Lung Nodule Classification using Deep 3D Residual with Multi Kernel Combined Attention Network (D3DR_MKCA)

S.Parveen Banu [1], Dr.M.Syed Mohamed [2]

[1] *Research Scholar, Reg.No.19111252272008, Dept. of IT, Sri Ram Nallamani Yadava College of Arts and Science, (Affiliated to Manonmaniam Sundaranar University,Abishekapatti, Tirunelveli-627012,Tamilnadu,India),Tenkasi,Tamilnadu.*

[2] *Asst.Professor, Dept. of IT, Sri Ram Nallamani Yadava College of Arts and Science, (Affiliated to Manonmaniam Sundaranar University, Abishekapatti,Tirunelveli-627012,Tamilnadu,India)*

[1] jesima83@gmail.com , [2] seyadumohamed@gmail.com

Abstract

Lung cancer is the cancer that spreads the fastest and is typically detected at an advanced stage. It may cause death with late diagnosing and improper treatment. A computer-aided detection method is required to categorise the lung nodule with the greatest degree of accuracy in order to avoid delays in diagnosis due to advancements in medical imaging methods like computed tomography (CT) scans. This study proposed a novel architecture D3DR_MKCA based on Deep Residual network incorporating convolutional block attention module (CBAM) which applied on different scale feature maps to classify lung nodules. CBAM improves the representation power of Residual Network. Initially lung nodules are efficiently segmented with the help of Location Aware Encoding Network and those segmented nodules are further classified into Adenocarcinoma, Small Cell Carcinoma, Large Cell Carcinoma, and Squamous Cell Carcinoma cancerous tissues with the help of proposed D3DR_MKCA deep architecture. A Large-Scale CT and PET/CT Dataset for Lung Cancer Diagnosis (Lung-PET-CT-Dx) are used for performance analysis and the D3DR_MKCA model archives F1-score up to 90.96%.

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1. Introduction

Lung cancer has been identified as one of the leading causes of mortality worldwide [1]. According to a World Health Organization (WHO) report, lung cancer was the second highest cause of death on 2020. Lung cancer cases increased more than 2.2 million in 2020.Cigarette smoking causes around 85 percent of lung cancer cases in men and 75 percent in women. The typical survival duration for advanced lung cancer is about only 12 months, despite numerous radiotherapy and chemotherapy treatments. However, early lung cancer diagnosis and proper treatment can significantly prevent deaths and improve the survival rates of patients. Lung nodules are tiny tissue lumps that might be cancerous or noncancerous, commonly referred to as malignant or benign. Malignant tissues develop quickly and can spread to other regions of the body, posing a health risk, whereas benign tissues are non-cancerous and do not grow rapidly.

Classifying lung nodules in a timely and correct manner is critical for the clinical treatment. There are various types of pictures utilized in medical imaging, but CT scans are often preferred since they produce less noise. However, manually reviewing such pictures can take a long time, and the correctness of the outcome is heavily dependent on radiologists' proficiency and experience. Hence automated lung cancer classification methods are highly demanded. Deep learning [2] has made significant progress in the field of Computer-Aided Diagnoses (CAD), such as medical image analysis [3], medical image segmentation [4], and medical image classification [5], among other things. Deep-learning-based CAD systems might aid physicians by providing second opinions and alerting those to potentially dangerous regions in their patient data. Many researchers have proposed several sorts of deep learning architectures to classify lung cancer.

This present study focus on lung nodule classification task, that is determine whether the patient's lung nodule is malignant and its type of cancerous tissues such as Adenocarcinoma, Small Cell Carcinoma, Large Cell Carcinoma, and Squamous Cell Carcinoma based on deep learning approaches. Initially the nodules are segmented from CT slice by Location Aware Encoding Network [6] and then the classification framework is applies for lung nodules. Classification of lung nodule is done based on a proposed deep residual network. This study also employs the convolutional based attention module (CBAM) in the proposed networks to support the network diagnosis procedure. The visual patterns and symptom descriptions will be characterized by the attention modules in CBAM. Convolutional block attention module (CBAM) is a strategy to improving the representation power of deep residual network. Two independent modules channel and spatial are used to apply attention-based feature refinement and obtain significant performance improvements while keeping the overhead low. The proposed design incorporates the learning capabilities of Residual network with Scale Integrated Alternate Link Model (SIAL-CNN) [7] and feature map and location based attention mechanism as Deep 3D Residual with Multi Kernel Combined Attention Network (D3DR_MKCA).The block diagram of the proposed work is shown in Figure 1

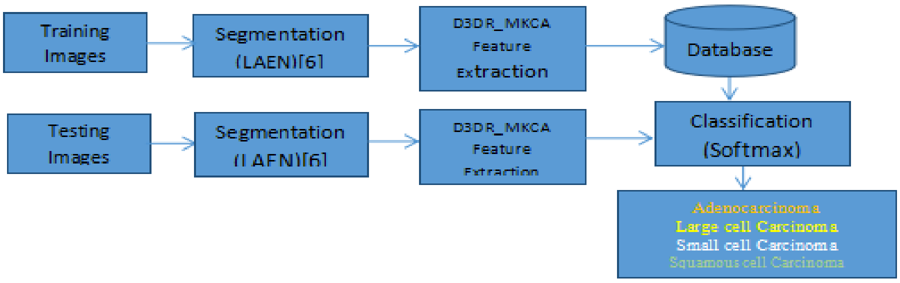


Figure 1: Block Diagram Lung nodule Segmentation and Classification

The main contribution of this work is summarized as follows:

1. Developed a novel architecture D3DR_MKCA based on Deep Residual network incorporating convolutional block attention module (CBAM) which applied on different scale feature map is proposed to classify lung nodules. CBAM improves the representation power of Residual Network.
2. Lung nodule classification accuracy is improved significantly compared to the traditional models.

2. Related Work

Many efforts were presented to increase the performance of automated systems when the trend shifted from lung nodule classification in the clinical context to the usage of pattern descriptions with expert expertise. Earlier approaches were used low level features to differentiate benign from malignant lesions. Sang Cheol Park et al. [8] used a genetic algorithm to pick the best imaging features for Interstitial Lung Disease (ILD) patients. Parveen et al. [9] have proposed an automatic system for lung nodule detection. Region growing and threat pixel identification methods are used to segment the image. Followed by segmentation, GLCM method is used to extract features. Lastly SVM with three kernels are applied for classify benign and malignant classes.

SurenMakaju et al. [10] used watershed segmentation algorithm to segment the input picture. After that, features for the segmented cancer nodules are recovered utilizing area, eccentricity, perimeter, diameter, centroid, and pixel mean intensity. Finally, a Support Vector Machine (SVM) was used to classify cancer nodules (SVM). Traditional computer-aided detection systems based on machine learning have low classification accuracy. Many earlier research extracted low-level data from lung nodule CT images as a step before classification, but convolutional Neural Networks can learn all of the deep features without the need of other techniques. CNN-based algorithms have recently shown promising results in the segmentation and classification of lung nodule CT images.

Kaviarasu et al. [11] proposed a new approach for lung segmentation using K-means clustering technique (K-CT) incorporated with Fuzzy C-means algorithm to improve diagnostic performance. Shen et al. [12] was developed a multi-crop CNN model for lung nodule classification that can extract significant nodule information automatically by cropping different areas from convolutional feature maps and performing max-pooling at different times. Van Ginneken et al. [13] have developed a novel pulmonary nodule detection system. They used 4096 off-the-shelf features, which are extracted from the pretrained OverFeat model and Linear Support Vector Machine (SVM) is used to detect lung nodule in CT images. For lung nodule classification, Jia Ding et al., 2017 [14] developed an architecture based on R-CNN with Deconvolutional structure and the first five groups of VGG-16 layers. After that, 3D DCNN is used to lower the false positive rate. Nibali et al. [15] have proposed the ResNet-18 network structure for lung nodule classification that merged a residual network, course learning, and migration learning. On test samples taken from the LIDC-IDRI dataset, a classification accuracy of 89.9% was achieved. Asuntha et al. [16] have proposed a new deep learning model to detect the lung nodules. The feature descriptors like Local Binary Pattern (LBP), Histogram of oriented Gradients (HoG), Scale Invariant Feature Transform (SIFT), wavelet transform-based features and Zernike Moment are used to extract features. For selecting the optimal feature, the Fuzzy Particle Swarm Optimization (FPSO) method is used. Classification is done using Deep learning methods. A novel FPSOCNN is used to reduce computational complexity of the network.

Sangamithra et al. [17] have proposed a four stage model for lung tumour detection. Median filter and wiener filter is employed to preprocess the input image followed by segmentation is done by using EK-mean clustering method. Gray-level co-occurrence matrix (GLCM) is applied to extract features from the segmented images. The Back Propagation Network (BPN) is used to classify lung cancer. Song et al. [18] have designed lung nodule classification using three different networks including Convolutional Neural Network (CNN), Stack Auto Encoder (SAE) and Deep Neural Network (DNN). Zhu et al. [19] employed 3D deep dual path networks (DPNs) and a variety of auxiliary features.Hua et al.[20] have proposed a deep belief network (DBN) and CNN to classify lung nodules, and achieved better results with deep architecture.

Liang et al. [21] have introduced a novel filtering technique to classify lung nodule that remove extraneous images and reduce the false-positives. Second, Faster R-CNN will be used to pinpoint the precise location of lung nodules. The study's findings suggest that this approach may accurately detect pulmonary nodules in CT scans, possibly assisting clinicians in the early detection of lung cancer. Li et al. [22] proposed an improved YOLO-V3 target detection network based lung nodule detection. The Mask-RCNN network is used in this article, and it is improved by using Densenet's dense block structure and the channel shuffle convolution approach. Nasrullah et al.[23] proposed an automated lung nodule classification using customized mixed link network (CMixNet) which is deep learning combined with multiple strategies.

Vas et al.[24] have proposed a new lung image classification approach. In this approach, the section of the image that was not needed has removed by preprocessing stage. To remove salt and pepper sounds, they utilised a median filter. The use of mathematical morphological operations allows for precise lung segmentation and tumour detection. The use of mathematical morphological operations allows for precise lung segmentation and tumour detection. Correlation, Energy, variance, difference entropy, homogeneity, correlation information measure, and contrast were taken from the segmented region and supplied to the feed forward neural network with back propagation algorithm for classification. Vaishnavi et al. [25] have developed a lung nodule detection algorithm. They employed a discretely sampled wavelet in the Dual-tree complex wavelet transform (DTCWT) for pre-processing. GLCM is a texture analysis approach that uses a second-order statistical method to calculate how distinct Gray level combinations co-occur in a picture. They employed a Probability Neural Network (PNN) classifier that was tested for both training and classification accuracy. This proposed study differs significantly from the prior techniques.

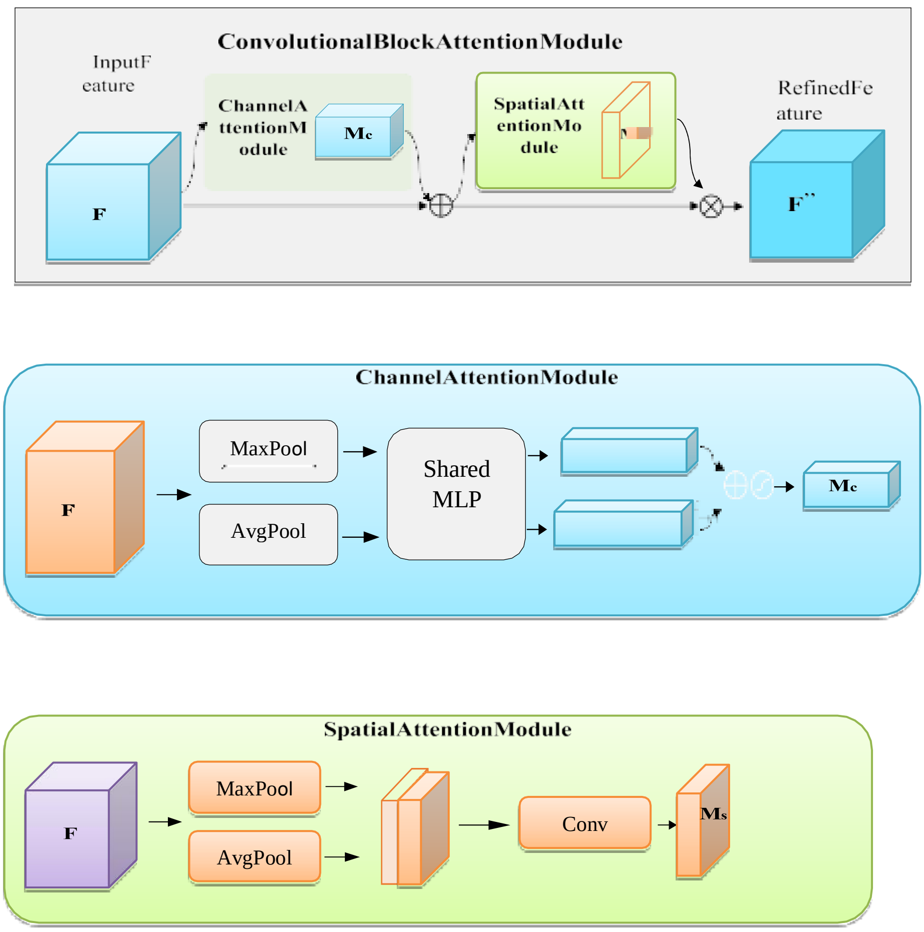
3. Proposed D3DR_MKCA

A. Convolutional Block Attention Module (CBAM)

Entire information on scene cannot provide clear understanding about that by human vision, but attention [26-29] on salient objects provide clear cut description of the image. Attention schemes focus on this property where prominent features are available on a scene or image.

Sanghyun et al [30] proposed Convolutional Block Attention Module (CBAM), a general and light-weight model, where both channel and spatial attentions are incorporated, and which can be embedded along with any CNN architectures. Architecture of CBAM is shown in the Figure 2. This approach is used to extract the most salient or important features of an image It consists of two kinds of attention modules.

First one is channel attention module and second one is spatial attention module. In channel attention module, feature maps are constructed with the help of convolutions operation which is called as channel coefficient. The final channel attention feature map is generated by multiplying the channel attention coefficient with previous feature map extracted from the input image. In the case of spatial attention module, it generate a single matrix with the size (Height X Width) of the original input with the location based feature for each position from all feature map which is known as spatial attention coefficient. This spatial attention coefficient will be multiplied with an input feature map and produce final output.



AvgPool – Average Pooling MaxPool - Maximum PoolingConv – Convolutional layer

MLP – Multiple Layer Perception - Sigmoid Layer $\oplus$ - Add $\otimes$ - Product

Figure 2: convolutionalblockattentionmodule(CBAM)

Let us consider a feature map derived from convolution layer Fas input with the dimension HxWxC. Where first channel attention block estimate the channel attention coefficient with the size 1x1xC with the help of global pooling, Multiple layer perception network and Sigmoid activation function and those coefficient multiplied with the feature map to provide channel attention coefficient applied feature map as F' which is shown in the Eq. (1).

$$F' = Ma(F) \otimes F \quad (1)$$

In the case of second module the spatial attention map Ms is derived with the help of Average and Maximum pooling process, and those concatenated pooled features further fed into convolution process to provide the a attention coefficient with the size HxWx1 ehich is going to multiplied with the channel based derived feature map to provide the final output as F''. This is shown in the Eq. (2).

$$F'' = Ms(F) \otimes F' \quad (2)$$

B. Residual Block

In order to extract the features with self-refined form residual block is adapted along with the proposed model in [7] ASIAL-CNN to extract all prominent features which is robust to scale. The residual block consists of two 3D convolution layers withand a short-cut connection. In the short-cut connection one 1x1xC 3D convolutional layer is applied and then added with the out extracted from second 3D convolution layer as shown in the figure 3. In this residual block Batch normalization (BN) and ReLU nonlinearity are used after all convolutional layers.

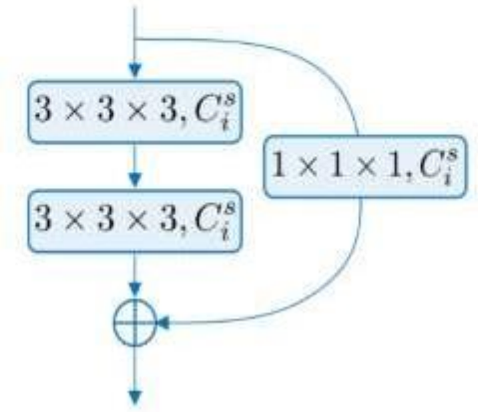


Figure 3: Residual Block

C. D3DR_MKCA

The proposed Deep 3D Residual with Multi Kernel Combined Attention Network (D3DR_MKCA) consists of five stage deep residual network with intermediate attention mechanism. The proposed model is shown in the below Figure 4.

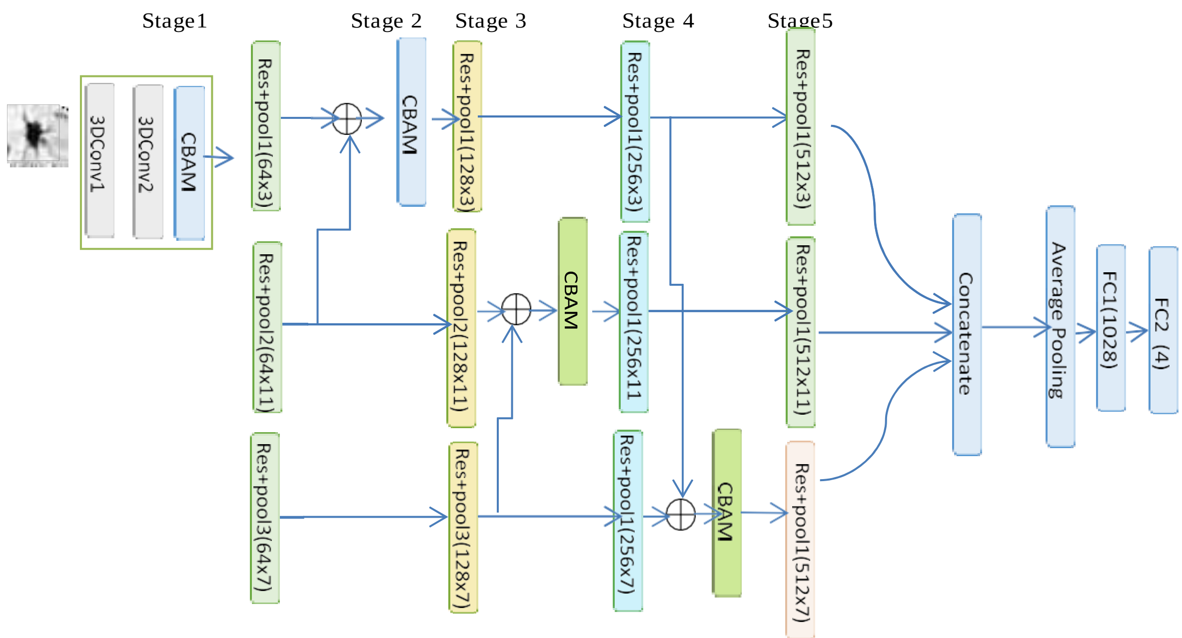


Figure 4: Proposed Architecture of D3DR_MKCA

In the stage 1, two 3D convolutional layers are used to extract features with filter size 3 and number of filters as 64 which is followed by CBAM block. This is shown in the following equation 1 and 2.

$$\mathrm{Conv}_{\mathrm{Stage1}} = \mathrm{3DConv}_{64\times3}(\mathrm{3DConv}_{64\times3}(\mathrm{noduleimg})) \quad (1)$$

$$\mathrm{CBAM}_{\mathrm{Stage1}} = \mathrm{CBAM}(\mathrm{Conv}_{\mathrm{Stage1}}) \quad (2)$$

The output from the stage 1 block is further processed with the Multi Scale Residual block with the concept of ASIAL-CNN in stage 2. In all subsequent stages(2,3 and4) three kinds of residual blocks are used with the filters scale as 3x3x3, 11x11x11 and 7x7x7. Each residual block followed by pooling in the form of 3D convolution layer with stride 2. Hence the dimension is reduced in the feature map. The following equations 3 to 5 shows the process of Residual block process in stage1.

$$\mathrm{Res}_{\mathrm{Stage2-1}} = \mathrm{ResBlock}_{64,3}(\mathrm{CBAM}_{\mathrm{Stage1}}) \quad (3)$$

$$\mathrm{Res}_{\mathrm{Stages2-2}} = \mathrm{ResBlock}_{64,11}(\mathrm{CBAM}_{\mathrm{Stage1}}) \quad (4)$$

$$\mathrm{Res}_{\mathrm{Stage2-3}} = \mathrm{ResBlock}_{64,7}(\mathrm{CBAM}_{\mathrm{Stage1}}) \quad (5)$$

In stage2 the output from the first and second residual blocks are added and fed into CBAM block to attain the Multi Kernel Combined Attention (MKCA) concept. Those attention based obtained feature is further supplied to the stage3 residual block 1. For the other two residual blocks the output from the previous stage residual blocks are directly utilized. This is shown in the following equations 6 to 9

$$\mathrm{CBAM}_{\mathrm{Stage2}} = \mathrm{CBAM}(\mathrm{Res}_{\mathrm{Stage2-1}} + \mathrm{Res}_{\mathrm{Stage2-2}}) \quad (6)$$

$$\mathrm{Res}_{\mathrm{Stage3-1}} = \mathrm{ResBlock}_{128,3}(\mathrm{CBAM}_{\mathrm{Stage2}}) \quad (7)$$

$$\mathrm{Res}_{\mathrm{Stages3-2}} = \mathrm{ResBlock}_{128,11}(\mathrm{Res}_{\mathrm{Stage2-2}}) \quad (8)$$

$$\mathrm{Res}_{\mathrm{Stage3-3}} = \mathrm{ResBlock}_{128,7}(\mathrm{Res}_{\mathrm{Stage2-3}}) \quad (9)$$

This process is repeated for stage 3 and stage 4 and MKCA is applied as shown in the figure 4 in alternative form. The process is clearly described in the following equations 10 to 17.

$$\mathrm{CBAM}_{\mathrm{Stage3}} = \mathrm{CBAM}(\mathrm{Res}_{\mathrm{Stage3-2}} + \mathrm{Res}_{\mathrm{Stage3-3}}) \tag{10}$$

$$\mathrm{Res}_{\mathrm{Stage4-1}} = \mathrm{ResBlock}_{256,3}(\mathrm{Res}_{\mathrm{Stage3-1}}) \tag{11}$$

$$\mathrm{Res}_{\mathrm{Stages4-2}} = \mathrm{ResBlock}_{256,11}(\mathrm{CBAM}_{\mathrm{Stage3}}) \tag{12}$$

$$\mathrm{Res}_{\mathrm{Stage4-3}} = \mathrm{ResBlock}_{256,7}(\mathrm{Res}_{\mathrm{Stage3-3}}) \tag{13}$$

$$\mathrm{CBAM}_{\mathrm{Stage4}} = \mathrm{CBAM}(\mathrm{Res}_{\mathrm{Stage4-1}} + \mathrm{Res}_{\mathrm{Stage4-3}}) \tag{14}$$

$$\mathrm{Res}_{\mathrm{Stage5-1}} = \mathrm{ResBlock}_{512,3}(\mathrm{Res}_{\mathrm{Stage4-1}}) \tag{15}$$

$$\mathrm{Res}_{\mathrm{Stages5-2}} = \mathrm{ResBlock}_{512,11}(\mathrm{Res}_{\mathrm{Stage4-2}}) \tag{16}$$

$$\mathrm{Res}_{\mathrm{Stage5-3}} = \mathrm{ResBlock}_{512,7}(\mathrm{CBAM}_{\mathrm{Stage4}}) \tag{17}$$

In the stage 5 the output from each multi kernel residual block are further concatenated in third axis mode and further processed by 3D Average pooling layer and final feature descriptor is generated with the help of fully connected layer with 1028 features and further classification is done with sigmoid function with FC of output as 4 classes with the help of average poolong and fully connected layer with softmax function as shown in the following equations 18 to 21.

$$\mathrm{Concat} = \mathrm{Concatenate}(\mathrm{Res}_{\mathrm{Stage5-1}}, \mathrm{Res}_{\mathrm{Stage5-2}}, \mathrm{Res}_{\mathrm{Stage5-3}}) \tag{18}$$

$$\mathrm{AP} = \mathrm{AveragePooling}(\mathrm{Concat}) \tag{19}$$

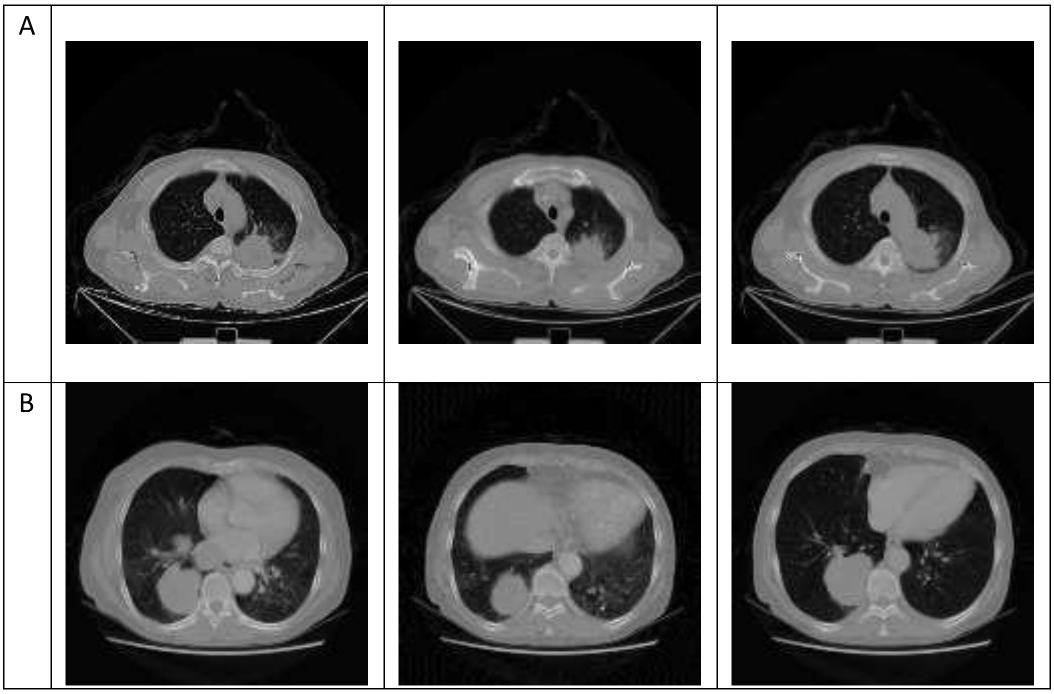
$$\mathrm{Fc} = \mathrm{fc1}_{(1028)}(\mathrm{AP}) \tag{20}$$

$$\mathrm{Out} = \mathrm{fc2}_{(4)}(\mathrm{fc1}) \tag{21}$$

4.Performance Analysis

The proposed work is analyzed with the help of the A Large-Scale CT and PET/CT Dataset for Lung Cancer Diagnosis (Lung-PET-CT-Dx) [31]. It consists of 436 Studies of 355patient's data in CT and PET/CT modality. Based on annotation each class has samples as 20894, 3116,201 and 4310 for the classes A,B,E and G. Among this 8010 slices are randomly selected from class Adenocarcinoma. For Small Cell Carcinoma and for Large Cell Carcinoma classes with augmentation 4116 and 1407 slices are used among this 80% used for training and 20% for testing. Squamous Cell Carcinoma class considers actual 4310 instances as it is for analysis, totally 17843 slices are used for this experiments. Sample slices for each classes are shown in the following figure 4.

From each CT and CT/PET slice the nodules are segmented with the help of Location Aware Encoding scheme [6]. The segmented nodule area is further resized to 48 X 48 dimensions. The model is developed with the help of torch and python 3.6. Model is trained with learning rate of 0.001, together with weight decay parameters of 5*10-4 and a momentum of 0.9, throughout the training stage. Using Adam optimizer is the best option here. It took us 50 epochs to complete the training phase with a batch size of 16. We ran our test on a server running Windows 10 and equipped with a Ryzen 7 CPU, 8 GB of RAM, and a 512 GB SSD, NVIDIA Geforce GTX-1650 GPU. A variety of performance criteria are used in a statistical study to assess the number of times the recommended model is effective in diagnosing abnormal lung nodules. In order to evaluate the efficiency of the implementation approaches, we had to standardize critical parameters in all experiments.



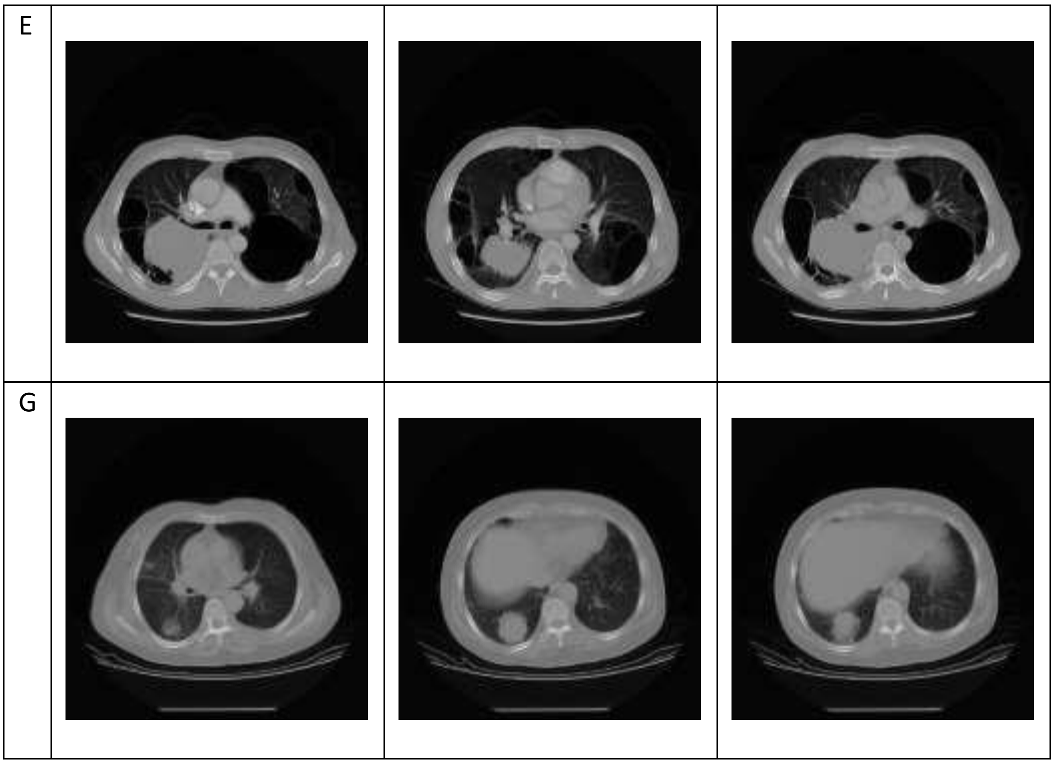


Figure 4: Sample CT Slices

Accuracy

This provides the overall output performance of the classified images. It isevaluated by measuring the ratio of accurate predictions with the total number ofinstance.

$$\text{Accuracy} = \frac{True\ Positive + True\ Negative}{True\ Positive + True\ Negative + False\ Positive + False\ Negative} \quad (22)$$

Precision

In precision, the proportion of truly positive patterns is labeled as positive witha total correctly or incorrectly classified positive samples.

$$\text{Precision} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}} \quad (23)$$

Recall

Recall is a measure needed to calculate the proportion of positive patternswhich are classified correctly.

$$\text{Recall} = \frac{\text{True Positive}}{\text{False Negative} + \text{True Positive}} \quad (24)$$

F1-score

F1-score the term used to find the harmonic mean values among the recall andprecision values.

$$\text{F1-score} = \frac{2*\text{Pr}*\text{Re}}{\text{Pr}+\text{Re}} \quad (25)$$

The following Table 1. Shows the class wise results obtained by the proposed method and existing SIAL-CNN[6] method with the all performance metrics. It clearly shows that the proposed D3DR_MKCA attains improved result compared to existing SIAL-CNN[6] and in our method instead of applying CBAM in all stages only in stage 1 is represented by D3DRCA_MK.

Table 1. Class wise performance analysis

METHODS	ACCURACY CLASSES				PRECISION CLASSES			
	A	B	E	G	A	B	E	G
(SIAL-CNN) [6]	0.915106	0.873786	0.851064	0.893271	0.959424	0.849057	0.816327	0.855556
D3DRCA_MK	0.930087	0.898058	0.868794	0.921114	0.957584	0.880952	0.830508	0.903299
D3DR_MKCA	0.940075	0.904126	0.886525	0.930394	0.966004	0.892216	0.847458	0.910329
	RECALL				**F1SCORE**			
	A	B	E	G	A	B	E	G
(SIAL-CNN) [6]	0.915106	0.873786	0.851064	0.893271	0.936741	0.861244	0.833333	0.874007
D3DRCA_MK	0.930087	0.898058	0.868794	0.921114	0.943635	0.889423	0.84922	0.912119
D3DR_MKCA	0.940075	0.904126	0.886525	0.930394	0.952863	0.898131	0.866551	0.920252

The overall performance is shown in the following Table 2. And its corresponding chart representations are shown in the following Figure 5 to Figure 8.

Methods	Accuracy	Precision	Recall	F1score
(SIAL-CNN) [6]	89.52%	87.01%	88.33%	87.66%
D3DRCA_MK	91.57%	89.31%	90.45%	89.88%
D3DR_MKCA	**92.52%**	**90.40%**	**91.53%**	**90.96%**

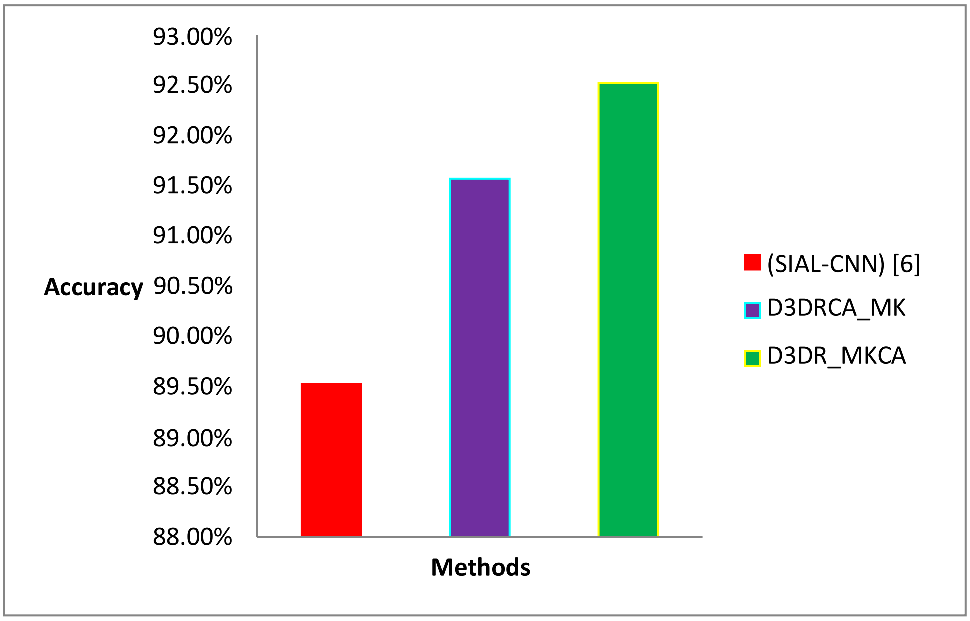
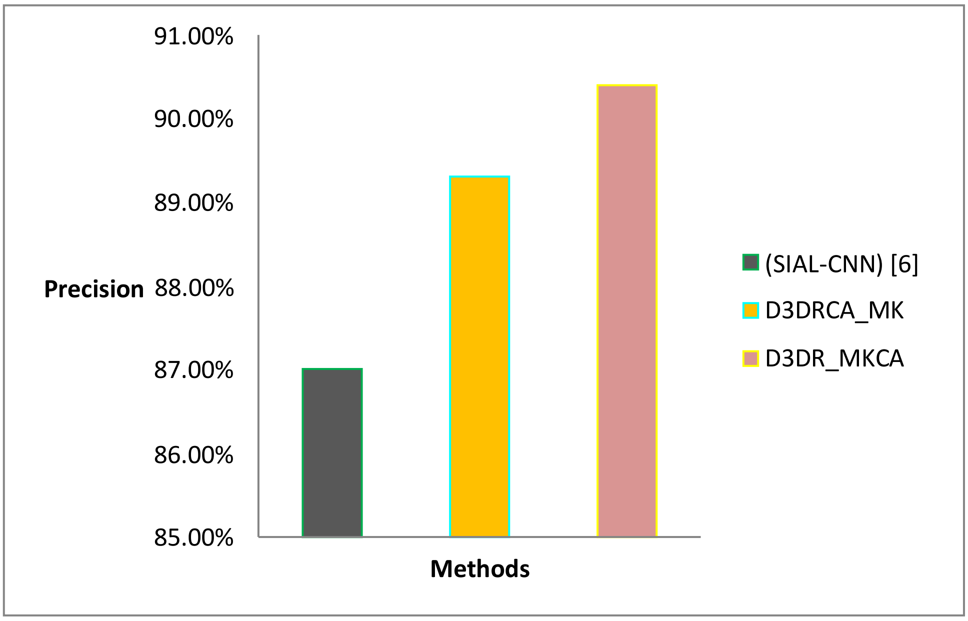
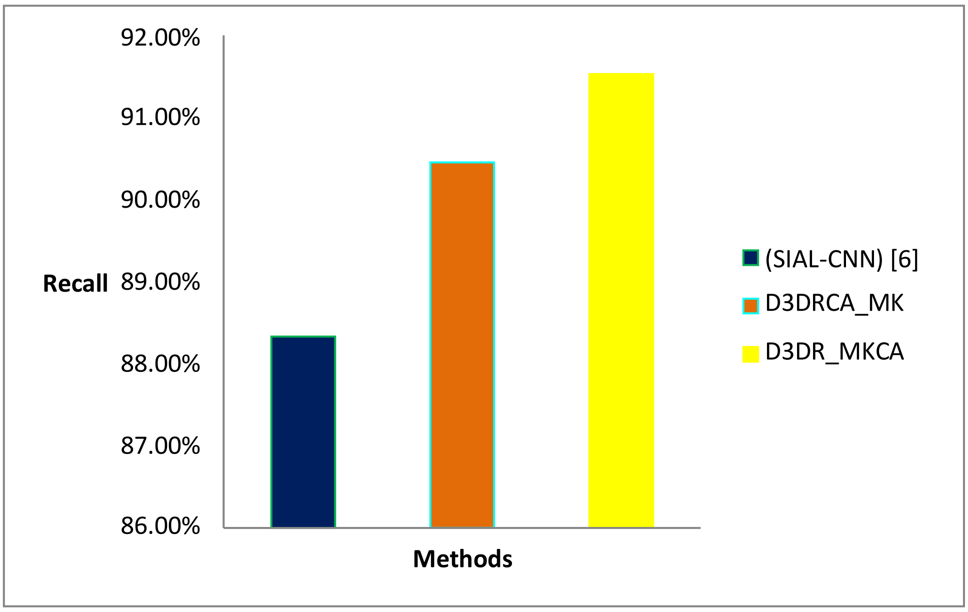


Figure 5: Analysis on Accuracy

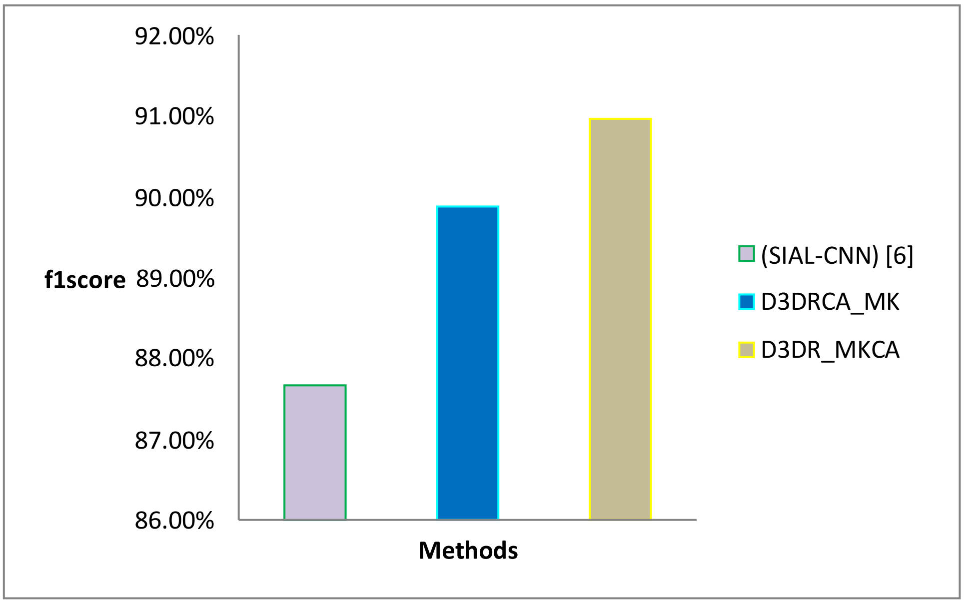
The method SIAL-CNN [6] has accuracy 89.52%,D3DR_MK has 91.57%, andD3DR_MKCA has 92.52%. Here, theD3DR_MKCAmethod attained accuracy better than the remaining methods. Accuracy value of the D3DR_MKCA method is 0.95 % higher than the D3DR_MK method D3DR_MK, 2.05% higher than the method SIAL-CNN [6] .



The method SIAL-CNN [6] has Precision 87.01%,D3DR_MK Has 89.31%, andD3DR_MKCA has 90.40%. Here, the D3DR_MKCA method attained Precision better than the remaining methods. Precision value of the D3DR_MKCA method is 1.09% higher than the D3DR_MK method. D3DR_MK 2.3% higher than the method SIAL-CNN [6] .



The method SIAL-CNN [6] has Recall 88.33%,D3DR_MK has 90.45%, andD3DR_MKCA has 91.53%. Here, theD3DR_MKCA method attained Recall better than the remaining methods. Recall value of the D3DR_MKCA method is 1.08% higher than theD3DR_MK methodD3DR_MK 2.12% higher than the method SIAL-CNN [6] .



The method SIAL-CNN [6] has F1score 87.66%, D3DR_MKHas 89.88%, and D3DR_MKCA has 90.96%. Here, theD3DR_MKCA method attained F1score better than the remaining methods. F1score value of the D3DR_MKCA method is 1.08% higher than the D3DR_MK method D3DR_MK, 2.22% higher than the method SIAL-CNN [6] .

Conclusion

This research proposes a unique deep neural network technique for lung nodule detection system that has segmentation and classification phases. In order to accurately segment the input CT images, Location Aware Encoding Network[6] architecture was used, which aids in the learning of more subtle characteristics. Developed a deep architecture D3DR_MKCA based on Deep Residual network incorporating convolutional block attention module (CBAM) which applied on different scale feature map is proposed to classify lung nodules. The channel and spatial attention mechanism combined with SIAL-CNN work flow improves the performance of cancerous tissue (nodule) classification. The experiment results on the Lung-PET-CT-Dx dataset show the efficiency of the D3DR_MKCA architecture. Proposed D3DR_MKCA method improves +2.05% of accuracy than the SIAL-CNN[7] model, and F1score of the D3DR_MKCA method is 2.22% higher than the SIAL-CNN model. This study reveals the higher performance of the suggested method in classifying lung nodules, which may be helpful for clinical diagnosis.

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