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False Positive Reduction of Lung Nodule Detection Using Deep Learning Techniques

P.Deepika, T. Prasanth, T. Dileep, Y. Ramu, R. Tanmayi

B. Tech, Department of CSE, GMR Institute of Technology, Rajam. Andhra Pradesh, India

ABSTRACT :

Lung cancer is among the most prevalent illnesses worldwide. One of the most prevalent malignancies that cannot be neglected and can result in death with inadequate medical attention is lung cancer.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 identify lung cancer in its earliest 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. Due to the heterogeneity of lung nodules in CT scans, including their varying size, shape, and texture, as well as their significant visual similarity between positive and negative lung nodules, there are certain causes for false-positive nodule identification. 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 medical CT scans used in the screening for lung cancer. It has an MHD format (.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, Deep Learning, Accuracy, False Positive.

I. INTRODUCTION

The key signs of lung cancer, which is the largest cause of cancer fatalities, are pulmonary nodules, abnormally growing lung tissue with a diameter of 3 mm to 30 mm. Lung nodule detection is one of the best means for screening at the early stages and diagnosis of lung cancer. One or more nodules will be present in the patient with lung nodules. Between 100 and 400 lung slices, the nodules frequently occupy only few pixels, making manual detection more challenging.Radiologists will have less burden to do when using an automated lung nodule detection method instead of manually diagnosing a large number of CT images.Generally, nodules take up a lot less space than the complete lung slice.There are typically two processes in the automated lung nodule detection system. First one is Nodule detection and second one is false positive reduction.The first process detection is that the suspicious lung nodules were found after a significant number of CT slices were analysed.This aids in the candidate's detection which also includes the significant number of false positives along with the actual nodules in the detection findings. False positives are nodules that look similar to real nodules.As can be seen, false positives seem like real nodules but frequently contain lymph nodes, blood arteries, or other structures.For complete nodule detection, the false positive reduction is carried out for the above reason.As accurately as possible,itseeks to differentiate candidates' actual nodules from fake nodules.

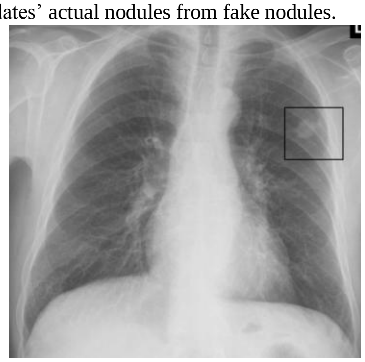

Fig1. Pulmonary Nodule

Cancer is one of the most threateningproblems in the world.One of the most prevalent cancers is lung cancer, 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, thatit eliminated over a quarter of all cancer-related fatalities. Lung cancer has a high death rate since its symptoms do not appear until the disease has advanced to its terminal stage.So if one has a reason to thing that they may have lung cancer, there are lot 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. An abnormal lump or nodule may be seen on an X-ray of the lungs as a result. However, a CT scan can identify minor lung lesions that an X-ray would miss.

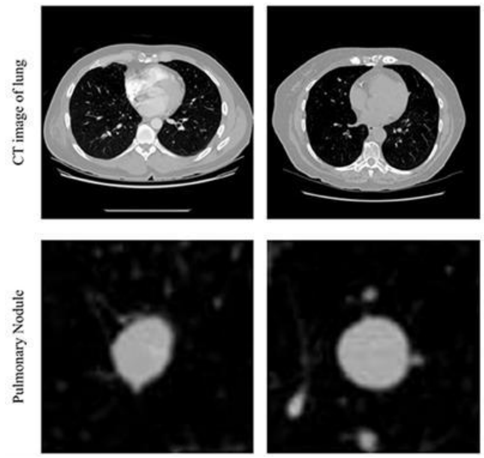

Fig2. CT images in lung and pulmonary nodule

Cancer is one of the most threatening health 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 amid 100 to 400 lung slices, frequently takes up only few pixelsof CT scan which makes manual detection more difficult. So to make it easier it is better to create a technique for detecting pulmonary nodules. 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.

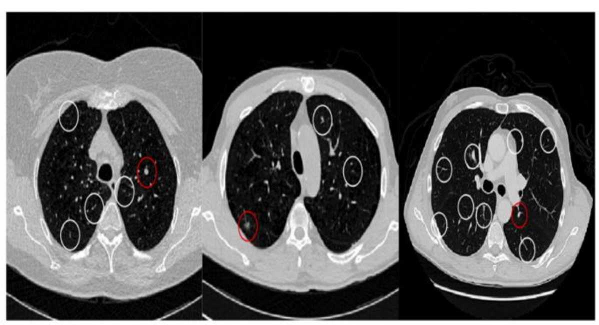

Fig3. Complete axial slices with nodules in red circles and non-nodules in white circle

As we pretty well know that the deep learning algorithms are bringing a noticeable changesthese days bysolve various problems in medical imaging fields.Various computer vision-related tasks including classification and segmentation are recent examples of deep learning applications in medical image analysis. Different medical imaging modalities can be employed for a variety of clinical applications because of their distinctive properties, varying responses to human body structure, and responses to organ tissue. In the clinic, projection imaging techniques like X-ray imaging, computed tomography (CT), ultrasound imaging, and magnetic resonance imaging are widely utilised for diagnosis. 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. The most extensively studied deep learning algorithms in the examination of the medical industry are CNNs.Rectified Linear Unit (RELU), pooling, and convolutional layers are used by CNNs to alter raw input images of pixels. Finally, these are sent into a fully connected layer that assigns class probabilities and sorts the input into the class with the highest probability.

Mittapalli and et al.,**[1]**proposed 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 reveals that there were many False Positives (FPs) removed during the first screening process, which are similar to the comparatively few True Positives (TPs), or cases of nodules, that are present. The dataset used is LUNA16 .In the preprocessing step, the voxel spacing, intensity normalisation, and lung region segmentation are modified. With a Competitive Performance Metric (CPM) score of 0.948, it has achieved success.

Zuo and et al.,**[2]**focused on 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). Despite being made out of blood arteries, lymph nodes, or other lesions, false positives look a lot like real nodules.In order to overcome misidentification issues brought on by a lack of spatial correlation information derived from conventional techniques or 2D networks, it learns the whole and three-dimensional discriminative information about nodules and non nodules. LUNA -16 dataset was used. A score of 0.9783, 0.8771, 0.9426, and 0.9925 were achieved for accuracy,sensitivity, precision, and specificity.In terms of the Competition Performance Metric (CPM), the result is 0.83.

Zhu and et al.,**[3]** proposed aMulti-ringed (MR) Forest framework to detect false nodules from total data. The LUNA16 Challenge dataset as well as data from the Affiliated Hospital of Liaoning University of Traditional Chinese Medicine (AHLUTCM) 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 reduces false positives using a form of target propagation by using a multi-ringed boosting cascade decision tree ensemble.CPM score of merged dataset is 0.865 and LUNA16 is 0.910.

D. A. B. Oliveira and et al.,**[4]** proposed aConvolutional 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 those given using typical 2D cross sections and comparable to those delivered by 3D CNNs utilising 16 times less data and operating at a 4x faster rate. This model has a 91.5%, 92.5% accuracy and precision.

R. Nagata and et al.,**[5]** presentedaAutomated detection of lung nodules in chest radiographs as it is vital to eliminate false negatives in the diagnostics of lung cancer using chest radiography. The JSRT database, which is a public database, has 125 photos with nodules.The two processes in this technique are the initial nodule candidate detection in chest radiographs and the classification of the discovered candidates as nodules and false positives.Numerous approaches used multilayer artificial neural networks (ANNs) trained by back-propagation for the classification of nodule candidates.False positives per image for the average of 40 data points with sensitivity sof 60.2, 69.8, and 74.5%.

Saien S and et al.,**[6]** proposed 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 scans from the LIDC and LIDC-IDRI databasesFollowing the discovery of nodule candidates, the 3D region of each candidate is reconstructed using the sparse field technique (SFM), which precisely segments objects.For each segmented candidate, several pertinent 2D and 3D features are then extracted.A classifier is then used to analyse the features and distinguish between actual nodules and non-nodules.The metrics used in this are sensitivity, specificity, FP score, AUC score.

Manickavasagam R and Selvan S**[7]**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 utilized to locate the lung nodules and stage classifications. Through the use of a consistency-based hierarchical feature selection technique, the texture features are retrieved and their best discrimination for a limited classification rate is obtained. The suggested model produced an accuracy of 95.3 and sensitivity of 92.1 which are higher than the values of GLCM with SVM Classifier.

Mundher Al-Shabi,Hwee Kuan Lee and Maxine Tan**[8]** had given in their publications saying that to classify nodules whether they are malignant or benign, they had proceed with a novel CNN architecture named Gated-Dilated networks. The dataset used is LIDC-LDRI.The nodules are between 3 to 30 mm upon which they worked. 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.

Rebecca L. Russell, and Andrew A. Berlin **[9]** had given in their publications saying that for lung cancer screening, they had presented a novel computer detection and diagnosis system by using the 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.

H. Tang and et al.,**[10]** proposed a Novel method where nodule candidate screening and false positive reduction are combined into an end-to-end architecture that was trained together.The first subsystem in this framework uses the 3D Nodule Proposal Network and subsequent nodule candidate classification for false positive reduction to differentiate between nodules and non-nodules.It makes use of the dataset from the Tianchi Competition, which consists of 800 CT scans from 800 patients with publicly available ground truth labels.By removing one third of the parameters from the corresponding two-step model, it minimises model complexity.The end-to-end system is outperformed by the two-state approach in terms of performance, with nodule detection accuracy rising by 3.88%.When compared to the prior state-of-the-art, separate two-stage nodule identification model without model ensemble, it boosts CPM by 3.88%.

Y. qin and et al.,**[11]**reported a computer-aided diagnostic (CAD) system that simultaneously reduces false positives and allows for reliable lung nodule detection.A comprehensive 3D CNN model and 3D U-Net architecture serving as the framework of a region proposal network(RPN) were used to produce candidate nodules.By using online hard negative example mining and multi-task residual learning to speed up the training process, it increases the nodule identification algorithm's accuracy.The weighted binary cross-entropy (WBCE) loss is used for classification problem due to the imbalanced nodule dataset.The datasetis LUNA16 that includes the lung CT scans. This method achieves accurate detection of pulmonary nodules while reducing false positives.

Y. Han and et al.,**[12]** To prevent lowering the sensitivity of nodule detection, an effective multibranch false positive reduction network is constructed.The grayscale history image (GHI) of the candidate nodules in multi-view is utilised as the input to the false positive reduction network after the 3D U-NET model, which is used to detect small pulmonary nodules during physical examination.Some data augmentation techniques, such as rotation and scaling are employed to lessen overfitting.Lung nodules from physical examination (LNPE1000) 1,000 samples are obtained, with nodules having an average diameter of 5.3 mm.With each CT confined with 0.25 and 0.45 false positive,the suggested method's sensitivities are 79.9% and 85.8%.

It will be helpful for doctors in clinical diagnosis to improve the efficiency.

Zhu'sand et al.,**[13]** focus was on the issue of standard lung nodules detection methods' low sensitivity and high rates of false positives.This article proposes an ensemble of convolutional neural network (E-CNN) framework and uses it to decrease the amount of false positives for the detection of lung nodules in chest radiography (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.Ensembling of differrnt CNNs can perform far better than the single CNN because a single CNN fails in extracting the essential features. Henceensembling of CNNs of different input scales-CNN1, CNN2, CNN3 is presented in this work. Without ensmbling the sensitivity is 57% whereas ensembling gives 84% on Japanese Society of Radiological Technology database .

Cao and et al.,**[14]**worked mainly to reduce false positives in lung nodule detection which takes place due to differences in lung nodules. Multi Branch Ensemble Learning method is presented which is a 3D neural network. VggNet, ResNet, InceptionV1 (IncepV1),Inception-V3 (IncepV3), InceptionResNet (IResNet) and DenseNet are the 6 architectures used in this paper among them 3D-VggNet,3D-InceptionResNet and 3D-DenseNetare been selected after experimentation. And it worked on LUNA16 dataset.

In Huang and et al.,**[15],**3D convolutional neural network CNN for lung nodule identification is reported.They use a local geometric model-based filter to produce false nodules, and they estimate the local orientation to further limit the variability of the structure.Additionally, the outcomes demonstrated the superiority of 3D CNN over 2D CNN for volumetric medical picture processing.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.

Chen and et al.,**[16]**to address the issues with deep convnet training, they suggested Lung Dense Neural Network (LDNNET) is an adaptive architecture based on convnets combining softmax classifier.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 have to be done during the earlier stage of lunge cancer diagnosis. LDNNET used data augmentation, thick connections, and dropout layers to lessen overfitting.Both the database KAGGLE DATA-SCIENCEBOWL-2017 (Kaggle DSB 2017) and the dataset LUNG Nodule Analysis 2016 (LUNA16) are used to classify lung nodules and lung cancerrespectively.LUNA16's accuracy, specificity, and sensitivity are 0.988396, 0.994585, and 0.982072, while Kaggle DSB 2017's are 0.999480, 0.999652, and 0.998974.The AUC for the two datasets is approximately 98%.

In Wangand et al.,**[17]** The vessel probability is measured by tubular-like features that can distinguish between different perspectives in an unique vessel segmentation method that is proposed to reduce false positives (FPs).Lung nodule malignancy levels can be distinguished using a variety of radiographic features, such as size, margin, nodular calcification, and nodular cavitation.Feature Extraction like Regions of Interest (RoI) Clustering, Edge Feature Extraction, Text Feature Extraction is done for better performance. Dataset used is LIDC.The edge features of the spatial outline are extracted using an edge orientation histogram (EOH), and the texture features of the samples of density distribution are extracted using a multi-scale path LBP (MSPLBP). 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. 78.14% on average for F1 Score and 0.8149 for AUC under PR curves.When analysing a CT set for classification of malignancy, it had an average accuracy of 95.88% and took an average of 176.26 seconds.

Cao and et al.,**[18]** suggested a Two-Stage Convolutional Neural Networks (TSCNN) for the detection of lung nodules.The improved U-Net segmentation network is established as an initial detection of lung nodules. By including the residual dense mechanism, this enhances the U-Net based segmentation network for recognising candidate nodules.A dual pooling structure is built into three 3D-CNN classification networks for false positive reduction.Dataset used is LUNA dataset.It created a sampling method for the nodule and used the U-Net segmentation architecture based on the ResDense structure to roughly find nodules.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%.

Zhangand et al.,**[19]**propseda 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 pictures utilised in this experiment came from the databases of the image database resource initiative (IDRI) and the lung image database consortium (LIDC).Our ML-CNN obtains 84.8% classification accuracy. For CNN-based lung nodule classification, MV-CNN uses multiple views as input channels, and it achieves binary and ternary classification accuracy of 94.59% and 86.09% respectively.

Aliand et al.,**[20]**centred on classifying lung nodules using SVM and AdaBoostM2 classifiers.Deep features from state-of-the-art DCNN models like VGG-16, VGG-19, ResNet-18, ResNet-50, ResNet-101, Google LeNet, Inception ResNet-V2 and Inception-V3 were used to classify lung nodules.On the LUNGx challenge dataset, a thorough performance evaluation of the SVM and AdaBoostM2 classifiers based on deep features was conducted.Dataset used is LUNGx dataset. After obtaining medical photos from the LUNGx database, simple image pre-processing techniques are used for contrast enhancement. Each DCNN's features are taken out and used to train the SVM and AdaBoostM2 classifiers.For ResNet-101 and GoogLeNet, the classification accuracy has grown from 76.88% to 86.28% and 67.37% to 83.40%, respectively.

Aliand et al.,**[21]** I was informed that lung nodules are important signs of lung cancer. It proposed transferable texture Convolutional Neural Networks (CNN) to improve the classification performance of pulmonary nodules in CT scans. In our method, an Energy Layer (EL) is used to extract textural characteristics from the convolutional layer. Nine layers make up the overall suggested CNN architecture for automatically extracting features and classifying potential lung nodule cancers as benign or malignant.On the LIDC-IDRI database, the training was carried out successfully using six times of cross-validation, yielding results for accuracy, recall, specificity, AUC, and error rates of 96.69%, 96.05%, 97.37%, and 3.30%, respectively.For accuracy, recall, specificity, and AUC score on the LUNGx database, our proposed texture CNN without TL (trained from start) achieved classification scores of 86.14%, 88.76%, 93.11%, and 92.63%.

Zhaoand et al.,**[22]**noted that a critical step in pulmonary nodule diagnosis is the minimization of false positives,So, false positive reduction is the main topic of this study.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 study offered a unique multiscale CNNs approach for reducing false positives in automatically detecting lung noduleswhich focuses on training time and accuracy. Three separate orthogonal 2D pictures were cropped instead of 3D CT cubes to preserve spatial information and reduce training time.A sensitivity of 95.2% and a specificity of 98.1% were achieved by the suggested multi-scale CNNs on the LUNA16 dataset.

Sunand et al.,**[23]**stated that due to heterogeneity and similarity of pulmonary nodules, there will be many chances of false positives in lung nodule detection. In order to get more representative properties of nodules for false positive reduction, a novel attention-embedded complementary stream convolutional neural network AECS-CNN is suggested in this research.Three functional blocks make up the proposed network: a block for classification, a complementary-stream block with an attention module for feature integration, and a block for attention-guided multi-scale feature extraction.Due to changes in nodule sizes, the network's inputs are multiscale 3D CT volumes. To obtain more contextual information about the nodules, a progressive multiscale feature extraction block with an attention module was then deployed. The proposed model achieved a sensitivity of 0.92 upon on LUNA16 dataset.

Drokinand et al.,**[24]** worked on a unique method for computer-aided detection (CAD) nodule candidate false-positive reduction (FPR).The suggested method utilises point cloud deep learning models and views input data as a point cloud rather than a 2D or 3D image, and uses deep learning models for point clouds. As opposed to conventional CNN 3D, point cloud models are faster during training and inference, need less memory are the focus of this paper.The baseline CNN 3D models are outperformed in experiments using PointNet, PointNet++, and DGCNN.The results reveal a baseline 3D CNN model on LUNA16 to have a FROC of 77.26 and a FROC of 85.98.

Shukla and et al.,**[25]**to detect lung nodules, they suggested a 2D SqueezeNet and 2D MobileNet Model.DNN is used which made the model lighter and uses less memory.It makes use of the LUNA 16 dataset, which is a collection of medical CT images of lung cancer.Mhd and raw are the image file formats. The dimensions of the images are 512 x 512.Pre-processing of images, segmentation, pre-processing of data, augmentation of data, model building, and network layers are the essential steps in the detection process.This unit of measurement is -500 HU for lung tissue, -1000 HU for air, 700 HU for bone, and 0 HU for all other tissues and blood. It not only satisfies the accuracy criteria, but also the Sensitivity and Specificity.

Xieand et al.,**[26]**to distinguish between malignant and benign nodules utilising the restricted data from chest CT images, a multi-view knowledge-based collaborative (MV-KBC) deep model was proposed. The LIDC-IDRI database in the Cancer ImagingArchive (TCIA) contains 1018 clinical chest CT scans withlung nodules obtained from seven institutions. In order to train a KBC submodel that has already been pre-trained using three ResNet-50 networks, the OA, HVV, or HS patches that were taken from each of the nine views of planes were combined with the enhanced data.Lung nodules are classified using an adaptive weighting by backpropagation by the networks that categorise the nodules into voxel and shape heterogeneity.The OA, HVV, and HS patches are the feature maps that were learned from the three different input image patch types.With an AUC of 95.70%, the lung nodules are classified by the MV-KBC model with an accuracy of 91.60%.

Mobiny'sand et al.,**[27]** work,Deep capsule network architecture and an LSTM controller with an external memory bank are the two sub modules that make up the MemoryAugmented Capsule Network (MEMCAP), which has been proposed.MEMCAP model uses the ADAM as aOptimizer. Three different datasets of CT images are collected are LUNA16, Incidental Lung Nodule Dataset and collected lung nodule dataset.Metalearning is used to train the MEMCAP model for domain adaptability in classification of lung nodules from CT scans. The decoder network then reconstructs the input from the final capsules, decreases the possibility of over-fitting by acting as a regularizer in an efficient manner.The MEMCAP technique classifies lung nodules with an accuracy of 84.7% and 89.1%. The MEMCAP architecture scores 84.1% and 90.2 on the AUROC scale.

Zuoand et al.,**[28]** presented a study that deals with candidate classification in lung nodule detection even with the variable sizes of lung nodules. The suggested model is a multi-resolution convolutional neural network (CNN), which extracts characteristics at various levels and resolutions from various depth layers in the network for the classification of lung nodule candidates. The classification of lung nodule candidates in this article used the knowledge transfer method.This improves the model to a new multi-resolution model that is suitable for the image classification task by transfer learning from the source CNN model that has been used for edge detectionOn the LUNA 16 dataset, the model classified lung nodule candidates with an accuracy of 0.9733, precision of 0.9673, and AUC of 0.9954.

Zhaiand et al.,**[29]** proposed a multi-task convolutional neural network (MT-CNN) framework to identify malignant nodules from benign nodules on chest CT scans.To automatically find pulmonary peri-fissural nodules, Ciompi et al. developed an ensemble classifier.Based on numerous 2-D pictures of the nodules, they categorised the nodulesand obtained AUC of 86.6%. Based on a mix of LeNet and AlexNet, Zhao et al. suggested a new agile CNN framework to deal with the difficulties of a small-scale medical picture library and the small size of the nodules and achieved an AUC of 87.7%. Anyhow, the above models cant deal with 3D images whereas with the merging of many 2-D models, the suggested architecture may learn the 3-D spatial information of nodules.The model has the maximum UAC (95.59%) in LIDC-IDRI and the highest AUC (97.3%) and specificity (96.8%) in LUNA-16.

In Ali'sand et al.,**[30]**work, to enhance the CAD system's classification performance, a decision level fusion technique for lung nodule classification has been developed.It assessed the effectiveness of Support Vector Machine (SVM) and AdaBoostM2 which got trained on the deep features extracted from some state-of-the-art transferable architectures. In this study, the most recent transferrable architectures were VGG-16, VGG-19, Google LeNet, 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. All DCNNs, with the exception of RestNet-101, showed good AdaBoostM2 performance on the features derived from last completely connected layers.The proposed method's accuracy resulted in a score of 90.46 upon available LUNA16 challenge dataset.

II. METHODOLOGY

An approach that is iterative and use different combinations of true and false positives to train the MCNN-CF model.And it performs 3D convolution calculations using 3D volumes as the input, which is a more efficient way to handle the spatial information of nodules. MRForest is an effective replacement for automated pulmonary nodule detection systems, satisfying both resource consumption and effectiveness.It has presented an efficient multi-scale data representation method for lung nodule false positive reduction using convolutional neural networks. It has proposed an Automated detection of lung nodules in chest radiographs using a false-positive reduction scheme based on template matching.An integrated strategy based on sparse field level sets and boosting algorithms to reduce false positives in the diagnosis of lung nodules.Also some proposed a GACM Gradient based Active Contour Model for segmenting the lung region from CT images and also a novel CNN architecture called as Gated-Dilated networks to classify nodule as benign or malignant. Some focused on a new computer aided detection and diagnosis system for lung cancer screening with low-dose CT scans that is based on 3D convolutional neural networks.Incorporating nodule candidate screening and false positive reduction into a single model, it had developed an end-to-end framework for nodule detection.It suggests a computer-aided diagnostic (CAD) method for expedient lung nodule detection and decreased false positive rates.It suggests developing a multi-branch, effective false positive reduction network to prevent lowering the sensitivity of nodule identification.An ensemble of convolutional neural networks is proposed in this article (E-CNNs) for false positive reduction of lung nodules. A Multi-Branch Ensemble Learning architecture based on the three-dimensional convolutional neural network is also suggested.Some focused on Proposed a computer-aided detection system that uses 3D convolutional neural networks for detecting lung nodules in low dose CT.

III.CONCLUSION

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. Due to the 3D nature of the lung nodules and their vast range of sizes and forms, reducing false positives in lung nodule detection is frequently a difficult task. In order to decrease false positives in lung nodule detection, the Convolutional Neural Network type of Artificial Neural Network is proposed in this research. Since the suggested approach is end-to-end, there is no need for manual feature extraction. All of the samples in this model were taken directly from the original CT images. Data augmentation techniques like Rotations, ZCA whitening, Shifting, Zooming, Flipping and many more is done for replication of the data. As a single CNN algorithm, the experiment's findings demonstrate i.e. VGG 16 by applying 3 layers using transfer learning gives the good performance which considerably streamlines the identification of lung nodules.

IV. FUTURE SCOPE

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.

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