WWW.IJRPR.COM

International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

A Survey on Lung Nodules Detection with CT-Images using Convolution Neural Network

Gunupuru Ravikumar, Amarasetti Venkata Narasimha, Daliya UmaKalyani, Dumberi Dilipchand, Abdul Rahaman, Gunapu Harika

Computer Science and Engineering, GMR Institute of Technology, (of JNTUK), Rajam, India

ABSTRACT

In present days lung cancer has place a major health issue that leads to the people death. The main reason for lung cancer is due to the nodules present in the lungs. The nodules nothing but a small type of growth that is present in the lungs. When the nodule size increases the stages of lung cancer increases and it leads to death. Here we have two types of lung nodules. One is Benign and other is Malignant nodule. The malignant nodule is the dangerous nodule which leads to human death very rapidly.Shortness of breath, wheezing or hoarseness, chest discomfort, back pain, and exhaustion are all signs of the lung nodules. Here we are using VGG16 model for detecting the lung nodules in the lungs. For this we are using LUNA16 dataset consists of lung images. These lung images are performed feature extraction using Enhanced super resolution for increasing the image quality. The proposed model is then compared with pre-trained model like InceptionV3 and CNN. The proposed model perform a better accuracy and it gave high accuracy compared to pre trained model. It executes very fast and gave better results.

Keywords—*:*Lung Cancer, Transfer Learning, Convolutional Neural Network, Computed Tomography, LUNA16,VGG-16.

Introduction

Lung carcinogenic is that the most typical malicious and is that the leading reason for cancer deaths worldwide. Lung Cancer deaths are increasing day to day. The main reasons for Lung Cancer is lung nodules. Lung Cancer is additionally called as Lung Carcinoma. A lung nodule is an abnormal growth that develops in the lungs. One person may have one nodule on the lung or several nodules. The Nodules develop

in one or both lungs. Lung nodules come in two different forms. Two types of nodules exist: benign and malignant. The Benign nodules are non-carcinogenic. They do not extend to remaining regions of the body. Most of them are benign. The Malignant Nodules are Cancerous and they spread all over the body very quickly. The malignant Nodules are led an individual to death. According to the reports approximately 18% death rates are cancerous. According to the ACS research, lung cancer has the greatest death rate at 26% and the lowest five-year survival rate at only 18%. Due to the lung nodules being discovered at an advanced stage and not being clearly identified at diagnosis, there is a low survival rate. So, it is important to detect the nodules and classify them at the advanced stage of Lung Cancer. The nodule is detected depending on extraction features. Extraction features includes size, texture, embryology as well as rate of broadening of the nodule. But CAD is failed to classify the malignant or benign one. So, the deep learning models are introduced to identify the benign and the malignant nodules. Deep learningapproaches such as CNN, Transfer Learning and Multiple Classifier voting are accustomed to detect and classify the lung nodule. CNN are used to enhance the accomplishment of classifying lung nodules in Computed Topography images. They give the accurate results in for classification and detecting the lung nodules. Convolutional, pooling, and fully linked layers are the three layers that comprise CNN. The CNNs uses convolutional layers to extricate features and each and every layer plays its role for extracting the nodules. The last convolutional layer, which is used is in fully-linked layers to extract all of the structure information, is responsible for extracting the complicated features. The initial convolutional layers extract the characteristics, such as tiny edges. While the convolutional and intermediate pooling layers retrieve the features with a high level of complexity. For more accurate results we are intended to use the 3D Thoracic MR Images.

We proposed the VGG16 for the lung nodule categorization problem on patient image dataset; LUNA16. The VGG team submitted the VGGNet architecture for the ILSVRCs 2014 and won the competition. It is created because they want to increase the intensity of the existing CNN model to sixteen and is referred to as VGG16. This technology allows us to precisely determine whether or not there are nodules in the lungs at an advance stage of lung carcinogenic, hence reducing the risk of mortality.

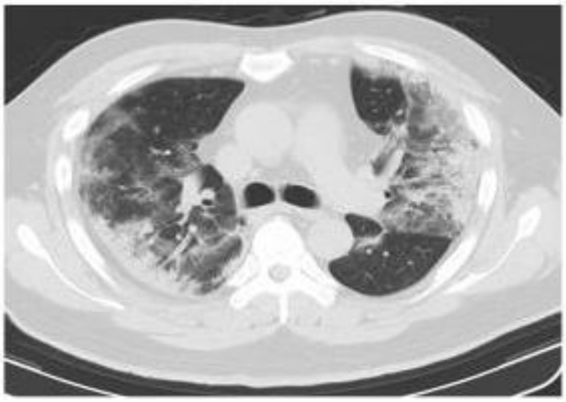


Fig 1. Sample diagram of Lung nodules.

Related Work

.In this paper the author describes about the transferable texture convolution neural network for lung nodule classification .Here he uses LUNGx and LIDC-IDRI datasets for classification of lungs. It can be detected by neural networks (CNN) with transfer learning and Energy Level.As Energy Layer is identical to the average pooling layer and it works like similar as pooling layer.During patch generation all the Computed Tomography images are converted to House field scales.Compared to LUNGx dataset the LIDC-IDRI dataset produce a better results and accuracy.[1].

The author creates an automated lung nodule recognition and categorizingdepends on multi- classifiers voting model. In pre-processing technique, they perform to reduce the size and noise in the image. In this we use multiple logistic regression and multilayer perceptron algorithms used for nodule classification. In order to perform the process we are using K-fold-cross validation. LIDC benchmark dataset is used for nodule detection in lungs images. The model approach has a better accuracy when it is compared with the other pre trained models.. It will detect false-positive rate and reduce to generate a final set of computer-aided design (CAD) marks. [2].

A DCNN algorithm is used for lung nodules detection on chest radiographs. The author describes the categorization of lung nodules in the olden days detected by chest radiography (CR). The CR scans are having a low resolution on the diaphragm and pulmonary nodules. The neural networks are used to recognize the pulmonary nodules in CR scans and also detect pulmonary edema, cardiomegaly, and pleural effusion. The convolutional neural network contains 25 layers and eight residual connections. The DCNN will handle noisy images of CR scans [3].

In this paper, the author describes the comparisons of fully connection, max-pooling layer, and taking the pixel size of Computer Topography images which are in convolutional neural (CNN) that consists of fully connected connection and dropout layer will be used in the lung dense neural network. The network uses Computer Topography images of lung nodule categorization which it took end-to-end benefits of deep learning and classifies Computerizes Topography images and they use decomposition method and the lung nodule decomposition (pre-processing). The LDNNET is utilized to reduce overfitting. [4].

In paper the author uses an Ensemble of Multi-Deep CNN model for lung nodules categorization using CT images. All the CT images are taken from the LIDC-IDRI dataset, which is a publicly available images contains 1020 cases. The proposed method contain 8 CNN designs into a single framework. In order to continue the process we are using 5-fold-cross validation. The ensemble model results fusing the detection of multiple CNN acquire better classification performance than the single CNN model..[5].

In this paper, the author describes a nodule size adaptive deep model for detection, false positive. A volumetric chest Computed Tomography scans are used for pulmonary nodule recognition using CNN based on adaptive detection and classification.3D images are taken for training the model because the nodule and vessel becomes more distinguishable. To acquire the aim of candidate detection, we follow a deep object detection model. The proposed model detects the nodules and as well as masses with spectrum. [6].

In this paper, the author describes the noticing of pulmonary nodules with a falser positive rate and low sensitivity with 2 dimensional and 3-dimensional convolutional neural network algorithms as the lung nodules which cannot have good accuracy values in CT scans. The author describes about lung nodules and analysis of neuropeptide correlation using deep learning. The U-net algorithm is used in this study to detect nodules in the lungs. Neuropeptide corella act as neuro-modulator neuropeptide, parallel substances in the haemoglobin of patients that will cause various types of lung injuries like nodules. When the lung nodules were decreasing, the accuracy rate is high because pulmonary sarcoidosis is affecting the accuracy rate. The 2-d and 3-d convolutional neural networks (CNN) were compared to reduce the high false -positive rate.[7].

In this Paper, the author surveys the modules which are used to detect lung nodules for causing lung carcinomic.The author puts his idea on pulmonary nodule categorization on CT images used forFractaInet model. We are using LUNA16-dataset for lung nodule categorization and achieved a better accuracy. Deep Learning approaches are used to classify the nodules. The techniques used are RNN algorithm, RRNN, SAE, Deep Residual Network, CNN and GAN. The accuracy of regularized multiple kernel learning algorithm is 96.35% which is high when checked with other algorithms in deep learning [8].

In this paper, the author describes the multi-discriminator (MDGAN) model is coincide with an encoder for the categorization of small and large lung nodules. Here they use unsupervised machine learning which contains unlabeled data for nodule identification.The goalof the paper is to detect the lung nodules even by using unlabeled data. The model has provided a more accurate and sensitivity contrast to other models. However, the excessive usage of discriminators only increases the complexity but not the efficiency. [9].

The lung nodule risk categorization in lungs from computed Tomography images used for deep CNN using transfer module. In this paper the author takes the DCNN using Scale transfer module. Here he used ZSDB dataset for nodule classification. The main purpose of training of dataset is multiple classification of lung nodules. After the function of the proposed model ,the author compares it with other pre trained models. This method failed to give accurate results for the un-uniform diffusion of lung nodules and also affects classification accuracy. [10].

The main model is depends up on the evaluation of deep learning algorithm in lung nodule recognition. In proposed model the author describes RCNN, SSD and YOLO for nodule detection. In object detection RCNN consists of two stages. The first part produces a region of interest. The second part classifier the output of object category. The YOLO consist of only one stage object detection. In data-preprocessing an automatic segmentation method is used to extract the features, LUNA dataset is used for lung nodule detection. Finally, they conclude that among the various detectors Faster-Recurrent CNN and Retina Net are the more giving with 35.75% and 34.65% precision.[11].

A novel deep learning framework for lung nodule identification in 3D CT images was created by the researchers. This created model is utilised to identify pulmonary nodules in lung Computer Topography images, and a CNN-based model that detects the extracted characteristics from pulmonary pictures automatically, then classifies the entire region as either having nodules present or not. They did this by using the open-source dataset LIDC. A collection of the dataset, containing a sizable number of 3536-positive and 3536-negative sample gathered from 300 Computer Topography scans, is utilised for the model. The overall weight of the data is substantial (123 GB). The suggested model produced results with decent sensitivity and accuracy.. [12].

The author described the “Malignant Lung Nodule Detection using Deep Learning”. Using Deep Learning, our model can identify cancerous lung nodules on CT-images. For the purpose of reducing false positives, the LIDC-IDRI dataset is the main dataset utilized along with a some tools from the LUNA-16 grand competition. 1018 CT images from high-risk individuals are included. In this, the lung areas were removed from the images using a preprocessing pipeline. The Deep CNN are thought to be the state-of-the-art technology in both patients imagination and object recognition applications due to their better object detection performance in natural pictures. This model produces a sensitivity of 84 percentage for classifying malignant pulmonary Nodules and recognizing their malignancy scores. [13].

"Deep learning-based lung nodule identification with impacts of slab thickness in maximum intensity at the nodule candidate detection stage," according to the scientists, is a method they suggested. The goal of this study was to determine the ideal nodule candidate detection setting by examining the impact of slab thinness on pulmonary nodule detection. They made advantage of the LIDC/IDRI dataset's publicly accessible data. 1020helical thoracic CT scan pictures from 1020 patients are included in the collection. The findings indicate that with 46 FPs/scan, 16 slab thicknesses had 96% detection sensitivity. The technique exhibited the maximum sensitivity for lung nodule detection for a single setup with 10 milli meter MIP pictures. The primary flaw in this analysis is the imbalance in the amount of data in the public databases. [14].

The authors proposed "On the performance of pulmonary nodule detection, segmentation, and classification”. The performance and clinical uses the most recent lung nodule screening and analysis methods are highlighted in this publication. This review makes it clear that the advancement of pulmonary nodule analysis methods uses the deep-learning algorithms enhanced nodule analysis's performance in a number of ways. To aid in the reading process for computed tomography (CT)[15].

To aid in the reading of CT scans, the author suggested a brand-new automated framework using a 2D (CNN) for lung nodule detection. The author suggested a system that uses two techniques, namely false-positive reduction and candidate nodule detection. Faster R-CNN is employed in a framework for candidate nodule identification. Numerous CNNs are used for the false-positive reduction approach together with the boosting-classifier concept, and the final output is determined by voting. Performance of the proposed technique is evaluated in light of the results of k-fold cross-validation using the FROC and competition performance metre (CPM). The trials on the LUNA16 dataset show that the suggested technique may precisely identify latent lung nodules. [16].

The author suggested a technique that uses Otsu segmentation and the fusion of deep learning characteristics to distinguish between lung nodules and non-nodules. To segment the lung nodule in this study, the Otsu approach was used with a morphological procedure. The best criteria are sequentially combined to classify lung nodules into benign and malignant groups. The experimental results demonstrate how well the proposed strategy performs when compared to current approaches using the lung image database consortium image database resource initiative (LIDC-IDRI). By finding abnormalities in tissue patterns, such as imbalanced wall thickening of lung bullae, this research can also be applied to other forms of lung ailments.[17].

The author of this research put up an end-to-end framework for nodule identification that combined false positive reduction with nodule candidate screening. Two subsystems are part of the proposed system. While the second subsystem largely employs classification models to discriminate between nodules and non-nodules, the first subsystem often generates candidates using segmentation-based approaches or the Regional Proposal Network (RPN). The system significantly lowers model complexity and interference time, which streamlines training and frees up resources. The suggested work implies it is preferable to build deep learning-based pulmonary module identification systems using an end-to-end architecture.[18].

For the purpose of detecting lung nodules, the author introduced two-stage convolutional neural networks (TSCNN). The initial step is to develop the identification of lung nodules using the upgraded U-Net segmentation network. To reduce false positives, three 3D-CNN classification networks are built using the second stage of the TSCNN architecture, which is based on the proposed dual pooling structure. The trials using the suggested architecture on the LUNA dataset demonstrated that it did achieve competitive detection performance.[19]

This research proposes a Faster R-CNN-based method for lung nodule identification. Lung nodules may be found using a quicker R-CNN algorithm, and the training set is employed to demonstrate the viability of this method. The pulmonary nodules may be loosely categorised into three groups: solitary lung nodules, lung nodules with vascular adhesion, and lungnodules with lung wall adhesion. The Dropout approach is employed in this study to avoid overfitting. The faster R-CNN detection algorithm utilised in this study, according to the author's proposal, is better than the original faster R-CNN detection algorithm in terms of detection accuracy as well as the already widely used R-CNN and fast R-CNN algorithm.. [20].

The author describes the Multiple-Scenario a Deep Learning Framework for the Design of Automatic Pulmonary Nodule Detection. The primary aim of this method is for providing the accurate and significantly decrease false positives in a huge number of image data for recognition of lung nodules. This proposed model has 2Dimension CT multiple-scenario images for the recognition of nodules. But this fails to get more accurate results while detecting the nodules. [21].

The author describes the multiple-view knowledge-based collaborative algorithm and the way it works. The objective of this method is to detect the presented nodules on chest Computed Tomography in the early stage. The proposed model has 3-Dimension lung nodule features by segmenting a 3-Dimension nodule into 9 fixed views. The author also introduced Computer Vision Technology to perform nodule detection. This method has a high accuracy rate, but failed in to obtain the identical performance as ImageNet Challenge on routine lung nodules. [22].

The author described the form and size of the nodule as they're the essential indicators of malignancy in carcinoma diagnosis. CNN is employed to look at the sampling of lung nodules in cross sections from different angles. The purpose of the study is to categorize lung nodules and calculate the likelihood that they are cancerous using CNN. proposed a thin, collective view cross section-based multi-selection CNN architecture that decreases the total data of the nodule by merging the data from its many samplings through a view maxpooling layer.[23].

The author discusses the use of MR lung imaging to identify lung nodules. Because the nodules' sizes vary, trimming each part to a specific size might not be practical. The author of this research suggested Faster Recurrent CNN sketched for Pulmonary Nodule Detection as a solution to this issue. In order to identify lung nodules in MR images, this is the initial step. The suggested model differs from nodule detection techniques used in computer topography in that it uses the complete image as input and doesn't require any further extraction. It can distinguish between nodules of various sizes and determine whether or not they are there. [24].

The author describes the detection of the nodules by Deep Reinforcement Learning. During this algorithmic program takes the entire Computer Topography image as raw data and it can be viewed as a group of states, and it produce aidentifications of whether or not a nodule is a present or not. By victimization, Reinforcement Learning will approach handling respiratory organ nodule performance. The purposed model is often in a learning state with each new subject, the model amplifies its learning by providing the new info and memory of historical info from previous subjects. It should facilitate avoiding wasting unwanted follow-up tests and value. [25].

The author provides the categorization and detection of pulmonary nodules using deep learning approach along with the multiple methods. The nodule detection accomplishment of the designed model was calculated on LIDC-IDRI on the idea of LUNA16's knowledge set split usesthe 5-fold cross-validation of image data. For categorization coaching, 3249 nodules are used that contain same numbers of negative and positive nodules. [26].

The author describes the deep learning method for classifying and identifying lung nodules in Computer Topography images. Finding big lung nodules on computer tomography images can be challenging and time-consuming. Models for computer-aided diagnostics are suggested to lessen this issue. Deep learning may provide peer-to-peer detection by learning the most crucial properties during the training of the dataset, which is one of the key advantages of employing it in computer-aided diagnosis systems. Because it uses the properties of nodules from several Computer Topography scans with adjusting the different parameters, this makes the neural network resilient to variance. The non-homogeneous scans inside the LUNA16 dataset, which is a subset of the LIDC-IDRI dataset, may be selected using several criteria. Here, he lists the pieces that aresupported a 2Dimension approach. [27].

The author tells the automatic detection of carcinoma using a non-homogeneous deep learning models for pulmonary nodule detection. Here LIDC dataset is used. This image dataset is employed to coach the subset of CNN's for collecting the feature extraction. The proposed automatic carcinoma recognition model consists of 2 modules: The nodule recognition module and the cancer finding evolutionary module. In the carcinomic risk evolutionary module, a group of 3DCNN-position models are trained to judge the anguish grade of the semantic features of lung nodules [28].

This paper describes a completely unique pulmonary nodule recognition and categorization of the model using one phase radar called "I3DR-Net." FPN may be a pyramidal-shaped neural network model which uses multi-scale method to extract features from the above pyramid layer which improve memory utilization because the feature maps become thicker as pyramid feature maps increase in size. Here they used LIDC Datasets which is publicly available to judge our proposed method [29].

The author tells the effect of Computerized Tomography construction settings on the working of a deep learning-approach for pulmonary nodule computer aided diagnosis system. Using a recently accessible deep learning lung nodule CADS, we evaluated a retrospective method for 24 chest Computer Topography scans that had been constructed at sixteen dissimilar reconstruction settings for 2 dissimilar iterative construction algorithms. These algorithms varied in slab thickness, kernel size, and iterative construction level strength. A total of 5780 nodules were discovered after 380 CT reconstructions from 22 individuals were examined.[30]

RESULTS

We calculate the execution of the VGG19 model on Training set. Model gets an average Accuracy score of 98.72%, and a intimate its robustness and efficiency. And the inceptionV3 model gets accuracy 88.33%. When the proposed model compared with inceptionV3, the proposed achieves a better accuracy and it is showing the robustness.

When coming to this section, this section compares all themethods that have been used in these references with the help ofa table which consists of advantages, limitations and theirresults.TABLEIprovidesadetailedoverviewofalltheautomatic summarization techniques. It also lists the futurescope.

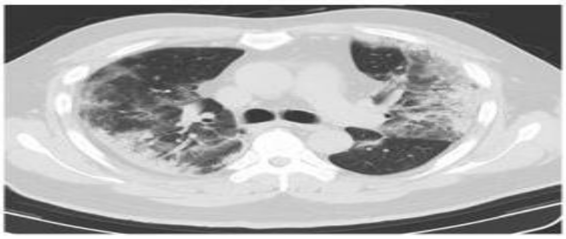
The evolution metrics:

1) Accuracy=TP+TN/TP+TN+FP+FN

2) RECALL=TP/TP+FN

3) PRECISION=TP/TP+FP

4) F1-SCORE=2/(1/RECALL) +(1/PRECISION)



S.NO	Technique	year	Description	Limitation	Advantages	Performance Metrics	Gaps
1	Imdad Ali, Muhammad Muzammil, Ihsan UL Haq, Amir A. Khaliq and Suheel Abdullah	2020	In this study, the author proposed the transferable texture Convolutional Neural Network (CNN) which combined with Energy Layer (EL) to detect the Lung Nodules and extracts features in the convolutional Neural Network (CNN).	The LIDC-IDRI dataset will compromises the accuracy values than working with LUNA 16 dataset.	The LUNA 16 dataset will show great results when it combined with transferable texture CNN architecture	Accuracyy :94.23% Recall:92.3% Specificity 87.2%	In future , it will discuss about the overall shape removal in the nodules in lung which classifies the texture features and effectiveness of the benign and malignant nodules.
2	Tanzila Saba	2019	In this study, Multiple classifiers voting are used to reduce the noise and enhance the image quality as it having multiple steps including lesion enhancement, segmentation, and features extraction.	Multiple classifier Voting will not deals with inner nodes as the layers of input, hidden and output are exposed to the feed-forward artificial neural network.	Logistic Regression, Multilayer perceptron, voted perceptron using k-fold cross-validation process are combined with Multiple classifiers voting for detection of lung Nodules.	Accuracy: 87.89% Sensitivity :90.56%	The author aims to develop the multiple classifier voting to improve the accuracy,sensitivity by reducing noise and enchance the image dataset in preprocessing stage.

3	Young Hoon Koo and Kyung Eun Shin	2021	In this study, Deep Convolutional neural network (DCNN) with jackknife alternative free-response ROC (JARROC) were compared with three groups of DCNN, radiologist without DCNN and radiologist with DCNN to detect Lung nodules in the old format of CR scan Images.	The Commercial DCNN software enhances observer performance and reproducibility but does not handle noisy images as DCNN alone detect fewer nodules than observer but improved false rate and sensitivity cannot be assist.	the DCNN will give better performance when combined with Roc and JAFROC results of specifying pulmonary nodules in noisy and clean images.	Sensitivity :87.8% specificity :90.2% p-value:0.583	The future aim of author is to achieve the detection of lung nodules in the CR images dataset with clean and no noisy images Dataset as ROC data obtained during extra validation of a DCNN revealed relatively reliable detection of pulmonary nodule.
4	Chen, Yerong, Fei Hu, Longfeng Feng, Taohui Zhou and Cheng Zheng	2021	In this study, Lung Dense Neural Network (LDNNET) network purposes the CT images of lung nodule with comparisons of dense connection, pooling layer and input pixel size of CT image which are in convolutional neural neural (CNN).	The Number of Parameters are reduced in network as disappearance of gradient during training process will restrict the improvement of accuracy of deep neural network.	LDNNET system proposes the Run to complete nodule detection in a single step by bypassing in the candidate selection to improve the traditional U-Net model.	Sensitivity :0.856 Accuracy: 0.94 Specificity :0.95	
5	Baihua Zhang, Shouliang Qi, Patrice Monkam, Chen Li, Fan Yang, Yu-Dong Yao and Wei Qian	2019	In this study, multi structural deep CNNs based method used to detect the pulmonary nodules.It explain whether it leads cancer or not.It contains a more layers in CNN	It produces Higher Computational Cost which Should be Less and Takes Less training Time.	It takes less amount time compared to previous models in detection of pulmonary nodules due to usage of multiple models.	Accuracy: 84.09%	The Accuracy can be increased once the LIDC-DRI dataset has been used to detection of Pulmonary Nodules.
6	Wang, J., Wang, J., Wen, Y., Lu, H., Niu, T., Pan, J., & Qian, D	2019	In this study, Pulmonary Nodule Detection in Volumetric Chest CT Scans Using CNNs-Based Nodule-Size-Adaptive Detection and Classification	It is impossible to find all nodules without any FPs. it may fail to find some nodules	The proposed model can simultaneously detect nodules and masses with a broad spectrum of appearance, regardless of their types, sizes and locations. Especially, it has superior performance in the detection of small nodules most often seen in the clinic that are difficult to find even by experienced radiologists.	sensitivity 75.6%	Nodule detection is the first task in our study. In the future, we will focus on estimation of the nodule's size , type (ground-glass, part solid, solid, benign and malignant, etc.) and location (18 pulmonary segments). These properties of a nodule should provide useful information for a doctor to help in establishing more accurate treatment plans.

7	Li Zhu and jianbo Gao	2021	In this study, it will detect the lung nodule with high false positive rate and low sensitivity with 2-d and 3-d dimensional convolutional neural network (CNN).	The detection sensitivity of 2D-CNN is much lesser than the 3D-CNN as average detection is greater in 3D-CNN.	Improved u-net model willl give better results in detection of candidate nodules than the traditional u-net model	Accuracy: 86.32% Sensitivity :89.45%	The authors aim to achieve the false rate prediction of lung nodules which show sensitivity of presence of nodules in lung but lung nodules are not present in CT scans
8	Amrita Naik and Damodar Raddy Edla	2021	In this study, the author discuss about the algorithms which are involved to classify the nodules in lung with deep learning.	The over fitting and processing time of deep neural network will cause issues in detection of the lung	It can directly extract features from the training set as the feature selection process is simple.	Accuracy: 90.12% Sensitivity :83.90% Specificity :92.66%	The author purpose that it will give better accuracy and specificity when it combined with multiple paths of CNN with training artificial
9	Yan Kuang, Tian Lan, Xueqiao, Gati Elvis Selasi, Qiao Liu and Junyi Zhang	2020	In this study, it describes about the multi-Discriminator Generative Adversarial Network (DCGAN) Model combines with encodes for the classification of Malignant and Benginn nodules.	Excessive usage of Discriminant may increase the Complexity but not the efficiency.	It is applicable for unlabeled data sets and takes less time in detecting Nodules and it also avoids overfitting.	Accuracy: 90.44%	In Future, this model is applicable to Partial dataset and other disease anomoly Detection
10	Jie Zheng, Dawei Yang, Yu Zhu, Wanghuan Gu, Bingbing Zheng, Chunxue Bai, Lin Zhao, Hongcheng Shi, Jie Hu, Shaohua Lu, Weibin Shi, Ningfang Wang	2020	In this study, it will detect the Pulmonary Nodules risk and classification in adenocarcinoma in the early-stage using Scale Transfer Module (STM) and Convolutional Neural Network (CNN).	They are failed to integrate the pulmonary nodules segmentation and feature extraction to achieve end-to-end CAD System.	The end-to-end CAD system to help lung cancer screening and auxiliary diagnosis, CAD system gives accurate results, STM-Net classifies the lung nodules with accuracy 95.455%.	Accuracy is 94.455%	The work is further extended to identify the small nodules.

11	Abdarahmane Traore, Abdoulaye O. Ly, Moulay A. Akhlouf	2020	In this study it describes the Evaluating Deep Learning Algorithms in Pulmonary Nodule Detection	R-CNNs had to search the objects with all possible boxes, the calculation time was very large and impractical for low calculation power computer such as a normal computer in the government hospital.	pulmonary nodule detection from 2D slices of CT scans	Accuracy 87.2%	Future work includes testing with more deep detectors, more feature extractors, advanced hyper-parameters optimizations.
12	Reza Majidpourkhoei 1 & Mehdi Alilou1 & Kambiz Majidzadeh 1 & Amin Babazadehsangar	2021	In this studty, the author describes A novel deep learning framework for lung nodule detection in 3d CT image using LIDC public dataset	The generalizability of the model is not known for other independent datasets.	it is light and fast. fast extraction of image features	accuracy = 90.1%, sensitivity = 84.1%, specificity =91.7%	In the future, it could be possible to extend the model to not only determine the nodules, but also to declare them cancerous or not.
13	Amrit Sreekumar, Karthika Rajan Nair, Sneha Sudheer, Ganesh Nayar H and Jyothisha J Nair	2020	In this study the author describes about the Malignant Lung Nodule Detection using Deep Learning using the LIDC-IDRI dataset	It needed additional training for preprocessed dataset to transform heavily imbalanced to upsampled.	By the C3D architecture it has increased the sensitivity of Malignant Lung Nodule Detection to 86 percent.	sensitivity of 86 %	The future work is to reduce the complexity of the network structure.
14	Sunyi Zhenga, Xiaonan Cui b,c ,Marleen Vonder d, Raymond N.J. Veldhuis e , Zhaoxiang Yec , Rozemarijn Vliegenthart b , Matthijs Oudkerkf , Peter M.A. van Ooijena	2020	In this study the author describes about the Deep learning-based pulmonary nodule detection: Effect of slab thickness in maximum intensity projections at the nodule candidate detection stages	The public dataset was imbalanced for the number of solid, part-solid, and non-solid nodules. Because more solid nodules were present.	In this model, the nodule candidate detection is to find as many true positives as possible, but on the other hand to keep the number of false positive findings as low as possible.	Sensitivity 90%	In future work, The MIP slab thickness of 10 mm and combined results from varying MIP settings can provide better results for false positive reduction
15	Dongdong Gu a,b , Guocai Liu a, Zhong Xue	2021	In this study the author describes about the On the performance of lung nodule detection,	The images used for training and testing nodule analysis algorithms	The method takes advantages of FPN for multi-resolution detection.	Sensitivity 91.4%	In future work, including AI technology could provide image and related

			segmentation and classification	may have excluded other pathological conditions.			information for assisting physicians
16	Hongtao Xiea Dongbao Yangb,c,Nanan Sunc , Zhineng Chend , Yongdong Zhanga	2019	In this study ,the author describes about the Automated Pulmonary Nodule Detection in CT Images Using Deep Convolutional Neural Networks	The proposed system used 3D lung CT images which are more complicated and influenced by the slice thickness, and both training time and resources needed for processing to detect the lung nodules.	The proposed system accurately detect the latent pulmonary nodules.	Sensitivity 87.1%	fusing more context information about the nodules, such as the connections with the surrounding blood vessels.
17	Tanzila Saba1 & Ahmed Sameh1 & Fatima Khan1 & Shafqat Ali Shad2 & Muhammad Sharif	2019	In this study ,the author describes about the Lung Nodule Detection based on Ensemble of Hand Crafted and Deep Features using LIDC-IDRI dataset	As the proposed model is used otsu segmentation and fusion of handcrafted and deep learning features the system takes more time for preprocessing of data	The experimental outcomes show better performance of presented approach as compared with the existing methods to detect the pulmonary nodule	Accuracy 95%	semantic segmentation will be utilized for this purpose and results will be evaluated on real patient data that is helpful for the radiologists in the detection of lung nodule
18	Hao Tang, Xingwei Liu , Xiaohui Xie	2019	In this study ,the author describes about the AN END-TO-END FRAMEWORK FOR INTEGRATED PULMONARY NODULE DETECTION AND FALSE POSITIVE REDUCTION	As the proposed system is a combination of two subsystems it will become complicated.	The system substantially reduces model complexity and interference time, there by simplifying the training process and reducing resources overhead	Sensitivity 91%	It suggests that an end-to-end framework is more desirable for constructing deep learning-based pulmonary nodule detection systems.
19	Haichao Cao, Hong Liu, Enmin Song, Senior Member,IEEE, Guangzhi Ma, Xiangyang Xu, Renchao Jin, Tengying Liu, and Chih-Cheng Hung	2019	In this study , the author describes about the A Two-Stage Convolutional Neural Networks for Lung Nodule Detection using LUNA datasets.	In the first stage, by using the U-Net segmentation architecture based on the ResDense structure for rough detection of nodules, data loss will be more	The proposed model detects the pulmonary nodule very accurately.	Accuracy 89%	The system can be improved by improving the U-Net segmentation architecture on the ReDense structure.

20	Ying Su1 , Dan Li1 , Xiaodong Chen2	2020	In this study, the author describes about the Lung Nodule Detection based on Faster R-CNN Framework using CT images.	By taking less input data it give less accuracy when compared to other techniques.	The proposed model uses Faster R-CNN has higher accuracy in detecting lung nodules than R-CNN and Fast R-CNN.	Accuracy 91%	Need to add benign small nodules to the data set. The data set of this experiment is only the large nodules marked by the radiologist, and many small nodules have not been added to the data set.
21	Qinghai Zhang and Xiaojing Kong	2020	In this study, Multi-Scene Deep Learning Framework (MSDLF) is efficient for increasing the accuracy and significantly reducing false positives in an enormous amount of image data in the detection of lung nodules	Initially they performed 2D CT multi-scene images for the identification of nodules but they don't get results with accuracy	The proposed Multi-Scene Deep Learning Framework (MSDLF) by the vesselness filter has better efficiency when compared to other previous methods such as INF, SCM, MV-KBC, CV .	Acuracy:94.7% Efficiency :93.6%	The work is further extended for scaling the small lung nodules
22	Yutong Xie, Yong Xia, Jianpeng Zhang, Yang Song, Dagan Feng, Michael Fulham and Weidong Cai	2018	In this study, t will detect the malignant lung nodules on chest in early stage using MV-KBC and CT scans	The CTs scans remains in the problematic due to the difficulty of lung nodule delineation caused by a large range of nodule shape and texture variation and the visual similarities shared by malignant and benign nodules	The 3D CNN separate benign from malignant lung nodules with higher accuracy and provide better images.	Accurcy :. 91.60%	The future work is to reduce the complexity of the network structure.
23	Pranjal Sahu, Dantong YU, Mallesham Dasari, Fei Hou and Hong Qin	2020	In this study, It proposes the Multi-section CNN for classifying in the Lung Nodules and the estimation of Probability of Malignancy Nodules.	Although, This method produced promising results, it had significant limitations, since it relieved on accurate delination among lung nodules.	The Light-weight Multi-section CNN architecture can be used for obtaining a compact representation of a lung nodule from it's volumetric Data.	Accuracy: 88.54%	It suggests that an end-to-end framework is more desirable for constructing deep learning-based pulmonary nodule detection systems.

24	Yanfeng Li, Linlin Zhang, Houjin Chen and Na Yang	2020	In this study, In this study, It proposes the lung nodule detection method for 3D thoric MR images based on deep learning with optimised parameters, spatial three channel input, transfer Learning, faster RCNN is designed for lung nodule detection.	The RPN of faster RCNN is trained where all anchors in the mini batch are extracted from the single image as it will take a lot of time until reaching Convergence.	This method is different from nodule detection methods in CT scans. The proposed method takes the whole image as input and no candidate image extraction is needed. Moreover, it can be detect nodule with different sizes and types	Accuracy: 89.12%	The work is further extended to identify the small nodules.
25	Issa Ali, Gregory R. Hart, Gowthaman Gunabushanam, Ying Liang, Wazir Muhammad, Bradley Nartowt, Michael Kane, Xiamei Ma and Ju Deng	2020	In this Paper, the author describes about the lung nodule detection using deep reinforcement learning using CT images.In this paper he uses more convolution layers.	It arises the cases of overfitting when large data sets are used in the lung nodule detection.	The Model can expands it's learning by factoring in new information and building probabilistic memory.	Accuracy: 94.78% Sensitivity :95.34%	In future, t will develop the model which accepts the large amount of Dataset.
26	Nasrullah Nasrullah , Jun Sang , Mohammad S. Alam , Muhammad Mateen , Bin Cai and Haibo Hu 1	2019	In this study , it describes the Automated Lung Nodule Detection and Classification Using Deep Learning Combined with Multiple Strategies	The reconstructed volumetric CT image was divided into 96 × 96 × 96 patches due to the limitations of GPU in terms of memory and processing	In medical IoT, which provides the advantages of recording and analyzing patient data for diagnosis.	Sensitivity 94.00 % Specificity 94.35 % Accuracy 94.17%	The Accuracy can be increased once the LIDC-DRI dataset has been used to detection of Pulmonary Nodules.
27	Diego Riquelme and Moulay A. Akhlouf	2020	In this study ,it describes theDeep Learning for Lung Cancer Nodules Detection and Classification in CT Scans	One of the current limitations is the data and their imbalanced nature.	It can perform and end-to-end detection by learning the most salient features during training.	Accuracy 87.4% Sensitivity 89.4%	Future works can further improve convolutional architectures for the purpose of lung cancer detection. Both the design of new architectures and the study of the existing ones could improve the performance and the computational cost especially for three-dimensional networks

28	Weilun Wang, Goutam Charkborty	2020	In this study,it describes the Automatic prognosis of lung cancer using heterogeneous deep learning models for nodule detection and eliciting its morphological features	In this work, we used only one nodule with highest malignancy value to assess cancer probability. Remaining values can be eliminated.	The first,the work in is an "end-to-end" model. Second, in our system, nodule detector, feature evaluator and regression model are independent.	Recall : 93.34%	We are working on to address this issue and expect improve accuracy in future.
29	Ivan William Harsono , Suryadiputra Liawatimena and Tjeng Wawan Cenggoro	2019	In this study,it describes theLung Nodule Detection and Classification from Thorax CT-Scan Using RetinaNet with Transfer Learning.	The medical image classification and detections using CNN are much harder to tackle compared to natural images detection and classification tasks because spatial information contained on 3D images	The contribution of this study is the exploration to use proposed method for detection and classification of lung nodular textures, which is inadequately studied in CAD development research.	Sensitivity 94.12%	In the future, the proposed method can be implemented in real-time CT-scan by integrating appropriate GPU, cloud-computing and software interface.
30	Stephan P. Blazis a, Dennis B.M. Dickerscheid a , Philip V.M. Linsen b , Carine O. Martins Jarnalo	2021	In this study ,it describes about the effect of CT reconstruction settings on the performance of a deep learning based lung nodule CAD system	Since it is based on our current clinical workflow, we do not evaluate how many nodules are being missed by the radiologist. Since patients are scanned only once, the datasets differ between both CT systems. Third, the diameter and volume measurements of the DL-	Image quality is directly influenced by the possible slicethickness and reconstruction filter settings and it is to be expected that DL-CAD systems will also be influenced to some extend by variations in these parameters as well.	sensitivity of 86 %	Future study could be done on including the nodule size measurements in the effect of reconstruction parameters.

Comparison Table with Pre-defined Models:

Network	Accuracy	Recall	Precision	F1-Score
VGG19	98.72	89.97	90.07	90.02
InceptionV3	88.33	89.94	88.62	88.94

Compared to the Inceptionv3 pre-defined model the VGG16 model gives higher accuracy and the processing-time taken for training of the model is less compared to other models. The advantage of VGG over Inceptionv3 is a lightweight deep neural network, VGG16 has less parameters and high classification accuracy. In order to reduce the number of neural network parameters and it improves the classification accuracy.

CONCLUSION

In this paper, we implemented an efficient solution to monitor the lung nodule detection using VGG16 model. Then the model is contrast with the Inceptionv3 and it gets the high accuracy. The model performs well and produce an accuracy of 98.72% on the labelled image dataset. It also produce data accretion techniques to deal with the shortage of dataset in the community.

.

By applying the technique, we will get the better results and will help for decision support systems by giving accurate results and the inspection will be done quickly or in a less period of time. By using this VGG19 we detect the nodules in the lungs. Compared to individual existence of modules these models gave better accurate results. We make our dataset openly available, as a favour to the analysis community, that will decrease the problem of shortage of training data.

Future Scope

Forfuturescope,theabovetechniquescanbedeveloped or implemented in such a way that they aremore robust in detecting multiple nodules in a lung images. Also, methods to identify type of nodules that can be proposed with more efficient pre-processing andfeature extractiontechniques.

REFERENCES.

[1] Ali, I., Muzammil, M., Haq, I. U., Khaliq, A. A., & Abdullah, S. (2020). Efficient lung nodule classification using transferable texture convolutional neural network. IEEE Access, 8, 175859-175870.

[2] Saba, T. (2019). Automated lung nodule detection and classification based on multiple classifiers voting. Microscopy research and technique, 82(9), 1601-1609.

[3] Koo, Y. H., Shin, K. E., Park, J. S., Lee, J. W., Byun, S., & Lee, H. (2021). Extra validation and reproducibility results of a commercial deep learning-based automatic detection algorithm for pulmonary nodules on chest radiographs at tertiary hospital. Journal of Medical Imaging and Radiation Oncology, 65(1), 15-22.

[4] Chen, Y., Wang, Y., Hu, F., Feng, L., Zhou, T., & Zheng, C. (2021). LDNNET: Towards Robust Classification of Lung Nodule and Cancer Using Lung Dense Neural Network. IEEE Access, 9, 50301-50320.

[5] Zhang, B., Qi, S., Monkam, P., Li, C., Yang, F., Yao, Y. D., & Qian, W. (2019). Ensemble learners of multiple deep CNNs for pulmonary nodules classification using CT images. IEEE Access, 7, 110358-110371.

[6] Wang, J., Wang, J., Wen, Y., Lu, H., Niu, T., Pan, J., & Qian, D. (2019). Pulmonary nodule detection in volumetric chest CT scans using CNNs-based nodule-size-adaptive detection and classification. IEEE access, 7, 46033-46044.

[7] Zhu, L., & Gao, J. (2021). Adoption of computerized tomography images in detection of lung nodules and analysis of neuropeptide correlative substances under deep learning algorithm. The Journal of Supercomputing, 77(7), 7584-7597.

[8] Naik, A., Edla, D. R., & Kuppili, V. (2021). Lung nodule classification on computed tomography images using fractal net. Wireless Personal Communications, 119(2), 1209-1229.

[9] Kaung, Y., Lan, T., Peng, X., Selasi, G. E., Liu, Q., & Zhang, J. (2020). Unsupervised multi-discriminator generative adversarial network for lung nodule malignancy classification. IEEE Access, 8, 77725-77734.

[10] Zheng, J., Yang, D., Zhu, Y., Gu, W., Zheng, B., Bai, C., ... & Wang, N. (2020). Pulmonary nodule risk classification in adenocarcinoma from CT images using deep CNN with scale transfer module. IET Image Processing, 14(8), 1481-1489.

[11] Traoré, A., Ly, A. O., & Akhloufi, M. A. (2020, July). Evaluating deep learning algorithms in pulmonary nodule detection. In *2020 42nd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC)* (pp. 1335-1338). IEEE.

[12] Majidpourkhoei, R., Alilou, M., Majidzadeh, K., & Babazadehsangar, A. (2021). A novel deep learning framework for lung nodule detection in 3d ct images. *Multimedia Tools and Applications*, *80*(20), 30539-30555

[13] Sreekumar, A., Nair, K. R., Sudheer, S., Nayar, H. G., & Nair, J. J. (2020, July). Malignant lung nodule detection using deep learning. In *2020 International Conference on Communication and Signal Processing (ICCSP)* (pp. 0209-0212). IEEE

[14] Zheng, S., Cui, X., Vonder, M., Veldhuis, R. N., Ye, Z., Vliegenthart, R., ... & van Ooijen, P. M. (2020). Deep learning-based pulmonary nodule detection: Effect of slab thickness in maximum intensity projections at the nodule candidate detection stage. *Computer methods and programs in biomedicine*, *196*, 105620.

[15] Gu, D., Liu, G., & Xue, Z. (2021). On the performance of lung nodule detection, segmentation and classification. *Computerized Medical Imaging and Graphics*, *89*, 101886.

[16] 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.

[17] Saba, T., Sameh, A., Khan, F., Shad, S. A., & Sharif, M. (2019). Lung nodule detection based on ensemble of hand crafted and deep features. *Journal of medical systems*, *43*(12), 1-12.

[18] Tang, H., Liu, X., & Xie, X. (2019, April). An end-to-end framework for integrated pulmonary nodule detection and false positive reduction. In *2019 IEEE 16th International Symposium on Biomedical Imaging (ISBI 2019)* (pp. 859-862). IEEE.

[19] Cao, H., Liu, H., Song, E., Ma, G., Xu, X., Jin, R., ... & Hung, C. C. (2020). A two-stage convolutional neural networks for lung nodule detection. *IEEE journal of biomedical and health informatics*, *24*(7), 2006-2015.

[20] Su, Y., Li, D., & Chen, X. (2021). Lung nodule detection based on faster R-CNN framework. *Computer Methods and Programs in Biomedicine*, *200*, 105866.

[21] Zhang, Q., & Kong, X. (2020). Design of automatic lung nodule detection system based on multi-scene deep learning framework. IEEE Access, 8, 90380-90389.

[22] Xie, Y., Xia, Y., Zhang, J., Song, Y., Feng, D., Fulham, M., & Cai, W. (2018). Knowledge-based collaborative deep learning for benign-malignant lung nodule classification on chest CT. IEEE transactions on medical imaging, 38(4), 991-1004.

[23] Sahu, P., Yu, D., Dasari, M., Hou, F., & Qin, H. (2018). A lightweight multi-section CNN for lung nodule classification and malignancy estimation. IEEE journal of biomedical and health informatics, 23(3), 960-968.

[24] Li, Y., Zhang, L., Chen, H., & Yang, N. (2019). Lung nodule detection with deep learning in 3D thoracic MR images. IEEE Access, 7, 37822-37832.

[25] Ali, I., Hart, G. R., Gunabushanam, G., Liang, Y., Muhammad, W., Nartowt, B., ... & Deng, J. (2018). Lung nodule detection via deep reinforcement learning. Frontiers in oncology, 8, 108.

[26] Nasrullah, N., Sang, J., Alam, M. S., Mateen, M., Cai, B., & Hu, H. (2019). Automated lung nodule detection and classification using deep learning combined with multiple strategies. *Sensors*, *19*(17), 3722.

[27] Riquelme, D., & Akhloufi, M. A. (2020). Deep learning for lung cancer nodules detection and classification in CT scans. *Ai*, *1*(1), 28-67.

[28] Wang, W., & Charkborty, G. (2021). Automatic prognosis of lung cancer using heterogeneous deep learning models for nodule detection and eliciting its morphological features. *Applied Intelligence*, *51*(4), 2471-2484.

[29] Harsono, I. W., Liawatimena, S., & Cenggoro, T. W. (2020). Lung nodule detection and classification from Thorax CT-scan using RetinaNet with transfer learning. *Journal of King Saud University-Computer and Information Sciences*.

[30] Blazis, S. P., Dickerscheid, D. B., Linsen, P. V., & Jarnalo, C. O. M. (2021). Effect of CT reconstruction settings on the performance of a deep learning based lung nodule CAD system. *European Journal of Radiology*, *136*, 109526.