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# Application of U-Net

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***Abstract*: Lung cancer (lung carcinoma) is a malignant tumor defined by unrestrained cell growth in lung tissues. Long-term tobacco smoking is the major cause of lung cancer. Radiographs and Computed Tomography (CT) are used to see the lung cancer. The diagnosis is performed by the process called bronchoscopy and can be confirmed by biopsy. CT is a lung screening device which is a non-nosy, painless and use low dose X-rays to display the CT images of the lung cancer. By rotating the X-ray beam, it allows the radiologist to observe exquisite stages or slices of the lungs. It finds out smaller nodules of most cancer with help of multi-slice spiral computed tomography scanner. The LIDC-IDRI dataset consists of medical images from various patients affected by lung cancer. The images are initially segmented using U-net architecture for discovering the cancer affected region. The lung nodules are further examined using Convolutional Neural Network (CNN) to identify whether it is Benign or Malignant tumor. Initial stages nodules are smaller in size and its seriousness can be monitored based on the curvature. The resultant will show the proper way to approach the treatment.**

***Keywords*: Biopsy, Computed Tomography (CT), Convolutional Neural Network (CNN), Lung nodules.**

## 1. Introduction

The 2015 Global Cancer Statistics displays that lung cancer accounts approximately 13% of 14.1 million cancer patients and 19.5% of cancer associated deaths every year [1]. The survival rate is around 60% if the tumor size is small and diagnosis were made early and the five-year survival rate for the cancer patients present with degree IV lung cancer is much less than five percentage [2]. Early lung cancer detection consequently offers the satisfactory to cure as shown in Figure 1.1. The number of cancer patients affected for every year is greater than breast, prostate, and colorectal cancers mixed. The most common type is non-small cellular lung cancer. Thirty percent of these type begin within the cells that shape the liner of the body's cavities and surfaces. Another thirty percent of instances begin in cells that line the passages of the respiration tract [3]. Typically, the frame programs cells to die at a sure degree of their existence cycle to avoid overgrowth.

Cancer overrides this training, causing cells to boom and multiply after they should not. The overgrowth of cells ends inside the development of tumours and the damaging effects of most cancers. In lung cancers, this pattern of cellular overgrowth takes vicinity within the lungs, which can be important organs for breathing and gasoline alternate.

Fig. 1. Image of Lung Cancer

CT is a lung screening device which is a non-nosy, painless and use low dose X-rays to display the CT images of the lung cancer. By rotating the X-ray beam, it allows the radiologist to observe exquisite stages or slices of the lungs. It finds out smaller nodules of most cancer with help of multi-slice spiral computed tomography scanner. A tumor or nodule is a mass of cells that grows at the lungs. It can be benign or malignant. By detecting malignant tumours in an early level with CT lung screening as shown in Figure 1.2, the cancer cells may be treated at a time even as the most cancers nonetheless has promising survival rates and is localized in the lungs. It is expected that over eighty percentages of lung cancers may be cured if detected at an early stage. Fifteen percentages of lung cancers are caught at early stage, making the 5-12 months survival rate for all levels of lung cancer 20 percentages [4]. Catching lung cancers in an early stage as well as at the identical time as it's localized to the lung is important.

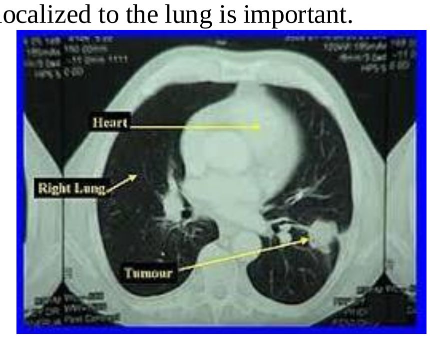


Fig. 2. Image of Lung cancer using CT image

CT lung screening is capable of detecting lung nodules as small as 2 or 3 millimeters. By catching malignant tumours while they are still small, they will be surgically eliminated before disease spreads to different areas of the body. The segmentation of lung tissues on chest image is a pre-processing step in developing the Computer-Aided Detection (CAD) gadget so you can lessen the quest location for lung nodules. Next, detection and segmentation of lung nodules from the available seek area are obligatory steps. In CAD structures for detection a category element categorizes the nodule applicants recognized. Even as a CAD gadget for prognosis classifies detected nodules into benign or malignant nodules. The nodule segmentation is a totally essential and critical step in loads of lung most cancers applications.

## 2. Related Work

The LIDC-IDRI database, A. P. Reeves et al [5] used Data from The Cancer Imaging Archive (TCIA) which incorporates 1018 clinical chest CT scans with lung nodules acquired from seven institutions. There is an associated XML record that details the places of nodules on each 512×512 slice. The lung nodule diameters variety from 3mm to 30mm. Each suspicious lesion is classified as a non-nodule, a nodule < 3 mm, or a nodule ≧3 mm diameter within the long axis. Only considered nodules ≧3 mm in diameter. Since nodules < 3 mm have been now not taken into consideration to be clinically relevant through current screening protocols [6]. The malignancy of each nodule turned into an evaluated with a 5-point scale from benign to malignant through as much as four skilled thoracic radiologists. The ones nodules which had been annotated by using at the least one radiologist for this study, calculated the median malignancy level (MML) of every nodule and annotated a nodule whose MML < 3 as benign, a nodule whose MML = 3 as uncertain and a nodule whose MML > three as malignant. Thus, there are 1301 benign, 612 unsure, and 644 malignant nodules.

D. Kumar et.al [7] proposes a Lung Nodule classification using deep features in CT images. The maximum patients detected with lung cancers these days are already at a complicated degree as lung cancers is hard to hit upon in early degrees. The purpose for failure in detecting lung cancers in early stages is that there is simplest a dime-sized lesion boom known as nodule inside the lung and by the point it is detected miles already too late for the affected person. These small lesions cannot be detected with the aid of X-rays and are best detectable by a CT scan. Even after the detection, it takes a large amount of attempt and revel in on the part of radiologists to hit upon and label the nodules as benign or as a probable case of malignancy [8]. Considering the huge quantity of cases encountered by way of radiologists each day there may be a consistent strain on them to analyze a big quantity of statistics and make a selection as quick as possible based at the evaluation. A viable approach to lower this burden at the radiologists is to use CAD structures as a 2-Dimension (2D) opinion that could robotically hit upon and examine lung nodules in CT images.

Another important standard to create a powerful CAD machine to classify is to use a feature or combination of functions that may successfully represent the shape and traits of region of interest in images. The use of deep neural networks for feature extraction in clinical photograph analysis and record that provides performance of an automatic unsupervised technique for function extraction from deep neural networks which is powerful as a supervised method. To examine the overall performance of the CAD tool the use of binary decision tree as a classifier, two hundred dimensional skills for every nodule were given as enter to the selection tree and classify into benign and malignant training had been obtained.

A. Heng et.al [9] proposes a Multilevel Contextual 3Dimesnions (3D) CNNs for False Positive Reduction in Pulmonary Nodule Detection. A computerized pulmonary nodule detection device specially consists of two steps: 1) candidate screening 2) false positive reduction. In candidate screening, a great quantity of coarse candidates is unexpectedly screened for the duration of the whole extent the use of numerous standards, depth thresholding, shape curvedness and mathematical morphology. In false superb reduction, effective classifiers together with discriminative functions are developed to reduce a huge quantity of false advantageous candidates.

The false positive reduction is the main method of an automated pulmonary nodule detection system and a number of efforts were devoted to enhancing the performance of this step. Automated identification of the pulmonary nodules from thoracic CT scans is, however the various hardest duties in computer-aided chest radiograph analysis for at least following two motives. The existence of those hard mimics might closely avert the detection procedure. Many researches have dedicated efforts to developing green and sturdy fake tremendous reduction algorithms that allows you to meet the aforementioned demanding situations.

Some of them endeavored to design representative features for pulmonary nodules by means of combining a hard and fast of discriminative characteristics of the nodules. Unfortunately, those handmade features have a tendency to suffer from restricted illustration capability and are inadequate to deal with the big versions of lung nodules. Recently with the notable successes of deep CNN in picture and video processing, the illustration capability of the excessive-level features which might be learned from massive quantities of education information has been broadly diagnosed. This also inspired some researchers to employ CNN in automated pulmonary nodule detection. Employ 2D multi-view convolutional networks to research representative capabilities for pulmonary nodule detection.

This technique can include exceedingly huge volumetric spatial information for detection by using extracting many 2D patches from in a different way orientated plane [10]. Superior to those works employing low-level handmade functions. However, this 2D CNNs primarily based solution nonetheless couldn't take full gain of 3D spatial contextual records of pulmonary nodules to unmarried them out from hard mimics and complicated environments.

Oquab. et.al [11] proposes a Lung cancer accounts for the highest wide variety of mortalities among all cancers in the world. Classification of lung nodules into malignant and benign is one of the maximum important tasks in this regard. A fast, robust and accurate system to address this challenge would not only save a lot of radiologist's time and effort, but would also enable the discovery of new discriminative imaging features. Significant successes in terms of improved survival rates for lung cancer patients have been observed due to improvements in CAD (Computer Aided Diagnosis) technologies and development of advanced treatment options.

Conventionally, the classification of lung nodules emerges as completed using hand-crafted imaging features which includes histograms, Scale Invariant Feature Transform, Local Binary Patterns and Histogram of Oriented Gradients. The extracted sets of capabilities had been then labelled by using a number of classifiers which includes Support Vector Machines (SVM) and Random Forests (RF). Recently with the success of deep CNN for image type, the detection and classification applications in clinical imaging have followed it for stepped forward characteristic analyzing. Tedious characteristic extraction and choice can now be circumvented using supervised high-level feature gaining knowledge. This has additionally attracted the attention of researchers working in Lung Nodule Detection and category with restrained success since the feature getting to know and classification were taken into-consideration as separate modules. In those frameworks a pre-trained CNN changed into handiest used for feature extraction while classification became primarily based on an off-the-shelf classifier consisting of Random Forests. In sharp comparison to these techniques to perform an end-to-quit education of CNN for nodule characterization while combining multi-view capabilities to reap improved characterization overall performance.

P. Fischer et al [12] propose a U-Net in Convolutional Networks for Biomedical Image Segmentation. While convolutional networks have already existed for a long time, their success turned into restrained because of the dimensions to be had training units and the scale of the considered networks. Since then, even larger and deeper networks had been trained the usual use of convolutional networks is on classification responsibilities, in which the output to a photograph is a single class label. However, in lots of visual obligations, specifically in biomedical image processing, the desired output ought to include localization, a category label is meant to be assigned to each pixel [13]. More-over heaps of training images are generally beyond reach in biomedical obligations. Trained a community in a sliding-window setup to predict the class label of every pixel via presenting a neighborhood region round that pixel as input.

## 3. System Architecture

The system architecture for detection of Benign or Malignant Lung Nodule using CT images is presented in Figure 3.1. From the input as CT image which is affected region on Lung Nodule. U-Net layers used for semantic segmentation of input image and used to classify whether cancer is Benign or Malignant.

The lung nodules had been detected and hence limited the scope of this study solely to benign-malignant nodule classification. To avoid the inaccuracy caused by nodule detection, defined the region of a nodule as the middle of the nodules center given by radiologists.

Based on nodule segmentation, a square ROI encapsulating the nodule on every slice is identified as a patch to symbolize the lung nodule's standard look. CNN use surprisingly little pre-processing as compared to other photo class algorithms. This approach makes the network learn filters used in the conventional algorithms were hand-engineered. This independence from earlier understanding and human attempt in characteristic layout is the main advantage which also helps us to find out whether the cancer is Benign or Malignant.

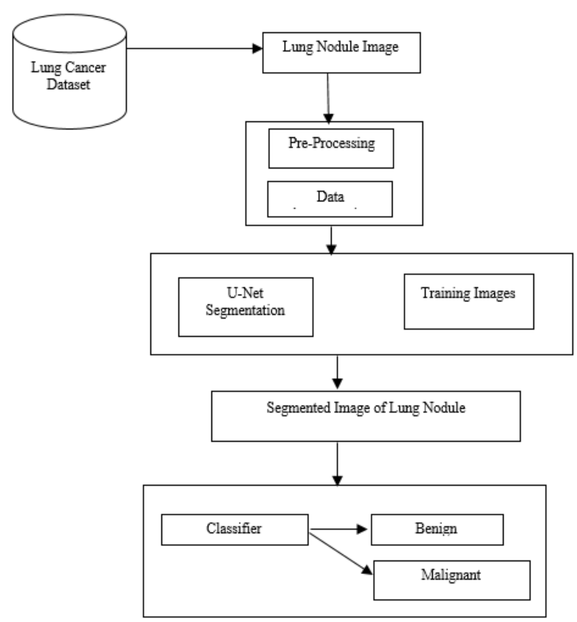


Fig. 3. System architecture of detection of lung cancer

## 4. System Implementation

### A. *Image Processing*

The image processing algorithm describes processes, Grey Scale image into histogram images and removal of noise from the histogram images is done in order to effectively extract the features from the input dataset which is described in algorithm 1.

*Algorithm 1*

1: Images is extracted from the input dataset and stored in a folder.

2: *for* each image in the folder *do*

3: Read images from folder
4: Convert CT Images into histogram images
5: Remove the noise from the histogram images
6: *end for*

The input image retrieved from dataset is shown in figure 4. The image pre-processing performs conversion of grey scale images to histogram images. The Grey Scale image is converted into histogram image to incorporate suitable deep learning methods. Figure 5 shows the converted histogram image from original input image.

Fig. 4. Input Image for Lung Cancer

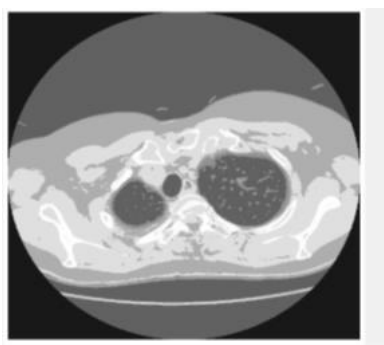

Fig. 5. Histogram Image for Lung Cancer

### *B. Data Augmentation*

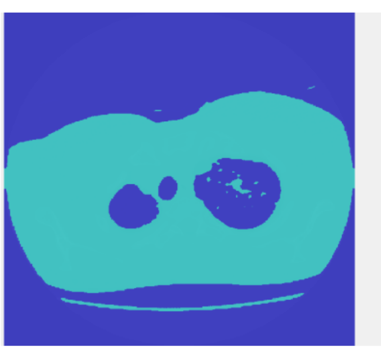

Fig. 6. Data Augmentation for Lung Cancer

The number of examples is insufficient to train a deep CNN network which often requires large number of training examples to generate extra training samples from the original data. The input data is augmented using rotation and scaling. The random rotation of the input patch along with two different scales (one for up-sampling and the other for down-sampling). By applying this data augmentation strategy is generate sufficient samples for both positive and negative examples to train our network shown figure 6.

### *C. U-Net for Semantic Segmentation*

The U-NET is used for Bio Medical Image Segmentation. First steps are the contraction direction, also referred to as the encoder which is used to capture the context in the image. The encoder is just a conventional stack of convolutional and max pooling layers. The second path is the symmetric increasing path additionally referred to as the decoder that is used to allow unique localization the usage of transposed convolutions.

The algorithm 2 explains the semantic segmentation of the cancer nodules for identification of the affected region. The U-NET network from the deep learning tool box in MATLAB. The layers of network in U-NET are created and the first layer is the encoder on the U-NET whereas the last layer is the decoder in the U-NET. The dataset is trained and tested, the input layers of the network is created and the augmented images are transferred as the input to the U-NET layer where the activation layer is initialized. By using the features extracted from the U-NET the images are segmented which helps in identifying the cancer affected region.

The structure seems like a U which justifies its call. The bottommost layer mediates between the contraction layer and the growth layer. It makes use of 3x3 CNN layers followed via 2x2 up convolution layer. A U-Net is a convolutional neural network structure that become evolved for biomedical picture segmentation. U-Nets were discovered to be very powerful for duties wherein the output is of similar length because the input and the output desires the amount of spatial decision. This makes them excellent for creating segmentation masks and for image processing along with first-rate resolution or colorization, shown figure 7.

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*Algorithm 2*

1: Install U-Net network from the deep learning tool box in MATLAB.
2: U-Net network is used and layer is created.
3: Adding the first is encoder on the U-Net network.
4: Max Pooling layers on the U-Net network
5: Last layer is decoder on the U-Net network.
6: Label the training and test dataset.
7: The input image
8: Create the input layers of network.
9: Augmented image is stored.
10: Activation layer is initialized.
11: Features from the U-Net is retrieved.
12: Image segmentation as output

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When convolutional neural nets are usually used with pictures for class, the photo is taken and down-sampled into one or greater classifications using a sequence of stride convolutions reducing the grid length every time. This makes the network format resemble a U form, a U-Net the down-sampling/encoder direction paperwork the left-hand side of the U and the up-sampling/decoder route bureaucracy the right hand a part of the U. For the up sampling/decoder direction several transposed convolutions accomplish this, each including pixels among and round the existing pixels. Essentially the opposite of the down-sampling route is performed which is shown figure 8.

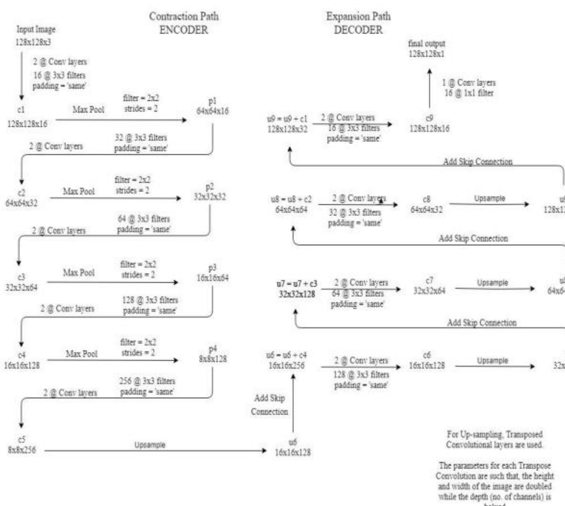


Fig. 7. U-Net architecture for semantic segmentation

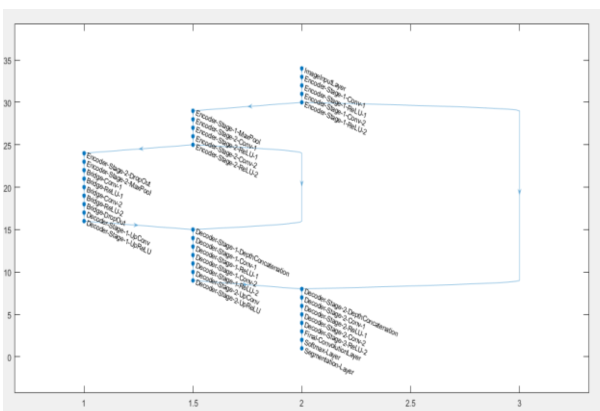

Fig. 8. U-NET work flow for Lung Nodule Segmentation

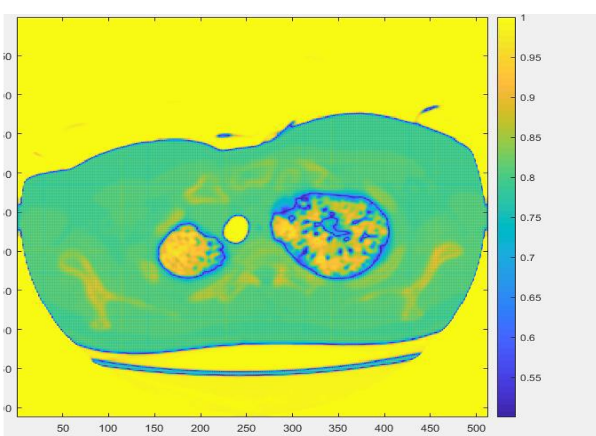

Fig. 9. Segment Image for Lung Cancer

To down sample, the image, convolution and pooling operations are used which convert a high-resolution image to a low-resolution image. By increasing the receptive field in max pooling operation helps to understand is there in the image. Transposed Convolution is the most preferred method to perform up sampling, which learns parameters through back propagation to convert a low-resolution image to a high-resolution image.

Basically, segmentation is a technique that splits image into regions. It is an image processing technique that permits us to separate tumor and textures in image. Segmentation is applied in applications including faraway sensing or tumour detection in biomedicine. So, the CT image is given as input to the U-Net pretrained model present in MATLAB to extract features from the image which is illustrated shown in figure 9. CNN helps to identify whether Benign or Malignant image which is illustrated shown in figure 10.

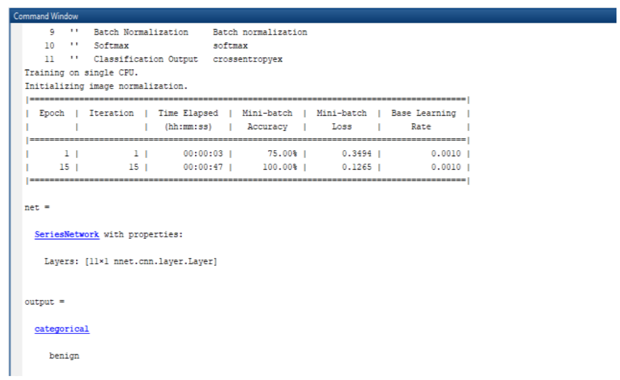


Fig. 10. Classification of Lung cancer

## 5. Conclusion

The implementation of U-NET for segmentation of the affected region achieves splendid performance on the LIDC-IDRI dataset. The Data Augmentation is used to reduce the noise from input image and it only needs very annotated images and has a very reasonable training. This assist in effectively detecting the impaired region. CNN identifies the Cancer nodule region in the CT images and classify as Benign and Malignant Lung Nodule. CNN proves be an efficient classifier for the dataset. In future work, to extend the proposed model to a semi-supervised learning framework, such that can use the nodules with an uncertain level of malignancy and unlabeled nodules as training samples to reduce the need for data annotation. Meanwhile, to investigate the compression of the CNN structure used in the model, with the aim of training the method computationally more efficient. Moreover, it will also be necessary to investigate the incorporation of other pathological information into the deep model for more accurate benign-malignant Lung Nodule classification.

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