U-Net: Convolution Neural Network for Lung Image Segmentation and Classification in Chest X-ray images

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Abstract. Medical Image analysis and diagnosis is an indispensable part of today's unpredictable and insanitary environment. Analysis takes long procedure to find disease and it needs screening of internal organs of human body. Clinical analysis takes more time and sometimes may result in failure. Chest X-ray images are fundamental visual mechanism for medical world. Lung chest X-ray images need more support from Medical Diagnosis and identification. Automatic segmentation in supervised learning needs training data and unsupervised learning approaches needs labelled images in addition to shape, size and texture variation in patients lung chest X-ray images require more assistance and support from medical radiologist. Some machine learning approaches failed to handle natural form of raw data visualisation in chest X-ray images. Deep learning models accept and process data in their own nature. Due to this nature deep learning approaches plays major role in medical image segmentation. It accesses large set of data and executes in little time and produce expected result effectively. Central impact of this paper is to deliver appropriate segmentation architecture for lung chest X-ray images. In this paper U-NET based convolution deep neural network is used for lung chest X-ray image segmentation and classification. 512 X 512 image sizes are used for training and testing. The intention of this method is to extract lung region from chest X-ray image and classify as nodule or non-nodule images and also cancerous or non-cancerous. The result indicates that the proposed method achieve high accuracy as 89.76% for segmentation and 98.40% for nodule classification and 98.79% for cancer classification.

Keywords: U-NET, segmentation, Classification, Nodule and Non Nodule, Malignant and Benign.

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1 Introduction

In chest X-ray image finding and examining object is a challenging task due to large deviation in patients X-ray shape, size and nature. For many decades medical images captured with the help of diverse forms like radiography, mammography, Computed Tomography (CT) and ultrasound. These images play vital role in early identification, detection and curing various nature of diseases. Chest X-ray images are basic and economic tool for human beings and help radiologist and physicians to find tumour, pneumonia and lung cancer etc. It is important to capture proper structure of lung to differentiate from other area of chest like heart and diaphragm. Due to lack of expert knowledge and support from computer aided tools the field of segmentation and classification moves to deep learning technique. Automatic segmentation of lung region is necessary for every step of computer-aided diagnosis. Segmentation is elementary step in disease diagnosis. Lung field segmentation gives conclusion regarding nodule and non-nodule portion in chest X-ray images. Classification in Convolution Neural Network (CNN) is easy and worldwide used technique for lung segmentation. Particularly deep learning enables CNN as most wanted for medical image segmentation. In this paper U-NET based CNN is used for lung segmentation and classification. This paper is organised as follows: Section 2 explores the related work in the literature, Section 3 describes data set description and pre-processing methods, Section 4 elucidates the proposed method used for segmentation and classification, Section 5 discussed the experimental results and Section 6 concludes the paper with key points to track the future research.

2 Related Works

Amruta et al.[14] proposed a computer vision based mango grading system. This model implemented on the basis of external parameters like ripeness, shape, size, defects. Dashehari dataset mangoes reached a test accuracy of 100%, 98.19% and 99.20% respectively. Integrated grading system which is based on formula achieves accuracy as 88.88%. Anupama et. al.,[8] discussed about Support Vector Machine and Convolution neural network (CNN) for image classification and compared the result of each technique. The proposed result shows that SVM provides satisfactory accuracy for binary classification and CNN contributes stable accuracy over binary and multiclass classification. Chang Wang et al.[16] offered a convolution neural network based segmentation method for retinal images. It works centred on Dense U-net and patch based learning were produced. Results were measured in terms of sensitivity, specificity, accuracy and area under each curve and reported this method produced higher accuracy. Intisar Rizwan I Haque et al.[3] discussed about basic deep learning segmentation methods, accuracy metrics, radiograph images available and finally need of data augmentation were discussed. Jeff Duryea et al.[2] proposed an automated algorithm for identifying left and right lung fields in chest X-ray images. Edge tracing and Edge correction has been done based on ROI, sensitivity and specificity finally the results were compared. Jonathan Long et al.[10] projected the fully convolutional network(FCN) for semantic segmentation. They used skip architecture that combines the deep, coarse layer information and FCN improves the speed of learning. Karen Simonyan et al.[12] experimented the depth of convolution neural network and its accuracy in large scale image recognition. ConvNet evaluated with different parameters. Classification is carried out by using ConvNet and result has been evaluated with help of single test scale and multiple test scale. Comparison was done among these test results and reported ConvNet performs well for large scale image recognition. Michelle Livne et al.[9] analysed brain vessel with the help of U-Net to help the treatment of cerebrovascular disease. Its performance was evaluated with Dice coefficient, Hausdorff distance and average Hausdorff distance. The results were compared with traditional graph cut segmentation method and identified that it performs well than graph cut method. They found U-net performs fine in large vessels and minimum in small vessels. Mohammad Tariqul Islam et al.[7] analysed and conducted experiment with JSRT dataset, Shenzhen dataset and Indiana chest X-ray dataset by deep convolutional network to identify various abnormalities in chest radiographs. To classify cardiomegaly deep learning method improves 17% than old methods. Deep learning based localization and classification achieves high result in identifying abnormalities. Mohammad Hesam Hesamian et al.[5] analysed various popular deep learning techniques for medical image segmentation and challenges accrued in segmentation. Olaf Ronneberger et al.[11] explained the importance of U-net in medical image segmentation. Rahib H. Abiyev et al.[1] used convolution neural network (CNN) for diagnosis of chest disease. CNN, back propagation (BPNNs) in supervised learning; competitive neural networks (CpNNs) in unsupervised learning also experimented to diagnose of chest diseases. Performance of each network were recorded and compared in terms of accuracy, error rate, training time. Rahul Hooda et al.[6] contributed a deep learning based segmentation method. It's a fully convolutional network works fine for segmentation of chest radiographs. It achieves 98.92% accuracy than old methods. Seok-Jae Heo et al. [4] used demographic variables for Convolution Neural Network (D-CNN) and Images for Convolution Neural Network (I-CNN) to detect tuberculosis. Chest radiographs in annual workers health examination data of 1000 images are used for this experiment and feature extraction is done with the help of VGG19, InceptionV3, ResNet50, DenseNet121, and InceptionResNetV2. When compared with the results of CNN models it is reported that CNN successfully detect the tumour and demographic values improve this performance. V. Thamilarasi et al.[15] proposed deep learning based classification algorithm for lung chest radiographs. Convolution neural network classifies the image as normal and abnormal and achieves accuracy as 86.67%. Wei song et al.[13] proposed a new deep learning algorithm with combination of encoder and decoder structure. Image dataset of gray scale electron microscopy and seabed mineral image has been used for experiment. The new improved U-net performed well in both images and found segmentation loss has been considerably reduced.

3 Materials and Methods

Deep learning methods need large dataset to produce effective results. In medical field, availability of such dataset is limited, particularly for lung chest X-ray images. JSRT database is used for segmentation and classification. It was originally developed by Japanese society of Radiological Technology. It covers 247 images which include 154 nodule images and 93 non nodule images. These images were at a size of 2048 $\times$ 2048 gray scale images in 12 bit depth and it is reduced to 512 $\times$ 512.

3.1 Preprocessing

It is a method to enhance the quality of image. It is used to enhance raw data or improve number of images in dataset by scaling and adjusting. Enhancement is done by variety of ways.

- Noise reduction
- Improve the quality of image
- Augmentation is done to increase the image count

In this experimental analysis

1. All jpg images are converted into .png format.
2. All images are resized into 512 $\times$ 512 wit RGB.
3. Ground truth images are also converted into 512 $\times$ 512 sizes.

Image augmentation is done by shift and rotation. It is used to increase the number of images in the training and testing set.

4 Proposed Method

The proposed method uses JSRT dataset for training, testing and evaluation. The evaluation is based on the accuracy. Deep learning is an emerging tool for Computer Aided Diagnosis (CAD). It plays on the basic concept of Artificial Neural Network (ANN). It allows more number of layers and provide path for better analysis and gives enhanced prediction of data. CNN imparts major role in deep learning.

Medical image analysis and Deep learning methods are always together to help radiologist to predict patient stages. It is extremely advanced way to use many neural networks and they are used to extract high level features from given source of data. It produces optimised solution for a given set of problem. Both segmentation and classification are done by using U-Net architecture. The following figure shows the methodology adapted in the proposed method.

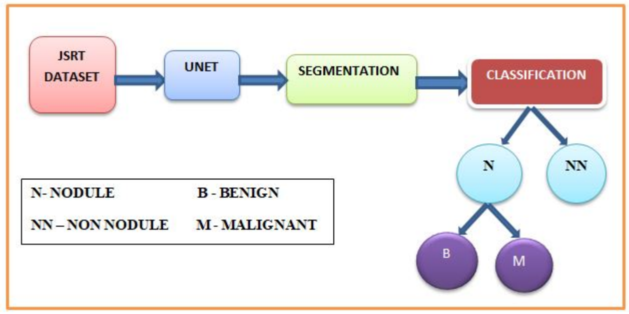

Figure 1: Proposed Method

4.1 U-NET Architecture

Fully convolution neural network plays a major role in deep learning. U-NET was originally developed by Olaf Ronneberger, Philipp Fischer and Thomas Brox in 2015 to process bio medical images. Its working nature is similar to auto encoders. It has three parts as down sampling (contracting) path, bottle neck and up sampling (expanding) path. The encoder compress the given input and decoder build output from the given encoder representation. The U-NET Architecture is given in Figure 2. During down sampling the contraction path is built based on 4 layers.

- 3x3 Convolutional Layer + relu activation function+ kernel initializer he normal+ same padding
- dropout layer
- 3x3 Convolutional Layer + relu activation function+ kernel initializer he normal + same padding
- 2x2 Max pooling

During up sampling the expansion path is built based on 4 layers It has 2D layer + 2 stride

- Image concatenate with respective contraction image.
- 3x3 Convolutional Layer + relu activation function + kernel initializer he normal + same padding
- 3x3 Convolutional Layer + relu activation function+ kernel initializer he normal+ same padding
- Adam optimizer- used to train deep learning models. It needs the compilation of keras model.

- Binary cross entropy- it is a loss function. It provides loss between true and prediction labels.
- Model training by using number of epochs and provide expected prediction.

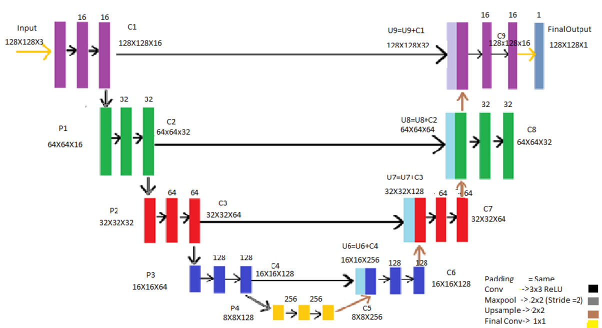

Figure 2: U-NET Architecture

Relu Activation function is responsible for transforming summed weighted input from the node into corresponding output for that input node. The Rectifier Linear Unit (ReLU) produce output if the input is positive, if not it will produce zero as output. It is most commonly used default activation function for neural network. It can easily train model and produce better performance. The output is x if x is positive else it gives 0.

$$RELUequation = A(x) = max(0, x) \quad (1)$$

Same padding is used which means zero padding, the given input image size and convolution output image size does not differ. Zero padding does not reduce the dimension and image information not reduced. Zeros are only added in the borders.

Kernel Initializer is used to initialize the weights. It used to convert data from given input space into another space.

Max pooling isused to denoise the image. It is used to down sample the input, reducing its dimensionality and reduce the computational cost. In non-overlapping sub regions it is applied as maxfilter.

It performs better than own family machine learning methods. Data augmentation techniques like shift and rotation are used to increase the number of images in the dataset. Improved dataset gives better result. Finally it provides improved result in lung image segmentation. Figure 3 shows the architecture used for segmentation.

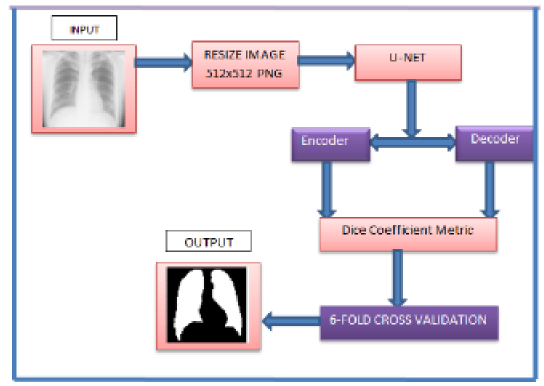

Figure 3: Architecture for Segmentation

4.2 Segmentation

Lung segmentation is most challenging and time consuming process in chest X-ray images. Many algorithms and methods available for lung segmentation, but most of the results achieve only minimum accuracy due to different shape, size and location of lungs. Segmentation is generally done based on Morphological operations, Region growing methods, Edge based methods and Machine learning based methods. Compared to traditional methods Machine leaning with deep neural networks works well to produce expected result. Particularly U-NET produce expected result within time and produce expected accuracy.

Usually Machine learning models are evaluated on the basis of true positives, false positives, true negatives and false negatives. To evaluate the perfection of result, the metrics Accuracy, dice metrics and 6 fold cross validation are used in this segmentation. Segmentation is done by changing few parameters like threshold value and seed value.

4.3 Evaluation metrics

Performance of model has been evaluated with the help of evaluation metrics. It is used to identify the quality of statistical or machine learning model. Following are some evaluation metric used in this segmentation.

4.3.1 Accuracy

It is a ratio between correct pixel prediction and total number of pixel prediction produced by architecture. The following formula is used for this calculation. TP represents True Positive, TN represents True Negative, FP represents False Positive and FN represents False

Negative.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (2)$$

4.3.2 Cross validation

To avoid the problem of over fitting cross validation has been performed. Given dataset has been divided into three parts as training set, validation set and testing set. The training set was split into k smaller sets. K-fold Cross validation separates the data into folds and some point each test set was used. 6 fold cross validation is used, which includes following steps:

- In the first iteration the model test by using first fold and the rest are used for training set by the model.
- In the second iteration the model test by using second fold and the rest are used for training set by the model.
- This process has been repeatedly continued for each fold until all six folds are used for testing data.

4.3.3 Dice Metrics

It is one of the most commonly used segmentation metric.

$$Dice\,Coefficient = \frac{2 \times area\ of\ overlap}{total\ no.\ of\ pixels\ in\ both\ images} \quad (3)$$

It plays on the positive correlation concept, if one says model A is best means others will say the same. It gives better accuracy for machine learning methods.

4.4 Classification

Classification is a process of labelling given set of Data into two different groups. It is one type of algorithm which process input data and produce output as classified in one category, it does not care about the given input was structured or unstructured. Classification of nodule and non-nodule is very important for early detection of cancer. Nodule classification takes more time for classification. It's a complex work for radiologist, it takes more time for radiologist to segregate group based on same features. Classification helps to identify and understand the similarities between objects.

Classification in deep learning needs more training images. Deep learning techniques performance depends on the accessibility of required data. Medical images always limit to some number. Gathering more chest radiographs was difficult task. To overcome this problem Data augmentation was done for all 247 images. To increase the dataset, various augmentation techniques have been used without affecting original dataset and image size. Most commonly employed rigid transformation is only used in this experiment. They are

- Shifting image as horizontally.
- Shifting image as vertically.
- Rotate image as 90 degree left.
- Rotate image as 90 degree right.

Classification is done for two lung classes

1. Nodule and Non nodule
2. Malignant and Benign

4.4.1 Nodule and Non nodule

A nodule contains some solid portions, but it is not always cancerous and to identify whether it's a malignant or benign again it is classified by using machine learning techniques. Non nodules don't have such solid parts. Machine learning provides better result for more images. The augmentation is done with every image in the JSRT dataset by rotation and augmented images have been used for nodule or non-nodule classification.

Tumor is most dangerous disease in the world. It disturbs the cell growth and those abnormal cells form a group and uncontrollably multiply and affect the human body. Tumors are solid or in fluid form. It can be developed in any part of the body. Proper diagnosis prolongs the life of human society. Majority of the tumors form in Lung portion. Machine learning techniques provide better path to eliminate long time analysis and diagnosis. Particularly deep learning techniques act as role of pathologist and classify Malignant and Benign in a fraction of second. It's a gift for lung chest X-ray images.

5 Result and Discussion

Experimental analysis was carried out for the proposed method.

- First the segmentation has been done
- Second nodule and non-nodule classification
- Third malignant and benign classification Analysis is done by changing various parameters.

For Segmentation following parameters has been changed.

5.1 Threshold Analysis

First threshold value has been changed and 5 to 8 values are provided as threshold value. For all threshold value the program has been run and recorded the output of segmentation and accuracy. The Table 1 shows the trial result.

Table 1: Threshold Value and Accuracy

$Threshold\ Value$	$Accuracy$
$Th = 5$	85.97%
$Th = 6$	89.97%
$Th = 7$	85.58%
$Th = 8$	82.65%

Based on the experiment best threshold for UNET segmentation is identified as Th=6.

5.2 Seed Value Analysis

Seed value has been changed to analyse the result. Seed value 1 to 5 has been experimented. It is identified that seed value has the influence in segmentation result. Experimental result shows that the seed value 3 is good for segmentation. Table 2 shows the accuracy of segmentation for different seed values.

Table 2: Accuracy at Different Seed Values

$S.No$	$Seed\ Value$	$Accuracy$
1	1	86.24
2	2	87.74
3	3	87.76
4	4	85.02
5	5	84.63

5.3 Six Fold Cross Validation

Six-fold cross validation has been performed and accuracy is obtained with the help of Dice coefficient. For each fold dice coefficient metric has been calculated separately. The details of segmentation in layers is given in Figure 4.The results of filters in each layer are given in Figure 5. Table 3 shows the 6-Fold cross Validation results.

Model: "model"

Layer (type)	Output Shape	Param #	Connected to
input_1 (InputLayer)	[(None, 512, 512, 3)	0	
lambda (Lambda)	(None, 512, 512, 3)	0	input_1[0][0]
conv2d (Conv2D)	(None, 512, 512, 16)	448	lambda[0][0]
dropout (Dropout)	(None, 512, 512, 16)	0	conv2d[0][0]
conv2d_1 (Conv2D)	(None, 512, 512, 16)	2320	dropout[0][0]
max_pooling2d (MaxPooling2D)	(None, 256, 256, 16)	0	conv2d_1[0][0]
conv2d_2 (Conv2D)	(None, 256, 256, 32)	4640	max_pooling2d[0][0]
dropout_1 (Dropout)	(None, 256, 256, 32)	0	conv2d_2[0][0]
conv2d_3 (Conv2D)	(None, 256, 256, 32)	9248	dropout_1[0][0]
max_pooling2d_1(MaxPooling2D)	(None, 128, 128, 32)	0	conv2d_3[0][0]
conv2d_4 (Conv2D)	(None, 128, 128, 64)	18496	max_pooling2d_1[0][0]
dropout_2 (Dropout)	(None, 128, 128, 64)	0	conv2d_4[0][0]
conv2d_5 (Conv2D)	(None, 128, 128, 64)	36928	dropout_2[0][0]
max_pooling2d_2(MaxPooling2D)	(None, 64, 64, 64)	0	conv2d_5[0][0]
conv2d_6 (Conv2D)	(None, 64, 64, 128)	73856	max_pooling2d_2[0][0]
dropout_3 (Dropout)	(None, 64, 64, 128)	0	conv2d_6[0][0]
conv2d_7 (Conv2D)	(None, 64, 64, 128)	147584	dropout_3[0][0]
max_pooling2d_3(MaxPooling2D)	(None, 32, 32, 128)	0	conv2d_7[0][0]
conv2d_8 (Conv2D)	(None, 32, 32, 256)	295168	max_pooling2d_3[0][0]
dropout_4 (Dropout)	(None, 32, 32, 256)	0	conv2d_8[0][0]
conv2d_9 (Conv2D)	(None, 32, 32, 256)	590080	dropout_4[0][0]
conv2d_transpose(Conv2DTranspo	(None, 64, 64, 128)	131200	conv2d_9[0][0]
concatenate (Concatenate)	(None, 64, 64, 256)	0	conv2d_transpose[0][0] conv2d_7[0][0]
conv2d_10 (Conv2D)	(None, 64, 64, 128)	295040	concatenate[0][0]
dropout_5 (Dropout)	(None, 64, 64, 128)	0	conv2d_10[0][0]
conv2d_11 (Conv2D)	(None, 64, 64, 128)	147584	dropout_5[0][0]
conv2d_transpose_1(Conv2DTrans	(None, 128, 128, 64)	32832	conv2d_11[0][0]
concatenate_1 (Concatenate)	(None, 128, 128, 128	0	conv2d_transpose_1[0][0] conv2d_5[0][0]
conv2d_12 (Conv2D)	(None, 128, 128, 64)	73792	concatenate_1[0][0]
dropout_6 (Dropout)	(None, 128, 128, 64)	0	conv2d_12[0][0]
conv2d_13 (Conv2D)	(None, 128, 128, 64)	36928	dropout_6[0][0]
conv2d_transpose_2(Conv2DTrans	(None, 256, 256, 32)	8224	conv2d_13[0][0]
concatenate_2 (Concatenate)	(None, 256, 256, 64)	0	conv2d_transpose_2[0][0] conv2d_3[0][0]
conv2d_14 (Conv2D)	(None, 256, 256, 32)	18464	concatenate_2[0][0]
dropout_7 (Dropout)	(None, 256, 256, 32)	0	conv2d_14[0][0]
conv2d_15 (Conv2D)	(None, 256, 256, 32)	9248	dropout_7[0][0]
conv2d_transpose_3(Conv2DTrans	(None, 512, 512, 16)	2064	conv2d_15[0][0]
concatenate_3 (Concatenate)	(None, 512, 512, 32)	0	conv2d_transpose_3[0][0] conv2d_1[0][0]
conv2d_16 (Conv2D)	(None, 512, 512, 16)	4624	concatenate_3[0][0]
dropout_8 (Dropout)	(None, 512, 512, 16)	0	conv2d_16[0][0]
conv2d_17 (Conv2D)	(None, 512, 512, 16)	2320	dropout_8[0][0]
conv2d_18 (Conv2D)	(None, 512, 512, 1)	17	conv2d_17[0][0]

Total params: 1,941,105
Trainable params: 1,941,105
Non-trainable params: 0

Figure 4: Details of Segmentation in layers

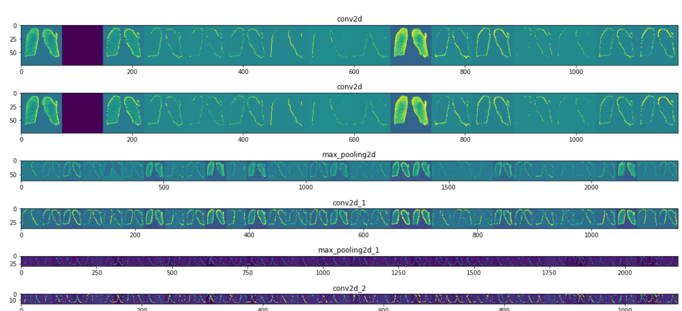

Figure 5: Results of Filters in Different Layers

Table 3: Experimental Result of 6-Fold Validation

No.of Folds	Dice Coefficient Result	
	Train	Tests
Fold 1	70.99%	71.07%
Fold 2	85.88%	87.79%
Fold 3	79.56%	82.80%
Fold 4	81.26%	83.65%
Fold 5	80.12%	81.23%
Fold 6	78.14%	79.24%

5.4 Classification

Figure 6 shows that U-NET training and validation accuracy.

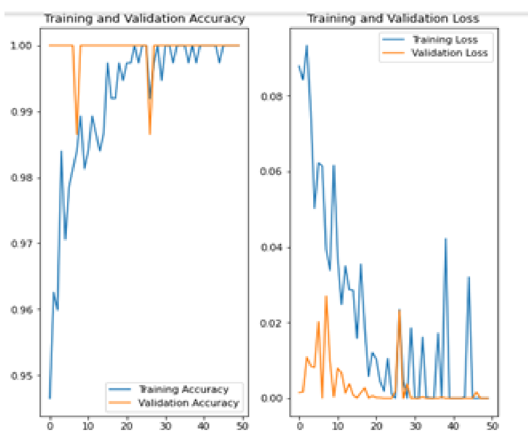

Figure 6: Training and Validation Accuracy

Deep learning techniques need more images to classify; Augmentation has also been done for Malignant and Benign nodule images. It classifies perfectly as Malignant or Benign and achieves 97.99% as accuracy. The following table 4 shows the classification accuracy of Nodule & Non Nodule and Malignant & Benign images.

Table 4: Classification Accuracy of Nodule or Non Nodule and Malignant or Benign

Classification	*Accuracy*
Nodule & Non nodule	97.99%
Malignant & Benign	98.79%

6 Conclusion

Medical images are milestone for today's radiological field to identify diseases and recommend proper treatment. Most of the time, it leads to false prediction due to its different nature. Chest X-ray images are most commonly used technique for lung cancer identification. Early detection of lung cancer avoids the death rate of patients. It's a difficult job for pathologist to segment and classify the chest X-ray images at the earliest. Chest is a place for many other organs too; separating lung from all other organ is very difficult one and time consuming process. When compared to traditional methods deep learning methods plays prominent role in medical image segmentation and classification due to its time management and accuracy. Particularly U-net works well than any other state of art methods for medical image segmentation. It has encoder, decoder structure and dropout layer to minimize the over fit problem. This proposed approach gives U-NET based deep learning method for segmentation and classification of lung chest X-ray images. These results depend on number of images trained and validated. Due to shortage of images augmentation technique has been done to increase the number of images. Accuracy of segmentation attained is 89.79% and many parameters changed in the program to check the variation in accuracy, Threshold and seed value has been changed and recorded. 6-Fold cross validation is performed. All these experiments find particular values suitable for segmentation. It is estimated that threshold value 6, and Seed value 3 are found as suitable for segmentation. Classification accuracy of nodule or non-nodule image is 97.99% and Classification of malignant or benign achieves 98.79%.

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