International Journal of Multidisciplinary Research and Growth Evaluation.

The CNN approach for the lung cancer detection: A review

Jogendra [1*], Amarinder Kaur [2]
[1] Lovely Professional University Jalandhar, Punjab, India
[2] Assistant Professor, Lovely Professional University Jalandhar, Punjab, India

* Corresponding Author: **Jogendra**

Article Info

ISSN (online): 2582-7138
Volume: 03
Issue: 01
March-April 2022
Received: 03-03-2022;
Accepted: 19-03-2022
Page No: 287-290

Abstract
Lung Cancer is one of the most deadly cancer in the world. It has a high demise rate and its cases are increasing day by day in throughout world due to people lifestyle. Cancer diagnosis and treatment has been one of the most difficult problems that humanity has encountered in past few year. If it has not been detected at early stage then the patient survival chance will be very less. Detecting lung cancer at early stage Computer Aided Diagnosis (CAD) has become an indispensable tool for supporting radiologists' CT interpretations. Its speedup the whole process of analysis of cancer. This paper describes a automatic method for classifying tumours seen on computed tomography scans of lung cancer as malignant or benign using a Convolutional Neural Network (CNN). For classification of computed tomography scan we use thresholding segmentation as initial segmentation to segment out lung tissue from computed tomography in CNN but this seems to be inadequate so that we modified U-Net trained to predict nodule. CT scans with segmented lungs were fetch into Convolutional Neural Networks to prove the CT scan as positive or negative for lung cancer based on the location. CAD system performance depend on various factor several training and testing stage, required lots of label data for training.

Keywords: Lung Cancer, Computed Tomography, Convolutional Neural Networks, Segmentation

1. Introduction
Lung cancer is the most prevalent form of cancer. Lung cancer is the third most common cancer worldwide rapidly growing cancer in people life due to their lifestyle. Its cause death of people around 1.7 million per year. According to World Health Organization report there are around 1.8 million lung cancer patient found every year. Cancer cases are increasing 13 percent every year. Early stage lung cancer detection and diagnosis has the better survival rate with later stage diagnoses having a worse prognosis.
For detecting cancer we need a well knowledge and trained pathologist which leads a high cost and not affordable by common people of the society. These things make cure process more complicated. By designing computer aided method we can detect cancer initial stage it reduced the cost as well as making treatment process fast. Our task is to detect the presence of lung cancer in patient CT scans of lungs with and without early stage lung cancer using a binary classification issue. To create an accurate classifier, we plan to use methods from computer vision and deep learning, especially 2D and 3D convolutional neural networks. The aim is to develop a computer aided diagnosis (CAD) system that takes patient chest CT scans as input and determines if the patient has lung cancer. To improve the precision of lung cancer diagnosis, we use comprehensive preprocessing techniques to obtain correct nodules. Furthermore, we conduct end-to-end CNN training from scratch in order to understand the neural network's full potential, i.e. to learn discriminative features.

2. Convolutional Neural Network
In current scenario convolutional neural network is mostly used model in visual recognition system. A CNN is designed in such a way that it learns the main features of various patterns in an adaptive manner by applying appropriate filters.

The model extracts the higher-level features of the input as we go deeper into the CNN layers. It use several convolutional layer and max pooling for extracting feature in hierarchical way from the hidden layer and the learning process properly assigns weights to the major functions, thereby performing the complicated task of feature development automatically.

CNN consists of several hidden layers such as the Pool layer, RELU layer and fully connected layer. CNN shares weights on the convolutionary layer which reduces memory size and increases network efficiency. The convolution layer creates a feature map by convolutioning different subregions of the input image with a trained kernel. When the error is tiny, a non-linear activation function is implemented via the RELU layer to increase the convergence properties. A region of the image or feature map are selected as the characteristic pixel in the pooling layer, and the pixel with the highest value among them or the average value is chosen as the representative pixel, resulting in a 2x2 or 3x3 grid being reduced to a single scalar value. As a result, the sample size is drastically reduced. Toward the output level, a standard Fully-Connected (FC) layer can be used in combination with convolutional layers. Convolution layer and pool layer are typically used in some combination in CNN architecture. The pooling layer usually performs two types of operations: maximum pooling and means pooling. The average neighbourhood is calculated within the feature points in mean pooling and within a maximum of feature points in max pooling. Mean pooling eliminates the error caused by the neighbourhood size restriction while preserving background data. Max pooling decreases the expected error in the convolution layer parameter caused by the mean deviation and thus preserves more texture detail.

3. Proposed Methodology

Initially CT scans are pre-processed with segmentation, standardization, downsampling and zerocentration. In the beginning, we fetch the 3D CT Scan in CNN as input but result is not so good so that we need further preprocessed the CT scan only region of interest. We use U-net for nodule candidate detection to classify regions of interest. then enter regions around nodules detected by the U-net into 3D CNNs to classify CT scans for lung cancer as positive or negative.

3.1 Pre-processing

Image pre-processing is initial operation on image in beginning level. Images are acquired from source like sensor and camera have some issue like high and low intensity, noised, blur and transformations of images (e.g. rotation, scaling, translation) etc. Hence preprocessing is need to improve the image data by suppressing distortions or enhancing certain image features essential for further processing.

3.2 Binary Image

A binary image is a digital image with only two possible pixel values. Binary images are also known as bilevel or two-level images. In digital image processing, binary images often appear as masks or as the product of operations like segmentation and thresholding.

3.3 Smoothing

It eliminates noise or other minor image fluctuations similar to high Frequency Domain deletion. Smoothing also blurs all sharp corners, which provide significant image information. Medium filtering is used to remove the noise from the images.

3.3.1 Median filter

The median of all the pixels under the kernel window is computed by the function cv2.medianBlur(), and the central pixel is replaced with this median value. This is a great way to get rid of salt-and-pepper noise filtered value for the central element in the Gaussian and box filters may be a value that doesn't exist in the original picture but in median filtering, however, central element is always replaced by a pixel value in the image. This effectively eliminates noise.

3.4 Enhancement

Images coming from different sources have different contrast, intensity so that it need to enhance before preprocess. It also Enhance pictorial information in images for humans, as well as other automated image processing techniques. The spatial domain and the frequency domain are the two primary types of image enhancement.

Gabor filter is a enhancement technique. it is fast and better than other technique.

3.4.1 Gabor Filter

The Gabor filter is a linear texture analysis filter that examines whether the image contains any particular frequency material in specific directions in a localised area around the point or region of analysis.

4. Image segmentation

Firstly we convert image pixel value in Hounsfield units (HU), used for measurement of radiodensity. We store 2D image slice into 3D image. When we take image of our lungs there are bone, outside air, and other substances that would make our data noisy so that we use image segmentation to remove all the things except lung tissues which is use to classify the lungs nodule. We use different kind of segmentation technique like thresholding, watershed and k-means clustering out of which watershed segmentation give qualitative result.

3.1 Thresholding Segmentation

Thresholding is an image segmentation technique in which the pixels of an image are changed to make the image easier to interpret. Thresholding is the process of converting a colour or grayscale image into a binary image, which is simply black and white. We most commonly use thresholding to pick areas of interest in a picture while ignoring the sections we don't care about.

3.2 Watershed Segmentation

After thresholding due to CT scan noise, many voxels that were part of lung tissue, particularly voxels at the edge of the lung, tended to fall outside the range of lung tissue radiodensity. As a result, our classifier would be unable to correctly identify image in which cancerous nodules are found at the lung's edge. To identify nodule at edge we use Marker-driven watershed segmentation. Its avoiding the over segmentation problem and the need for manual marking both the edges and the field.

4. Image classification

Classification is a technique to make the group of data point

having same property.

4.1 Alex Net
AlexNet is a convolutional neural network that has been pre-trained. Its trained over a million images from ImageNet and it has 8 deep layer and can classify image in 1000 different categories. Network take input image size 227*227 and network has rich technique to represent image. Alexnet identify new set of image process is called transfer learning it is quicker and simpler than training a new network. Network include 11x11, 5x5,3x3, convolutions, max pooling, dropout, data augmentation, ReLU activations, SGD with momentum. As an image moves through one convolution layer, the first layer's output becomes the second layer's input. This happens with each successive convolutional sheet.

4.2 Pooling layer
Pooling layer is a nonlinear layer. It deals with the image's width and height, performing a down sampling procedure on them. As a consequence, the size of the image is diminished. That means it compress only required image area.

4.3 Fully connected layer
After completion of pooling layer we attached fully connected layer for taking information about convolution network output information. End of the network fully connected layer is attached and its-generate n dimensional vector for selecting desirable class.

4.4 Soft maxing
Various multiclass classification approaches, such as multinomial logistic regression, use the SoftMax function. In the final layer of a neural network-based classifier, the SoftMax function is often used. A non-linear version of multinomial logistic regression is obtained by training such networks under a log loss or cross-entropy regime. A softmax activation function produces a vector whose set of values reflects the probability of a class or event occurring.

5. Literature Review
In [8[Suna W. et al., compared three deep learning algorithms: Convolutional Neural Network (CNN), Deep Belief Networks (DBNs), and Stacked Denoising Autoencoder (SDAE) to a conventional image feature-based CAD framework. Eight layers of convolutional and pooling layers alternately make up the CNN architecture. There were approximately 35 extracted texture and morphological features for the conventional compared to algorithm. For training and classification, these features were fed into a kernel-based support vector machine (SVM). The CNN method achieved an accuracy of 0.7976, which was slightly better than the standard SVM's 0.7940. They used the public databases of the Lung Image Database Consortium and Image Database Resource Initiative (LIDC/IDRI), which included 1018 lung cases.

In [9], J. Tan et al., Using a Deep Neural Network and a Convolutional Neural Network, a prototype framework for detecting lung nodules was created, its reduce the false positive rate for the detected nodules. Four convolutional layers and four pooling layers make up the CNN. The filter had a depth of 32 and a diameter of 3,5. For around 85 patients, the used dataset was obtained from the LIDC-IDRI. The sensitivity that resulted was 0.82. DNN achieved a false positive reduction of 0.329.

In [10], Sumita Mishra, Naresh Kumar Chaudhary, Pallavi Asthana, and Anil Kumar et al., The proposed 3D Deep CNN uses CT volume to automatically extract 3D features for pulmonary nodule classification. We've shown that our 3D Deep CNN model can perform equally and achieve a 94.8 percent accuracy without a lot of pre-processing and with minimal computational resources. The dataset used in the work is Luna which is based on publicly available Lung Image Database Consortium and Image Database Resource Initiative (LIDC/ IDRI) data. Using a suitable data augmentation technique, the proposed model's output could be improved even further. While data augmentation using axes swapping was attempted in this study, there was no substantial change, and over-fitting could be minimised by using a drop out layer

In [11], Researchers used the LUNA 16 dataset to perform a two-stage convolutional neural network technique. The input CT image is refined in the first step, and For improvised classification, the second stage uses simplified Google Nets. Out of 888 thoracic cancer images, the authors were able to obtain an accuracy of 89.6% by using 90% for training and 10% for research. The researchers used 11 Deep CNN models on the LUNA 16 dataset in [15]. They were incorporated into a modified CNN architecture, and transfer learning was used. It was possible to achieve an accuracy of 88 percent (0.94)

[12] P. Mohamed Shakeel et al., For their study, they used the Cancer Imaging Archive (CIA) dataset. The noise is eliminated using a weighted mean histogram equalisation method, and the segmentation is carried out using the Improved Profuse Clustering Technique (IPCT). They use deep 765 for cancer prediction. Auckland University of Technology is the only approved licenced user. IEEE Xplore was used to download this document on October 29, 2020 at 04:59:35 UTC. There are certain limitations. Instantly trained neural networks can be learned. The accuracy of the device is 98.42 percent.

[13], S. Sasikala, M. Bharathi, B.R. Sowmiya et al., proposed using CNN to identify and diagnose lung cancer using CT scan images. They worked with MATLAB and had two phases of training: the first phase was to extract useful volumetric features from the input data, and the second phase was classification. With 96 percent precision, their proposed method could distinguish between cancerous and non-cancerous cells.

6. Problem Identification
Many strategies for lung cancer detection have been developed in recent years using a neural network method. Early detection of lung cancer is first most step to stop cancer. Main issue are that algorithm are fail to identify the exact size and localization of cancerious tissue. Its also fail to reduce false positive and false negative percentage. Models are not producing accuracy upto the mark.

For early detection of lung cancer we recommends annual screening for people at high risk of developing lung cancer.

Alexis Arnaud's technique for lung cancer diagnosis addresses the issue of tumour localization and characterization. Due to the high complexity of the built procedure, the execution time is extremely long. Techniques must be established that can reliably localise and describe tumour portions in the shortest period of time.

7. Future Work
The class activation maps are then evaluated in order to fine-

tune the network so that it can operate in situations where it has previously failed. The big issue here is that a lot of significant data is lost in the process, and CNN is a poor representation of the human visual system. CNN uses max-pooling to solve the problem of class invariants, but we need class equivalence for biomedical images. The strongest neural network is the capsule neural network, which stores and mimics the human vision system using class equivalence. Its significance suggests that capsule neural networks can learn faster and produce more accurate results with less data.

8. Conclusion

Image analysis is used to diagnose lung cancer. The identification of a cancer nodule involves three stages. CT scan images are used to detect the presence of cancer nodules. Furthermore, there are two steps that make up the pre-processing. Those two processes are image enhancement and image segmentation. The image enhancement stage improves the interpretability of details in the image for human viewers. Gabor filter, fast fourier transform, log gabor filter, and auto enhancement are just a few of the enhancement algorithms available. Image segmentation is the second stage of pre-processing. The aim of image segmentation is to divide a digital image into meaningful regions and classify objects or relevant information within them.The segmentation process' output is sent to the feature extraction point. Feature extraction uncovers characteristics such as location, perimeter, and irregularity. The cancer cell recognition module detects abnormalities in the lungs based on the extracted features. In this study, the GLCM and CNN approaches will be used to locate and characterise cancer portions from CT scan images. The proposed method is implemented in MATLAB, and the accuracy of the results is evaluated.

9. References

1. Centers for Disease Control and Prevention, Lung cancer statistics. https://www.cdc.gov/cancer/ lung/statistics/, 2016.
2. Li, Linlin Shen, Suhuai LuoA. Solitary Feature-Based Lung Nodule Detection Approach for Chest X-Ray Radiographs, IEEE journal of biomedical and health informatics. 2018; 22:2.
3. Chon N Balachandar, P Lu. Deep convolutional neural networks for lung cancer detection, tech. rep., Stanford University, 2017.
4. Prajwal Rao, Nishal Ancelette Pereira, Raghuram Srinivasan Convolutional neural networks for lung cancer screening in computed tomography (CT) scans, 2017, 21.
5. Using Deep Learning for Classification of Lung Tumors on Computed Tomography Images.
6. Li, Linlin Shen, Suhuai Luo A. Solitary Feature-Based Lung Nodule Detection Approach for Chest X-Ray Radiographs, IEEE journal of biomedical and health informatics. 2018; 22:2.
7. Mayo Clinic Staff. Tests and diagnosis. http:// www.mayoclinic.org/diseases-conditions/ lung-cancer/basics/tests-diagnosis/ con-20025531, 2015.
8. W Sun, B Zheng, W Qian. Computer aided lung cancer diagnosis with deep learning algorithms, in SPIE Medical Imaging, International Society for Optics and Photonics. 2016; 9785:97850Z-97850Z.
9. J Tan, Y Huo, Z Liang, L Li. A comparison study on the effect of false positive reduction in deep learning based detection for juxtapleural lung nodules: Cnn vs dnn, in Proceedings of the Symposium on Modeling and Simulation in Medicine, MSM '17, (San Diego, CA, USA), pp., Society for Computer Simulation International. 2017; 8:1-8:8.
10. Huang X, Shan J, Vaidya V. Lung nodule detection in CT using 3D convolutional neural networks IEEE, International Symposium on Biomedical Imaging. IEEE, 2017.
11. Yang T, Hu J, Wang J, Lyu S Banerjee, SH Ling. Lung nodule classification using a novel two-stage convolutional neural networks structure, in Proceedings of the 2019 41st.
12. Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), Berlin, Germany, 2019.
13. P Shakeel, MA Burhanuddin, M Desa. Lung Cancer Detection from CT Image Using Improved Profuse Clustering and Deep Learning Instantaneously Trained Neural Networks, Measurement, vol. 145,May 2019, doi: 10.1016/j.measurement. 2019.05.027
14. S Sasikala, M Bharathi, BR Sowmiya. Lung Cancer Detection and Classification Using Deep CNN, 2019.