Grenze International Journal of Engineering and Technology, Jul Issue

A Survey of Deep Learning for Lung Nodule Classification

Priyanka Gupta[1] and Anand Prakash Shukla[2]
[1]Department of Computer Science & Engineering, Ghaziabad- India
Email: Priyankavg02@gmail.com
[2]KIET Group of Institutions, Ghaziabad-201206, India
Email: ap.shukla@kiet.edu

***Abstract*—Deep learning algorithms, especially convolutional networks, have quickly risen to prominence as the preferred method for analysing medical images. However, several deep learning approaches have been used in lung nodule classification in recent years, and they have shown impressive outcomes as compared to many other state-of-the-art approaches. This paper presents a systematic comparison of Multiple deep learning approaches for lung nodule classification have been used in the past, as well as variations applied to deep learning design to enhance the classification program's accuracy and also discuss the main deep learning concepts relevant to medical image analysis and also help to concludes that new problems in nodule classification must be resolved in order to identify malignant lesions at an early stage.**

***Index Terms*— Lung Nodule Classification, Deep Learning, Medical Imaging.**

I. INTRODUCTION

Deep learning (DL) has been commonly used in a range of medical imaging challenges and has gained improved process in a number of medical application areas, ushering us into the artificial intelligence (AI) era. Medical imaging, on the other hand, poses special obstacles to DL strategies. Lung cancer are among the most dangerous and widespread forms of cancer in the world, in terms of both new patients and fatalities. Lung cancer survival has improved significantly over the last decade, from a median overall survival of 11 months to a 17.8% 5-year survival rate. Early identification and treatment of lung cancer improves the sufferer's chances of survival. Lung cancer diagnosis requires classifying tumours as benign or malignant, which is achieved using image mining techniques known as classification. Image classification is the primary domain wherein Deep Neural Networks play the most essential role in medical image processing. [1] Sensibly identifying image by subject is a vital way to collect helpful info from wide image set. The classification module in the mining method is typically called classifier. The object detection problem, which is concerned with classification of images, is one of the most important problems in computer vision. The numerical properties of different image features are evaluated, and data is grouped into categories. Most innovative classification methods, such as fuzzy sets, artificial neural networks, and expert systems, have been commonly used for image classification in recent years, and each of them has its own set of issues and has a lower rate of precision. Cancers are graded clinically as small-cell lung carcinoma (SCLC) or non-small-cell lung carcinoma (NSCLC), with SCLCs accounted for 15% of the overall lung cancer population and NSCLCs accounting for 85%. [4] Adenocarcinoma, Squamous-cell carcinoma, and

Grenze ID: 01.GIJET.7.2.6_1

Large-cell carcinoma are the three subtypes of NSCLC. Adenocarcinoma is by far the most common form of lung cancer, accounting for 40% of all lung cancer cases. For prognostication and treatment planning, it is essential to categorise the form of malignancy based on histopathology and immunohistochemistry as shown in Fig. 1. [3].

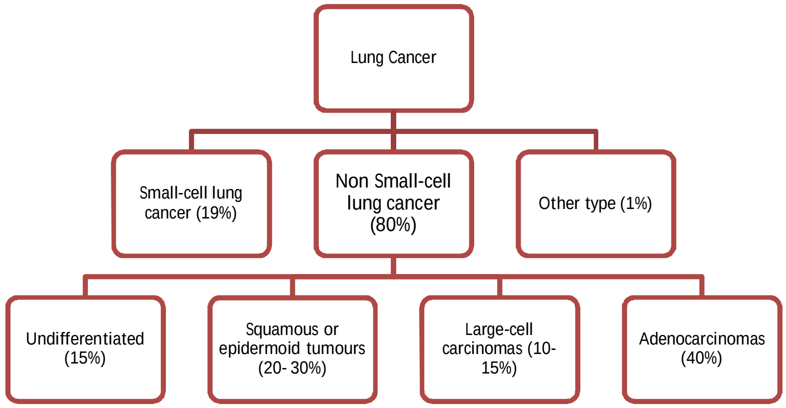

Fig. 1. Classifications of Lung Tumors

A. Use for a Diagnostic Tool

Sadly, lung cancer signs occur early in the disease's development, when it is no longer treatable. After all, there are two main concerns to consider: (1) Failure to understand lung cancer's presenting signs and (2) Taking longer to finish diagnostic investigations. [3] About two-thirds of people had advanced lung tumours at the time of surgery, according to a survey published in Southern Norway (stage IIIB and IV). Delays in medical imaging result in a rise in tumor size and level, which has a negative effect on lung cancer diagnosis. [5]

To diagnose and stage lung cancer, a chest X-ray, CE-CT (Contrast-Enhanced Computed Tomography), Computed Tomography (CT) Scan, MRI, Positron Emission Tomography (PET) Scan, and other research methods can be used. While chest X-rays have been used for screening, they have not proven to be successful in detecting tumors early. Low-dose CT scans (LDCTs) have been used in recent years to screen people that are at a higher risk of cancer in the future. The term "screening" refers to a procedure that is used to diagnose illness in individuals that have not yet received treatment. LDCT scans may aid in the detection of unhealthy areas in the lungs that may be cancerous.

B. Deep Learning

Deep learning has increased in popularity as a branch of machine learning in recent years. Deep neural networks have obtained impressive results in the fields of face recognition, object detection and image classification thanks to a vast amount of available data and the powerful computing strength of GPUs, as well as other images, and it's also been applied to disease diagnosis. The key issues with increasing network depth in the deep learning process are gradient explosion and gradient disappearance. Data normalization and initialization is the traditional solution to the gradient problem, which solves the problem but degrades network output. While the depth has increased, the failure rate has risen. There are several different types of images used in medical imaging, but computer tomography (CT) +scans are usually favored because they all have less noise. Deep learning has been shown to be the most effective tool for classifying diagnostic imaging entities and extracting features. Many researchers have suggested many types of deep learning architectures to classify lung disease.

Today, a number of deep learning networks are in use, including: Recurrent Neural Network (RNN), Deep Boltzmann Machine (DBM), Auto encoder, Convolution Neural Network (CNN) and many more. [3] Below mention different Architectures for Deep Learning shown in Fig. 2.

According to Fig. 2, Deep learning is not really a single technique, but instead a set of algorithms and optimization techniques that can be used to solve a variety of problems. Learning is focused on training the neural network with example data and rewarding them based on their performance; the more data available, the better. The fundamental architecture of deep learning is the artificial intelligence system (ANN). ANN has led to the development of a number of algorithm variations. To gain a basic understanding of deep learning and artificial neural networks.

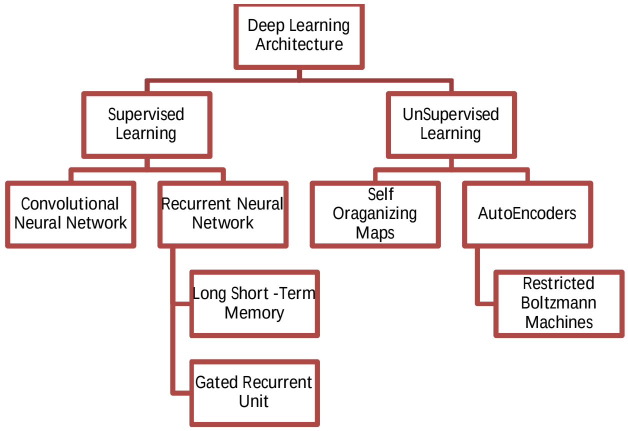

Fig. 2. Architecture for Deep Learning

The problem space in which the goal to be determined is explicitly labeled inside the training data is referred to as supervised learning. Recurrent neural networks and Convolutional neural networks, as well as some of their variants, are the most common supervised deep learning architectures. A CNN is a layered neural network which was motivated by the visual cortex of animals. In image processing tasks, the structure is especially useful. The RNN is one of the fundamental access networks that other learning algorithms are designed, The key difference between a traditional a recurrent network and multilayer network is that a recurrent network may have connections that feed back into previous layers rather than being fully feed-forward. By using traditional neuron-based neural networks, the LSTM used the idea of a memory cell. As a feature of its inputs, the processing unit will maintain its value for a short or long time, allows cells to recognize what's essential rather than just its last calculated value. Current CNN and LSTM applications have resulted in video and image captioning systems that caption images and videos in linguistic form. The image and video processing is done by the CNN, and the LSTM is learned to translate the CNN performance into linguistic form. The GRU is easier than the LSTM, can be learned faster, and can execute tasks more efficiently. The LSTM, on the other hand, can become more informative, and with much more details, it can yield different results.

In Unsupervised learning applies to a given problem in which the data being used for training has no goal name, SOM (Self-organized map) is a neural network that reduces the size of the input data set to construct clusters. In many ways, SOMs differ from standard artificial neural networks. In Autoencoders is the type of ANN is consists of three layers: input, secret, and output, As during learning process, an error function is used to calculate the difference between both the input and output layers, and the weights are changed to mitigate the error. Since there is no details to which to evaluate the outputs, autoencoders use backward propagation to learn continuously. Autoencoders are known as self-supervised algorithms as a result of this. A two-layered neural network is referred to as an RBM (Restricted Boltzmann Machines). Input and secret layers are the frameworks. Each node in a noticeable network is connected to a nodes in a hidden units in RBMs. Nodes in the input and hidden layers are often linked in a typical Boltzmann Machine. In a RBM, nodes inside a level are not related due to its computational difficulty. RBMs are defined as generative models because the reproduced input is often different from the current source. In truth, that's the most important distinction between an autoencoder and a deterministic model.

A guided graph links the nodes of a recurrent neural network, and the network remembers the previous input to estimate the output. [6] The recursive neural network is composed of RNN in which all inputs have the same set of weights. For natural language processing, both recurrent and recursive neural networks are used.[3] A Deep Convolution Network is a deep network comprised of many connected hidden layers of restricted Boltzmann machines, but the units within each layer are not linked. The DBN and the Deep Boltzmann Machine are both unsupervised learning mechanisms, but the hidden layers are linked in an undirected manner. Speech and image recognition are also possible with DBN. [7] Autoencoders are commonly used for image denoising and feature extraction. To extract features from images, a convolution neural network uses a series of convolution layers, followed by a completely full connection. A convolutional network that skips several layers is known as a Deep Residual Network. Convolution Restricted Boltzmann Machine (CRBM) is an acronym for Convolution Restricted Boltzmann Machine. In terms of image classification, CNN has proven to be the most successful. Over-fitting and processing time are two major problems with deep neural networks. When a network learns a sequence in the training set but is unable to learn patterns outside it, this is known as over fitting. As a result, the training set must be broad and well-balanced in order to cover all potential patterns that could happen in the real time.

II. Deep Learning for Lung Nodule Classification

A. Initial Considerations

In this figure.3 show that Benign (not Cancer) Tumor cells can only expand internally and cannot grow by metastatic disease or penetration. Malignant (cancer) tissues infiltrate neighboring tissues, join blood vessels, and spread to other parts of the body. Related to its violent nature and late diagnosis at advanced stages, Lung cancer is among the most common cancer-related death rates. Lung cancer is a type of cancer is critical for a person's life, and it is a difficult problem to solve. In most cases, computed tomography (CT) and chest radiographs (X-rays) scans are used to diagnose malignant nodules: The existence of benign nodules, on the other hand, can lead to erroneous judgments. The benign and malignant nodules have a striking similarity in their early stages. For lung nodule identification and classification, we used two deep three-dimensional (3D) customised mixed connection network (CMixNet) architectures, because of deep convolutional neural networks' (CNN) recent achievements in image analysis To detect nodules, a faster R-CNN based on features from CMixNet and U-Net, such as encoder–decoder architecture, was used. [8].

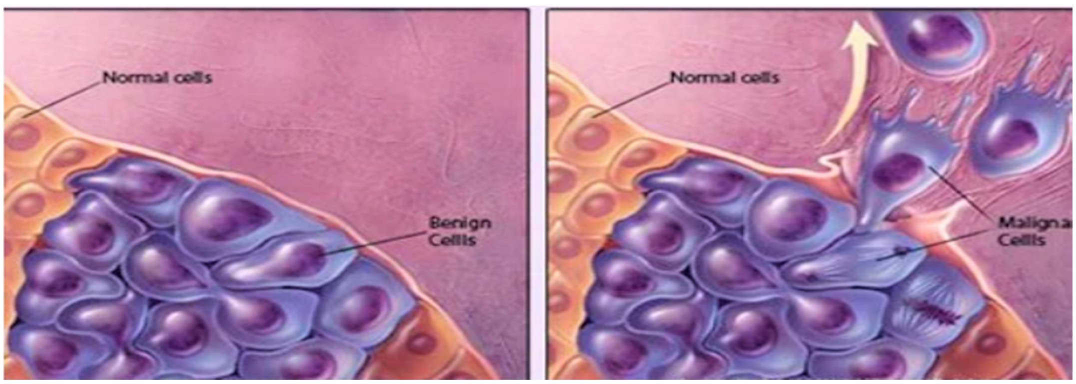

Fig. 3. Benign vs. Malignant Tumors

To help the surgeon make correct decisions, computer-assisted lung cancer detection is needed. The CAD success functions as a proper diagnosis for the radiologist, enhancing radiological diagnosis accuracy and reducing the time it takes to read an image. There are two types of CAD systems: 1) CADx (Computer Aided Diagnostic), 2) CADe (Computer Aided Detection). CADe is used to analytic methods while CADx is used to assess tumors malignancy and staging.

Machine Learning methods and techniques are commonly used in lung cancer diagnosis and prognosis. They can diagnose lung disease with just 0.11 mSv of radiation. At standard doses, For lung cancer detection, machine learning were found to have a sensitivity of 91.5–95.9%. [9]

The following are the two major concepts to lung nodule classifier: (1) Radiomics, that is based on extracting picture attributes from a lung CT scan. (2) Neural Network - based with Convolutions (CNN). The model is developed using a radiomics method that extracts either 2D or 3D feature maps of lung nodules. To define the tumour, it also needs an effective Feature Extraction algorithm & Lung Segmentation. Another side, CNN does not always necessitate a feature extraction and segmentation stage. CNN, on the other hand, necessitates a very big dataset.

Picture Collection, Image Segmentation, Image Pre-processing, Lung Nodule Classification and Feature Extraction, and are the 5 steps in the Radiomics method to Lung Nodule Classification exhibited in fig 4. All of these systems has its own set of difficulties. For eg, the best image acquisition and reconstruction protocols must be defined and established. Segments must also be stable and require minimal operator feedback. Features must be produced that faithfully represent the difficulty of the specific quantities, but they must not be excessively complicated or duplicate. In addition, informatics databases allowing the inclusion of feature representation and annotations, as well as biological and personal data, must be developed. After this, since radiomics is not a mature field of research, the computational methods used to interpret these data must be optimized. [10].

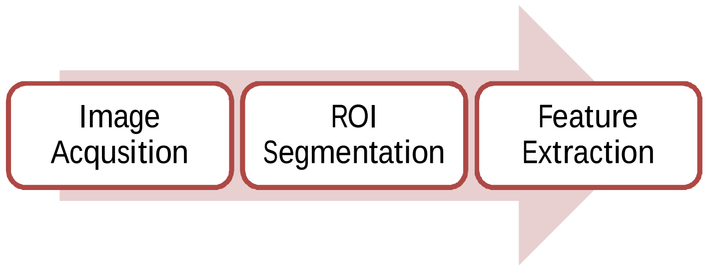

Fig: 4. The fundamentals of radiomic classification

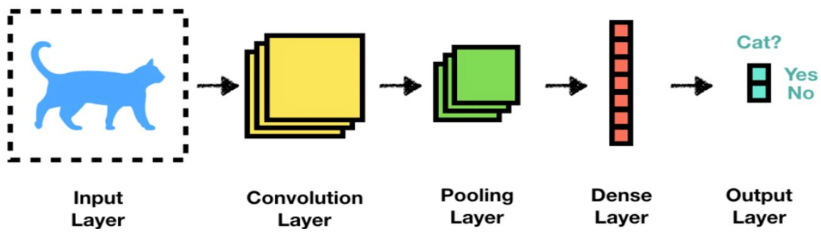

Fig: 5. The fundamentals of CNN classification

B. CNN (Convolution Neural Network)

The key premises in using a deep Neural Network to classify a lung nodule. The information is transferred through a sequence of convolution operation with filters, pooling layers, completely connected layers, and soft - max layers in the CNN architecture exhibited in fig. 4. Classification of images requires extracting features from an image in order to classify trends in a dataset. Then use an ANN for image classification might be incredibly computationally expensive because the learnable parameters will become incredibly high.

a) Input Layer

You may use an existing dataset or create your own image dataset to solve your own image classification task. Kaggle.com is a good place to start looking for datasets. You must create a tensor with the data's form. You can do this with the tf.reshape module. Throughout this module, they must announce the tensor to reshape as well as the tensor's form. A first statement is the data's characteristics, which are described in the function's argument.

b) Convolution Layer

It's the first stage, and it is responsible for extracting the various representations of the input images. In this layer, the convolution mathematical operation can be done between the input image and a filter of a particular size MxM. Sliding the filter over the input image yields the absolute value between both the filter and the parts of the input image in terms of the sum of the filter (MxM). The result is the Function diagram, which includes information about either the images corners and edges. This function vector is then moved on to other stages, which use the source images to learn a number of other features.

c) Pooling Layer

During a Convolutional Layer, a Pooling Layer is usually applied. The primary goal of this layer is to shrink the preprocessed feature map in order to minimize operational errors. These are achieved by decreasing the relationships between layers and operating on each feature map separately. Depending on the method, different forms of pooling activities exist.

In Max Pooling, the external wall is gathered from the feature diagram. Mean Pooling is used to measure the total of the elements in a pre - specified sized Image section. The total number of the items in the predefined section is calculated using Sum Merging. Between the Convolutional Layer and the FC Layer, the Pooling Layer typically acts as a connection

d) Dense Layer

The title suggests that the neurons in a network layer are fully connected (dense). Growing neuron in a layers receives feedback from most of the neurons in the layer before it, making them densely linked. This layer is a completely associated layer, which means that each layer's neurons are connected to those in the next layer.

This layer learns features from so many previous layer's combinations, while a convolutional layer focuses on high level of performance with a small repetitive region.

e) Output Layer

As previously stated, the output layer in a CNN is a completely connected layer that flattens and sends the input from the other layers in order to convert the result into the class labels needed by the network.

III. RELATED WORK

Gowri Laksshmi et al. [1] proposed Entropy Weighted Residual Convolution Neural Network is used to complete the ensemble classification integration (EWRCNN). Finally, the findings are contrasted between the tests, and the addition of rule-based classification increased the CAD system's detection accuracy as FP elimination with Faster R-CNN alone was lower. The goal of this review is to use CT and X-ray images to classify and predict the correct lung cancerous nodule. Shabi M et al. [2] proposed a new approach for predicting the malignancy of nodules that uses a global feature extractor to analyse the size and shape of the nodule, as well as a local feature extractor to examine the nodule's density and composition. The deep Local–Global network can retrieve both locally and globally features with precision. Naik et al. [3] provides a thorough comparison of Multiple deep learning methods for lung nodule classification have been used in the past, as well as modifications added to deep learning design to enhance the classification system's validity. This paper concludes that new problems in nodule classification must be resolved in order to identify malignant lesions at an early point. Samaiya Dabeer et al. [11] Using a CNN-based method, it was proposed to diagnose cancer in a histopathological picture. MITOS- ATYPIA14, and BreakHis were used to build the initial data set (UC Irvine Machine Learning Repository). A database network called BreakHis was used. The RGB colour model samples were used to train the model, which included 2480 benign and 5429 malignant samples. To begin, the deep net is implemented by first processing the images in the dataset. Data redundancy must be minimised because it adds to system complexities and is redundant. The accuracy was found to be 90.55 percent for the benign and 94.66 percent for the malignant groups, respectively. Panpan et al. [13] Studies in lung computed tomography (CT) images from the readily viewable LIDCIDRI database are used to validate this method. The ten-fold cross-validation approach yielded an average accuracy of 98.23% and a false positive rate of 1.65 percent. As compared with the traditional support vector machine (SVM)-based CAD scheme, our approach improved accuracy by 9.96%. In comparison to the InceptionV3 & VGG19 model convolutional neural networks, the number of false positives fell by 2.07% and 2.22 %, accordingly. Meng et al. [16] To compare the clinical significance of a deep learning-based lung nodule segmentation and classification algorithm to other CT enhancement techniques. Another well approach was put to the test on 363 new tests using two parameters: density classification accuracy and nodule segmentation Dice coefficient. The variance analysis of various different modeling approaches was used to statistically evaluate the results under 3 different testing techniques. Under various CT modeling techniques, a deep learning algorithm combining 3D convolution neural network and recurrent neural network (rnn) has shown to be reasonably constant in segmentation and classification of lung nodules. Trajanovski et al. [17] The deep learning - based model: (i) generalises well throughout all datasets, with AUCs ranging from 86 to 94 percent; (ii) outperforms the commonly used PanCan Risk Model, with an AUC of 11 percent higher; (iii) outperforms the state-of-the-art in lung transplantation as represented by the results of the Kaggle Data Science Bowl 2017 contest; (iv) performs similarly to radiologists in predicting cancer risk at the individual stage. Ashhar et al. [18] To distinguish lung tumours into benign and malignant groups, researchers used LIDC-IDRI databases to test the efficiency of five newly established Convolutional Neural Network architectures: SqueezeNet, GoogleNet, ShuffleNet, DenseNet, and MobileNetV2. The accuracy, sensitivity, specificity, and position under the receiver operator are all used to evaluate their efficiency. GoogleNet is the best CNN structure for CT lung tumour detection, according to research observations, with a precision of 94.53 percent, a specificity of 99.06 percent, a sensitivity of 65.67 percent, and an AUC of 86.84 percent. Asuntha et al. [22] This study employs innovative Deep learning approach for detecting the position of tumour lung nodules. Learning is used to classify features in this case. FPSOCNN is a novel FPSOCNN that aims to minimize complexities of CNN. Wavelet transform-based functions, Histogram of directed Gradients (HoG), Local Binary Pattern (LBP), Scale Invariant Function Multimedia Tools Applications Transform (SIFT), and Zernike Moment are all used in this study. After removing the texture, the good function is chosen using a geometric, volumetric, and Fuzzy Particle Swarm Optimization (FPSO) algorithm. Huang et al. [23] On CT scan images of the lung, an unique method merging DTCNN and ELM is suggested for effective and precise automatic benign–malignant nodules analysis. DTCNN has demonstrated an amazing high extraction performance, while ELM has also been suggested as an optimized and effective classifier. On the LIDC-IDRI dataset, the suggested DTCNN-ELM approach obtained a precision of 94.57 percent, and on the FAHGMU database, it achieve a precision of 100 percent.

TABLE 1: IMAGE RECOGNITION TECHNIQUES IN LUNG NODULES: A COMPARISON

Reference	Dataset	Techniques	Result
Panpan et al. [13]	LIDC-IDRI	SVM based CAD System	**Accuracy- 98.23%**
Naik et al. [14]	LUNA-16	CNN. SVM	Accuracy- 93.53% Sensitivity – 86.62% Specificity – 96.55%
Ali et al. [15]	LUNGx	SVM, Ada Boost M2 algorithm, Deep-CNN	Accuracy – 90.46%
Meng et al. [16]	Public dataset	3D-CNN, RNN	Accuracy- 98.67%
Trajanovski et al.[17]	NLST (National Lung Screening Trail)	CT Lung Screening	Accuracy – 94%
Ashhar et al. [18]	GoogleNet LIDC-IDRI	CNN, CT	Accuracy- 94.53% Sensitivity –65.67% Specificity – 99.06% AUC – 86.84%
Cohen et al.[19]	LIDC/IDRI/NLST	CNN features a 3D roto translation community	Sensitivity- 96.4%
Yang et al. [20]	LUNA 16	CNN Boosting	Sensitivity- 86.42%
Zuo et al. [21]	LUNA 16	MR-CNN	Accuracy- 97.33% Sensitivity –97.26% Specificity – 97.38%
Asuntha et al. [22]	LIDC & Private data	Fuzzy Particle Swarm Optimization(FPSO) & CNN	Accuracy- 95.62% Sensitivity –96.23% Specificity – 95.89%
Huang et al.[23]	LIDC-IDRI & FAM-GMU	Extreme Learning Machine & Deep transfer, CNN	Accuracy – 94.57%

IV. CONCLUSION

Lung cancer is one of the most deadly diseases that have ever occurred. Sadly, once this disease has progressed to a significant degree or reached a critical point, it is extremely difficult to treat. Computer-Aided Detection (CAD) is a rapidly evolving technology that aids in the detection of cancer by feeding in specific inputs including patient-related data. The output of CNN architectures, such as GoogleNet, LIDC-IDRI, LUNA-16, NLST, as well as others, are studied and contrasted in order to distinguish between benign and malignant tumours in CT images of the lungs. As a result, further research is only needed to improve the accuracy of tumors in CT images.

ACKNOWLEDGEMENT

I would like to express my heartfelt gratitude to my mentor, "Dr. Mr. Anand Prakash Shukla," for his expert advice and assistance in finishing my Research Paper. I would also like to express my sincere thanks to Director Sir "Dr. (Col) A Garg" for supplying me with all of the required facilities.

REFERENCES

[1] K.S. Gowri Laksshmi, Dr. R. Umagandhi,"FALSE POSITIVE REDUCTION BASED ON ANATOMICAL CHARACTERIZATION USING DEEP LEARNING NEURAL NETWORK IN LUNG NODULE DETECTION",

European Journal of Molecular & Clinical Medicine, 2020, Volume 7, Issue 8, Pages 5296-5303.

[2] Al-Shabi M, Lan BL, Chan WY, Ng KH, Tan M. Lung nodule classification using deep Local-Global networks. Int J Comput Assist Radiol Surg. 2019 Oct;14(10):1815-1819.

[3] Naik, A., Edla, D.R. Lung Nodule Classification on Computed Tomography Images Using Deep Learning. *Wireless Pers Commun* **116,** 655–690 (2021).

[4] Denisenko, T. V., Budkevich, I. N., & Zhivotovsky, B. (2018). Cell death-based treatment of lungadenocarcinoma. Cell Death and Disease, 9, 117.

[5] Rolke, H. B., Bakke, P. S., & Gallefoss, F. (2007). Delays in the diagnostic pathways for primary pulmonary carcinoma in Southern Norway. Respiratory Medicine, 101(6), 1251–1257.

[6] Li, X., & Wu, X. (2015). Constructing long short-term memory based deep recurrent neural networks for large vocabulary speech recognition. In IEEE international conference on acoustics, speech and signal processing (pp. 4520–4524). IEEE.

[7] Jin, X., Ma, C., Zhang, Y., & Li, L. (2017). Classifcation of lung nodules based on convolutional deep belief network. In 2017 10th International symposium on computational intelligence and design (ISCID), Hangzhou (pp. 139–142).

[8] Nasrullah Nasrullah, Jun Sang, Mohammad S. Alam, Muhammad Mateen, Bin Cai, Haibo Hu , Automated Lung Nodule Detection and Classification Using Deep Learning Combined with Multiple Strategies, Sensors (Basel) 2019 Sep; 19(17): 3722. Published online 2019 Aug 28. doi: 10.3390/s19173722.

[9] Schwyzer, M. (2018). Automated detection of lung cancer at ultralow dose PET/CT by deep neural networks—Initial results. Lung Cancer, 126, 170–173.

[10] Kumar V, Gu Y, Basu S, Berglund A, Eschrich SA, Schabath MB, Forster K, Aerts HJ, Dekker A, Fenstermacher D, Goldgof DB, Hall LO, Lambin P, Balagurunathan Y, Gatenby RA, Gillies RJ. Radiomics: the process and the challenges. Magn Reson Imaging. 2012 Nov;30(9):1234-48.

[11] Dabeer S, Khan MM and Islam S 2019 Cancer diagnosis in histopathological image: CNN based approach Informatics in Medicine Unlocked 16:100231.

[12] Patra R. (2020) Prediction of Lung Cancer Using Machine Learning Classifier. In: Chaubey N., Parikh S., Amin K. (eds) Computing Science, Communication and Security. COMS2 2020. Communications in Computer and Information Science, vol 1235. Springer, Singapore.

[13] Panpan Wu, Xuanchao Sun, Ziping Zhao, Haishuai Wang, Shirui Pan, Björn Schuller, "Classification of Lung Nodules Based on Deep Residual Networks and Migration Learning", *Computational Intelligence and Neuroscience*, vol. 2020, Article ID 8975078, 10 pages, 2020.

[14] Naik, Amrita and Edla, Damodar Reddy. 'Lung Nodule Classification Using Combination of CNN, Second and Higher Order Texture Features'. 1 Jan. 2021 : 1 – 9.

[15] I. Ali, M. Muzammil, I. U. Haq, A. A. Khaliq and S. Abdullah, "Deep Feature Selection and Decision Level Fusion for Lungs Nodule Classification," in IEEE Access, vol. 9, pp. 18962-18973, 2021.

[16] Meng XL, Xing ZJ, Lu S, "A deep learning-based lung nodule density classification and segmentation method and its effectiveness under different CT reconstruction algorithms". 2021 Feb;101 (7):476-480.

[17] S. Trajanovski, D. Mavroeidis, "Towards radiologist-level cancer risk assessment in CT lung screening using deep learning", Computerized Medical Imaging and Graphics,2021,101883,ISSN 0895-6111.

[18] S.M. Ashhar, Mokri, S. Salasiah, A. Rahni." Comparison of deep learning convolutional neural network (CNN) architectures for CT lung cancer classification", **International Journal of Advanced Technology and Engineering Exploration; Bhopal** Vol. 8, Iss. 74, (Jan 2021): 126-134.

[19] Winkels, M., & Cohen, T. S. (2019). Pulmonary nodule detection in CT scans with equivariant CNNs. Medical Image Analysis, Medical Image Analysis, 55, 15–26.

[20] Xie, H., Yang, D., Sun, N., Chen, Z., & Zhang, Y. (2019). Automated pulmonary nodule detection in CT images using deep convolutional neural networks. Pattern Recognition, 85, 109–119.

[21] W. Zuo, F. Zhou, Z. Li and L. Wang, "Multi-Resolution CNN and Knowledge Transfer for Candidate Classification in Lung Nodule Detection," in IEEE Access, vol. 7, pp. 32510-32521, 2019.

[22] Asuntha A, and Srinivasan A 2020 Deep learning for lung Cancer detection and classification. Multimedia Tools and Applications pp 1-32.

[23] X. Huang, Q. Lei, T. Xie, Y. et al."Deep Transfer Convolutional Neural Network and Extreme Learning Machine for lung nodule diagnosis on CT images", Knowledge-Based Systems, Volume 204, 2020, 106230, ISSN 0950-7051.