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Assignment Item 4 : Annotated Bibliography

ITC 571 EMERGING TECHNOLOGY AND INNOVATION

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**Abstract**

The use of deep learning based lung cancer classification has been used increasingly for the early diagnosis of lung cancer but because of several reasons such as: lack of robust deep learning -based system , complexity of nodule structure , lack of proper lung segmentation technique , high false positive result ,lack of best feature extraction and less amount of medical imaging data for training deep learning model , it has been difficult to get high classification performance . This paper intended to investigate and identify the different approach and algorithms that best fits the aim towards getting high lung classification performance. The algorithms like Optimal deep neural network(ODNN), convolutional neural network(CNN), Deep convolutional neural network(DCNN), modified gravitational search algorithm(MGA), Random forest(RF), support vector machine(SVM), etc. and different segmentation and feature extraction techniques are discussed here for the best lung nodule classification result for the early identification of benign and malignant nodule.

We introduce Data, Classification technique and View (DCV)as main components of the system that concern for the better lung nodule classification results along with with them different intermediate components such as Lung nodule segmentation, Feature extraction, Feature reduction are also defined. These components are key for providing better classification performance result which helps radiologist for early diagnosis of lung cancer. The deep learning based lung nodule classification system we have proposed uses image data having different dimensionality as input to the deep learning based classifier which provides lung nodule classification to be viewed by radiologists for the lung cancer classification.

We evaluated the proposed DCV system by classifying 30 state-of-art research papers in the field of deep learning based lung nodule classification system. Through this paper, readers will get the result of deep learning based lung classification system. Also, readers will understand the classification groups, validation criteria, future gaps of the 30 literature reviews about the deep learning technology and how they are trying to give the best classification solution.

*Keywords: Lung nodule, lung cancer, Deep learning, feature extraction, classification, CT lung image*

1. **Introduction**

Deep learning based classification has become popular in the medical domain for the classification of different types of cancer cells such as lung cancer, brain cancer, breast cancer, etc. The main purpose of deep learning in lung cancer classification is to improve the nodule classification performance for assisting the radiologists in the early diagnosis of lung cancer (Masood, et al., 2018). The more accurate classification performance can be achieved by avoiding human interaction during the different stages of classification mostly in the pre-processing of data, nodule segmentation, and feature extraction stages. pre-processing, nodule segmentation and feature extraction stages are useful for getting data more suitable data. Such data are provided to the deep learning based classification technique for the classification of a lung nodule. The result obtained from classifier can be viewed by radiologists for early diagnosis of lung cancer.

Deep learning has been using in the field such as computer vision, speech recognition, natural language processing since a long time for the classification. Recently it is becoming more popular in medical image processing because of its promising result in medical image analysis. It has the ability to uncover multiple levels of features from training sets without any need of complex structure (Silva, Silva Neto, Silva, & Paiva, 2017). There is a different state-of-art system based on the deep learning such as VGG-16, Unet, etc. which are used in medical image classification (Xie, Yang, Sun, Chen, & Zhang, 2019). These state-of-art techniques are useful for image classification. We can adopt this system using transfer learning in the medical image classification. Though the deep learning based system provides high classification performance in the cancer classification the use of deep learning is not being efficient because of the limited data set in the medical field for the training of the model.

We perform the review of the usefulness of the classification technique by classifying 17 state-of-art publications which clearly describes the deep learning based lung cancer classification system. These paper were chosen to demonstrate the active group of authors from 151 papers in the field of lung cancer classification. We perform verification of those technologies based on the classification performance rate, computational complexity and false positive that technique provides.

The rest of the paper is organized as follows. we begin with the definition of deep learning based classification. This is followed by a discussion of the previous work in section 2 of the literature review. In section 3, we propose our system component and provide a brief definition of components. This is followed by the classification of 30 publication in classification section 4. In section 5 we perform system verification . in section 6, we explore the different components we did not described and point out the future work for the improvement. Conclusions are given in section 7.

Deep learning is a subset of machine learning in artificial intelligence(AI)which has the ability to learn from the unstructured data in an unsupervised manner. Deep learning has the ability to analyze the images and a large set of data to generate the insight form it (Jung, Kim, Lee, Lee, & Kang, 2018). Deep learning has become popular in the medical field for the cancer classification, detection and prediction because of its ability to extract the features from training datasets without any complex structure (Silva, Silva Neto, Silva, & Paiva, 2017). However, deep learning technique requires a large amount of data set to extract the feature properly. In this paper, we have proposed a deep learning based lung cancer classification system to assist radiologist for early diagnosis of lung cancer.

1. **Literature Review**

Previous lung cancer classification models have not focused on all aspect which is necessary for better classification results for e.g. some of them focused on data (2D and 3D), some of them focused on lung nodule segmentation to reduce the false positive , some of them focused on feature extraction and feature reduction to provide the best feature , some of them focused on only one type of nodule (solid or complex nodule only) and some of them focused on supervised, semi-supervised and unsupervised classifier.

In the following section, we are going to discuss a number of proposed classification solutions that have a contribution to the specific aspect of the solution**.**

* 1. **Deep Neural Network**

There are a number of papers presented a deep learning based nodule classification techniques**.** (Lakshmanaprabu, Mohanty, Shankar, Arunkumar, & Ramirez, 2019)**,** proposed an optimal deep learning model which is optimized by implementing the Modified Gravitational Search algorithm (MGSA). The solution uses lung CT image data as input, extraction of the histogram, texture and wavelet features and feature reduction using Linear Discriminate Analysis(LDA) algorithm. This solution avoids the human involvement and decreases the computational time with performance having a sensitivity of 96.2%, specificity of 94.2% and accuracy of 94.56% for the classification of solid nodules. However, this solution cannot perform well in the classification of ground glass optic(GGO) and non-nodules plus the use of LDA can only distinguish images containing anomalies. (Yutong, Jianpeng, Yong, Fulham, & Yanning, 2018) presented a solution which uses lung nodule slice as an input , compute the deep feature by using Deep convolutional neural network , texture feature using gray level co-occurrence matrix (GLCM) and Fourier shape descriptor is used for shape-based feature from the region of interest (ROI), These feature are fused by using AdaBoost network which is Backpropagation neural network(BPNN) for the nodule classification which provides AUC of 96.65%, 94.45%, 81.24% for three different datasets .Though the deeper CNN gives the best classification performance it is easily over-fit because of a small set of data. (Masood, et al., 2018)proposed a computer-assisted decision-support system using deep learning based system and metastasis information from a sensor connected on the patients' body.This solution uses deep fully convolutional neural network for the classification of detected lung nodules into the stage. This solution was tested in different datasets having varying scan condition and provides an accuracy of 84.58% which is higher than the current state-of-art technique. this solution uses Gabor filter for the image quality enhancement and thresholding is applied for the segmentation of ROI. The dice score for this classification is 91.34% which is better than accuracy. The main limitation of this solution is having more false positive result because of the use of different datasets with varying scanning quality. (Naqi, Sharfi, & Jaffar, 2018)proposed a deep learning based model for the detection and classification of a lung nodule. It uses fractional-order Darwinian particle swarm optimization to extract the lung region based on optimal gray level threshold and the nodule candidate detection is performed, 2 D and 3D geometric and texture feature are combined and deep learning method based on autoencoder and softmax layer is used for the classification and reduction of false positive. The solution provides the sensitivity of 95.6 %, accuracy 96.9% and specificity of 97.0% with false positive 2.8 FP/scan.

**2.2. Convolutional neural network**

(Liu, Hou, Qin, & Hao, 2018)proposed a Multi-view multi-scale CNN system which not-only classifies the solid nodules but also performs the classification of ground glass optic(GGO) and non-nodules as well. It takes the nodule having at least agreement level 2 from the three different datasets and perform icosahedron-based spherical partition, perform view sorting based on high-frequency content analysis to get the dynamic view and finally CNN is trained as finely tuned using max-pooling to get more than 90% classification rate in three different types of data set which is better result in comparison to (Shin, et al., 2016),. However, This solution can not classify nodule less than 3mm and involve the human interaction in the leveling of nodule which is a factor for the less classification result. (Shen, et al., 2017)proposed a Multi-crop convolutional neural network(MC-CNN) which directly model the raw nodule patches and perform the building of end-to-end machine learning architecture to avoid the time-consuming segmentation and feature extraction steps and provides the high classification performance in comparison to other state-of-art techniques. However, this solution only uses the deep feature for the nodule classification which is not efficient to get high classification result. (Silva, Silva Neto, Silva, & Paiva, 2017) presented two algorithms evolutionary convolutional neural network and genetic algorithm where the genetic algorithm is used for the optimization of CNN. It uses the CT image annotated by radiologists and applies otsu and particle swarm optimization algorithm to get the local nodule information and this information is passed to CNN for the classification of benign and malignant nodule where the CNN is optimized by using a genetic algorithm. This solution provides a sensitivity of 94.64 %, the specificity of 95.14 %, the accuracy of 94.78% and AUC of 0.949 which is high in comparison to other techniques.It also avoids the steps of feature extraction and selection. (Silva, Valente, Silva, Paiva, & Gattas, 2018)presented two algorithms convolutional neural network(CNN) and particle swarm optimization(PSO) to optimize the performance of CNN and reduce the false positive. This solution takes the 3D CT image as input and provides the sensitivity of the false positive reduction of 87% and reduce the computational complexity by avoiding the feature extraction and manual search for feature extraction step.

(Filho, Silva, Paiva, Nunes, & Gattass, 2018)introduce a CNN method which uses phylogenetic diversity index based texture feature as an input to the CNN and provides the accuracy of 92.63 %, the sensitivity of 90.7 %, the specificity of 93.47% and AUC of 0.934 for the classification of a benign and malignant lung nodule.

* 1. **support vector machine(SVM) classifier**

(Yuan, Liu, Hou, Qin, & Hao, 2018) proposed a multi-class support vector machine-based classifier for the classification of a lung nodule. It uses a combination of statistical and geometrical feature based on multiple kernel learning(MKL) where the statistical feature is calculated from multi-view multi-scale CNN and geometric feature is calculated from Fisher vector encoding which is based on shift invariant feature transform(SIFT) and provides the classification rate of 93.1% for all king of nodules . However, it cannot perform well in the small nodule less than 3mm. (Shi et al.,) proposed an SVM based classifier for the classification of the nodule. It employee CNN based state-of-art technique called VGG-16 for the deep feature extraction based on transfer learning which is used as input for SVM. This solution provides the overall sensitivity of 87.2% with 0.39 FP which is higher than other techniques. However, The use of VGG to characterize the medical images is very difficult because VGG-16 was made for the processing of other image having RGB but not the grayscale medical images. (Dhara, Mukhopadhyay, Dutta, Garg, & Khandelwal, 2016)presented a for the pulmonary nodule classification. This solution reduces the human involvement, perform the calculation of shape based, margin based and texture based features and select the relevant feature set for the better classification result and finally feature set is used for the classification of lung nodules. The resulting solution provides acceptable classification result for the different configuration of data sets.

* 1. **Random forest algorithm(RF)**

(Wang, Elazab, Wu, & Hu, 2017) presented a CAD system which uses cost-sensitive random forest(CS-RF) algorithm for lung nodule classification which combines the deep feature from non-medical training ad handcrafted feature for the false-positive reduction. It uses the Principle component analysis(PCA) for the lung nodule visibility, Active shape model(ASM) to obtain the ROI, Laplacian of Gaussian(gLoG) method for obtaining candidate nodule and finally, combined hand-crafter feature and deep feature are used for the classification. The solution gives the sensitivity of 69.3 % and specificity of 96.2 % with an FP rate of 1.45. This solution provides less sensitivity which means it cannot classify nodule properly.

(Li, Li, Tian, & Zhang, 2018)proposed an improved fandom forest-based classifier for the classification. Nodule segmentation is performed based on an improved random walk algorithm , combine the intensity , geometric and texture feature which is calculated by using grey-level co-occurrence matrix , rotation invariant uniform local binary pattern and Gabor filter to generate the best feature set which is used as input to the classifier to provide the sensitivity of 0.92 and AUC of 0.95 .

* 1. **Best solution**

Finally,(Lakshmanaprabu, Mohanty, Shankar, Arunkumar, & Ramirez, 2019)provides the lung nodule classification solution with the sensitivity of 96.2 %, specificity of 94.2 and accuracy of 94.56% which provides output on four stages namely pre-processing, feature extraction, feature reduction, and classification and finally the view. This solution is not talking about nodules like ground glass optic(GGO) and non-nodule classification. This solution uses simple filtering and contrast enhancement in the pre-processing stage so we can implement other technique such as normalize spherical sampling, nodule radii estimation and view selection steps for the improvement of nodule quality so that the solution can provide better classification solution for the complex nodules as well.

Out interpretation of the deep learning based lung cancer classification system is shown in below fig. 1. we can compare out DCV component with this solution input CT image is a raw data, the data obtained from the feature reduction is analyzed data and the data obtained from the feature reduction is derived data,ODN classifier is used as a classification technique and three results are shown in view to be reviewed by radiologist .

Fig.1 depiction of the lung nodule classification

There were many deep learning based lung cancer classification system proposed in the past. however, most of them are based on the old technique and does not perform classification on both solid and complex types of nodules. We have proposed a DCV based system which is based on data, classification technique, and view. In the next section, we describe the three-factor of DCV components with classes and sub-classes.

1. **System Component**

The taxonomy of the data, classification technique, and view (DCV) were proposed based on the current and past deep learning based lung cancer classification systems. The system was built with the help of radiologists and machine learning experts. Iterative refinement of this taxonomy has been performed to get the most relevant factor for the creation, validation and the evaluation of the system.

When we search for the very first time , the search result gave 151 results, among them 40 of them met inclusive criteria of our proposed work as follows: The publications that described the lung nodule classification based on deep learning and feature extraction were included, the publications that proposed a lung nodule segmentation based on deep learning were included, those papers which proposed false positive reduction were considered, That publication which provides definite classification view were considered. We have selected the paper published between 2016 to 2019 so 20 of them were excluded because of they have published before 2016, 15 of them were excluded because they were review based papers, 40 of them were rejected because they were other then Q1 and Q2 papers, 5 of them were written in a foreign language, not in English , 31 of them did not use feature extraction and deep learning they use other technologies such as genetic algorithm, patient monitoring using wearable sensors for the cancer classification.

Based on literature review in the related papers and prior knowledge in the related field, in order to provide assistance to radiologist in early lung cancer diagnosis, there should be good CADx system which provides good nodule classification performance so three points should be considered: 1) what kind of input data should be used, 2) how effective nodule classification can be performed by using such input 3) how the result can be best displayed. so, we classify deep learning based lung cancer classification system based on three factors: input imaging data, classification techniques, view.

The first factor in DCV taxonomy is data. There are different kinds of imaging data used in the system including patient-specific data , visually processed data having attributes such as dimensionality , semantic , modality , whether data are obtained from certain database, whether the data obtained from pre-processing, segmentation, feature extraction, feature reduction and whether it represent a real or virtual object in the end view of the classification. Second, the classification techniques and algorithms that are used for the classification of the benign nodule and malignant nodules from the input imaging data. Lastly, the classification of lung cancer is based on the view of the result obtained from the above-used classification technique or algorithm. These three components, their sub-classes, and their relations are shown in fig2. The components and classes with their most inherent attributes and the values they can take are shown in table 1.

Fig2. Classification Taxonomy of three components(data, classification technique and view) as well as their classes and subclasses. The relationship between classes is shown in solid line and the relationship between sub-classes are shown in dashed line . classification step is associated with the view component to show the result of the classification.

**3.1. sub-components**

In this section, we are going to define and explain three components that are used in our system data, classification, and view, as well as their subclasses. moreover, we are going to provide the reasons why each factor is used in this system along with the diagram of classes and sub-classes.

**3.1.1. Data**

In this project, we have considered two classes of data among them one is raw imaging data, and another is visually processed data. In general, the raw imaging data, prior knowledge data which came from CT scan and labeling by radiologists can be viewed directly .however other data such as Analysed imaging data, derived data undergoes several processing to become visually processed data.

Patient-specific data, these data such as X-ray image, Lung CT image, labeled CT images are imaging data obtained from a patient who is going for diagnosis of the lung cancer.

Visually processed data, these data are such data which are used for the assistance of classifier to get high classification performance and some of them are used to show to the patients and radiologists.

Different sub-classes of data are shown in fig3.

**Fig3.data sub-classes of the system**

**3.1.2. Classification Technique**

The main purpose of this project is to identify a good lung cancer classification technique so the use of classification technique is very important. The classification technique is a method, algorithm, model or system presented by particular research paper we have reviewed. This is a deep learning based system which undergoes several processing under a hidden layer to get the required classification result. There are many such techniques has presented by different papers among them some of them are optimal deep neural network(ODNN), convolutional neural network(CNN), support vector machine(SVM), Random forest(RF) algorithm which takes 2D and 3D image features and undergoes several processing for the classification. sub-classes of classification techniques is shown is below fig 4.

**Fig4. Different sub-classes of classification techniques**

**3.1.3. View**

The main task of view component is to show the lung nodule classification result . with the help of the view component radiologists, patients, and other related persons can view the result. The display is the specific device to show the result to end viewer. The display has different attributes such as resolution, view field, and size. Different hardware and interaction tools such as a mouse, monitor, keyboard, etc are also used in the view component. View sub-classes are shown in below fig 5.

**Fig5. Different sub-classes of view component**

**3.2. purpose of each sub-component**

**3.2.1. Data**

Data is important for two aspects one is for input to the system and another is data that need to show to end user. here, for the input of the system, we need CT image or X-ray data and other intermediate data as processed data. The data that is used to show the output is viewed by the radiologists to show further confirm the malignancy and benignity of the lung nodule. There are different attributes to which raw data is subjected such as CT image size, nodule slice size, contrast, mean, SD, etc. The classification technology is based on deep learning, as we know deep learning needed a large number of datasets for the good classification result so many of the paper mentioned about augmentation technique to increase the amount of the data for the better characterization of the nodule.

**3.2.2.Classification technique**

The main purpose of this research is to identify the best lung cancerous nodule classification for the early diagnosis of lung cancer. There are different papers showing the use of the different machine learning technique such as convolution neural network, Deep neural network which uses 2D and 3D input for the classification. The main purpose of using such classification techniques is a better classification result of the lung nodule for early and accurate diagnosis of lung cancer so technique which gives the best result is very important for this project.

**3.2.3. View**

In this project, the view is important for the confirmation of the result produced by deep learning technique. The classification result produced by the model should be view by the radiologists for further confirmation of the result. In this project, view mostly show classification result with accuracy, sensitivity, and specificity in the receiver operating curve(ROC). Another use of view component is to show the result to the patients**.**

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