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An early-stage classification of Lung Nodules by an Android based application using Deep Convolution Neural Network with Cost-sensitive loss function and Progressive scaling approach

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ABSTRACT

Minimization of the death proportions of lung cancer there is a requirement of a computer-aided diagnosis (CAD) system for early-stage detection and classification of lung nodules. This paper has proposed two novel approaches based on deep learning techniques improvement of the classification accuracy of lung nodules in computed tomography (CT) scans. Our first approach uses Two-dimensional Convolution Neural Network architecture for automatic feature extraction and classification of lung candidates as cancer nodules or noncancerous nodules. In the second approach, we have used the progressive scaling technique in which we have started with small size images(n x n) and train the model than we gradually increase the size of image(In the ratio of 2n x 2n) and train again this approach give promising result to increase classifier result. We have measured our approaches on the Lung Image Database Consortium image collection (LIDC/IDRI) dataset expected by the LUNA16 challenge. After experimenting with models we have created an android mobile application using the TensorFlowlite framework which is taking lung CT scan as an input and produce benign or malignant probability in the given scan. Experimental results proved that our deep learning architecture with a combination of cost-sensitive loss function and augmentation of minority class has produced an accuracy of 96.9%, the sensitivity of 96.2%, and specificity of 97.2 %. In the second approach of progressive resizing, we have graduated with an increase in the testing accuracy.

Key words: Computer-aided diagnosis, Cost-sensitive function, Tensorflowlite, Alexnet, 2DCNN, LUNA16, Progressive resizes, Sensitivity.

1. INTRODUCTION

As per the survey of the Indian Council of Medical Research (ICMR), there were 1.45 million new cancer cases detected and as per the prediction of ICMR, this will increase up to 1.73 million in 2020. Among these lung cancers: an estimated 0.114 million (83,000 in males and 31,000 in females) new cases during 2016 and that will increase to 0.14 million in 2020[3]. Another survey has done by the American Cancer Society (ACS) in 2012[1]. They have found a total of 1800000 cases of lung cancer all over the world. The below Table I indicates the number of lung cancer cases percentage-wise in different countries. Lung cancer is the second most common cancer in American men and women. It's also the leading cause of cancer-related deaths for both American men and women. One in every four cancer-related deaths is from lung cancer. The main cause of lung cancer is considered to be cigarette smoking. There is 23 times in men & 13 times in women more chance of developing lung cancer, who smokes. About 14% of new cancer cases in the United States are lung cancer cases. That equals about 234,030 new cases of lung cancer each year. There are two main types of lung cancer: 1. Non-small cell lung cancer (NSCLC) 2. Small cell lung cancer(SCLC). Roughly 85% of people diagnosed with lung cancer each year have NSCLC and rest have SCLC. The average age of a lung cancer diagnosis is 70, with the majority of diagnoses in adults over the age of 65. A very small number of lung cancer diagnoses are made in adults under age 45.

Table 1: Lung cancer survey by ACS [1]

Country	Lung cancer cases (%)
China	35.8
Europe	22.5
Middle East & North Africa	2.9
India	3.9
Northern America	13.1
Sub-Saharan Africa	0.9
Other East & Central Asia	15.6
Latin America & the Caribbean	4.5
Oceania	0.8

Mainly there are four levels of Lung Cancer stages. If we talk about the survival rate of both the types concerning levels, Table 2 & 3has given five-years survival rate percent.

Table 2: NSCLC survival rate

Stage	Five-year survival rate
1A	92 percent
1B	68 percent
2A	60 percent
2B	53 percent
3A	36 percent
3B	26 percent
4, or metastatic	10 percent, or <1%

Table3: SCLC survival rate

Stage	Five-year survival rate
1	31 percent
2	19 percent
3	8 percent
4, or metastatic	2 percent

So, early cancer detection and survival can be the biggest issue in the medical domain. Lung cancer is that type of cancer that is largely detected not only in India but all over the world. After diagnosed with lung cancer in the US, the patient cannot survive more than 5 years. The survival rate is only 17% and this is even lesser in developing countries [2]. There were different data modalities available for the detection of lung cancer in the medical image domain (ex. MRI, CT, PET) but we have selected CT scan images in the form of DICOM, RAW, etc. formats because These high-tech scans produce 3D images. These scans can not only identify tumors earlier but also spot them when the tumors are smaller and more treatable by surgery. According to Doi[3], 30% of lung nodules may be missed by the radiologists due to overlaps between them and other normal anatomic structures. For the automation and early detection of lung cancer, we have tried to detect the same with the use of some state-of-art techniques[21, 22] of Deep Learning especially 2D and 3D Convolution Neural Networks (CNNs) and tried to apply the concept of transfer learning for the early-stage detection of lung cancer. The challenges we have faced like the development of such an algorithm that accurately determines when lesions in the lungs are cancerous. Also, the reduction of the false-negative rate was a challenging task. The overall goal of our research is to develop such algorithm or system by which we can predict early-stage cancer and increase the survival rate of patients. Radiologists can get more time with the patients. As per the Torre et al. [4] research, nodules may be tiny (<10 mm) or big (>30 mm). To find out tiny nodules it is like we have to find out a 10 mm nodule in the search space of 400 * 400 * 200. Additionally, CT scans have lots of noise values in terms of air, bone, tissues, water, blood, etc. So basic lung cancer classification process we have to follow is described in fig. 1**.**

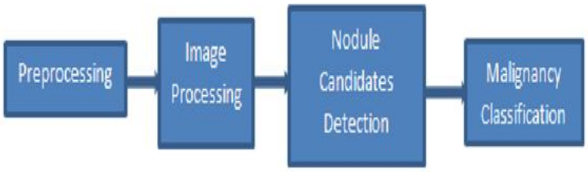

Figure 1: Lung Cancer classification pipeline

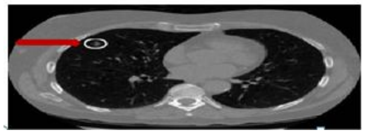

Figure 2: Lung Nodule example

Our objective is to enhance the precision of CADe systems by exploiting the advantage of deep learning [9] and to provide more mobility transform that system into a mobile application using the TensorFlowlite framework. In detail, we propose a new 2D deep convolutional neural network architecture with the cost-sensitive loss function and augmentation techniques for boosting classification accuracy and provide a more sensitive model towards lung cancer detection. Our 2nd approach of progressive resizing also has produced good classification results. To provide better feasibility to the radiologists we have created a TensorFlowlite framework based android mobile application.

2. RELATED WORK

For a deep understanding of image-related data with the use of the convolution process convolution neural network has provided advancement in artificial neural networks[23]. This network is inspired by the human biological visual structure so it works very effectively and efficiently for the problems of image recognition[22]. It also works irrespective of image size and scale. This architecture has provided a “neighbors” approach instead of a fully connected network that was there in the fully connected artificial neural network architecture. Due to this “neighbors” approach, we can reduce the number of connections of neurons or the number of weight much lesser than the fully connected network [10]. By this, we can reduce the problem of over fitting which is very common in fully connected networks. It will also take less time for training concerning fully connected architecture. CNN has many variations in terms of the number of layers. In below table 4 we have listed some of the variations of CNN architectures. These variations are invented to solve the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) annual contest.

Table 4: ILSVRC competitioncnn architecture variances [18]

Year	CNN Variations	Developed by	Rank	Top-5 error rate	No. of parameters
1998	LeNet(8)	Yannlecun			60 Thousand
2012	AlexNet(7)	Alex Kriz- Krizhersky,GeoffreyHinton,llyasutskever	1st	15.39 %	60 million
2013	ZFNet()	Matthew Zeiler and Rob Fergus	1st	14.89 %	-
2014	GoogleleNet(19)	Google	1st	6.67%	4 million
2014	VGGNet(16)	Simonyan,zisserman	2nd	7.39%	138 million
2015	ResNet(15)	Kaiming He	1st	3.69%	

Manipulating the benefits of deep learning [7, 8], several methods are presented to increase the classification accuracy of lung nodule candidates in CT scans [5]. Here we have given information about the researcher and there results for lung nodule detection and classification in terms of accuracy, sensitivity, and specificity.

Giang et al. [6, 11] proposed 15-layers 2D-CNN architecture with the CNN blocks approach. To increase classification accuracy they have introduced focal loss function instead of BCE function. The proposed method can gain up to 97.2% accuracy and 96.0% sensitivity and 97.3 specificity of lung nodule classification.

Li and Cao et al. [12] projected a 2D-DCNN to classify nodule candidates as a nodule or non-nodule. The suggested system was trained and validated on 62,492 regions-of-interest (ROI) image patches mined from 1,010 CT scans of the LIDC/IDRI dataset. The proposed method has produced 86.4% accuracy and 89.0% sensitivity of lung nodule classification.

Kuruvilla [13] proposed a CAD system for the classification of lung nodule cancer. The tests confirmed that the method obtains an accuracy of 93.3%, a sensitivity of 91.4%, and specificity of 100%. For determining non-nodule this method showed very promising results.

W-J Choi and T-S Choi [14] presented a lung nodule detection system using hierarchical block classification. The proposed method shows a very good accuracy of 97.6%, a sensitivity of 95.2%, and a specificity of 96.2% for lung nodule detection.

Setio et al. [15] proposed multiview CNN (ConvNets) to classify lung nodule candidates. The method was trained on LIDC/IDRI dataset by the LUNA16 challenge. The tests show that the method able to achieve a sensitivity of 90.1%. Torres et al. [16] used a feed-forward neural network (FFNN) as a nodule candidate classifier. The training and testing of the application has done on the LIDC/IDRI dataset. Results showed sensitivity up to 89.1%. [17] S. G. Armato et al. have used 1,186 lung nodules from LIDC-IDRI chest CT images and delivered these nodules as positive candidates for researchers. The results of the challenge show that the best distinct recognition system can obtain up to 92.9% sensitivity of lung nodule detection.

3. RESOURCES AND APPROACHES

3.1 Data

In our research, we have used the LUNA16 challenge dataset which was extracted from the LIDC/IDRI dataset [19]. This dataset matched with our objective of lung nodule classification. So we have used that dataset for our research. The dataset includes 888 thoracic CT scans with annotation .csv file and candidates.csv file. In this annotation.csv file 1186 patients ID with X, Y, Z coordinates and cancerous nodule diameter in mm suggested by 4 different radiologists. The second file available with the dataset is candidates file in which includes 551066 nodules among these probable nodules only 1351 nodules marked as cancerous nodules. So there was lots of imbalance in data.

In our research, we use 1351 positive candidates and 5549715 negative candidates to detect lung nodules. The numbers of positive and negative nodules candidates are extremely imbalanced for training and testing models. To handle this kind of imbalance we have used data augmentation techniques that we describe in the next session.

3.2 Data Augmentation:

To handle data imbalance we have decided to under-sample the majority class and augment the minority class [11]. There are 1069 samples available for positive class (we have removed some samples which are very near to lung boundaries). For training the model we have augmented positive samples two times more so in total 3207 samples and under the majority classes such that we can have 1:3 distributions. So finally we have 12828 total samples among them non-nodule class samples 9621 and nodule class samples 3207. For augmentation of minority class we have performed below operations:

1. Rotation : 180,90,45 degree random rotation
2. Horizontal flip
3. Vertical flip
4. Horizontal and vertical shift

We elect not to apply non-deviating alterations, like stretching or skewing, zooming, blurring, for the significance of nodule's shape for the detection process.

3.3 Structure of CNN Architecture

We have created two different architectures for our training process. The design of the architectures is given in **Fig. 3** (Model-1[M-1]) and **Fig. 4**(Model-2[M-2]). Model-1 consists of 7 2D-convolutions (Conv2D) layers each layer followed by Batch- Normalization function and ReLU activation function. 1st, 4th, and 5th Conv2D layers have 64 numbers of filters, 2nd and 6th Conv2D layers have 128 numbers of filters and 3rd and 7th Conv2D layers have 512 numbers of filters. After Conv2D layers next layer is flatten layer after that there are 3 fully connected (FC) layers. 1st FC having 512 nodes, 2nd FC having 128 nodes and the end we have 2 nodes and sigmoid activation function that will classify and give probabilities of input being in a nodule or non-nodule class. Model-2 having Conv2D blocks instead of individual Conv2D. In Each block, 3 Conv2D layers are there. Model-2 has 3 such a Conv2D blocks are there and each block follows Maxpooling2D at the end. Model-2 has three FC layers among that first two having 512 nodes and last having 2 nodes. In the last FC network, we have organizeda sigmoid activation function that will classify and give probabilities of input being in a nodule or non-nodule class. Model-2 is very similar to LcdNet proposed by Giang Son Tran el [11]. To select the best architecture among these two we have performed some of the operations that will optimize our architectures and give the best performance.

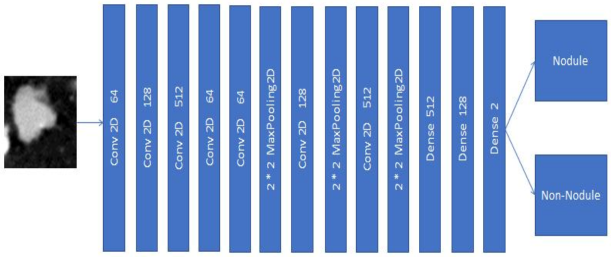

Figure 3: Model – 1(Lung Nodule Detection Net (LndNet))

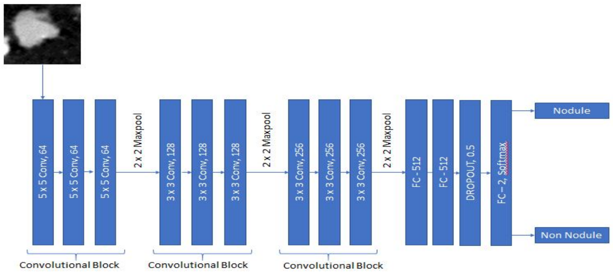

Figure 4: Model-2 (2DCNN block architecture)

3.4 Activation functions

We have trained both of the architectures with three well known activation functions ReLU, LeakyReLU and ELU [21] [table 6]. We have measured the performance concerning

Accuracy, Sensitivity, and Specificity. Our overall objective is to find out a more sensitive network that can produce high sensitivity because our projector system is a nodule-non-nodule detection system in lung CT scans. Cancer detection networks must be sensitive. The below table V and graph suggested that Model-1 with ReLU Activation Function gives High performance in three of the aspects. LeakyReLU equally performs well. For the initial stage, we have stared with binary cross-entropy loss function and adam as an optimizer.

Table 5: Model-1 and Model-2 using different activation functions

Model	Activation	Specificity	Accuracy	Sensitivity
M-1	ELU	97.16	94.01	81.2
M-2	ELU	96.56	92.97	73.04
M-1	**LeakyReLU**	**96.82**	**94.64**	**86**
M-2	LeakyReLU	92.68	91.49	85.81
M-1	ReLU	96.34	94.45	86
M-2	ReLU	91.27	90.56	87.23

Table 6: ELU, LeakyRelu and Relu activation functions comparisons [24]

Sr. No	Activation Functions	Advantages	Disadvantages
1.	ELU $R(z) = \begin{cases} z, & z > 0 \\ \alpha.(e^2 - 1) & z \le 0 \end{cases}$	It can produce negative outputs, becomes a smooth and slow and good alternative for ReLU.	For z > 0, it can blow up the activation output range of [0,∞].
2.	ReLU $R(z) = \begin{cases} z, & z > 0 \\ 0, & z \le 0 \end{cases}$	It can resolve vanishing gradient problem. It is less computationally expensive than other activation functions.	We can use it within the hidden layers only. It may lead to a vanishing gradient problem. It will blow up the activation because of its range.
3.	LeakyReLU $R(z) = \begin{cases} z, & z > 0 \\ \alpha.z, & z \le 0 \end{cases}$	We can use it to fix the dying ReLU problem by putting some negative slop.	We cannot use complex classification problems. In some of the cases, it performs bad than Tanh and Sigmoid.

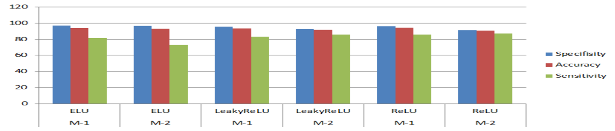

Figure 5: Graph of Above Table 5.

3.5 Loss Functions

At the initial stage for identifying best architecture we have tested three loss functions like Binary-cross entropy (BCE), Hinge and Squared Hinge loss on two models with LeakyReLU Activation function. Based on the experiment and according to the functionality of the loss functions and for our binary classification problem best loss function is BCE. We have shown an experimental result graph that justifies BCE is preforming well among all three loss functions.

Table 7: Loss Functions Experimental Results Using LeakyreluActivation Function.

Model	Loss Function	Specificity	Accuracy	Sensitivity
M-1	**BCE**	**96.34**	**94.45**	**87**
	Hinge	96.04	93.77	82
	Squared-Hinge	97.4	94.08	78.4
M-2	BCE	92.68	91.49	85.81
	Hinge	96.56	92.47	73.05
	Squared-Hinge	94.4	85.69	50.26

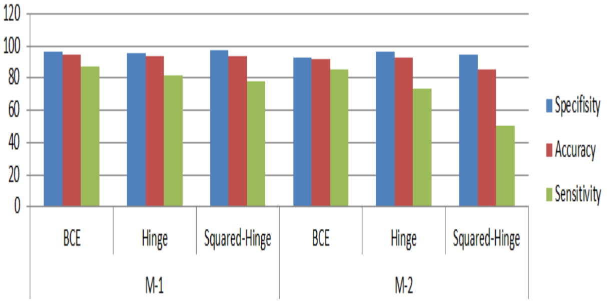

Figure6: Graph of Above Table 7.

3.6 Optimizers

For now, we have finalizedRelu/LeakyReLU as an activation function and BCE as a loss function for M-1 and M-2. Now with this background our next experiment for three different optimizers like Adam, Rmsprop and Stochastic gradient (SGD). The below table VIII shows experimental results on M-1, M-2 with activation functions ReLU/Leakey ReLU and optimizer BCE. After all these experiments we have finalized our CNN architecture with 7 convolution2D layers, 3 MaxPooling2D layer, and 3 fully-connected layers. For more optimization of the model, we have also tested for the best batch size and number of Convolution layers. We have tested 6,7,8,9 convolution layer networks with different batch sizes like 32, 64,128 and 256. Among all 7 layer convolution networks with 128 batch sizes have the best accuracy, sensitivity, and specificity. Finally, we have optimized our architecture with the LUNA16 dataset which is currently the smallest architecture for the classification of nodule and non-nodule candidates. For the sake of inquisitiveness, we have also tried LeakeyReLUactivation function with adam optimizer and that combination gives us high Accuracy, Sensitivity, and Specificity with compare to all other combinations. Table VIII shown below shows the results for the same.

Table 8: Experiments with different optimizers

Model	Optimizer	Accuracy	Sensitivity	Specificity
M-1	Adam with ReLU	95	87	97.3
M-1	**Adam with LeakyReLU**	**95.2**	**90.1**	**97.2**
M-1	RMSProp	94.14	85.10	96.04
M-1	SGD	94.63	80.14	97.68
M-2	Adam	90.56	85.5	91.26
M-2	RMSProp	90.57	85.6	91.27
M-2	SGD	94.38	77.66	97.91

Till now we have optimized our architecture and got reasonable accuracy compared to other researchers. Our aim to make such a CAD system that can classify nodule or non-nodule. Cancer detection systems must be sensitive enough that can identify cancer even at a very early stage. So after this stage, our focus is to make architecture or model sensitive that can decrease the false-negative ratio. As a result, we can reduce the chances of a patient having cancer but not detected by the system.

3.7 Making our model Sensitive

To do so we thought will training if we give more weightage to the minority class in our case CT scan containing nodule. Data is so imbalanced in our case. Data augmentation was not enough to increase accuracy and sensitivity. So we decided that make such a loss function that can give more weightage to minority class and less weightage to the majority class while training according to their frequency. By this thought, we decided to modify binary loss function in such a way that it will become more sensitive towards minority class. Binary cross-entropy function defied as y = −y log (p) − (1−y) log (1−p), where y is the class binary indicator (0 or 1) and p is predicted probability, for instance, belonging to class 1. To incorporate the weights of two classes (0 and 1) into the cross-entropy, one can define sensitive cost function: y = −w_0ylog (p) – w_1 (1−y) log (1−p), in which w_0 and w_1 are the weights for class 1 and 0, respectively.

3.8 Mobile application development using TensorFlow lite

To provide our CAD system real-time access and mobilityit is better to transfer this all things into the mobile application so it can add more dimension to it. For transferring this thing into android mobile application we have used the TensorFlow lite framework.

Algorithm for Lung nodule detection mobile application:

1. Save your trained model.h5 or model.hdf5 (This file will have optimized weights)
2. Transfer this model.h5 in to TensorFlow lite model (file extension is .tflite)
3. Save your trained model.h5 or model.hdf5 (This file will have optimized weights)
4. Transfer this model.h5 in to TensorFlow lite model (file extension is .tflite)
5. If your model size still very large after converting into .tflite you can convert .tflite file into .pb file. It will occupy less size of your model
6. Make appropriate GUI for android application [**Fig. 7**] Load your .pb or .tflite file in your application
7. Load some testing files and test with application. [**Fig. 7**]

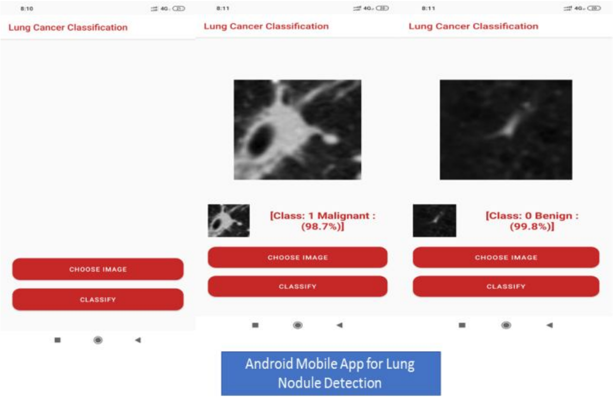
8:10
8:11
8:11
Lung Cancer Classification
Lung Cancer Classification
Lung Cancer Classification
[Class: 1 Malignant : (98.7%)]
[Class: 0 Benign : (99.8%)]
CHOOSE IMAGE
CLASSIFY
CHOOSE IMAGE
CLASSIFY
CHOOSE IMAGE
CLASSIFY
Android Mobile App for Lung Nodule Detection

Figure 7: GUI for our LndNet android application

4. EXPERIMENTAL RESULTS

4.1 Experimental setup

A. Preprocessing:

For the standardization of CT scan images, we required to accomplish data preprocessing. Firstly we have converted each 3D CT scan slice into a 2D grayscale .jpeg image. We abstract one non-overlying image spot of size pixels for each annotation of both nodule and non-nodule examples. We have removed observations that are very near to the boundaries of slices (< 40 pixels). **Figure 8** illustrates some extracted image patches using this method. The extracted image's intensity I am then scaled to the Hounsfield unit $I_{HU}\in$ [-1000,400])and linearly normalized to range using the transformation $I_{norm}=(I_{HU}+1000)/1400$ before being used as input for training the model (figure 8).

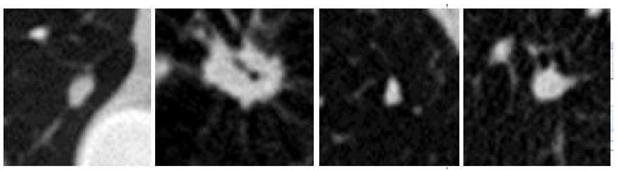

Figure 8: Some of the extracted ROI from LUNA16 data

B. Performance measurement:

Accuracy (capability to distinguish benign and malignant nodule cases correctly), sensitivity (capability to define the malignant nodule cases correctly), and specificity (capability to define the benign nodule cases correctly) are used to quantify the exactness of the classification. Generally, for binary classification problems, these kinds of metrics are widely used and equations for them as follow:

$$ACCURACY = \frac{TP + TN}{TP + TN + FP + FN}$$

$$SENSITIVITY = \frac{TP}{TP + FN}$$

$$SPECIFICITY = \frac{TN}{TN + FP}$$

Where, TP: True Positives, TN: True Negatives, FP: False Positives, FN: False Negatives.

C.

D. Systems configuration:

Hardware: We have implemented our experimental results on Intel(R) Core(TM) i-7-8700k CPU with 3.70GHz, 32 GB RAM and 64 bit-operating system. This has support of NVIDIA graphics card. The configuration of the Graphics card is NVIDIA GFORCE TITAN Xp with 3840 Cuda cores. Some of the experiments we have done on Kaggle cloud platform they are providing tesla K10 GPU for experimental purpose.

Software: We implement our system using Keras 2.1.1 with TensorFlow 1.3 as the backend, along with CUDA 9.0 for GPU acceleration. Our CAD system is implemented with Python 3.6.5.

E. Outcomes and Deliberations

For the lung nodule detection system, we have followed two different approaches to boost up our classifier's accuracy.

Table 9: LndNet and other pre-train model testing results

Sr. No	Models	Dataset	Scans	Accuracy	Sensitivity	Specificity
1	**LndNet-BCE**	**LIDC/IDRI**	**888**	**95.25**	**89.23**	**97.2**
2	ResNet50	LIDC/IDRI	888	94.14	89.007	94.02
3	GoogleNet or InceptionV3	LIDC/IDRI	888	93.77	81.97	96.26
4	VGGNet(16)	LIDC/IDRI	888	93.46	82.59	95.63
5	AlexNet	LIDC/IDRI	888	93.52	89.007	94.47
6	LeNet	LIDC/IDRI	888	88.47	72.94	90.74

Approach 1: Using sensitive cost loss function

By giving different values of sensitive cost function variables w0 and w1 we have increased our classifier's performance. The below table X shows experimental results of ourNetworkLcdNetCost-sensitive function (CSF) having different batch sizes and epoch values. These experiments we have done without the k-folding cross-validation technique. After applying stratified k-folding techniques we have achieved more accurate results showed intable 11**.**

Table 10: Sensitive Cost Function Experiments

	Input Network		**Sensitive cost function**		**Performance**		
Sr. No.	**Epochs**	**Batch Size**	**W0**	**W1**	**Accuracy**	**Sensitivity**	**Specificity**
1	20	32	0.1	0.9	91.1	78.3	95.5
2	30	32	0.2	0.8	93.56	82.3	96.3
3	50	32	0.3	0.7	92.9	84.2	96.7
4	25	32	0.2	0.8	93.2	84.5	97.43
5	20	64	0.4	0.5	94.53	86.3	97.22
6	30	64	0.5	0.5	93.2	88	97.23
7	25	64	0.3	0.7	95	79.85	97.1
8	**25**	**128**	**0.6**	**0.4**	**96**	**95.7**	**97.3**
9	25	128	0.5	0.5	95.2	93.2	96.1
10	25	256	0.5	0.5	94.83	90.1	97

We have tested our network with k-folding validation testing. In which stratified k-folding (k=10) has given high accuracy. Our LndNet with CSFand stratified k-folding has produced promising results and these results are very much similar to LcdNet-FL-Giang Son Tran and LcdNet-CE Giang Son Tran[20] work. Accuracy and specificity little less than the work suggested by Giang Son but we can able to reach high sensitivity with our LndNet-CSF in table 9.we have provided a comparison table 11 of related work results on the LUNA16 dataset in terms of accuracy, sensitivity, and specificity.

Table 11:SCF and validation techniques results

Sr No	Sensitive cost function	Validation technique	Accuracy	Sensitivity	Specificity
1	No	Without k-folding	96	95.7	97.3
2	Yes	k-folding	96.1	95.9	97.5
3	**Yes**	**With stratified k-folding**	**96.9**	**96.2**	**97.2**

Approach 2: Progressive resizing or scaling

Progressive resizing is a technique for building CNNs that can be very helpful during the training and optimization phases of a machine learning project. Here we have given different steps that we have performed while applying Progressive resizing or scaling to our LUNA16 CT scan dataset.

1. Download and format the data.
2. Define the data generators: Data generators are on the fly image transformers and are the recommended way of providing image data to models in Keras. They let you work with on-disk image data too large to fit all at once inmemory. And they allow you to preprocess the images your model sees withrandom image transformations and standardizations, a key technique for improving model performance.
3. Define the model.
4. Fit the model.
5. Applying progressive resizing: To build a classifier we have started to form tiny n x n (20 x 20) imagesthat perform well. The second step is resizing our model up to 2n x 2n (40 x 40) images. We do this using transfer learning. Transfer learning is the technique of reusing layers and weights from previous models when building new ones.
6. Define the model.
7. Fit the model.
8. Applying progressive resizing: To build a classifier we have started to form tiny n x n (20 x 20) imagesthat perform well. The second step is resizing our model up to 2n x 2n (40 x 40) images. We do this using transfer learning. Transfer learning is the technique of re-using layers and weights from previous models when building new ones.

Table 12: Comparison table with other works

Work	scans	Dataset	Performance		
			Accuracy	Sensitivity	Specificity
Proposed LndNet-CSF	**888**	**LIDC/IDRI**	**96.9**	**96.2**	**97.2**
LcdNet-FL-Giang Son Tran[11]	888	LIDC/IDRI	97.2	96	97.3
LcdNet-CE-Giang Son Tran[11]	888	LIDC/IDRI	95.6	90.2	96
Setio[15]	888	LIDC/IDRI	95	91.1	-
Li et al. [12]	1010	LIDC/IDRI	86.4	87.1	
Kuruvilla and Gunavathi [13]	155	LIDC/IDRI	93.3	91.4	100
Choi and Choi [14]	58	LIDC/IDRI	97.6	95.2	96.2

9. Appends a max-pooling layer, which downsamples 40 x 40 → 20 x 20—the expected input size for our old model.
10. Removes the first convolutional layer from our old model (it helps in reducing overfitting).
11. Reattaches rest of the layers of our old model into the new one.
12. Freeze old convolutional and fully-connected layer weights in place.
13. Repeat steps 5 to 12 to create a new model for 80 x 80 image size.

Below table showing experimental results of progressive sizing with transfer learning

Table 13: Progressive resizing results on luna16 dataset

Sr.No:	Image size	Accuracy	Sensitivity	Specificity
1	20 x 20	90.23	78.38	96.0
2	40 x 40	94.20	85.16	96.5
3	80 x 80	96.2	91.2	97.8

5. CONCLUSION AND FUTURE WORK

In Lung nodule detection application sensitivity of a network is a very important part. To improve the model accuracy and sensitivity our proposed LndNet-SCF and progressive resizing approaches have produced very promising results. For further enhancement, one can try with 3D images and gather a history of the patient that maybe help full for getting more accuracy. For more sensitivity, one can increase w0 value in CSF but more value may decrease the accuracy and specificity of the classification result. Using Deep CNN with CSF is an excellent classifier with 96.9% accuracy, 96.2% sensitivity, and 97.2% specificity.

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