3D Image Classification from CT scan

Abstract:

The rapid advancements in machine learning, graphics processing technologies and the availability of medical imaging data have led to a rapid increase in the use of deep learning models in the medical domain. This was exacerbated by the rapid advancements in convolutional neural network (CNN) based architectures, which were adopted by the medical imaging community to assist clinicians in disease diagnosis. Since the grand success of AlexNet in 2012, CNNs have been increasingly used in medical image analysis to improve the efficiency of human clinicians. In recent years, three-dimensional (3D) CNNs have been employed for the analysis of medical images.

In this project, we trace the history of how the 3D CNN was developed from its machine learning roots, we provide a brief mathematical description of 3D CNN and provide the pre-processing steps required for medical images before feeding them to 3D CNNs. We review the significant research in the field of 3D medical imaging analysis using 3D CNNs (and its variants) in different medical areas such as classification, segmentation, detection and localization. We conclude by discussing the challenges associated with the use of 3D CNNs in the medical imaging domain (and the use of deep learning models in general) and possible future trends in the field.

Existing System:

Medical images have varied characteristics depending on the target organ and the suspected diagnosis. Common modalities used for medical imaging include X-ray, computed tomography (CT), diffusion tensor imaging (DTI), positron emission tomography (PET), magnetic resonance imaging (MRI), and functional MRI (fMRI). In the past thirty years, these radiological image acquisition technologies have enormously improved in terms of acquisition time, image quality, resolution and have become more affordable. Despite improvements in hardware, all radiological images require subsequent image analysis and diagnosis by trained human radiologists.

Besides the significant time and economic costs involved in training radiologists, radiologists also suffer from limitations due to their lack of experience, time and fatigue. This becomes especially significant because of an increasing number of radiological images due to the aging population and more prevalent scanning technologies that put additional stress on radiologists. This puts a focus on automated machine learning algorithms that can play a crucial role in assisting clinicians in alleviating their onerous workloads.

Proposed System:

Deep learning refers to learning patterns in data samples using neural networks containing multiple interconnected layers of artificial neurons. An artificial neuron by analogy to a biological neuron is something that takes multiple inputs, performs a simple computation and produces an output. This simple computation has the form of a linear function of the inputs followed by an activation function (usually non-linear). Examples of some commonly used non-linear activation functions are the hyperbolic tangent (tanh), sigmoid transformation and the rectified linear unit (ReLU) and their variants.

While the features captured by early hidden layers are generally shapes, curves or edges, deeper hidden layers capture more abstract and complex features. Historical methods for automated classification of images involves extensive rule-based algorithms or manual feature handcrafting, which are time-consuming, have poor generalization capacity and require domain knowledge. All this changed with the advent and demonstrated the success ofCNNs. CNNs are devoid of any manual feature handcrafting, require little preprocessing and are translation-invariant.

In CNNs, low-level image features are extracted by the initial layers of filters and progressively higher features are learnt by successive layers before classification. The commonly seen X-ray is an example of a two-dimensional (2D) medical image. The machine learning of these medical images is no different from CNNs applied to classify natural images in recent years, e.g., the ImageNet Large Scale Visual Recognition Competition. With decreasing computational costs and powerful graphics processing (units (GPUs) available, it has become possible to analyze three-dimensional (3D) medical images, such as CT, DTI, fMRI, Ultrasound and MRI scans using 3D deep learning.

These scans give detailed three-dimensional images of human organs and can be used to detect infection, cancers, traumatic injuries and abnormalities in blood vessels and organs. The major drawback in the application of 3D deep learning on medical images is the limited availability of data and high computational cost. Further, there is a problem of the curse of dimensionality. However, with the recent advancements in neural network architectures, data augmentation techniques and high-end GPUs, it is becoming possible to analyze the volumetric medical data using 3D deep learning.

Software Tools:

1. VS Code
2. TensorFlow
3. Keras
4. Jupyter Notebook
5. Anaconda
6. Matplotlib
7. Python3

Hardware Tools:

1. Laptop
2. Operating System – Windows 11
3. RAM: 16GB
4. ROM: 4GB
5. Fast Internet Connectivity
6. GPU