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A Brief Overview on Deep Learning Methods For Lung Cancer Detection Using Medical Imaging

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ABSTRACT

In this paper, deep learning methods for lung cancer detection are discussed. Lung cancer is one of the most common types of cancer which is responsible of millions of death over the years. Early and correct diagnosis will help the patient to overcome the disease timely. Medical imaging is assisting the radiologists and physicians to diagnose this kind of cancer. Computer aided diagnosis is also playing its part with an objective of better and accurate results. Major objective of this paper is to provide the current trends in relation to deep learning architectures such as (CNN) Convolution Neural Networks (2D and 3D), R-CNN (Region based convolution neural network), DBF (Deep Belief networks), DNN (Deep neural networks), VGG-16 CNN, U-net Convolution Networks, SDAE(Stacked De-noising Autoencoders) etc. This paper provides a short review considering the research trends from the last five years, i.e. 2015-2019. Tabular view of datasets, sample sizes and success rates are also demonstrated in the latter half of the paper for better understanding of the latest computational methods.

Keywords--*CNN**,** Deep learning, Medical Imaging, Computer aided diagnosis, lung nodules*

1 INTRODUCTION

Lung cancer is a sort of lung tumour which occurs primarily due to uncontrolled cell growth in lung tissues. Smoking is the major cause identified over the years which is accounted to be 90% of lung cancers [1]. Various diagnostic methods are developed over the years for the diagnosis of lung cancer. There could be physical symptoms which are indicative towards this cancer development, such as: joint pains, immediate weight loss, headache, bleeding, facial swelling, blood clots etc. These symptoms are analyzed by physicians through various screening methods, such as spirometer can be used which measures the quantity of breath air

[2]. Medical imaging can also be utilized for examine the patient, such as: CT scans (Computed tomography) and Chest X-rays. Computational methods are developed over the years for enhancing the prediction capabilities. Machine learning algorithms are utilized for the imparting training and expert systems can be developed for the prognosis and diagnosis of lung cancer at any level. Due to the complexities and varieties in the samples, traditional machine learning algorithms are not suitable enough, so CAD systems are trained using deep learning methods now a days.

Convolution Neural Networks are one of the most commonly used deep learning architectures as identified in the literature. CNN defines and compute features automatically. During training phase input and output labels are presented to the system and accordingly it analyses the patterns. It consists of convolution and pooling layers, where in convolution layer defines features and parameters and pooling layer accumulates computations with similar permutations [3]. Other most commonly used deep learning method is Deep Neural Network where numbers of hidden nodes are increased in normal neural network. DNN does not consist of the convolution layer, and all of its layers are connected to each other [4]. DNN can be used for image pattern recognition and classification, as it can detect the correct mathematical manipulation to convert the input into output[5].

State of the art methods have also depicted Deep Belief Network to be the other architecture which is commonly incorporated for the development of CAD systems. It is also known as generative graphical model which consists of multiple layers of hidden units, where layers are connected to each other but there is no link between units within each layer.DBN can be visualized as a combination of RBMs(Restricted Boltzmann Machines), where there is no connection between hidden units [6].Autoencoders are also used implemented as deep learning architectures for classifying cancerous and non-cancerous images. It is two-layered network that accepts input and performs data encoding either using linear or non-linear transformation [7].Autoencoders comes under the unsupervised learning algorithms, as it makes use of inexpensive unlabeled data [8].R-CNN is another improvisation in the traditional CNN where CNN is used to classify image regions within an image, hence they are much useful in detecting lung abnormalities, as region specific search is performed [9]. It starts its search by selecting several proposed regions from an image and then labelling is performed to formulate boundaries and offset.

U-net convolution architectures are also introduced by many researchers, following its advantages over traditional deep learning approaches. These kinds of architectures are primarily used for achieving fast and precise image segmentation. It consists of top-down and bottom-up layers in order to formulate a U-shaped structure [10].They are originated from fully conventional networks. The remaining part of the paper is focused on the unique CAD

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systems developed over the five years for lung cancer/lung nodule detection. Review of literature section demonstrates the computational methods in detail and later part gives tabular view of important points gathered from the research articles.

2 REVIEW OF LITERATURE

Various deep learning methods for lung cancer detection have been identified in the state of the art. Higher accuracy levels and correct diagnosis are making these methods suitable enough to carry out medical activities. Diagnostic system which can extract deep features from autoencoder is proposed which can classify tested image into malignant or benign [7].For classification purpose binary decision tree has been used. Nodules extraction has been performed from 2D CT images, which are automatically fed into autoencoder. Following more intensive research in deep learning, Sun et al. [11] presented traditional CAD system which is compared with the three commonly used deep learning methods, such as: Convolutional Neural Network, Deep Belief Networks, Stacked Denoising Autoencoder. On carrying out the comparison Deep Belief Networks outperformed the other implemented methods. These methods are implemented on CT images where, marking on nodes are done by radiologists in prior. In these systems entire work is done on the 2D characteristics, but later on, Fan et al. [12] represented, 3D Convolutional Neural Network for achieving better accuracies and results. The proposed method starts with the conversion of image into its equivalent mask, where in various sub steps are performed such as: threshold segmentation, corrosion and expansion. Following other steps, 3D CNN is built upon 3D convolutional autoencoder. On testing the proposed method, it outperforms SVM in terms of accuracies, which clearly signifies the utility of deep learning methods.

Research is continued in terms of 3D CNN modelling and Jin et al. [13] proposed a CAD system based on 11 layered 3D CNN architecture which is trained using segmented lung images. ReLU non linearity and Sigmoid functions are implemented as activation and classification methods. The proposed method improves the diagnostic accuracy as compared to the traditional AlexNet architecture. The major step involves the lung separation, which is obtained using binary mask conversion and appropriate threshold value. Li et al.[14] presented a novel approach for the identification of lung masses, which can further assist in the diagnosis of lung cancer. For achieving this, Region-based Convolution Neural Network architecture is trained which presents fast and accurate results, as compared to other methods for lung mass detection. System is embedded with feature extraction techniques where in

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RESNET performed much better as compared to VGG16. Rossetto and Zhou [15] presented ensemble of CNN system which works on the voting system, which predicts from two kinds of pre-processed images. During pre-processing step images with and without smoothing effects are supplied to the proposed CNN architecture and later on predictions are made. For smoothing the image, gaussian filter has been applied.

Song et al. [4] implemented three deep learning methods: Convolution Neural Network(CNN), Deep Neural Network(DNN) and Stacked Autoencoder (SAE) for the classification of benign and malignant CT images. All methods are implemented on the given dataset and CNN gives better results as compared to the other given methods. Convolution neural network has been used in connection with two layers, such as: Convolution and Pool layer. The major benefit of CNN lies in fact that, with the same number of hidden units, they are much easier to train as there are fewer parameters as compared to fully connected networks.

Gu et al.[16] proposed a CAD system with 3D deep convolutional neural network with a multi-scale prediction strategy. This prediction strategy includes multi-scale cube prediction and clustering for achieving better results. These strategies are implemented with a vision of detecting extremely small nodes which were difficult to detect using traditional 3D CNN architecture. Jakimovski and Davcev [5] developed DNN(Deep Neural Network) based diagnostic system with additional layers of convolution and max pooling. Medical images(Magnetic Resonance imaging) is used as a source data set for the identification of lung cancer. The proposed DNN architecture is tested against a slow progressing lung cancer, which will also calculate the threshold limit at which the testing can be stopped to determine the cancer stage.

CAD systems with CNN and R-CNN(Region based) is presented by Kido et al. [9] which stressed upon the importance of image based CNN and R-CNN CAD systems over feature based systems where image feature extraction has to be performed as an additional step. Moreover the presented system is helpful in the detection of lung nodules and diffuse lung diseases. Technically, R-CNN offers benefit over CNN in terms of dealing with those regions that are likely to have object (or region of interest).It creates bounding boxes using a selective search. It wraps the region into square box and passes it to the standard CNN and later on support vector machines (SVM) is used to classify it among lung nodules or some kind of diffuse lung disease. Shaziya et al. [10] developed system based on U-net convolutional network which implements data augmentation for improved lung segmentation. U-net consists of ConvNet layers which are arranged in a top-down and bottom-up manner in order form U-shaped architecture. Top-down path is also known as contraction path which is there to capture the context of the image, whereas bottom up path also termed as expansion path is used to localize the area of interest. Another CAD system implementing U-net for lung segmentation is proposed by Tekade and Rajeswari [17]. It applies 3d multipath VGG-like network which is evaluated on 3D cubes for achieving better results. VGG-16 structure has been utilized which consists of convolutional and pooling layers.

Bhalerao et al.[3] represented CAD system which incorporates image pre-processing before going for the actual training of the CNN model. Pre-processing comprises of conversion of image from RGB to gray-scale and final step is to acquire the binary format of gray-scale. RGB images are very complex to handle, so the pre-processing phase helps to assist the deep learning model. CNN architecture will take binary image as an input followed by two steps: Convolutional filtering and Max Pooling. Liu et al. [18] presented a system, with an objective of reducing false positives. For achieving the said objective, cascade method for the lung nodule detection system using CNN has been proposed. This method comprises of pre-training of object detection network, so that area of interest can be obtained, such as lung nodule. Later non-nodule filter is applied on the output of the detection network for obtaining better results. Geng et al. [19] proposed a CAD system with the combination of VGG-16 and dilated convolution. Dilated convolution can increase the receptive field area of the convolution kernel, but the number of parameters is unchanged. Not only this, the size of the feature map of the output also remains unaltered. Proposed system also uses the feature of hyercolumn to increase the power of proposed algorithm.

Shakeel et al. [2] presented a CAD system with an approach of de-noising using weighted mean histogram equalization followed by image segmentation using improved profuse clustering technique. After obtaining the region of interest, deep learning instantaneously trained neural network (DITNN) is trained to predict the lung cancer. Comparisons are performed with the state of the art of the methods and results are better in terms of diagnosis.

3 OBSERVATIONS

This paper represents a brief overview of the deep learning methods implemented for the lung cancer detection from the medical images. Some of the notable observations are already quoted in the review of literature section, but this section highlights the gains from the review conducted. Other important points related to deep learning methods in the literature are represented in the Table 1, such as: Image type, Dataset, Sample size and the success rate. This set of information is useful as if someone wants to carry out further research in the implementation of deep learning methods over medically available datasets.

Table 1: Summary of deep learning methods for lung cancer detection

Author	Deep learning	Image	Dataset	Sample	Results

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	architecture	type		Size	
Kumar et al.[7]	Autoencoder	CT	LIDC(Lung Image Database Consortium)	Images of 1010 patients	Accuracy:75.01% Sensitivity:83.35% False positive: 0.39/Patient Cross validation: 10 folds
Sun et al. [11]	CNN, DBF,SDAE	CT image slices obtained using down sampling and rotation	LIDC(Lung Image Database Consortium)	174412 samples with 52X52 pixel	Accuracies: CNN: 79.76% DBNs: 81.19% SDAE: 79.29%
Fan et al.[12]	3D CNN	CT	Not specified	1500 Scanned images	Accuracy:67.7%
Jin et al. [13]	3D CNN, Activation / classification: ReLU nonlinearity sigmoid functions	CT	Kaggle Data Science Bowl 2017	1397 Scanned images	Accuracy:87.5%
Li et al.[14]	RCNN, Feature extraction: RESNET	Chest radiographs	JSRT(Japanese society of Radiological Technology), JRS(Japanese Radiological Society) and Teaching library at Gansu	626 images resized by 512X512 pixel	Average precision based on RESNET:52.38%
Rossetto and Zhou [15]	Multiple preprocessing methods followed	CT	Kaggle Data Science Bowl 2017	1500 original images with	Accuracy:97.5%

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	by ensemble of CNN			150,000 slices	
Song et al.[4]	CNN,DNN,SAE	CT	LIDC-IDRI	4581 images	Best accuracy: CNN (84.15%) Senstivity:83.96% Specificity:84.32%
Gu et al.[16]	3D Deep CNN with multi scale cube prediction and clustering	CT	LUNA16 database	888 thin-slice scans with 1186 nodules	CPM(Competition performance metric) score: 0.7967
Jakimovski and Davcev [5]	DNN	CT	Data from local hospital	70 images	Certainty rate:75%
Kido et al. [9]	R-CNN	CT	Not specified	Lung nodules:163 samples, Diffuse lung disease:372 samples	Accuracy without data augmentation:95.2 Accuracy with data augmentation:99.4
Shaziya et al.[10]	U-net Convolutional network	CT	Not spcified	267 scanned images	Accuracy:96.78%
Tekade and Rajeswar. [17]	Image segmentation: U-net architecture. Deep learning model: 3D-VGG evaluated on 3D	CT	LIDC-IDRI, LUNA16, Kaggle Data Science Bowl 2017	35000 3D Cubes	Accuracy:95.60%

	Cubes				
Bhalerao et al.[3]	CNN	CT	LIDC	910 scanned images	Accuracy:94.34%
Liu et al. [18]	CNN	Chest X-Rays	JSRT and AUCM	JSRT:154 images, AUCM: 2806 images	JSRT recall:0.79 AUCM recall:0.91
Geng et al. [19]	Combination of VGG-16 and dilated convolution	CT	Images collected from local hospital	1937 images	Dice similarity coefficient:0.9867
Shakeel et al. [2]	Deep learning instantaneously trained neural network(DITNN)	CT	Cancer Imaging Archive(CIA)	5043 images	Accuracy:98.42%

CT: Computed tomography

4 CONCLUSION

The main objective of this paper is to throw light on the current research trends in lung cancer detection using deep learning methods. From the literature, it can be concluded that 3D CNN is most widely used deep learning architecture due to its convolution and pooling layers. Most widely used datasets are LIDC, LUNA16, Kaggle data science bowl 2017 which offers appropriate number of samples for imparting training to the deep learning models. Various researchers also prefer data from the hospitals where live samples can be collected and image marking is performed from the experts like: Doctors and radiologists. Most commonly used medical imaging is computed tomography, but due to its expensive nature, some researchers have taken X-rays radiographs as their source datasets. Further research can be carried out where deep learning methods can be developed for the detection of some other kinds of cancers which are life threatening.

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