that when the depth increases, we get saturated accuracy and then deteriorate rapidly.

So in n this model, instead of consecutively feeding the stacked layers with the feature map, a residual map is fed to every few layers.

That is, connections are skipped, giving the network greater flexibility and redirecting derivatives by skipping some layers.



In the following example, FCNN was used to perform a precise task related to medical imaging, namely, to identify melanoma. FCNN outperforms CNN with the ability to predict pixels accurately, and this adds more value than retail tasks.

Summary

In this paper, we summarized the most common network structures used in the processing of medical images and provided a glimpse of the most important techniques used, the most important neural training networks, and the goal they can achieve. We also talked about the most important effective solutions to deal with some difficulties in this area. It can help researchers choose the right neural network structure for their problem.

Conclusion

Analysis of images of medical abnormalities and lesions from the challenges of diagnosing and predicting diseases, especially because of the heterogeneous nature of abnormalities in terms of form, size, location and symptoms. It has therefore become important to rely on AI techniques that help provide more accurate information and less human effort.

ML-based healthcare systems need effective ways to extract features, and advanced neuron networks specifically designed to solve the challenges of understanding medical images can be relied upon.

It is important to note that the literature reviewed in this paper focused on researchers' interest in using CNN to overcome many challenges in understanding the medical image. Many CNN types were discussed and presented their most important features and uses and how they evolved to become more appropriate for the processing and analysis of medical images.

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