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False Positive Reduction of Lung Nodule Detection using Deep Learning Techniques

A project report submitted in partial fulfilment of the requirement for the award of degree of

BACHELOR OF TECHNOLOGY

In

COMPUTER SCIENCE AND ENGINEERING

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CERTIFICATE

This is to certify that the thesis entitled **False Positive Reduction of Lung Nodule Detection using Deep Learning Techniques** submitted by **Potnuru Deepika (19341A05D5), Thota Prasanth (19341A05G9), Thondupu Dileep (19341A05G8), Yerramsetti Ramu (19341A05J2)** and **Rayagada Tanmayi (19341A05E3)** has been carried out in partial fulfilment of the requirement for the award of degree of **Bachelor of Technology** in **Computer Science and Engineering** of **GMRIT, Rajam** affiliated to **JNTUK, KAKINADA** is a record of bonafide work carried out by them under my guidance & supervision. The results embodied in this report have not been submitted to any other University or Institute for the award of any degree.

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ABSTRACT

Lung Cancer is one of the most common maladies around the world. Lung cancer is one of the most common cancer that cannot be ignored and cause death with late health care. An accurate lung cancer nodule detection and it's false positive reduction could speed up and also improves the survival of the humans. A lung or pulmonary nodule is an abnormal growth that is sometimes found during a Computed Tomography (CT) scans of the chest that forms in a lung. Present, CT scans are helping doctors to detect the lung cancer in the early stages. Majority of lung nodules aren't a sign of lung cancer but some could lead to major severity upon ignorance. So it is necessary to detect lung nodules. But there might be the chances of some False Positive nodules which leads to major problem. Some reasons for false positive detection of nodules is due to the heterogeneity of lung nodules in CT images like variable size, shape, texture and due to high similarity of visual characteristics between positive lung nodules and non positive lung nodules. Recent developments in Deep Learning Techniques shows the ability to analyze medical images have been astounding. The dataset for the work is LUNA-16. It is a collection of lung cancer screening i.e., the medical CT images. It is in the format of MHD(.mhd). The performance of the nodule detection model is evaluated with an accuracy which gives the percentage of correctly classified in the comparison to the ground truths.

Keywords: *Lung Nodule, Computed Tomography Scan, VGG Net, ZCA Whitening, False Positive.*

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LIST OF SYMBOLS & ABBREVIATIONS

AH-LUTCM	: Affiliated Hospital of Liaoning University of Traditional Chinese Medicine
ANN	: Artificial Neural Networks
AUC	: Area Under Curve
CNN	: Convolutional Neural Network
CPM	: Competitive Performance Metric
CT	: Computed Tomography
DL	: Deep Learning
FP	: False Positive
LIDC-IDRI	: Lung Image Database Consortium (LIDC) and Image Database Resource Initiative
LUNA	: Lung Nodule Analysis
MCNN-CF	: Multi Scale Convolutional Neural Network with Compound Fusions
MHD	: Meta Image Header
MRI	: Magnetic Resonance Imaging
PL	: Pooling Layer
RELU	: Rectified Linear Unit
RNN	: Recurrent Neural Network
SFM	: Sparse Field Method
SVM	: Support Vector Machine
TP	: True Positives
VGG	: Visual Geometry Group
ZCA	: Zero – phase Component Analysis

1. INTRODUCTION

Pulmonary Nodules abnormally grown lung tissue whose diameter in between 3 mm and 30 mm and these are the primary indicators of lung cancer which is the leading cause of cancer deaths. Lung nodule detection is one of the best means for screening at the early stages and diagnosis of lung cancer. The patient with lung nodules will have only one or a few nodules which often occupies few pixels between 100 to 400 lung slices, and makes manual detection more difficult. The automated lung nodule detection system will reduce the burden on radiologists for manually recognizing a large number of CT images.

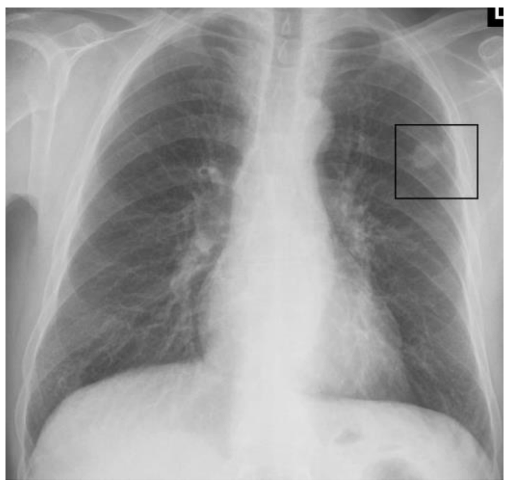

Fig1.1 Pulmonary Nodule

Generally, nodules occupy a much smaller area than the entire lung slice does, the automated lung nodule detection system is generally divided into two steps. First one is Nodule detection and second one is False positive reduction. The detection refers to the candidate's detection that were suspected lung nodules from a large set of CT slices.This help to detect the candidates detection that includes many real nodules as possible in the detection results, but allows for a large group of false positive rate. False positive refers to that nodules which resembles the true nodules. It can be seen that false positives are similar to true nodules in appearance, but are often composed of blood vessels, lymph nodes, or others. For this reason, the false positive reduction is done to complete nodule detection. It aims to distinguish true nodules from false nodules as accurately as possible from candidates.

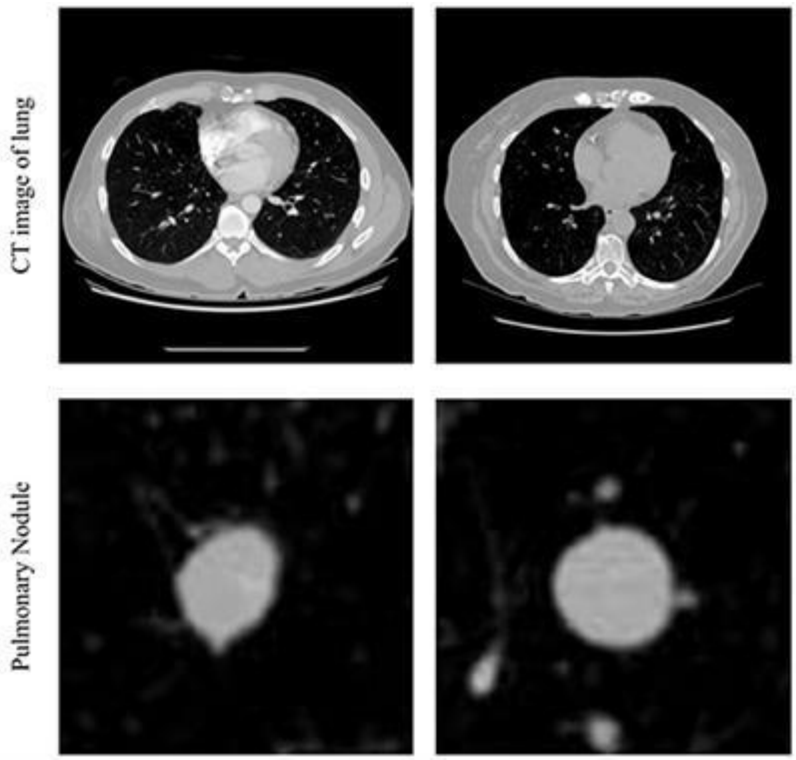

Fig1.2 CT images in lung and pulmonary nodule

Cancer is one of the most threatening health problems in the world. In that, lung cancer is one of the most common cancers but that doesn't represent that one can take it easy and neglect it because the mortality rate of lung cancer is the high among all other type of cancers. Lung cancer is one of the major leading cause for cancer deaths, that destroyed nearly 1/4th of all cancer related deaths.The reason for high mortality rate of lung cancer is because its symptoms become recognizable only after the cancer reaches to the final phase. So if one has a reason to think that they may have lung cancer, there are several number of tests to look for cancerous cells and to rule out the other conditions. One such tests is through the nodules detection in the lungs. For this an X-ray image of the lungs may reveal an abnormal mass or nodule. But a CT scan can reveal small lesions in the lungs that might not be detected on an X-ray. These nodules present in the lungs are the abnormally grown lung tissue whose diameter isin between 3 mm and 30 mm on an average and these are the primary indicators of lung cancer.

For a patient with lung nodules, there might be generally one or multiple nodules in his/her lung. So having nodules in the lungs doesn't mean a person is suffering with lung cancer. These nodules found in lungs may be malignant or benign. Malignant nodules must be treated. Doctors first need to detect the nodules and then diagnose them to see whether these lung nodules are cancerous or non cancerous. But during detection phase, the nodule often occupies few pixels among 100 to 400 lung slices of CT scan which makes manual detection more difficult. So to make it easier it is better to develop a pulmonary nodule detection system. Basically, lung nodule detection have two phases, 1) Detection of the candidate nodules in the CT images, 2) Screening out true nodules from a large number of candidate nodules. The second phase is nothing but false positive reduction phase which means that during the detection phase, there might be some chances where some non nodules like blood vessels are also considered to be as nodules. Diagnosing such type of nodules furtherly doesn't make any sense. So it is necessary to remove false nodules form the data.

Fig1.3 Complete axial slices with nodules in red circles and non-nodules in white circle

As we pretty well know that the deep learning algorithms are bringing a noticeable changesthese days bysolve various problems in medical imaging fields.Recent deep learning applications in medical image analysis include various computer vision related tasks like classification, detection, segmentation.Different medical imaging modalities have their unique characteristics and different responses to human body structure and organ tissue and can be used in different clinical purposes.The frequently used image modalities for diagnosis in clinic involve projection imaging like X-ray imaging, computed tomography (CT), ultrasound imaging, and magnetic resonance imaging (MRI).But it is not possible to train the model with these images/ scans directly. It need some data preparation steps. Then the obtained data is been fed to deep learning models to classify , detect or segment the useful abnormal growth in the body structures, tumours to diagnose for further disease cure. Machine learning can also be used but it cannot deal good with large datasets and it is difficult for manual feature extraction. Where as deep learning models are far better in dealing with larger datasets and gives its best when coming to extracting the efficient features. CNNs are the most researched deep learning algorithms in medical field analysis. CNNs take an input image of raw pixels and transforms it through convolutional layes, Rectified Linear Unit(RELU) layers and pooling layers. These are finally feeds into a fully connected layer which assigns class probabilities, and thus classifying the input into the class with highest probability.

2.LITERATURE SURVEY

[1] Mittapalli, P. S., & Thanikaiselvan, V. (2021). Multiscale CNN with compound fusions for false positive reduction in lung nodule detection. *Artificial Intelligence in Medicine*, 113, 102017.

The paper proposes a new Convolutional Neural Network (CNN) architecture called Multi Scale CNN with Compound Fusions (MCNN-CF). It uses multi scale 3D patches as inputs and performs a fusion of intermediate features at two different depths of the network in two diverse fashions. It also tells that a large number of False Positives (FPs) extracted during the initial screening procedure which is closely resembling the relatively fewer True Positives (TPs) i.e. nodule instances that are present. Dataset used is LUNA 16.Modification of voxel spacing, intensity normalization, and lung region segmentation is performed in the preprocessing step. It has obtained a Competitive Performance Metric (CPM) score of 0.948.

[2] Zuo, W., Zhou, F., & He, Y. (2020). An embedded multi-branch 3D convolution neural network for false positive reduction in lung nodule detection. *Journal of digital imaging*, *33*(4), 846-857.

The objective of this paper is to predict real nodules from a large number of pulmonary nodule candidates by novel 3D convolution neural network (CNN). False positives are similar to true nodules in appearance, but it composed of blood vessels, lymph nodes or other lesions. It learns the complete and three-dimensional discriminative information about nodules and non-nodules to avoid some misidentification problems caused due to lack of spatial correlation information extracted from traditional methods or 2D networks. LUNA -16 dataset was used. Accuracy of 0.9783, a sensitivity of 0.8771, a precision of 0.9426, and a specificity of 0.9925 were obtained. Competition Performance Metric (CPM) score is of. 0.83.

[3] Zhu, H., Zhao, H., Song, C., Bian, Z., Bi, Y., Liu, T., ... & Cai, W. (2019). MR-forest: a deep decision framework for false positive reduction in pulmonary nodule detection. ***IEEE Journal of Biomedical and Health Informatics*, *24*(6), 1652-1663.**

Multi-ringed (MR) Forest framework has been proposed for false positive reduction in pulmonary nodule detection. Dataset is taken from the Affiliated Hospital of Liaoning University of Traditional Chinese Medicine (AH-LUTCM) and also LUNA16 Challenge dataset were used. The model was performed on both the datasets. The proposed method is done into three stages. First is Standardization and reconstruction of spherical harmonics model, Second is extracting the feature vectors by multi-ringed scanning, Final one is Predicting the final results using cascade forest It employs multi-ringed boosting cascade decision tree ensemble to reduce false positives by a variant of target propagation. CPM score of merged dataset is 0.865 and LUNA16 is 0.910.

[4] D. A. B. Oliveira and M. P. Viana, "An efficient multi-scale data representation method for lung nodule false positive reduction using convolutional neural networks," 2018 IEEE 15th International Symposium on Biomedical Imaging (ISBI 2018), 2018, pp. 269-272, doi: 10.1109/ISBI.2018.8363571.

Convolutional neural networks (CNNs) have been widely used for image analysis in many different fields for a variety of purposes. The dataset used is LUNA dataset. It is publicly available and demonstrates which represent that allows 2D CNNs to achieve very good results. Superior to the ones delivered using regular 2D cross sections and similar to the ones delivered by 3D CNNs using16 times less data and running 4 times faster. The accuracy and precision for this model is 91.5%,92.5%

[5] R. Nagata, T. Kawaguchi and H. Miyake, "Automated detection of lung nodules in chest radiographs using a false-positive reduction scheme based on template matching," 2019 5th International Conference on BioMedical Engineering and Informatics, 2019, pp. 216-223, doi: 10.1109/BMEI.2012.6512916.

Automated detection of lung nodules in chest radiographs is important to reduce false negatives in the diagnoses of lung cancers using chest radiography. We are using 125 images with nodules in the JSRT database which is a public database. This technique consists of the following two steps : detection of initial nodule candidates in chest radiographs ; classification of the detected candidates into nodules and false positives. For classification of nodule candidates, many schemes used multilayer artificial neural networks (ANNs) trained by back-propagation. False positives per image for sensitivity values of 60.2, 69.8, and 74.5% on the average of 40 data set.

[6] Saien S, Moghaddam HA, Fathian M. "A unified methodology based on sparse field level sets and boosting algorithms for false positives reduction in lung nodules detection." Int J Comput Assist Radiol Surg. 2018 Mar;13(3):397-409. doi: 10.1007/s11548-017-1656-8. Epub 2017 Aug 9. PMID: 28795318.

A hybrid under-sampling/boosting algorithm called RUSBoost is applied to analyze the features and discriminate real nodules from non-nodules. The proposed method was evaluated using 70 CT images from the LIDC and LIDC-IDRI databases. After detecting nodule candidates , 3D region of each candidate is reconstructed using the sparse field method (SFM) , in order to accurately segment objects. In the next step, some relevant 2D and 3D features are extracted for each segmented candidate. Then, a classifier is applied for analyzing the features and discriminating real nodules from non-nodules. The metrics used in this are sensitivity, specificity, FP score, AUC score.

[7] Manickavasagam, R., & Selvan, S. (2019, April). GACM based segmentation method for Lung nodule detection and classification of stages using CT images. In *2019 1st International Conference on Innovations in Information and Communication Technology (ICIICT)* (pp. 1-5). IEEE.

Manickavasagam R and Selvan S(2019) had given in their publications saying that they proposed a GACM(Gradient based Active Contour Model) for segmenting the lung region from CT images. The dataset used is LIDC (Lung Image Database Consortium). The Support Vector Machine is used to carry out the lung nodule detection and stage classifications. The texture features are extracted and its optimal discrimination is achieved for finite classification rate through consistency-based hierarchical feature selection algorithm. The proposed model achieved accuracy of 95.3 and sensitivity of 92.1 which are higher than the values of GLCM with SVM Classifier.

[8] Al-Shabi, M., Lee, H. K., & Tan, M. (2019). Gated-dilated networks for lung nodule classification in CT scans. *IEEE Access*, *7*, 178827-178838

Mundher Al-Shabi,Hwee Kuan Lee and Maxine Tan(2019) had given in their publications saying that they proposed a novel CNN architecture called as Gated-Dilated networks to classify nodule as benign or malignant. The dataset used is LIDC-LDRI.Their work focuses on the wide diameter variation of the nodules, which can range anywhere between 3 and 30 mm They applied five consecutive GD layers then pooling layer then to sigmoid activation function layer.It predicts whether it is malignant or benign. The proposed model achieved accuracy of 92.57 and AUC of 0.954.

[9] Ozdemir, O., Russell, R. L., & Berlin, A. A. (2019). A 3D probabilistic deep learning system for detection and diagnosis of lung cancer using low-dose CT scans. *IEEE transactions on medical imaging, 39*(5), 1419-1429.

Rebecca L. Russell, and Andrew A. Berlin (2020) had given in their publications saying that they proposed a new computer detection and diagnosis system for lung cancer screening with low-dose CT scans. The dataset used is LUNA16.The designed system is totally based on 3D-CNN. The patient image is given for preprocessing and then by performing segmentation the nodules are extracted and asper nodule feature extractions the patient diagnosis is done. The 3DCNN model achieved a AUC score of 0.87 and recall of 0.93.

[10] H. Tang, X. Liu and X. Xie, "An End-to-End Framework for Integrated Pulmonary Nodule Detection and False Positive Reduction," 2019 IEEE 16th International Symposium on Biomedical Imaging (ISBI 2019), 2019, pp. 859-862, doi: 10.1109/ISBI.2019.8759244.

A Novel End to End framework for nodule detection, integrating nodule candidate screening and false positive reduction into one model, trained jointly. In this framework the first subsystem uses 3D Nodule Proposal Network, and subsequent nodule candidate classification for false positive reduction to distinguish nodules from non-nodules. It usess tianchi competition dataset,which contains 800 CT scans from 800 patients with released ground truth label. It reduces model complexity by eliminating one third of the parameters of the corresponding two-step model. The end-to-end system also improves performance, increasing nodule detection accuracy by 3.88% over the two-step approach. It increases 3.88% improvement on CPM compared to previous state-of-art separate two-stage nodule detection model without model ensemble.

[11]Y. Qin, H. Zheng, Y. -M. Zhu and J. Yang, "Simultaneous Accurate Detection of Pulmonary Nodules and False Positive Reduction Using 3D CNNs," 2018 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), 2018, pp. 1005-1009, doi: 10.1109/ICASSP.2018.8462546.

A computer-aided diagnosis (CAD) system for simultaneous accurate pulmonary nodule detection and false positive reduction. To generate candidate nodules a full 3D CNN model and 3D U-Net architecture as the backbone of a region proposal network (RPN). It improve the accuracy of nodule detection by adopting multi-task residual learning and online hard negative example mining strategy to accelerate the training process. The weighted binary cross-entropy (WBCE) loss is used for classification problem due to the imbalanced nodule dataset. The dataset is used is LUNA 16 which is a collection of lung cancer medical CT images. This method achieves accurate detection of pulmonary nodules while reducing false positives.

[12] Y. Han et al., "Efficient False Positive Reduction Method for Early Pulmonary Nodules Detection in Physical Examination," 2021 IEEE International Conference on Bioinformatics and Biomedicine (BIBM), 2021, pp. 876-881, doi: 10.1109/BIBM52615.2021.9669737.

An effective multi-branch false positive reduction network is built to avoid reducing the sensitivity of nodule detection. A 3D U-NET model is used for detecting small pulmonary nodules in physical examination and then the grayscale history image (GHI) of the candidate nodules in multi-view is used as the input of the false positive reduction network. In order to reduce overfitting, some data enhancement methods are used, such as rotation and scaling. 1,000 samples of Lung Nodules from Physical Examination (LNPE1000) are collected, in which nodules are with the average diameter of 5.3mm. The sensitivities of the proposed method are 79.9% and 85.8% with each CT contained with 0.25 and 0.45 false positive. It will be helpful for doctors in clinical diagnosis to improve the efficiency.

[13] Li, C., Zhu, G., Wu, X., & Wang, Y. (2018). False-positive reduction on lung nodules detection in chest radiographs by ensemble of convolutional neural networks. *IEEE Access, 6,* 16060-16067.

This paper is aiming at the problem that traditional lung nodules detection method can only get low sensitivities with a lot of false positives. This propose a framework of ensemble of convolutional neural networks (E-CNNs) and use it to reduce the number of false positive on lung nodules detection in chest radiographs (CXRs). Ensemble of convolutional neural networks E-CNNs directly detect lung nodules, which omits the lung field segmentation procedure also avoids the loss of true lung nodules of traditional detection. A single CNN may not learn all the essential features to distinguish a nodule from various non-nodule structure,but multi different CNNs can deal with more non-nodules.Hence proposed the Ensemble of CNNs of different input scales- CNN1, CNN2 and CNN3. E-CNNs achieves a sensitivity of 84% while other three single CNN can only get 57% on the Japanese Society of Radiological Technology database .

[14] Cao, H., Liu, H., Song, E., Ma, G., Xu, X., Jin, R., ... & Hung, C. C. (2019). Multi-branch ensemble learning architecture based on 3D CNN for false positive reduction in lung nodule detection. *IEEE access, 7,* 67380-67391.

This paper focuses on false positive reduction in lung nodule detection which is caused due to heterogeneity of lung nodules and their similarity to the background. This paper propose a Multi-Branch Ensemble Learning architecture based on the three-dimensional convolutional neural networks (MBEL-3D-CNN) for the false positive reduction. The multi-branch network model based on the modules namely 3D-VggNet,3D-InceptionResNet and 3D-DenseNet. This paper implemented six common network architectures namely VggNet, ResNet, InceptionV1 (IncepV1), Inception-V3 (IncepV3), InceptionResNet (IResNet) and DenseNet. Then, it selected the three network structures (VggNet, IResNet and DenseNet) through experimental verification. The dataset used is LUNA16 and the experimental results show that MBEL-3D-CNN architecture can achieve better screening results.

[15] Huang, X., Shan, J., & Vaidya, V. (2017, April). Lung nodule detection in CT using 3D convolutional neural networks. In *2017 IEEE 14th International Symposium on Biomedical Imaging (ISBI 2017)* (pp. 379-383). IEEE.

This paper proposed a new computer-aided detection system that uses 3D convolutional neural networks CNN for detecting lung nodules in low dose computed tomography. They generate nodule candidates using local geometric model based filter and further reduce the structure variability by estimating the local orientation. The results also showed the advantages of 3D CNN over 2D CNN in volumetric medical image analysis. The main limitations of this work are GGO and juxta pleural nodules were not addressed, also it was limited to cross validation. The dataset used in this work is Lung Image Database Consortium LIDC.

[16] 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.

Lung Dense Neural Network (LDNNET) is an adaptive architecture based on convnets combining softmax classifier which is utilized to alleviate the problems of training deep convnets.The classification of lung nodules is important for the diagnosis of lung cancer based on CT images for instance nodule, non-nodule and cancer, non-cancer. It is the first step in the early diagnosis of lung cancer. Data enhancement, dense connection and dropout layer were utilized in LDNNET to reduce overfitting. Datasets were LUng Nodule Analysis 2016 (LUNA16) for lung nodule classification and database KAGGLE DATA-SCIENCE-BOWL-2017(Kaggle DSB 2017) for lung cancer classification. Accuracy, specificity and sensitivity on LUNA16 are 0.988396, 0.994585 and 0.982072 and on Kaggle DSB 2017 are 0.999480, 0.999652 and 0.998974. AUC for both two datasets is over 0.98.

[17] Wang, B., Si, S., Cui, E., Zhao, H., Yang, D., Dou, S., & Zhu, J. (2020). A fast and efficient CAD system for improving the performance of malignancy level classification on lung nodules. *IEEE Access, 8*, 40151-40170.

A novel vessel segmentation method is proposed which measures vessel likelihood by tubular-like structures discriminating from multiple views to to reduce false positives (FPs). A diversity of radiographic characteristics of lung nodule e.g., size, margin, nodular calcification, and nodular cavitation, can be used to differentiate malignancy levels of lung nodule. Feature Extraction like Regions of Interest (RoI) Clustering, Edge Feature Extraction, Text Feature Extraction is done for better performance. Dataset used is LIDC. Edge Orientation Histogram (EOH)is used to extract edge features from the spatial outline and a multi-scale path LBP (MSPLBP) to extract the texture feature of the density distribution samples. The usage of the enhancement result of Frangi filter for this method helped to detect tubular-like structures which ensures the completeness of lung nodule regions. Average F1_Score of 78.14% and AUC value under PR curves of 0.8149. It performed a average accuracy of 95.88% and consumes average 176.26 seconds for evaluating a CT set on malignancy level classification.

[18] 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.

A Two-Stage Convolutional Neural Networks (TSCNN) for lung nodule detection is proposed. The improved U-Net segmentation network is established as an initial detection of lung nodules. This improves the U-Net based segmentation network for detecting candidate nodules by adding the residual dense mechanism. A dual pooling structure is built into three 3D-CNN classification networks for false positive reduction. Dataset used is LUNA dataset. It has used the U-Net segmentation architecture based on the ResDense structure for rough detection of nodules, and designed a sampling strategy for the nodule. Further 3D-CNN based ensemble learning architecture were used to eliminate false positive nodules. Here, the max pooling layer in 3D-CNN is replaced with the proposed dual pooling layer. The competition performance metric (CPM) score by CNN is 92.5%.

[19] Zhang, M., Li, H., Pan, S., Lyu, J., Ling, S., & Su, S. (2021). Convolutional neural networks-based lung nodule classification: A surrogate-assisted evolutionary algorithm for hyperparameter optimization. ***IEEE Transactions on Evolutionary Computation*****,** ***25*****(5), 869-882.**

A multilevel convolutional neural network (ML-CNN) is built for lung nodule classification, and the hyperparameter configuration is optimized by the proposed nonstationary kernel based Gaussian surrogate model. A surrogate-assisted evolutionary strategy is introduced to solve hyperparameter optimization for ML-CNN, which utilizes hyperparameter importance-based mutation as the sampling method for efficient candidate points generation. The lung nodule images in this experiment are from the lung image database consortium (LIDC) and image database resource initiative (IDRI) database. Our ML-CNN achieves competitive classification accuracy of 84.8%. MV-CNN utilizes multiple views as input channels for CNN-based lung nodule classification which obtain a 94.59% and 86.09% accuracy for binary and ternary classification.

[20] Ali, I., Muzammil, M., Haq, I. U., Khaliq, A. A., & Abdullah, S. (2021). Deep feature selection and decision level fusion for lungs nodule classification. ***IEEE Access*****,** ***9,*** **18962-18973.**

Lung nodule classification by using SVM and AdaBoostM2 classifiers. The lung nodule classification was performed on deep features from state-of-the-art DCNN models such as VGG-16, VGG-19, ResNet-18, ResNet-50, ResNet-101,GoogLeNet, InceptionResNet-V2 and, Inception-V3. Performed a comprehensive performance evaluation of SVM and AdaBoostM2 classifiers based on deep feature on LUNGx challenge dataset. Dataset used is LUNGx dataset. Basic image pre-processing techniques are applied for contrast enhancement after acquiring medical images from LUNGx database. The features are extracted from each DCNN to train SVM and AdaBoostM2 classifier. The classification accuracy is increased from 76.88% to 86.28% for ResNet-101 and 67.37% to 83.40% for GoogLeNet.

[21] 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.

Lung nodules are vital indicators for the presence of lung cancer. It proposed transferable texture Convolutional Neural Networks (CNN) to improve the classification performance of pulmonary nodules in CT scans. An Energy Layer (EL) is incorporated in our scheme, which extracts texture features from the convolutional layer. Overall proposed CNN architecture comprises of nine layers for automatic feature extraction and classification of pulmonary nodule candidates as malignant or benign. The training was done successfully by six-fold cross-validation and achieved an accuracy, recall, specificity, AUC, and error rate of 96.69%, 96.05%, 97.37%, 99.11%, and 3.30%, respectively, on LIDC-IDRI database. The achieved classification score of our proposed texture CNN without TL (trained from scratch) for accuracy, recall, specificity, and AUC score on LUNGx database are 86.14%, 88.76%, 93.11% and 92.63%.

[22] Zhao, D., Liu, Y., Yin, H., & Wang, Z. (2022). A novel multi-scale CNNs for false positive reduction in pulmonary nodule detection. *Expert Systems with Applications*, 117652.

False positive reduction is a significant stage in pulmonary nodule detection, So this paper focuses on false positive reduction. Many of the existing false positive reduction based models are mainly 3D CNNs due to its high sensitivity of detection result but these models require long training time. This paper proposed a novel multiscale CNNs method for false positive reduction in automate pulmonary nodule detection which focuses on training time and accuracy. Instead of using 3D CT cubes, three different orthogonal 2D images are been cropped for saving spatial information and shortening training time. The proposed multi-scale CNNs attained a sensitivity of 95.2% and 98.1% for the specificity on LUNA16 dataset.

[23] Sun, L., Wang, Z., Pu, H., Yuan, G., Guo, L., Pu, T., & Peng, Z. (2021). Attention-embedded complementary-stream CNN for false positive reduction in pulmonary nodule detection. ***Computers in Biology and Medicine*, *133*,** **104357.**

Due to heterogeneity and similarity of pulmonary nodules, there will be many chances of false positives in lung nodule detection. In this paper, a novel attention-embedded complementary-stream convolutional neural network AECS-CNN is proposed to obtain more representative features of nodules for false positive reduction. The proposed network has three function blocks-attention-guided multi-scale feature extraction, complementary-stream block with an attention module for feature integration and classification block. The inputs of the network are multiscale 3D CT volumes due to variations in nodule sizes followed by a gradual multiscale feature extraction block with an attention module was applied to get more contextual information regarding the nodules. The proposed model achieved a sensitivity of 0.92 upon on LUNA16 dataset.

[24] Drokin, I., & Ericheva, E. (2020, October). Deep learning on point clouds for false positive reduction at nodule detection in chest CT scans. In ***International Conference on Analysis of Images, Social Networks and Texts*** **(pp. 201-215). Springer, Cham.**

This paper focuses on a novel approach for false-positive reduction (FPR) of nodule candidates in Computer-aided detection CAD. The proposed approach considers input data not as a 2D or 3D image, but rather as a point cloud, and uses deep learning models for point clouds. This paper focuses on point cloud models as they require less memory and are faster both in training and inference compared to traditional CNN 3D. Experiments were conducted with PointNet, PointNet++, and DGCNN which outperforms baseline CNN 3D models. The results show 85.98 FROC versus 77.26 FROC for baseline 3D CNN models on LUNA16.

[25] Shukla, V. V. K., Tanmisha, M., Aluru, R., Nagisetti, B., & Tumuluru, P. (2021, January). Lung Nodule Detection through CT Scan Images and DNN Models. In *2021 6th International Conference on Inventive Computation Technologies (ICICT)* (pp. 962-967). IEEE.

2D SqueezeNet and 2D MobileNet Models are used for detecting the lung nodules. DNN as it reduces the use of memory and it made the model light-weight. LUNA 16 dataset which is a collection of lung cancer medical CT images is used. The format of the images is mdh and raw. The dimensions of the images are 512 x 512. Steps for detecting mainly follows image pre-processing, segmentation, data preprocessing, data augmentation, model construction, network layers. The Hounsfield Units (HU) which is a quantitative measure of radiodensity, which acts as a cycle of thresholding. This unit of measure for lung tissue is - 500 HU while that of air is - 1000 HU, bone is around 700 HU and different tissues and blood have a 0 HU. It not only satisfies the accuracy criteria, but also the Sensitivity and Specificity.

[26] Xie Y, Xia Y, Zhang J, Song Y, Feng D, Fulham M, Cai W. Knowledge-based Collaborative Deep Learning for Benign-Malignant Lung Nodule Classification on Chest CT. IEEE Trans Med Imaging. 2019 Apr;38(4):991-1004. doi: 10.1109/TMI.2018.2876510. Epub 2018 Oct 17. PMID: 30334786.

A multi-view knowledge-based collaborative (MV-KBC) deep model to separate malignant from benign nodules using limited chest CT scans data. The LIDC-IDRI database in the Cancer Imaging Archive (TCIA) contains 1018 clinical chest CT scans with lung nodules obtained from seven institutions. The OA, HVV or HS patches extracted on each of nine views of planes, together with the augmented data, were used to train a KBC submodel which is pre-trained with three ResNet-50 networks. The networks that characterize the nodules into voxel and shape heterogeneity too classify lung nodules with an adaptive weighting by backpropagation. The feature maps learned from three types of input image patches are OA, HVV an HS patches. The MV-KBC model achieved an accuracy of 91.60% for lung nodule classification with an AUC of 95.70%.

[27] Mobiny, A., Yuan, P., Cicalese, P. A., Moulik, S. K., Garg, N., Wu, C. C., ... & Nguyen, H. V. (2021). Memory-augmented capsule network for adaptable lung nodule classification. ***IEEE Transactions on Medical Imaging*, *40*****(10), 2869-2879.**

Memory-Augmented Capsule Network(MEMCAP) is composed into two sub modules are deep capsule network architecture and composed of an LSTM controller with an external memory bank. MEMCAP model uses the ADAM as a Optimizer. Three different datasets of CT images are collected are LUNA16, Incidental Lung Nodule Dataset and collected lung nodule dataset. MEMCAP model trained with meta-learning to perform domain adaptation in classification of lung nodules from CT scans. The decoder network then reconstructs the input from the final capsules, effectively works as a regularizer that reduces the risk of over-fitting. MEMCAP method achieves 84.7% and 89.1% accuracy for classifying lung nodules. The MEMCAP architecture achieves AUROC score of 84.1% and 90.2.

[28] Zuo, W., Zhou, F., Li, Z., & Wang, L. (2019). Multi-resolution CNN and knowledge transfer for candidate classification in lung nodule detection. ***Ieee Access*, *7*, 32510-32521.**

This paper presents a study that deals with candidate classification in lung nodule detection even with the variable sizes of lung nodules. The proposed model is a multi-resolution convolutional neural network (CNN) that extract features of various levels and resolutions from different depth layers in the network for classification of lung nodule candidates. This paper used the knowledge transfer method in the classification of lung nodule candidates. This transfer knowledge from the source CNN model which has been applied to edge detection and improve the model to a new multi-resolution model which is suitable for the image classification task. The model achieved an accuracy of 0.9733, a precision of 0.9673, and an AUC of 0.9954 for lung nodule candidate classification on LUNA 16 dataset.

[29] Zhai, P., Tao, Y., Chen, H., Cai, T., & Li, J. (2020). Multi-task learning for lung nodule classification on chest CT. *IEEE access*, *8*, 180317-180327.

This paper proposed a multi-task convolutional neural network (MT-CNN) framework to identify malignant nodules from benign nodules on chest CT scans. Ciompi et al. constructed an ensemble classifier to automatically recognize pulmonary peri-fissural nodules. They classified nodules based on multiple 2-D views of the nodules and obtained AUC of 86.6%. Zhao et al. proposed a new agile CNN framework to deal the challenges of a small-scale medical image database and the small size of the nodules based on the hybrid of LeNet and AlexNet and achieved an AUC of 87.7%. Anyhow, the above models cant deal with 3D images whereas The proposed architecture can learn the 3-D spatial information of nodules with the fusion of multiple 2-D models. The model has achieved the AUC (97.3%) and specificity (96.8%) in LUNA-16, and highest UAC (95.59%) in LIDC-IDRI.

[30] Ali, I., Muzammil, M., Haq, I. U., Khaliq, A. A., & Abdullah, S. (2021). Deep feature selection and decision level fusion for lungs nodule classification. *IEEE Access*, *9*, 18962-18973.

This paper proposed a decision level fusion technique for lung nodule classication to improve the classification performance of CAD system. It evaluated the performance of Support Vector Machine (SVM) and AdaBoostM2 which got trained on the deep features extracted from some state-of-the-art transferable architectures. The state-of-the-art transferable architectures used in this paper are VGG-16, VGG-19,GoogLeNet, Inception-V3, ResNet-18, ResNet-50, ResNet-101 and InceptionResNet-V2. The results showed that SVM is more robust and efficient for deep features when compared to AdaBoostM2. It is observed that the AdaBoostM2 performed well on the features extracted from last fully connected layers of all DCNNs, except RestNet-101. The proposed technique achieved accuracy score was 90.46 upon available LUNA16 challenge dataset.

Sl.no	Technique (i.e. author names with reference number)	year	Description	Limitations	Advantages	Performance metrics	Gaps
1	Mittapalli Pardha Saradhi, Thanikaiselvan V	2021	An iterative approach in which several mixtures of false positives and true positives are used for training the proposed MCNN-CF model.	The model's confidence is inferior in a few nodule instances leading to their misclassification as non-nodules.	Model has shown high confidence in the classification of most of the variety of nodules with prediction probabilities greater than 0.9.	Competition Performance Metric (CPM)score – 94.8%	System finds either lack of or too much contextual information in those cases and also to improve the performance with the inclusion of static features.
2.	Wangxia Zuo, Fuqiang Zhou, Yuzhu He	2020	It takes 3D volumes as the input and carries out 3D convolution calculation, which can more effectively deal with the spatial information of nodules	The number of nodules with other sizes is relatively small and less well represented in the training set.	The model can learn more subtle features of the target, including features of different scales and levels, and process spatial correlation information of 3D samples more effectively.	Accuracy - 92.83%, Sensitivity – 87.71%, Precision -91.26%, specificity- 99.25% and CPM score – 83%	Nodules larger than 12 mm in diameter, the prediction confidence is lower

3	Hongbo Zhu, Hai Zhao, Chunhe Song, Zijian Bian, Yuanguo Bi, Tong Liu, Xuan He, Dongxiang Yang , Wei Cai	2019	MR-Forest is a successful substitution to satisfied both resource-consuming and effectiveness for automated pulmonary nodule detection systems.	The nature of 2D CNNs determines that its feature volumes can merely include the limited 3D spatial information.	Advantages of our work in four aspects: influence of the different nodule model size, effectiveness of the multiple features fusion, the contextual spatial information, and cascaded architecture.	Competition Performance Metric (CPM)score – 91%	It has been the frontrunner of the 2D schemes, but its performance still exists significant gaps with the performance of the 3D counterparts due to the finite imaging planes of the schemes.
4	A. B. Oliveira and M. P. Viana	2018	It has proposed an efficient multi-scale data representation method for lung nodule false positive reduction using convolutional neural networks.	Our model provides very competitive computational time and data usage when compared to 3D models, with a superior accuracy when compared with regular 2D cross sections.	3D CNNs using 16 times less data and running 4 times faster than 2D CNN.	Accuracy – 91.5% and Precision – 92.5%	It involve exploring different functions for modelling the data representation and improving the CNN architecture itself to achieve over state-of-art results using compact data representations.

5	R. Nagata, T. Kawaguchi and H. Miyake	2019	It has proposed an Automated detection of lung nodules in chest radiographs using a false-positive reduction scheme based on template matching	However, ANNs trained by back-propagation have disadvantages that they have many parameters which have to be determined by trial and error and they may require an enormous amount of time for their training	In addition, it does not need feature selection because it uses subimages of the original chest images as nodule templates and non-nodule templates	Sensitivity – 74.5%	It can even improve the performance of lung nodule classification by exploring the relations among different views.
6	Saien S, Moghaddam HA, Fathian M	2018	A unified methodology based on sparse field level sets and boosting algorithms for false positives reduction in lung nodules detection.	It needs to have manually design related featiures for later classification, which greatly limits the scalability of the method.	Nodule borders were segmented finely such that tiny non-nodule attached parts were excluded; simultaneously, desired missed parts were included	Sensitivity – 85% AUC score.	The practical implementation, applicability for different nodule types and adaptability in handling the imbalanced data classification insure the improvement in lung nodules detection by utilizing this new approach.

7	Manickavasagam, R., & Selvan, S.	2019	proposed a GACM Gradient based Active Contour Model for segmenting the lung region from CT images..	Limited to find the growth rate of the nodule, estimating the size and location of the nodule	Experimentation results says that proposed hybrid model outperforms when compared with existing methods in lung image classification.	Accuracy – 95.3%, sensitivity-92.1%	Can be extended to find the growth rate of the nodule, estimating the size and location of the nodule for classification of stages of lung cancer.
8	Al-Shabi, M., Lee, H. K., & Tan, M.	2019	proposed a novel CNN architecture called as Gated-Dilated networks to classify nodule as benign or malignant.	Proposed model requires an object detector model to identify the nodule locations before classifying them as benign/malignant.	Unlike other models, it can also deal with variations in the nodules.	Accuracy -92.57%, AUC-95.4%	Planned to built a fully-automated nodule classification scheme that can automatically detect the nodule locations like CAD scheme for lung nodule detection.
9	Ozdemir, O., Russell, R. L., & Berlin, A. A.	2019	Proposed a new computer aided detection and diagnosis system for lung cancer screening with low-dose CT scans that is based on 3D convolutional neural	Though 3D CNN models are effectively used to analyze lung CT scans, the performance is still lacking due to datasets used to train our models which lack large nodule	Develop an end-to-end system of higher and robust performance and eliminates the need for false positive reduction stage.	AUC score-87%, recall-93%	Built patient reject option as part the training strategy and learn models that would automatically reject the most uncertain decisions.

			networks.	annotations.			
10	Hao Tang; Xingwei Liu; Xiaohui Xie	2019	It had proposed an end-to-end framework for nodule detection, integrating nodule candidate screening and false positive reduction into one model.	The proposed framework has a relatively high computational complexity due to combination of 2 sub-systems.	It reduces the model complexity and inference time. It increases nodule detection accuracy over the previous model.	CPM(competition performance metric)-89%,accurcy-87%	It can be developed using deep learnung techniques.
11	Y. Qin, H. Zheng, Y. -M. Zhu and J. Yang	2018	It proposes a computer-aided diagnosis (CAD) system for simultaneous accurate pulmonary nodule detection and false positive reduction.	It uses 3D patch-based training is adopted with patch size of 128 × 128 × 128 due to the limitation of GPU	The densely connected structure reuses nodules features and boosts feature propagation	CPM-89%, FROC	It can be developed for clinacal applications
12	Yu Han; Hongggang Qi; Yan Liu; Zhijun Guo; Qian Xu; Qiang Lin; Haitao	2021	It proposes an effective multi-branch false positive reduction network is built to avoid reducing the	The computational amount and time cost of the 3D Resnet is higher.	It avoids the degradation caused by the increase in the number of network layers.	Sensitivity – 85.8%	It can be helpful to further to improve the efficiency of doctors in clinical diagonsis.

	Liu; Junying Lu		sensitivity of nodule detection.				
10	Hao Tang; Xingwei Liu; Xiaohui Xie	2019	It had proposed an end-to-end framework for nodule detection, integrating nodule candidate screening and false positive reduction into one model.	The proposed framework has a relatively high computational complexity due to combination of 2 sub-systems.	It reduces the model complexity and inference time. It increases nodule detection accuracy over the previous model.	CPM(competition performance metric)-89%,accurcy-87%	It can be developed using deep learnung techniques.
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12	Yu Han; Honggang Qi; Yan Liu; Zhijun Guo; Qian Xu; Qiang	2021	It proposes an effective multi-branch false positive reduction network is built to	The computational amount and time cost of the 3D Resnet is higher.	It avoids the degradation caused by the increase in the number of network layers.	Sensitivity – 85.8%	It can be helpful to further to improve the efficiency of doctors in clinical diagonsis.

	Lin; Haitao Liu; Junying Lu		avoid reducing the sensitivity of nodule detection.				
13	Li, C., Zhu, G., Wu, X., & Wang, Y.	2018	This propose a framework of ensemble of convolutional neural networks (E-CNNs) for false positive reduction of lung nodules.	The CT is considered to be the most effective imaging method but it used chest radiographs (CXRs)	Usage of Ensemble CNN increases the sensitivity when compared to single CNN.	Sensitivity-84%	Working on CT images as it is the better imaging method.
14	Cao, H., Liu, H., Song, E., Ma, G., Xu, X., Jin, R., ... & Hung, C. C	2019	This paper propose a Multi-Branch Ensemble Learning architecture based on the three-dimensional convolutional neural networks for the false positive reduction.	The model cannot deal with various orientations	MBEL-3D-CNN architecture can achieve better screening results since it used ensemble learning.	CPM score-87.3%, sensitivity, recall	plan to develop a candidate lung nodule detection by the Deconvolutional Single Shot Detector.
15	Huang, X., Shan, J., & Vaidya, V.	2017	Proposed a computer-aided detection system that uses 3D	GGO and juxta pleural nodules were not addressed.	The 3D CNN performs better over 2D CNN in volumetric medical image analysis.	FROC curves , Sensitivity-90%	Will test the prooposed method on separate test data, explore versatile

			convolutional neural networks for detecting lung nodules in low dose CT.				candidate generators for developing complete system that for all nodule types.
16	Ying Chen , Yerong Wang , Fei Hu, Longfeng Feng, Taohui Zhou, Cheng Zheng	2021	It had done the classification of lung nodules and the classification of lung cancer with good performance.	LDNNET does not use semantic segmentation and positioning	It has been designed in preprocessing, dense connection, input image size, pooling layer and depth of neural network on dataset which has given good performance.	Accuracy – 98.8%, specificity – 99.4%, sensitivity – 98.2%	It can have more effective network structures to extract common features from images of different types and performing cross-type matching to improve the performance.
17	Bin Wang, Shuaizong Si, Enuo Cui, Hai Zhao, Dongxiang Yang, Shengchang Dou, Jian Zhu	2020	It recognizes irregular vascular structures robustly and sensitively, and achieve fast vessel segmentation.	The multi-view scheme with the overall response calculation is less time-consuming and can save time for our CAD system.	A fast and efficient system to evaluate the malignancy level of lung nodules and reduces the False Positives (FP).	Accuracy – 95.88%, F1-Score – 78.15%, Precision -81.49%	It should be directed at improving the specificity of vessel segmentation and reducing the influence of binarization
18	Haichao Cao , Hong Liu , Enmin Song, Senior Member,	2020	It had proposed a data augmentation method called random mask which	It needs to have manually design related features for later classificatio	It has proposes a two-phase prediction scheme, which is a prediction method to quickly have rough segmentation and then perform the	Competition Performance Metric (CPM) - 92.5%	Due to the limitations of the experimental platform, It can’t achieve 3D detection, only 2D layer-by-layer

	IEEE, Guangzhi Ma, Xiangyang Xu, Renchao Jin, Tengying Liu , Chih-Cheng Hung		can convert randomly paired positive (negative) samples into negative (positive) samples	n, which greatly limits the scalability of the method.	fine segmentation in a smaller local region.		detection is done.
19	. A. B. Oliveira and M. P. Viana	2018	It has proposed an efficient multi-scale data representation method for lung nodule false positive reduction using convolutional neural networks.	Our model provides very competitive computational time and data usage when compared to 3D models, with a superior accuracy when compared with regular 2D cross sections.	3D CNNs using 16 times less data and running 4 times faster than 2D CNN.	Accuracy – 94.5%	It involve exploring different functions for modelling the data representation and improving the CNN architecture itself to achieve over state-of-art results using compact data representations.
20	R. Nagata, T. Kawaguchi and H. Miyake	2019	It has proposed an Automated detection of lung nodules in chest radiographs using a false-positive reduction	However, ANNs trained by back-propagation have disadvantages that they have many parameters which have	In addition, it does not need feature selection because it uses subimages of the original chest images as nodule templates and non-nodule templates	Accuracy – 86.28%	It can even improve the performance of lung nodule classification by exploring the relations among different views.

			scheme based on template matching	to be determined by trial and error and they may require an enormous amount of time for their training			
21	Saien S, Moghaddam HA, Fathian M	2018	A unified methodology based on sparse field level sets and boosting algorithms for false positives reduction in lung nodules detection.	It needs to have manually design related featiures for later classification, which greatly limits the scalability of the method.	Nodule borders were segmented finely such that tiny non-nodule attached parts were excluded; simultaneously, desired missed parts were included	Specificity – 93.11%, Accuracy – 86.14%, Recall – 88.76%, AUC – 92.63%	The practical implementation, applicability for different nodule types and adaptability in handling the imbalanced data classification insure the improvement in lung nodules detection by utilizing this new approach.
22	Zhao, D., Liu, Y., Yin, H., & Wang, Z.	2022	This paper proposed a novel multiscale CNNs method for false positive reduction in automate pulmonary nodule detection which focuses on training time	3D CNNs will extract more significant features but this model used 2D CNN.	Instead of 3D CT cubes, three different orthogonal 2D images are been cropped for saving spatial information and shortening training time.	Sensitivity – 95.2%, Specificity – 98.1%,	Should build a 3D CNN model which takes less training time

			and accuracy.				
23	Sun, L., Wang, Z., Pu, H., Yuan, G., Guo, L., Pu, T., & Peng, Z.	2021	a novel attention-embedded complementary-stream convolutional neural network is proposed to obtain more representative features of nodules for false positive reduction.	The effect of the unbalanced dataset could not be removed by the proposed network.	The proposed model obtain more representative features of nodules for false positive reduction.	Sensitivity - 92%	Adequate use of the unbalanced dataset may improve the performance of the network in FPR, like nodule augmentation by generative adversarial networks rather than shifting or rotation.
24	Drokin, I., & Ericheva, E.	2020	Experiments were conducted with PointNet, PointNet++, and DGCNN which outperforms baseline CNN 3D models for false positive reduction.	The dataset without applying any techniques leads to overfitting.	Do not impose restrictions on the size of the input image.	FROC	Check performance of tests on other datasets from different sources.
25	Shukla, V. V. K., Tanmisha, M., Aluru, R., Nagisetti,	2021	It mainly focuses on detecting the nodules present in the lung CT	It does not perform segmentation and identifying the harmful	It not only satisfies the accuracy criteria, but also the Sensitivity and Specificity.	Accuracy – 89.34%,	It can may be conceivable to stretch out the present model to decide

	B., & Tumuluru, P.		scan images and detect lung cancer in early stage.	knobs.			the specific area of the harmful knobs.
26	Yutong Xie, Yong Xia, Jianpeng Zhang, Yang Song, Dagan Feng, Michael Fulham, Weidong Cai	2019	A Knowledge-based Collaborative Deep Learning model for classification of Benign-Malignant of Lung Nodules on Chest CT scans.	The proposed MV-KBCmodel has a relatively high computational complexity during training and time - consuming.	The higher classification accuracy can be achieved by having the three ResNet-50 nertworks.	Accuracy – 91.06%, AUC – 95.7%.	It cannot perform well when there is increase in the noise level.
27	Aryan Mobiny, Pengyu Yuan, Pietro A Cicalese, Supratik K Moulik, Naveen Garg, Carol C Wu, Kelvin Wong, Stephen T Wong, Tian Cheng He, Hien V Nguyen	2021	A deep neural network architecture trained with meta-learning to perform domain adaptation in lung nodule classification from CT scans.	It requries an external-memory equipped networks capable of rapidly encoding new data and storing them in a stable, addressed that can selectively be accessed when needed.	It consists ofa CapsNet feature network that extracts features and high-level semantic structures across domains of input volume.	Accuracy – 89.1% and AUROC – 90.2%	The performance may decrease due to large domain shifts with deep networks

28	Zuo, W., Zhou, F., Li, Z., & Wang, L.	2019	Proposed model is multi-resolution convolutional neural network (CNN) that extract features of various levels and resolutions from different depth layers.	2D CNN method is limited in capturing the contextual information between slices. High chances of false identification of nodules.	It can solve the multi resolution problem i.e it can also deal with the images of variable sizes and variable shapes.	Accuracy – 97.33%, Precision -96.73%, AUC-99.54	2D CNN method is limited in capturing the contextual information between slices, thus a 3D CNN model may be considered for the future work.
29	Zhai, P., Tao, Y., Chen, H., Cai, T., & Li, J. (2020).	2020	This paper proposed a multi-task convolutional neural network (MT-CNN) framework long nodule classification.	The model with the improper image reconstruction loss threshold leads to overfitting.	Compared to models that use 3D CNN for lung nodule detection, the proposed model achieved the best performance.	AUC-97.3%, Specificity-96.8%.	It can even improve the performance of lung nodule classification by exploring the relations among different views.
30	Ali, I., Muzammil, M., Haq, I. U., Khaliq, A. A., & Abdullah, S. (2021).	2021	It evaluated the performance of Support Vector Machine (SVM) and AdaBoostM2 which got trained on the deep features extracted from some	The model cannot deal with various orientations of new test data.	By using the decision level fusion technique, it can improve the performances of the SVM and AdaBoostM2.	Accuracy, Gmean, Precision, Recall, Specicity and Error Rate, AUC – 90.46%	Test the proposed models on various test data in check of best accuracy.

			state-of-the-arttransferablarchitectures				

Table 2.1 Comparison Table

3. METHODOLOGY

3.1 Dataset :

The LIDC/IDRI data set is publicly available including the annotations of nodules by four radiologists.It contain 888 CT scans. The LIDC/IDRI database contains annotations which were collected during a two-phase annotation process using 4 experienced radiologists. Each radiologist marked lesions they identified as non-nodule, nodule < 3 mm, and nodules >= 3 mm.

The data is structured as follows:

subset0.zip to subset9.zip: 10 zip files which contain all CT scans

annotations.csv: csv file that contains the annotations used as reference standard for the 'nodule detection' track

sampleSubmission.csv: an example of a submission file in the correct format

candidates.csv: the original set of candidates used for the LUNA16 workshop. This file is kept for completeness.

candidates_V2.csv: csv file that contains an extended set of candidate locations for the ‘false positive reduction’ track.

evaluation script: the evaluation script that is used in the LUNA16 framework

lung segmentation: a directory that contains the lung segmentation for CT images computed using automatic algorithms

additional_annotations.csv: csv file that contain additional nodule annotations from our observer study. The file will be available soon

3.2 Proposed Method :

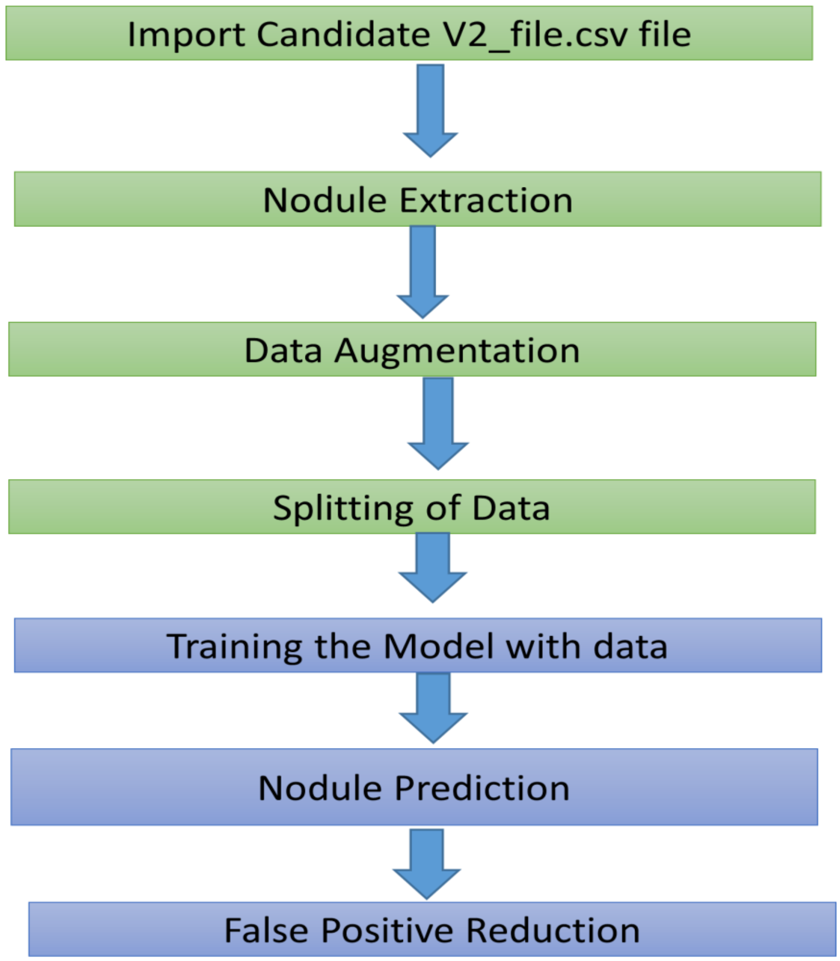

Fig3.1 Flowchart of proposed work

3.3 Deep Learning :

Deep learning is a machine learning technique that teaches computers to do what comes naturally to humans. In deep learning the model learns how to classify the images,text,audio and video. It is a subpart of machine learning which on the other hand is a subset of Artificial Intelligence which the algorithms inspired by human brain which contain nodes and connection between the nodes. It can transfer the information between all the nodes. The architectures like deep neural networks, deep belief network, deep reinforcement learning, recurrent neural network and convolution neural network are applied to speech recognition, natural language processing, biometric authentication etc..., The design of the neural network is based on the structure of the human brain. Just as we use our brains to identify patterns and classify different types of information, neural networks can be taught to perform the same tasks on data.

Neural networks enable us to perform many tasks, such as clustering, classification or regression. With neural networks, we can group or sort unlabeled data according to similarities among the samples in this data. Or in the case of classification, we can train the network on a labeled dataset in order to classify the samples in this dataset into different categories.

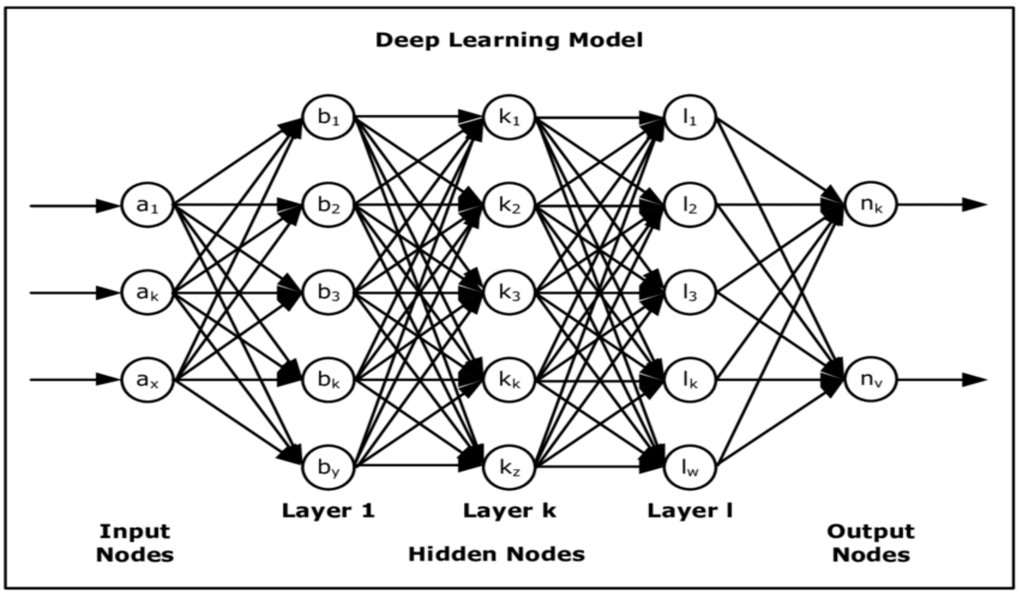

Fig3.2 Deep Learning Model

3.4 Convolutional Neural Network :

In deep learning, Convolution Neural network(CNN) is a class of artificial neural networks(ANN) is commonly used for analyze visual imagery purpose.it is particularly used for finding patterns in images to recognize objects, faces and scenes. CNN inspired by the human brain which contains nodes and each node is connected to all other nodes.it takes the input from the convolution layer and pass the information to all the layers and with the help of bias and weights the image is detected.by using the sigmoid the image is detected A convolution neural network has tens or hundreds of layers to detect the different features of an image.

A simple CNN consists of an input layer, followed by a stack of a convolutional layer with a certain activation function (CL) and a pooling layer (PL), the fully connected layer, and a final classification activation layer. The convolution layer and pooling layer are used for feature extraction and the layers fully connected layer and output layer is used for classification purpose. The convolution layer takes the input as input and produce feature maps. And the pooling layer is reduced the size of feature maps .so the usage of memory is reduced by reducing the size of images and it is also avoid the over fitting. And the regularization techniques are used to reduce over fitting and also improves the accuracy. fully connected layer is used for classification purpose by using the activation function like sigmoid, SoftMax are used for binary and multiclass classification.

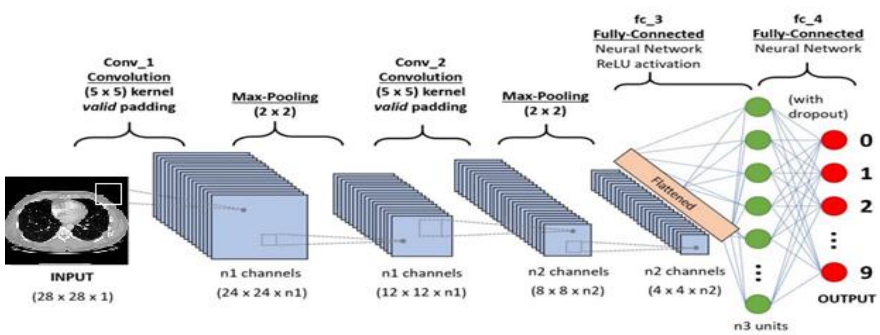

Fig3.3 Convolutional Neural Network Model

Convolutional neural networks are distinguished from other neural networks by their superior performance with image, speech or audio signal inputs. The layers of a CNN consist of an input layer, an output layer and a hidden layer that includes multiple convolutional layers, pooling layers, fully connected layers and normalization layers.

They have three main types of layers, which are:

• Convolutional layer

• Pooling layer

• Fully-connected (FC) layer

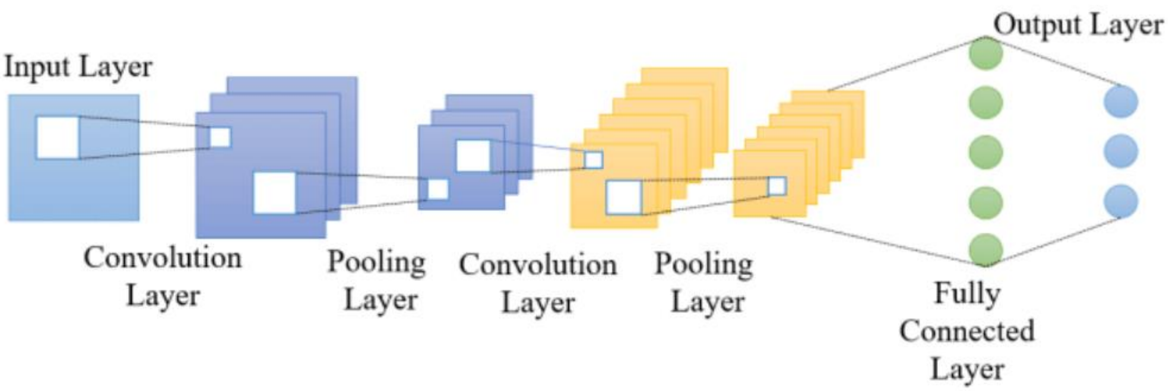

Fig3.4 Convolutional Neural Network Layers

Convolutional layer: - This is the initial layer that extracts the different features from the input photos. The convolution mathematical process is done between the input image and a filter of a specific size MxM in this layer. The dot product between the filter and the sections of the input image with regard to the size of the filter is taken by sliding the filter across the input image (MxM). The Feature map is the result, and it contains information about the image such as its corners and edges. This feature map is then supplied to further layers, which learn a variety of other features from the input image. The convolutional layer is the core building block of a CNN, and it is where the majority of computation occurs. It requires a few components, which are input data, a filter, and a feature map.

Convolution preserves the relationship between pixels by learning image features using small squares of input data. It is a mathematical operation that takes two inputs such as image matrix and a filter or kernel. Convolution is basically filtering the image with a smaller pixel filter to decrease the size of the image without loosing the relationship between pixels.

The dimension of the image matrix is $h \times w \times d$.

The dimension of the filter is $fh \times fw \times d$.

The dimension of the output is $(h-fh+1) \times (w-fw+1) \times 1$.

Pooling layer :- A Pooling Layer is usually applied after a Convolutional Layer. The major goal of this layer is to reduce computational expenses by reducing the size of the convolved feature map. This is accomplished by reducing the connections between layers and operating on each feature map independently. There are numerous sorts of Pooling operations, depending on the mechanism utilized. The largest piece from the feature map is used in Max Pooling. The average of the elements in a predefined sized Image segment is calculated using Average Pooling. Sum Pooling calculates the total sum of the components in the predefined section. The Pooling Layer is commonly used to connect the Convolutional and Fully Connected Layers.

When constructing CNNs, it is common to insert pooling layers after each convolution layer to reduce the spatial size of the representation. Basically we select a pooling size to reduce the amount of the parameters by selecting the maximum, average, or sum values inside these pixels. Stride is the number of pixels shifts over the input matrix. When the stride is 1 then we move the filters to 1 pixel at a time. When the stride is 2 then we move the filters to 2 pixels at a time and so on. Maximum pooling or max pooling is a pooling operation that calculates the maximum or largest value in each patch of feature map.

Fully connected layer:- The Fully Connected (FC) layer connects the neurons between two separate layers by combining the weights and biases with the neurons. The last several layers of a CNN Architecture are usually positioned before the output layer. The previous layers' input images are flattened and supplied to the FC layer in this step. After that, the flattened vector is sent via a few additional FC layers, where the mathematical functional operations are normally performed. The classification procedure gets started at this point. Fully Connected layers in a neural networks are those layers where all the inputs from one layer are connected to every activation unit of the next layer. In most popular machine learning models, the last few layers are full connected layers which compiles the data extracted by previous layers to form the final output. It is the second most time consuming layer second to Convolution Layer. Flattening layer which converts the data into 1-dimensional array for inputting it into the next layer. Dense Layer is simple layer of neurons in which each neuron receives input from all the neurons of previous layer, thus called as dense. Thus, dense layer is basically used for changing the dimensions of the vector. Dense layers also applies operations like rotation, scaling, translation on the vector.

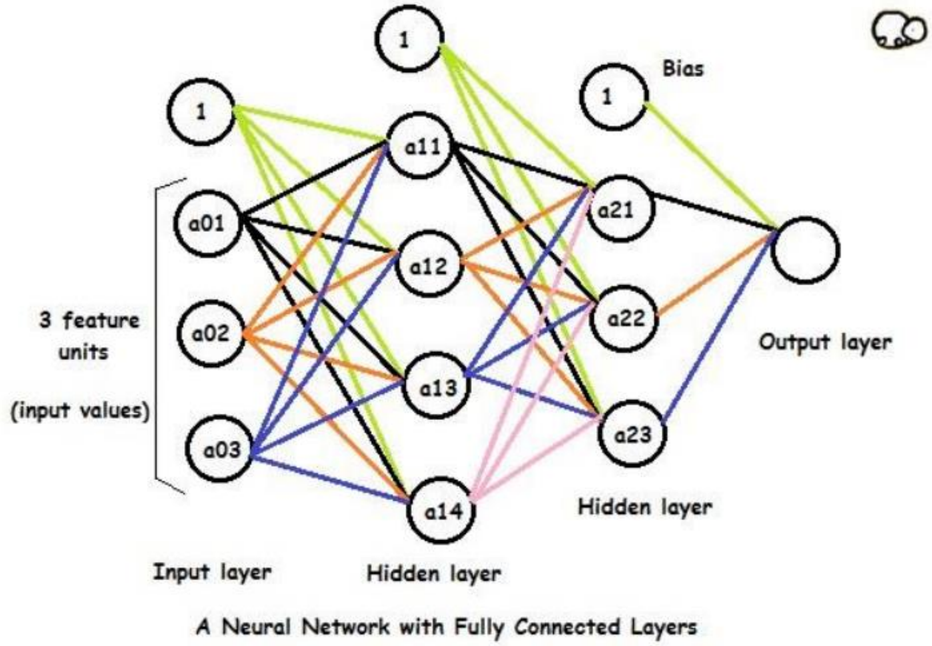

Fig3.5 A Neurak Network with Fully Connected Layers

3.5 VGG16 Network :

A Convolutional neural network is also known as a ConvNet which is a kind of artificial neural network. A Convolutional neural network has an input layer, an output layer, and various hidden layers.VGG16 is a type of Convolutional Neural Network that is considered to be one of the best computer vision models to date. VGG was developed to increase the depth of such CNNs in order to increase the model performance. The creators of this model evaluated the networks and increased the depth using an architecture with very small (3 × 3) convolution filters, which showed a significant improvement on the prior-art configurations. They pushed the depth to 16–19 weight layers making it approx — 138 trainable parameters. The 16 in VGG16 refers to 16 layers that have weights. In VGG16 there are thirteen Convolutional layers, five Max Pooling layers, and three Dense layers which sum up to 21 layers but it has only sixteen weight layers i.e., learnable parameters layer.Most unique thing about VGG16 is that instead of having a large number of hyper-parameters they focused on having convolution layers of 3x3 filter with stride 1 and always used the same padding and Max pool layer of 2x2 filter of stride 2. The convolution and max pool layers are consistently arranged throughout the whole architecture. Conv-1 Layer has 64 number of filters, Conv-2 has 128 filters, Conv-3 has 256 filters, Conv 4 and Conv 5 has 512 filters. Here, We are reshaping 48*48*48 image into 192*192*3 and training the model VGG16 with input shape with 192*192*3.

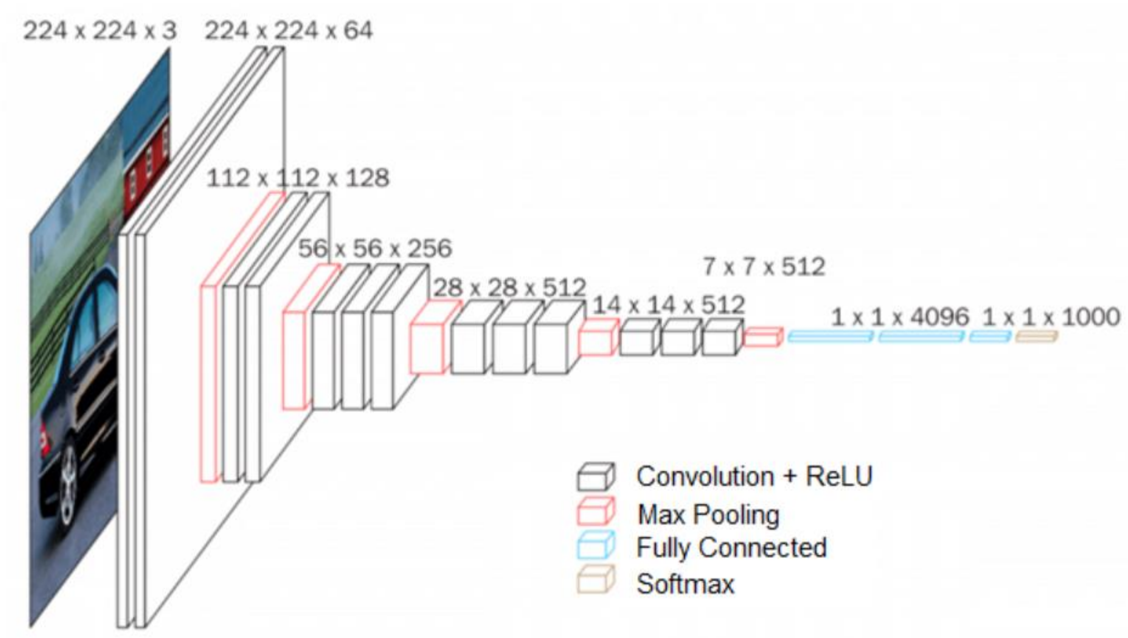

Fig3.6 VGG16 Architecture

3.6 Transfer learning:

Low-level features learned for task A should be beneficial for learning of model for task B.This is what transfer learning is. Nowadays, it is very hard to see people training a whole convolutional neural networks from scratch, and it is common to use a pre-trained model trained on a variety of images in a similar task, e.g models trained on ImageNet (1.2 million images with 1000categories), and use features from them to solve a new task. When dealing with transfer learning, we come across a phenomenon called freezing of layers. A layer, it can be a CNN layer, hidden layer, a block of layers, or any subset of a set of all layers, is said to be fixed when it is no longer available to train. Hence, the weights of freezed layers will not be updated during training. While layers that are not freezed follows regular training procedure. When we use transfer learning in solving a problem, we select a pre-trained model as our base model. Now, there are two possible approaches to use knowledge from the pre-trained model. First way is to freeze a few layers of pre-trained model and train other layers on our new dataset for the new task. Second way is to make a new model, but also take out some features from the layers in the pre-trained model and use them in a newly created model. In both cases, we take out some of the learned features and try to train the rest of the model. This makes sure that the only feature that may be same in both of the tasks is taken out from the pre-trained model, and the rest of the model is changed to fit new dataset by training.

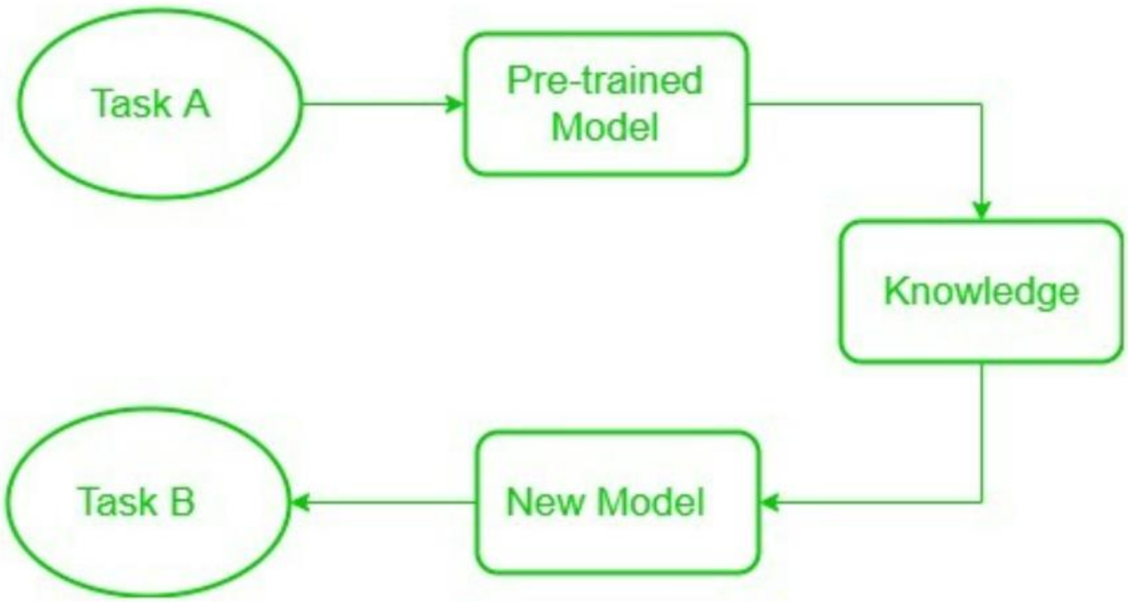

Fig3.7 Block Diagram of Transfer Learning

4. RESULTS & DISCUSSION

In this paper the transfer learning model i.e., VGG-16 is proposed. It is pre-trained model which is used for object detection and classification algorithm which is able to classify. Three layers were added to pre-trained model. The three layers are flatten, dense, dropout. The LUNA-16 dataset contains the ratio of 1:632 of true nodules and false nodules. By this, there was a good performance of accuracy was obtained. The metrics used for classification of false nodule / true nodule is precision, recall, F1-score. The accuracy obtained by using VGG-16 model is 90% .

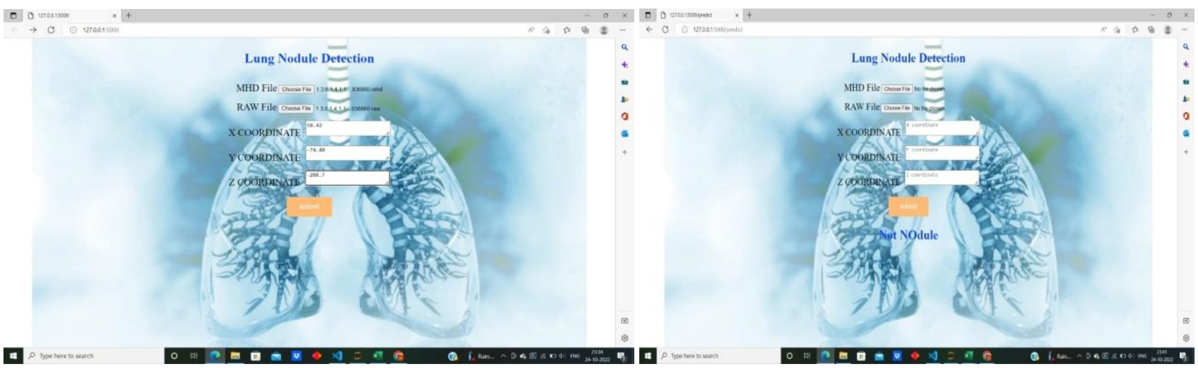

Fig4.1 Non – Nodule Detected Result

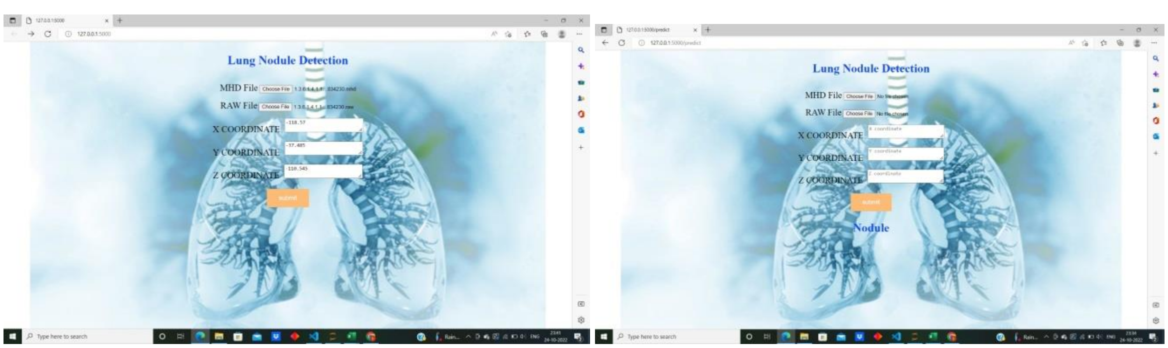

Fig4.2 Nodule Detected Result

	Precision	Recall	F1-Score
0 (False Nodule)	0.92	0.83	0.90
1 (True Nodule)	0.81	0.99	0.89
Weighted Average	0.92	0.90	0.90

Table 4.1 Performance Metrics Table

5. CONCLUSION & FUTURE SCOPE

This project presents an approach for False Positive Reduction of Lung Nodule Detection using Deep Learning Techniques. The Lung Nodule Analysis (LUNA 16) dataset have many nodules which are both True and False Nodules. By using the whole dataset for Lung Cancer classification purpose, it becomes more difficult for cardiologists. The false positive reduction in lung nodule detection is challenging job often as the lung nodules are 3D and are having a wide variation in sizes and shapes. A kind of Artificial Neural Network i.e. Convolutional Neural Network is proposed in this paper to reduce false positives in lung nodule detection.. The proposed approach is an end-to-end approach which indicates there is no manual feature extraction. The samples used in this model are all given from the original CT images only. Data augmentation techniques like Rotations, ZCA whitening, Shifting, Zooming, Flipping and many more is done for replication of the data. The experiment results show that as a single CNN algorithm i.e. VGG 16 by applying 3 layers using transfer learning gives the good performance which greatly simplifies the detection process of lung nodules.

A 3D CNN model should be taken into consideration in our future study because the 2D CNN method has limitations in terms of obtaining contextual information between slices of the nodule. Some types of nodules in the LUNA - 16 dataset are not fully represented or highlighted, which could result in erroneous nodule identification. So, preprocessing should be performed before training will help identify these candidates. Incorporation of a fully-automated nodule classification scheme which can automatically detect the nodule candidates or locations. As the size of the LIDC-IDRI dataset is a limitation for training the algorithms as many hyper parameters in each layer require very large datasets to obtain good training results. In the LUNA16 dataset, only 543,381 of the 551,065 candidates were successfully cut out in the size of 18 18 18, indicating that some other candidates are too close to the edge to be cut out and should be carefully considered. Additionally, it would be beneficial to learn models that would automatically reject the decisions with the highest degree of uncertainty. Additionally, to enhance the lung categorization system's effectiveness by examining the connections between various points of view. The robustness of medical image analysis needs to be improved CNN.

APPENDIX

#importing the Libraries

```
import os
import numpy as np
import pandas as pd
from PIL import Image
import keras
from matplotlib import pyplot as plt
import matplotlib
import PIL
from PIL import Image
import glob
import tensorflow as tf
from tensorflow.keras.layers import Dense, Flatten, Dropout, InputLayer
from tensorflow.keras.models import Sequential, Model, load_model
```

#Loading Dataset

```
directory_path = r'D:\LUNA16\classsification'
images = []
image_labels = []
image_height = 48
image_width = 48
train_df = pd.read_csv('D:\LUNA16\classsification\Train.csv')
for index in range(train_df.shape[0]):
    data = train_df.iloc[:, :].values
np.random.shuffle(data)
```

```
    # For Image
        images = data[:, 1:]
    # For Labels
        labels = data[:, 0]
image=[]
for filename in images:
    print(filename)
    for i in filename:
        print(i)
        print(type(i))
```

#Reshaping the data

```
img_array = np.load(i, allow_pickle=True)
img_array=img_array.reshape(192,192,3)
image.append(img_array)
print(type(labels))
img = np.array(image)
image_labels = np.array(labels)
```

#Splitting the data

```
from sklearn.model_selection import train_test_split
X_train, X_val, y_train, y_val = train_test_split(img, image_labels, test_size=0.2)
```

#VGG16 Model

```
from tensorflow.keras.applications import vgg16
vgg16_model = vgg16.VGG16(weights = "imagenet", include_top = False,
input_shape=(192,192,3))
for layer in vgg16_model.layers:
layer.trainable = False
```

```
x = vgg16_model.output
x = Flatten()(x)
x = Dense(units = 512, activation = "relu")(x)
x = Dropout(rate = 0.25)(x)
x = Dense(units = 256, activation = "relu")(x)
output = Dense(units = 43, activation = "softmax")(x)
vgg16_modified_model = Model(inputs = vgg16_model.input, outputs = output)
vgg16_modified_model.compile(
    optimizer="Adam",
    loss = "sparse_categorical_crossentropy",
    metrics = ["accuracy"]
)
vgg16_modified_model.summary()
```

OUTPUT :-

```
Model: "model"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input_1 (InputLayer)        [(None, 192, 192, 3)]     0

 block1_conv1 (Conv2D)       (None, 192, 192, 64)      1792

 block1_conv2 (Conv2D)       (None, 192, 192, 64)      36928

 block1_pool (MaxPooling2D)  (None, 96, 96, 64)        0

 block2_conv1 (Conv2D)       (None, 96, 96, 128)       73856

 block2_conv2 (Conv2D)       (None, 96, 96, 128)       147584

 block2_pool (MaxPooling2D)  (None, 48, 48, 128)       0

 block3_conv1 (Conv2D)       (None, 48, 48, 256)       295168

 block3_conv2 (Conv2D)       (None, 48, 48, 256)       590080

 block3_conv3 (Conv2D)       (None, 48, 48, 256)       590080
```

```
block3_pool (MaxPooling2D)  (None, 24, 24, 256)      0

block4_conv1 (Conv2D)       (None, 24, 24, 512)      1180160

block4_conv2 (Conv2D)       (None, 24, 24, 512)      2359808

block4_conv3 (Conv2D)       (None, 24, 24, 512)      2359808

block4_pool (MaxPooling2D)  (None, 12, 12, 512)      0

block5_conv1 (Conv2D)       (None, 12, 12, 512)      2359808

block5_conv2 (Conv2D)       (None, 12, 12, 512)      2359808

block5_conv3 (Conv2D)       (None, 12, 12, 512)      2359808

block5_pool (MaxPooling2D)  (None, 6, 6, 512)        0

flatten (Flatten)           (None, 18432)            0

dense (Dense)               (None, 512)              9437696

dropout (Dropout)           (None, 512)              0

dense_1 (Dense)             (None, 256)              131328

dense_2 (Dense)             (None, 43)               11051

=================================================================
Total params: 24,294,763
Trainable params: 9,580,075
Non-trainable params: 14,714,688
_________________________________________________________________
```

X_train = np.asarray(X_train).astype(np.float32)

y_train = np.asarray(y_train).astype(np.int32)

X_val = np.asarray(X_val).astype(np.float32)

y_val = np.asarray(y_val).astype(np.int32)

#Training the Model

epochs = 20

```
history = vgg16_modified_model.fit(X_train, y_train, validation_data=(X_val, y_val),epochs =
epochs, batch_size = 32)
```

OUTPUT :-

```
Epoch 20/20
132/132 [==============================] - 445s 3s/step - loss: 0.2395 - accuracy:
0.9000 - val_loss: 0.3125 - val_accuracy: 0.8705
```

```
vgg16_modified_model.save("VGG16new2.h5")

test_df = pd.read_csv('D:\LUNA16\classsification\Test2.csv')

for index in range(test_df.shape[0]):

        data = test_df.iloc[:, :].values

np.random.shuffle(data)

    # For Image

        fig = data[:, 1:]

    # For Labels

num = data[:, 0]

fig1=[]

for filename in fig:

    print(filename)

    for i in filename:

        print(i)

        print(type(i))

img_array = np.load(i, allow_pickle=True)

img_array=img_array.reshape(192,192,3)

        fig1.append(img_array)

X_test = np.array(fig1)

X_test = X_test/255.0

X_test = np.asarray(X_test).astype(np.float32)

from keras.models import load_model

model=load_model("VGG16new2.h5")
```

```
y_pred1 = np.argmax(model.predict(X_test), axis=1)

print(y_pred1)

from sklearn.metrics import classification_report

from sklearn.metrics import accuracy_score

print("Accuracy Score:")

print(accuracy_score(y_pred1, y_test1) *100)

print(classification_report(y_pred1, y_test1))
```

Accuracy Score:
89.84198645598194

	precision	**recall**	**f1-score**	**support**
0	0.92	0.83	0.90	257
1	0.81	0.99	0.89	186
accuracy			0.90	443
macro avg	0.90	0.91	0.90	443
weighted avg	0.92	0.90	0.90	443

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