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Detection of Lung Cancer using Computed Tomography CT-Scan Images

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Abstract: *Cancer is one of the most serious and widespread disease that is responsible for large number of deaths every year. Among all different types of cancers, lung cancer is the most prevalent cancer having the highest mortality rate. Computed tomography scans are used for identification of lung cancer as it provides detailed picture of tumor in the body and tracks its growth. Computed Tomography is preferred over other imaging modalities, visual interpretation of these CT scan images may be an error prone task and can cause delay in lung cancer detection. The algorithm for lung cancer detection is proposed using methods such as median filtering for image preprocessing followed by segmentation of lung region of interest using mathematical morphological operations.*

Keywords: Computed Tomography, mortality, median filter

I. INTRODUCTION

Lung cancer is a type of cancer that begins in the lungs. Your lungs are two spongy organs in your chest that take in oxygen when you inhale and release carbon dioxide when you exhale. Lung cancer is the leading cause of cancer deaths worldwide. People who smoke have the greatest risk of lung cancer, though lung cancer can also occur in people who have never smoked.

The risk of lung cancer increases with the length of time and number of cigarettes you've smoked. If you quit smoking, even after smoking for many years, you can significantly reduce your chances of developing lung cancer. Lung cancer is a type of cancer that begins in the lungs. Lungs are two spongy organs in your chest that take in oxygen when you inhale and release carbon dioxide when you exhale.

Hence we have developed a project to detect lung cancer by using 2D & 3D convolution neural network with the help of CT images.

II. RELATED WORK

An entire full 3D convolutional neural network architecture is constructed with the segmented lung volumes as input from low-dose CT scans for early cancer detection. The two major steps are segmenting the entire lung volume from thorax CT volume and constructing a 3D CNN model for deep spatial feature extraction, training and testing[1].Compare different CNN Methods for Lung Cancer Detection with different Dataset.[2].Lung cancer is detected using CT images. Deep Neural Network can be used which could be effective way for finding cell growth region from CT scan images by 1.Image pattern recognition 2.image classification.Implemented simple 3DCNN.[3].

III. BACKGROUND STUDY OF DEEP LEARNING METHODS

3.1 Convolutional Neural Network

CNN is a deep learning algorithm that considers a input image and allots the learning weights and bias value for various classes in an image and tries to differentiate them from one to another. The convolutional neural network has been made major advancement which can be implemented on an embedded system with a low-resolution input image and low very complexity. We have used the following layers in our project:

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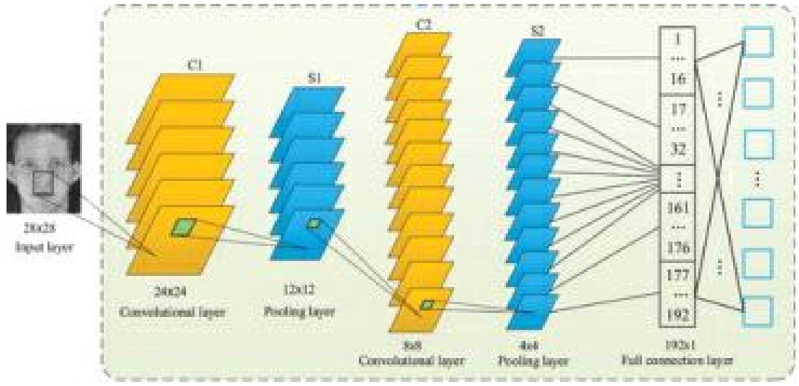


3.2 2 D Convolutional Neural Network

This is the standard Convolution Neural Network which was first introduced in Lenet-5 architecture. Conv2D is generally used on Image data. It is called 2 dimensional CNN because the kernel slides along 2 dimensions on the data as shown in the following image.

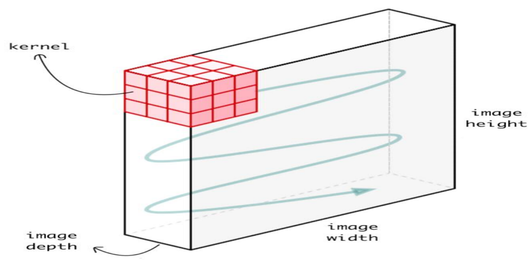
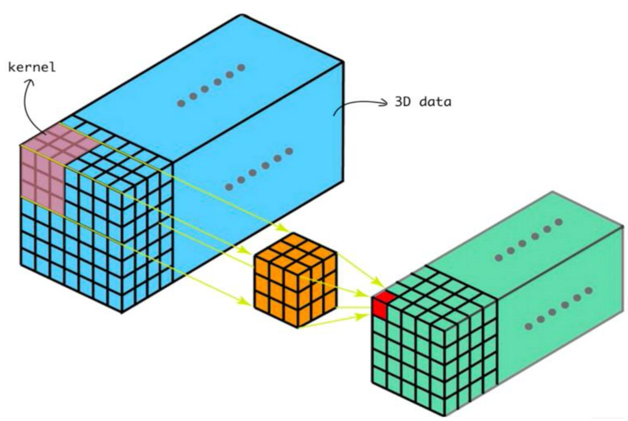


Fig 2: 2D convolutional neural network architecture

3.3 3 D Convolutional Neural Network

In Conv3D, the kernel slides in 3 dimensions as shown below. Conv3D is mostly used with 3D image data. Such as Magnetic Resonance Imaging (MRI) data. MRI data is widely used for examining the brain, spinal cords, internal organs and many more. A Computerized Tomography (CT) Scan is also an example of 3D data, which is created by combining a series of X-rays image taken from different angles around the body. We can use Conv3D to classify this medical data or extract features from it.



3.4 Dataset

In this study, we have used the Lung Cancer detection dataset from Kaggle which contains 711 CT images of lungs which is infected from cancer cells and not having cancer cells

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After then, data augmentation techniques will be utilized to increase the dataset size. Additionally, the content-based image retrieval technique can assist in the avoidance of image duplication issues.
The resolutions of the images in the dataset range from 250 x 350 pixels. The training images will be allocated as follows in our framework: 70% for training, 20% for validation and 10% for testing.
The sample images are divided into three sections at random (train, validation and test).

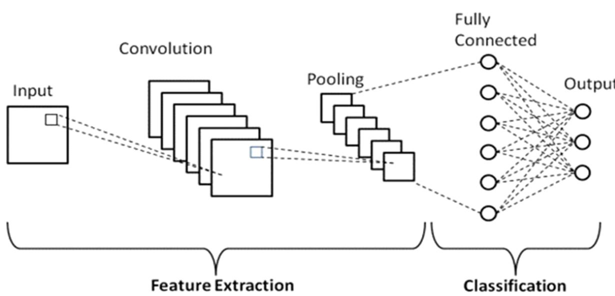
IV. ARCHITECTURE

4.1 Pre-Processing on Image

The image is pre-processed before being sent to the model. Normally, images are in RGB colour, but we transform them to grey scale with a single monochrome channel before sending them to the model to avoid undesired noise. When providing input to the model, the user may give a picture of a different size, so we must transform that image to that size. We've utilised a 100-pixel image here.

4.2 Feature Extraction

This is the procedure for converting input data into a set of features that best represent it. We can minimise the size of a feature if we want to delete it. Various operations including pooling, normalisation, and other operations can be used in this process. We turn the 2D matrix into a flatten array and then transfer it to the dense layer after extracting the feature. CNN models were created using a sequential model from the Keras package, with 2D convolution layers added initially for core processing.



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After that pooling layer were used for summarizing the previous layers learning and reducing the dimension of feature map. Thereby reducing the calculations and in a way making it more immune to variation in dataset, i.e., generalizing.
Flattening layers were implemented for single dimension feature map. In the end Dense layers i.e., fully connected layers were used for classifying it in two classes.

V. CONCLUSION

In this paper we proposed the fully automatic deep learning based method for detection of lung cancer in whole slide histopathology images. CNN architectures were compared and the first one shows higher AUC and patch classification accuracy. Presented results shows that convolutional neural networks have potential to perform lung cancer diagnose from whole slide images, but more effort is needed to increase classification accuracy. In future work next steps will be increasing the training set size, adding image augmentation and stain normalization. Also, we will try training from the scratch instead of using pre trained weighted images.

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