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A Survey on Pulmonary CT Image Classification in Deep learning

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ABSTRACT

Image Classification in deep learning is a recently developed Soft computing method to classify image data with pixel information in a way that only hybrid technique can do better access using the pixel data in the aspect of performance measures. Classification is used to predict the unknown data. Deep learning is a cascade of nonlinear transformation in a hierarchical model as well as convert feed forward deep architecture worked on any image size.

Lung Cancer is one of the leading diseases in the world and increased in many countries. The eight years overall survival rate is just 17%. Early to remove lung cancer surgically will ensure the survival of the patient. Before surgery a doctor needs help of radiologists suggestion. In digital era, fast CAD's system plays a vital role in surgery. In this junction, medical image analysis, image classification, image detection and diagnosis involved much in past decades. Pre-processing and Segmentation are the preliminary basic works for binary classification.

KEYWORDS: *Image Pre-processing, Image Enhancement, Descriptor, Image Classification*

I . INTRODUCTION

The purpose of this section is to review the recent literature with respect to lung cancer detection systems.

1.1 PreProcessing

Several image processing techniques for the detection of lung cancer by using CT images are reviewed in (Niranja.G et al., 2017). The lung cancer detection is carried out by splitting the review in different aspects such as pre-processing, nodule segmentation and segmentation. The recent trends in lung nodule detection are presented in (Rabia Naseem et al., 2017). Additionally, the performance of the recent lung nodule detection techniques are compared and presented. In (Devi Nurtiyasari et al., 2017), a lung cancer classification system is proposed on the basis of wavelet recurrent neural network. This author employs wavelet to remove the noise from the input image and the recurrent neural network is utilized for classification. However, this author could not achieve better specificity rates and this implies that the false positive rates of the work are greater.

The lung cancer detection algorithm based on FCM and Bayesian classification is presented in (Bhagyarekha.U et al., 2016). In this paper, FCM is applied to achieve segmentation and the GLCM features are extracted. Based on the feature set, the Bayesian classifier is employed to distinguish between the normal and cancer affected CT images. Yet, the results of this work are not convincing in terms of sensitivity and specificity rates. In (Manasee KurKure et al., 2016), a lung cancer detection technique that relies on genetic approach is proposed. However, this work involves more time complexity and the number of connected objects have been calculated by assigning 1 to inside and 0 to outside of the object that shows brain MRI image based on threshold technique to improve the skull stripping performance (Nilesh Bhaskarrao Bahadur et al., 2017).

1.2 Segmentation Techniques

Image segmentation by different methods was done by many people. Some of them are Local entropy image segmentation (Ali Shojaee Bakhtiari et al., 2007; L.Goncalves, J.Novo, 2016), Discrete cosine texture feature (Chi-man pun et al., 2010), parallel algorithm for grey scale image (Harvey et al., 1996), Clustering of spatial patterns and watershed algorithm (Kai-Jian et al., 2010), Medical image segmentation (Prasantha H.S. et al., 2010), Finite bivariate doubly truncated Gaussian Mixture model (Rajkumar 2010), Random set of view of texture (Ramana Reddy 2010), Sobel operator technique, Prewitt technique, Kiresh technique, Laplacian technique, Canny technique, Roberts technique and Edge maximization Technique (Salem Saleh 2010), Mathematical image processing (Sun hee kim 2010), Simple algorithm for image denoising (Vijaya 2010), Iterative regularized likelihood learning algorithm (Zhiwu Lu 2006), Automatic model selection and unsupervised image segmentation by Zhi Wu Lu (2007), finite mixtures and entropy regularization by Zhi wu Lu (2008).

As described by the Sun Hee Kim the following steps are followed in image processing for counting the number of mosquitoes in a room (1) The acquisition of the image. (2) The extraction of the region of the mosquitoes. The intensity and the property of the location of the mosquitoes considering the image. (3) Reduction of the image to smaller size to process in matlab. The image processing is applied to separate the region of mosquitoes and backgrounds. Then the smaller size is obtained by processing it in paint. (4) Use array editor convert the image to values. The recognized mosquitoes by the method of the array editor conversion from the matlab software. (5) Identify the cluster where mosquitoes are present. The place where the mosquitoes are there shows lesser value because of darkness. Here the raw figure converted into values that can be processed by computer algorithms. The conversion of the figure to a smaller size is done and the image is converted to array editor values (Harvey A et al., 1996).

In (Xia Li et al., 2017), an algorithm is proposed to detect the pulmonary nodules based on cascade classifier. This work detects the pulmonary nodules and classifies them into normal and benign. A learning method is based on cascade classifier and applied over the detected pulmonary nodules. This work focuses more on accuracy rates, rather than on sensitivity and specificity rates. A technique to detect lung nodules from a series of CT slices is presented in (May Phu Paing, 2017). This work segments the lung nodules by applying Otsu’s threshold along with some morphological operations. The geometric, histogram and texture features are extracted from the segmented nodules to carry out the process of classification. The Multilayer Perceptron (MLP) is employed as a classifier and this work involves computational overhead. In (S.Avinash et al., 2016), a Gabor filter and watershed segmentation based lung cancer detection technique is proposed. The process of segmentation is carried out by watershed segmentation approach and the Gabor features are extracted from the CT images. This technique does not include the process of classification and it stops itself with segmentation.

A large number of lung segmentation methods have been proposed. Among them, bidirectional differential chain code combined with machine learning framework is able to correctly include the just a pleura nodules into the lung tissue while minimizing over under segmentation. This method is capable of identifying low-dose, concave/convex regions (Shiwen Shen 2015). In the Hessian-based approach, 3D lung nodule has been segmented in the multiscale process through the combination of Shape Index and Curvedness methods. Image characteristics, Nodule position, nodule size, and nodule characteristics are included in this approach. Eigenvalues are computed from the 3 x 3 Hessian Matrix (L.Conclaves et al., 2016).

2 Feature Vectors

The feature types of the pulmonary nodule in CT images are important cues for the malignancy prediction (A.McWilliams et al., 2013, V.K.Patel et al., 2013), diagnosis and advanced management (D.P.Naidich et al., 2013, M.K.Gould et al., 2013). The texture features of nodule solidity and semantic morphology feature of speculation are critical to differentiating of pulmonary nodules and other subtypes. Meanwhile, other semantic features like calcification pattern, roundedness and margin clearness are shown to be helpful for the evaluation of nodule classification. The nodule may be found in bronchial tubes or outside of the bronchial tube. If the nodule<=3mm the detection of malignancy is difficult. The determination of clinical characteristics may differ from patient to patient and depends on the experience of the observer.

Computer-aided diagnosis (Shiwen shen, Alex A.T.Bui et al., 2015) is an assistive software package to provide computational diagnostic references for the clinical image reading and decision making support. The histogram feature (Sherly Alphonse, Dejey Dharma, 2016) for the high-level texture analysis helps to extract nodule feature. The bag of frequencies descriptor is developed that can successfully distinguish 51 spiculated nodules from the other 204 non-spiculated nodules (Ciompi et al., 2015). However, the mapping from the low-level image features toward the high-level semantic features in the domain of clinical terms is not a straightforward task. This semantic feature assessment maybe useful for clinical analysis. The Lung Image Database Consortium (LIDC) dataset for its rich annotation database supports the training and testing CAD scheme (S.G.ArmatoIII et al., 2011).

Absorption and scattering of light rays are the two major issues that cause reduced quality of images. Several methods have been proposed to enhance the quality of the pulmonary images. Histogram equalization technique and Contrast stretching methods are capable of enhancing the image quality. Contrast Limited Adaptive Histogram Equalization (CLAHE) has been applied to improve the image contrast. Otsu's adaptive thresholding method form image segmentation has been effective for many applications. This provides bright backgrounds for images. Various thresholding techniques such as Local, Global and Multilevel thresholding have been applied for the segmentation of pulmonary nodules images. The texture feature descriptor that has been widely used for image classification is Local Binary Pattern. Pican et al., have used GLCM's twenty-four types of features for extraction and for each image suitable features have to be chosen for extraction. Hence there is a need for efficient feature descriptor for the classification process. In past years Neural Network is performed for classification. The process is time-consuming. K-Nearest Neighbour as a classifier with Euclidean distance was used to classify nodules. Padmavathi et al., (2010) have classified images using a probabilistic neural network which gives better results than SIFT algorithm with three classes of the dataset. Eduardo et al., have classified images using nine machine learning algorithms such as Decision Trees, Random Forest, Extremely Randomised Trees, Boosting, Gradient Boosted Trees, Normal Bayes Classifier, Expectation Maximization, NN and SVM. Bhuvaneswari.P et al., (2015) have classified coral and textures using KNN by considering K=1 and the accuracy was reported as 90.35%.

In (K.Gopi et al., 2017), a technique based on Ek-means algorithm and Support Vector Machine (SVM) is presented to recognize and classify a lung tumor. This work pre-processes the CT images for removing the unwanted information by means of thresholding approach. The Threshold value calculated by Zack's Algorithm in white blood cell segmentation by F.Sadglian et al., 2009. The regions of interest alone are extracted and the Gray Level Co-occurrence Matrix (GLCM) features are extracted. Gray level co-occurrence matrix texture features of CT image of small solitary pulmonary nodules(Vishal K Patel,K Naik, 2015), which can profit diagnosis lung cancer in earlier by five combined patient level features inertia, entropy, correlation, difference-mean and sum-entropy (Huan Wang et al., 2010). Finally, SVM is utilized to distinguish between the cancerous and non-cancerous areas. An early lung cancer detection mechanism is proposed in (Rachid Sammouda et al., 2016), which exploits Hopfield Neural Network classifier for extracting the lung areas from the CT images. The edges of the lung region lobes are detected by bit planes and the diagnostic rules are framed to detect the abnormality.

A lung cancer detection technique, which is based on Local Energy based Shape Histogram (LESH) and machine learning technique are introduced .Initially, this work pre-processes the CT images by Contrast Limited Adaptive Histogram Equalization (CLAHE) and the LESH features are extracted. Machine learning algorithms such as Extreme Learning Machine (ELM) and SVM are applied. This work is efficient but the computational overhead can still be decreased by altering the feature extracting technique. Shape features (Ashis et al., 2016) are easily extracted by HOG (Histogram of Oriented Gradients) feature descriptor (Chen J et al., 2014). The other method which is extension of HOG detected whole human detection using EXHOG (Extended Histogram of Gradients) feature descriptor (Amit et al., 2011). HOG method always deals with 180-degree angle whereas EXHOG method considers 360 degrees. A Variety of Shape-based, margin-based and texture-based features are analyzed to improve the accuracy of classification. These results are evaluated in terms of area under the receiver-operating-characteristic-curve in Ashis Kumar et al., (2016) paper. Nodules are categorized with rank1, rank2, rank3, rank4 and rank5 with malignancy ratings solid, part-solid and Non-solid. Based on 2D Shape-Based Features and 3D Shape-Based Features the Nodules Features are extracted. Han et al., introduced 3D Haralick features. Fourteen Haralick features (1973) were computed from each GLCM matrix. The maximum correlation coefficient is not considered in our experiment, as it is computationally expensive (Han et al., 2014). Several shapes based, margin based and texture based features are computed to represent the pulmonary nodules.

A set of relevant features is determined for the efficient representation of nodules in the feature space. Han et al., introduced 3D Haralick features considering nine directions which provide better classification performance than five directions. The performance of classification is evaluated in terms of area (A), under the receiver operating characteristic curve (Ashis Kumar Dhara et al., 2016). Predicting membrane protein sequences in imbalanced data set is often handled by a decision tree, AdaBoost, random and rotation forest, SVM and naive Bayes classifiers. The random forest has good performance except for classes with fewer samples (E.Siva Shankari et al., 2017). Local Binary Pattern is an incredibly well-known texture feature descriptor (D.Jeyabharathi, Dejey 2016) that has been used in many application such as facial recognition (Ani brown et al., 2017), texture classification and coral image classification. Contrast Limited Adaptive Histogram Equalization (CLAHE) (Ani brown et al., 2017) has been applied for coral images to improve the image contrast and equalize the image histogram effectively.

The relational feature provides information about the relational and hierarchical structure of the regions related to a single object or a group of objects. Neural Network classifiers and SVM classifier

2.1 DCNN as Feature Vector

Eduardo et al., have used wavelet filters to extract texture feature from OpenCV library (Shiela et al.,) and have determined the counts of corals by extracting texture features using LBP descriptor because they use the information from eight directions around a pixel (Huan Wang 2010). Deep feed-forward ANN analyses the visual imagery. Artificial Neural Networks consist of a method of solving problems related to science through simple models that mimic the human brain, including their behaviour. An ANN is armed by small modules which simulate the operation of a neuron. In ANN with a minimum number of layers are used. Because the dimension of ANN is very limited. Deep feed-forward ANN analyses the visual imagery. The convolutional neural network has hundreds of hidden layers, using filters can extract the data. When the target reaches the value no change in weight. In sentiment classification, RNN network is highly preferable. Recurrent Neural Network uses the loop to translate sequence to sequence. This happens by sequence to a single output. Neurons within the same layer are not connected. So in RNN, the neurons in the layers are connected. RNN is the best for Reinforcement learning. Imagenet is suitable for Visual recognition challenges. Instead of autoencoder, we can use Conditional Random Field (CRF) model or deep sequential model.

Handwritten digit recognition using backpropagation over a coalitional network makes a good change. Alexnet, Zfnet, VGGnet, Googlenet, and MsresNet are the other Neural models. CNN was introduced by Lecun et al., 1998, CNN allows multiple features to be extracted at each hidden layer. Convolutional Neural Network is used to classify tumors seen in lung cancer screening, have special properties such as spatial invariance and allows to multiple feature extraction. The deep CNN has been shown widely that the accuracy of prediction increases dramatically (Prajwal Rao et al., 2016). Lecun et al., have written a paper that CNN has been shown to eliminate the necessity of handcrafted feature extractors in gradient-based learning applied to document recognition (Lecun et al., 1998). Hence, multiple characteristics can be extracted and the learning process assigns weights appropriately to significant features. So automatically performing the difficult task of feature engineering in hierarchically. AlexNet using binary classification gives challenging visual task in face recognition.

Convolutional Neural Networks are alternative type of neural network. This method can be useful to reduce variations in spectral and model correlations in signals. Speech signals exhibit both properties, hence CNN's are more effective model for speech compared to Deep

Neural Networks. In prior the number of convolutional layers, filter size and pooling size needed is decided. Secondly, investigate an appropriate number of hidden units and best pooling strategy. Then find how to incorporate speaker-adapted features. Finally, give the importance of sequence training for speech tasks. During Hessian free sequence training of CNN's, using ReLU+dropout can be done the process (Prajwal Rao et al., 2016). Convolutional Neural network recognizes face using a Self-Organizing Map (SOM) neural network and a CNN. MatConvNet is an open source for the convolutional neural network. In XNOR networks or Image Net, both the filters and the input to convolutional layers are binary. The filters are approximated with binary values resulting in 32x memory savings.

The paper Arnaud A.A Setio et al., 2015 showed the multi-view ConvNet. This is very much suited for false positive reduction and achieved good results for the nodule detection task of lung CT images. CNN is an automated Preprocessing architecture so no need to do preprocessing again. In Deep Learning (Qing zeng song, lei zhao, xing ke, 2017) images or videos may profit from preprocessing, whose job may become much easier (Jodogne and Piater, 2007, Legenstein et al., 2010, Cuccu et al., 2011). A dominant dictionary like texture descriptor, texton is proposed as a feature (Beijbom et al., 2012). Deep learning has proved a popular and powerful method in many medical imaging areas. In (QingZeng Song et al., 2017) paper CNN, DNN, and SAE are designed for lung cancer calcification. The experimental result achieved the best performance with accuracy among the three architectures.

3 Classification

The prerequisite of classification is, designing a suitable image processing procedure. In remote sensor data, a thematic map is a good method of suitable classification especially significant for improving classification accuracy. Non-parametric classifiers are neural network and decision tree classifier. The knowledge-based classification has become an important approach for multisource data classification.

Remotely sensed data vary in spatial, radiometric, spectral, and temporal resolutions. Both airborne and space borne sensor data included remotely sensed data. Understanding the strengths and weaknesses of different types of sensor data is the basic need for the selection of suitable remotely sensed image data for image classification.

Barnsley (1999) and Lefsky and Cohen (2003) showed the characteristics of different remote-sensing data in spectral, radiometric, spatial, and temporal resolutions and angularity. The selection of suitable data is the first important step for a successful classification for a specific purpose (Phinn et al., 2000, Lefsky and Cohen 2003). It requires considering such factors as user’s need, the scale and characteristics of a study area, the availability of various image data and their characteristics, cost and time constraints, and the analyst’s experience in using the selected image. Scale, image resolution, and the user’s need are the most important factors affecting the selection of remotely sensed data. Selecting potential variables like spectral signatures, vegetation indices, transformed images, textual information, multitemporal images multi-sensor images used in sensor image classification. Principal component analysis, minimum noise fraction transform, discriminant analysis, decision boundary feature extraction, nonparametric weighted feature extraction, wavelet transform and spectral mixture analysis used for feature extraction to reduce the data redundancy inheritance to extract specific land information. The optimal selection of spectral bands for classification has been elaborately discussed in previous literature (Mausel et al., 1990, Jensen 1996). The Region of Interest classification using low-level and high-level features. Here region of interest meant with lung nodule. Classification method used is binary classification.

An automatic lung nodule segmentation and classification technique are proposed in the 2006 D.Lu paper (D.Lu and Q.Weng, 2006). Initially, the images are pre-processed by different thresholding techniques and morphological operations. The areas of interest alone are extracted by means of apriori information and Hounsfield Units. SVM is employed for achieving the task of classification. The SVM classifier is an experimental evaluation of its accuracy, stability and training speed in deriving land cover classifications from satellite images (Huang.C 2002). The results of this work can still be improved in terms of sensitivity and specificity. In remote sensor data and the multiple features of data, selection of a suitable classification method are especially significant for improving classification accuracy. Non-parametric classifiers such as neural network, decision tree classifier, and knowledge-based classification have increasingly become important approaches for multisource data classification. Integration of remote sensing, geographical information systems, and expert system emerges as a new research frontier. More research is needed to identify and reduce uncertainties in the image-processing chain to improve classification accuracy. In many cases, a hierarchical classification system is adapted to take different conditions into account. The PSO-SGNN method segment the cavitary nodules which adapted region growing algorithm. PSO-Self Generating Neural Forest (SGNF) based classification algorithm is used to cluster regions (J-j Zhao et al., 2015). Lung region growth can be calculated by area and eccentricity of nodule (Senthil Kumar Krishnamurthy et al., 2017). Support Vector Machine is a group of theoretically superior machine learning algorithms, found competitive within classifying high dimensional data sets. Satellite images are classified through this method and compared with Maximum likelihood, neural network and decision tree classifiers using three variables and seven variables. SVM uses Kernel functions in the original data area into linear ones in a high dimensional space. When seven variables were used in the classification, the accuracy achieved better when polynomial order p increased. However, an experiment using arbitrary data points revealed that misclassification error (Chengquan Huang et al., 2012). Coral reef image classification employing Improved LDP for feature extraction paper results indicate that ILDP feature extraction method tested with five coral datasets and four texture data sets achieves the highest accuracy and minimum execution time (Ani Brown et al., 2017).

Motivated by these existing research works, aims to present a reliable lung cancer detection algorithm, which can prove better sensitivity and specificity rates with minimal time complexity. The following section elaborates the proposed approach along with the overview of the work. Object-based classification approach is less explored compare to pixel-based classification. The result based on quick bird satellite image indicates that segmentation accuracies decrease with increasing scales of segmentation. The negative impacts of under segmentation errors become significantly large at large scales. There are both advantages and limitations in object-based classification and their trade-off determines the overall effect of object-based classification, dependent on the segmentation scales. For the large scales, object-based classification is less accurate than pixel-based classification because of the impact of large under-segmentation errors (D.Lu and Q.Weng, 2006). Multiple features of remote sensor data are improved by selecting a suitable classification method. Nonparametric classifiers such as neural network, decision tree classifier, and knowledge-based classification have become important for multisource data classification. Integration remote sensing, geographical information systems, and expert system emerge with mapping as another research line. In texture analysis of an image, the LBP method takes an important role. Particularly LBP helps to extract the features in subclassification of medical CT lung nodules. Bin size of the image shows the pixels range in each area. The bin complexity reduced by introducing a new operator in the existing pattern.

3.1 Classifiers

Machine learning algorithms such as Extreme Learning Machine (ELM) and SVM (E.Siva Shankari, D Manimegalai et al., 2017; Ani Brown Mary Dejey Dharma, 2017), KNN, Decision Tree, Random Forest classifiers are applied. Extreme learning machines are feedforward neural networks for classification and feature learning with a single/multiple layers of hidden nodes, where parameters of hidden nodes need not be tuned. This work is efficient but the computational overhead can still be decreased by altering the feature extracting technique.

A new lung cancer detection technique based on the Mumford-Shah algorithm is proposed in (Janudhivya et al., 2016). This work removes the Gaussian noise by applying a sigma filter and the regions of interest are segmented by otsu's thresholding and Mumford-shah model is applied. The texture features (Huan Wang, Xlu Hua Guo et al., 2010) are extracted from the extracted regions by spectral texture extraction technique and the classification is done by multi-level slice classifier. However, the classification accuracy of this work can be improved further.

In (Mustafa Alam, 2016) a lung nodule detection and segmentation technique are proposed on the basis of a patch based multi-atlas method. This work chooses a small group of atlases by matching the target image with a large group of atlases in terms of size and shape based feature vector. The lung nodules are then detected by means of a patch-based approach and the Laplacian of the Gaussian blob detection technique is utilized to detect the segmented area of the lung nodule. However, the images utilized for testing is very minimal and hence, the efficiency of this work cannot be determined.

A work to enhance the lung nodules is presented in (Fan Xu et al., 2016). This work exploits a three-dimensional multi-scale block Local Binary Pattern (LBP). This filter can distinguish between the line based regions and the edges effectively. This work focuses only on enhancement, which is just a part of this proposed approach.

The gap between computational and semantic or minimal features (Shihong Chen, Jing Qin, Jing Qin et al., 2016) have to be overcome by hybrid feature vectors and Convolutional Neural Network method. It is observed that there may relations among speculation, texture, margin etc in pulmonary CT image. The LIDC bench mark dataset is adapted and applied to various feature vectors and classifiers with possible combinations.

CONCLUSION

Combination of more than two Model Studies for the different pulmonary CT Image features are reviewed in the context of Nodule and Region of Interest recognition. The prior work has shown the performance evaluation of the Hybrid model system under the different trait combination scheme, Identification rate, a technique adopted, databases and the number of objects used. Important attributes are summarized. The combination of angle, shape features is suggested. Among the studies reported in the previous section, it claims that the hybrid model are used to achieve the performance than another multimodel system.

REFERENCES

i. Abdulrazzaq, M.M., Shahrul Azman Noah, X-Ray Medical Image Classification based on Multi Classifiers , 4th International Conference on Advanced Computer Science Applications and Technologies, 2015.

ii. Aghbari Zaher Al, Kaneko Kunihiko, Akifumi Makinouchi: "Content-trajectory approach for searching video databases," IEEE Transactions on Multimedia 2003, 5(4):516-531.

iii. Ali Shojaee Bakhtiari, Ali Asghar Beheshti Shirazi and Amir Sepasi Zahmati, "An Efficient segmentation Method Based Local Entropy Characteristics of Iris Biometrices", World Academy of Science , Engineering and Technology, 28, 2007, 64-68.

iv. Amit Satpathy, Xudong Jiang ,Extended Histogram of Gradients with Asymmetric Principal Component and Discriminant Analysis for human detection, 2011.

v. Arevalillo-Herráez Miguel, Ferri Francesc J, Domingo Juan: "A naive relevance feedback model for content-based image retrieval using multiple similarity measures," Pattern Recogn 2010, 43(3):619-629.

vi. Armato, S.G., III, et al., "The lung image database consortium (LIDC) and image database resource initiative (IDRI); a completed reference database of lung nodules on CT scans", Medical Physics. vol 38, pp 915-931, 2011.

vii. Ashis Kumar et al, "A combination of shape and texture features for classification of pulmonary nodules in lung CT images", J Digit Imaging, 2016.

viii. Bhagyarekha U. Dhaware ; Anjali C. Pise, "Lung cancer detection using Bayasein classifier and FCM segmentation", International Conference on Automatic Control and Dynamic Optimization Techniques, 9-10 Sept, Pune, India, 2016.

ix. Bhuvaneswari, P., A. Brintha Therese, "Detection of cancer in lung with KNN classification using genetic algorithm", Elsevier, 2015.

x. Chen Jau-Yuen, Taskiran Cuneyt, Albiol A, Delp E, Bouman C: "Vibe: A compressed video database structured for active browsing and search,". 2001.

xi. Chen W, Gao X, Tian Q, Chen L. A comparison of autofluorescence bronchoscopy and white light bronchoscopy in detection of lung cancer and preneoplastic lesions: a meta-analysis. Lung Cancer. 2011, 73:183–8.

xii. Chi-Man Pun and Hong-Min Zhu, "Image segmentation using Discrete Cosine Texture Feature, International Journal of computers Issue1,Volume 4, 2010, 19-26.

xiii. Choupo Anicet Kouomou, Laure Berti-Équille, Morin Annie: "Optimizing progressive query-by-example over preclustered large image databases," CVDB '05:

Proceedings of the 2nd international workshop on Computer vision meets databases New York, NY, USA; 2005, 13-20, ACM.

xiv. Ciompi, F., et al., “Bag of frequencies: A Descriptor of pulmonary Nodules in Computed Tomography Images”, IEEE Transactions on Medical Imaging, Vol 34, pp 962-973, 2015.

xv. Devi Nurtiyasari ; Dedi Rosadi ; Abdurakhman, "The application of Wavelet Recurrent Neural Network for lung cancer classification", International Conference on Science and Technology - Computer, 11-12 July, Yogyakarta, Indonesia, 2017.

xvi. Duplaga Mariusz, Juszkiewicz Krzysztof, Leszczuk Mikołaj, Marek M, Papir Zdzisław: “Design of Medical Digital Video Library,” Proc Fourth International Workshop on Content-Based Multimedia Indexing CBMI’2005 Riga, Latvia; 2005, Content Based Multimedia Indexing.

xvii. Gibbs JD, Graham MW, Bascom R, Cornish DC, Khare R, Higgins WE, “Optimal procedure planning and guidance system for peripheral bronchoscopy”, IEEE Trans Biomed Eng. 2014 , 61(3):638-57

xviii. Goncalves, L., J.Novo, A. Canpilho,”Hessian based approaches for 3D lung nodule segmentation”, Expert system with Application, 2016.

xix. Goodfellow IJ, Courville A, Bengio Y. Scaling up spike-and-slab models for unsupervised feature learning. *IEEE Trans Pattern Anal Mach Intell*. 2013;35(8):1902-1914. doi:10.1109/TPAMI.2012.273

xx. Gopi, K. ; J. Selvakumar, "Lung tumor area recognition and classification using EK-mean clustering and SVM", International Conference on Nextgen Electronic Technologies: Silicon to Software, 23-25 March, Chennai, India, 2017.

xxi. Gould, M.K., et al., “Elevation of individuals with pulmonary nodules when is it lung cancer? Diagnosis and management of lung cancer American college of chest physicians evidence based clinical practice guidelines” Chest, vol 143, 2013.

xxii. Grega Michał, Leszczuk Mikołaj: “The prototype software for video summary of bronchoscopy procedures with the use of mechanisms designed to identify, index and search,” chapter in BRONCHOVID: The Computer System for Bronchoscopy Laboratory Integrating the CT-Based Bronchoscopy and Transbronchial Needle-Aspiration Biopsy Planning, Virtual Bronchoscopy, Management of the Bronchoscopic Procedures Recordings, Automatic Image-Based Data Retrieval, Artifact and Pathology Detection and Interactive 2D & 3D Visualization Springer-Verlag; 2010, 587-598.

xxiii. Harvey A, Cohen computer science and computer engineering La Trobe University Bundoora 3083 Parallel algorithm for gray scale image segmentation Harvey A. Cohen, Parallel algorithm for gray –scale image segmentation, proc. Australian and new Zealand conf. Intelligent information systems, ANZIS- 96,Adelaide, Nov 18-20, 1996, pp 143-146.

xxiv. Huan Wang, Xiu-Hua Guo, Zhong-wei Jia et al,” Multilevel binomial logistic prediction model for malignant pulmonary nodules based on texture features of CT image”, European Journal of Radiology, 2010, Elsevier.

xxv. Janowski Lucjan, Suwada Krzysztof, Duplaga Mariusz: “Fast MPEG-7 image features-based automatic recognition of the lesion in the bronchoscopic recordings,” chapter in BRONCHOVID: The Computer System for Bronchoscopy Laboratory Integrating the CT-Based Bronchoscopy and Transbronchial Needle Aspiration Biopsy Planning, Virtual Bronchoscopy, Management of the Bronchoscopic Procedures Recordings, Automatic Image-Based Data Retrieval, Artifact and Pathology Detection and Interactive 2D & 3D Visualization Springer-Verlag; 2010.

xxvi. Jeyabharathi, D., Dejey, “Vehicle Tracking and Speed Measurement System (VTSM) Based on Novel Feature Descriptor: Diagonal Hexadecimal Pattern (DHP)”, Visual Communication and Image Representation, 2016.

xxvii. Jianping Fan, Elmagarmid Ahmed K, Member Senior, Xingquan Zhu, Aref Walid G, Wu Lide: “Classview: Hierarchical video shot classification, indexing, and accessing,”. IEEE Trans on Multimedia 2004, 6:70-86.

xxviii. Johnson Scott B: “Tracheobronchial injury,” In Seminars in Thoracic and Cardiovascular Surgery. Volume 20. Spring; 2008:(1):52-57.

xxix. Jóźwiak Rafał, Przelaskowski Artur, Duplaga Mariusz: “Diagnostically Useful Video Content Extraction for Integrated Computer-aided Bronchoscopy Examination System,” Advances in Intelligent and Soft Computing, 57, Computer Recognition Systems 3 Springer; 2009, 151-158.

xxx. Kai-jian XIA, Jin-yi CHANG , Jin –cheng ZHOU, “An Image segmentation based on clustering of spatial patterns and watershed algorithm (IJCNS) International journal of computer and network security, 2(7), 2010, 15-17.

xxxi. Kavuru MS, Mehta AC: “Applied Anatomy of the Airways,” In Flexible Bronchoscopy.
2 edition. Edited by: Ko-Peng Wang, Ahtul C. Mehta and J. Francis Turner. Blackwell Publishing Company; 2004.

xxxii. Lee Ho Young, Lee Ho Keun, Ha Yeong Ho: “Spatial color descriptor for image retrieval and video segmentation,” IEEE Transactions on Multimedia 2003, 5(3):358-367.

xxxiii. Lee WL, Chen YC, Hsieh KS. Ultrasonic liver tissues classification by fractal feature vector based on M-band wavelet transform. *IEEE Trans Med Imaging*. 2003. doi:10.1109/TMI.2003.809593

xxxiv. Leszczuk Mikołaj: “Analiza możliwości budowy internetowych aplikacji dostępu do cyfrowych bibliotek wideo,” PhD thesis AGH University of Science and Technology, Faculty of Electrical Engineering, Automatics, Computer Science and Electronics, al. Mickiewicza 30, PL-30059 Krakow, Poland; 2005.

xxxv. Lombardo Alfio, Morabito Giacomo, Giovanni Schembra: “Modeling intramedia and intermedia relationships in multimedia network analysis through multiple timescale statistics,” IEEE Transactions on Multimedia 2004, 6(1):142-157.

xxxvi. Lu, D. & Q. Weng, “A survey of image classification methods and techniques for improving classification performance”, International Journal of Remote Sensing, 2007, 823–870.

xxxvii. Manasee Kurkure ; Anuradha Thakare, "Lung cancer detection using Genetic approach", International Conference on Computing Communication Control and automation, 12-13 August, Pune, India, 2016.

xxxviii. May Phu Paing ; Somsak Choomchuay, "A computer aided diagnosis system for detection of lung nodules from series of CT slices", International Conference on Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology, 27-30 June, Phuket, Thailand, 2017.

xxxix. McWilliams, A., et al.," Probability of cancer in pulmonary nodules detected on first screening CT", New England Journal of Medicine, Vol, 369, pp. 910-919, 2013.

xl. Naidich, D.P., et al., "Recommendations for the management of subsolid pulmonary nodules detected at CT: a statement from the Fleischner society", Radiology, vol 266, 2013.

xli. Niranjana, G.; M. Ponnavaikko, "A Review on Image Processing Methods in Detecting Lung Cancer Using CT Images", International Conference on Technical Advancements in Computers and Communications, 10-11 April, Melmaruvathur, India, 2017.

xlii. Nixon M, Aguado A. Feature extraction by shape matching. *Featur Extr Image Process Comput Vision, Second Ed*. 2008:161-216. doi:10.1016/B978-0-12-396549-3.00003-3

xliii. Nixon MS, Aguado AS. Low-level feature extraction (including edge detection). In: *Feature Extraction & Image Processing for Computer Vision*. ; 2012:137-216. doi:10.1016/B978-0-12-396549-3.00004-5