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LUNG CANCER DETECTION USING U-NET MODEL AND INTEGRATION OF CONVOLUTIONAL AND RECURRENT NEURAL NETWORK

Muhammad Shahid Mehmood[*1], Muhammad Zaman[2], Humaira Yasmeen[3]

[*1,2] *Department of Computer Science & IT, Superior University,10 KM Lahore-Sargodha Rd, Sargodha, Punjab(40100),Pakistan.*
[3] *Department of Computer Science & IT, University of Education Jauharabad.*

[*1]shahidkhan.ak16@gmail.com, [2]mzamancui@gmail.com, [3]yasmeenhumaira56@gmail.com

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Corresponding Author: *

Abstract
With a high death rate, lung cancer is one of the most serious and widespread illnesses, presenting a serious public health concern. In this sense, a fully automated diagnosis technique for lung tumor identification is achieved by appropriately segmenting lung tumors utilizing Computed Tomography (CT) scans, Magnetic Resonance Imaging (MRI), and X-rays. As technology develops and data becomes more accessible, radiologists might employ computer tools for tumor segmentation to save valuable time. This work's main goal is to use the U-Net model and the combination of convolutional and recurrent neural networks to detect lung tumor segmentation from CT scans. We used the 260-patient LUNA 16 dataset to train and assess our model. With this proposed approach, we establish a deep.

INTRODUCTION

Let's discuss about lung cancer, the causes, and the numerous types of cancer. Following that, the imaging modalities and datasets exploited in our proposed technique are described. We go over our problem description and the fundamental goal and purpose of the proposed system in the last section. Malignancy, another name for cancer, is the unchecked growth of aberrant cells. It can happen anywhere in the body. In essence, cancer is a group of related conditions that all affect cells. The tiny units that make up all living things, including the human body, are called cells.The human body is made up of billions of cells. When aberrant cells proliferate and spread rapidly, cancer illness results. Cells in the body divide, grow, and know when to stop growing. They eventually die as well. Unlike healthy cells, cancer cells do not divide as they should; instead, they merely grow and divide in the wild. Usually, cancer cells group together to become tumours. A developing tumour turns into a cancerous cell, which can damage the body's essential tissues and kill the healthy cells that surround it. Someone may become very ill as a result.Malignant growth cells can occasionally split off from the original tumour and move to other parts of the body, where they continue to grow and form new tumours. Cancerous growth spreads in this way. When a tumour spreads to another area of the body, it is called metastasis. Figure 1.1 shows both healthy and malignant cells.

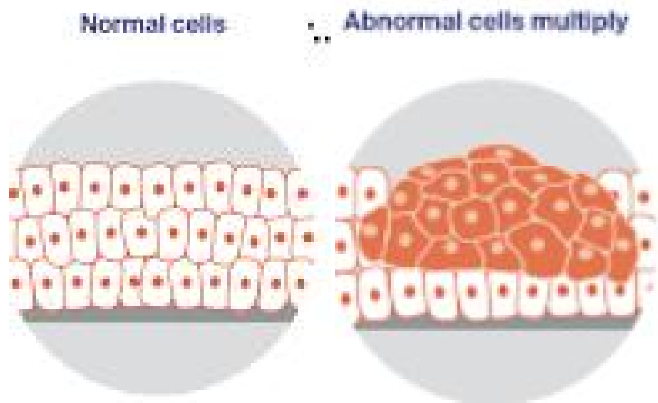


Fig 1.1

There are two or three main causes of cancer, but only a few may be prevented. According to data released in 2014, 480,000 people die each year from cigarette smoking in the United States. In addition to smoking, significant alcohol consumption, obesity, physical inactivity, and poor diet are risk factors for the disease. It is impossible to prevent the causes of those particular malignant growth. These days, age is the most fundamental factor of escape hazard. According to the Yank Most Malignancies Society, physicians in America treat 87 percent of cases of the most common tumors in people who are 50 years of age or older. Cancer, sometimes known as a tumour, is a vast institution of diseases rather than a single illness. Nearly every organ in the body is affected by cancer, and each of its anatomical and molecular subgroups needs a different therapeutic strategy. Cancer affects patients, their families, and society as a whole, and it can strike anyone at any age or gender. In 2015, the majority of cancers accounted for eight deaths worldwide, making them the second leading cause of mortality. Almost one in six fatalities worldwide are caused by eight million deaths. The most current WHO study states that 9.6 million individuals worldwide lost their lives to cancer in 2015. The National Cancer Institute, which did not omit any malignant growths from the skin or pores, stated that carcinoma is the most prevalent state of most diseases in the United States. It is characterized by malignant growths in the prostate and lungs.

1. LITRATURE REVIEW

Convolutional Neural Networks (CNN), Deep Belief Networks (DBNs), and Stacked De noising Auto encoders (SDAE) are three unique deep learning computations that were implemented and compared to the traditional photo highlight-based CAD framework. Eight convolutional and pooling layers make up the CNN engineering, which trades well. Approximately 35 surface and morphological highlights were eliminated for the conventional as compared to the computation. The part-based help vector machine (SVM) was used to prepare and order these highlights. The CNN approach's calculated exactness was 0.7976, which was just slightly higher than the traditional SVM's 0.7940. They used approximately 1018 lung cases from the open datasets of the Lung Image Database Consortium and Image Database Resource Initiative (LIDC/IDRI). (Sowmiya, T., and others, 2014)

In order to reduce the number of false positives for their detected knobs, they proposed a structured system that used a convolutional neural network and a deep neural system. There are four pooling layers and four convolutional layers in the CNN. The size of the canal was 3, 5, and its profundity was 32. The dataset that was used was obtained for approximately 85 patients from the LIDC-IDRI. The affectability that resulted was 0.82. DNN obtained a false positive decrease of 0.329. (J. Tan and others, 2017)

This approach suggested a framework that uses back-engendering to train the CNN's loads in order to recognise lung knobs in the sub-volumes of the CT image. On lung knobs that each of the four radiologists commented on, this framework achieved affectability of 78.9% with 20 fake positives and

71.2% with 10 FPs for each sweep. (R. Golan and colleagues, 2016) This study collects CT images of 70 patients with pneumonic knobs for testing. tests that have a thickness of 2 mm and a size of 512, which are distinguished by radiologists. Specifically, they are composed of 2232 CT images from 38 patients with loneaspiratory knobs (SPN), 17 patients with vascular bond pneumonic knobs (VAPN), and 15 patients with pleural grip pneumonic knobs (PAPN). 42 highlights, comprising shape, force, and texture highlights, were used after the district of interest was eliminated in order to fit the SVM model. (Zhou and others, 2016)

In order to identify multi-size aspiratory knobs in thoracic CT examinations, they implemented a CAD conspiracy. For the full LIDC/IDRI dataset, the achieved prepareability is 85.6% with only 8 FPs/filter. The CAD plot carried out a typical 9. affectability of 68.4% on various autonomous heterogeneous test sets using only 8FPs/filter. (Gupta and others, 2018)

A few veils were applied for thresholding. Hounsfifield Units (HU) are used to identify dubious Regions of Interest (ROI). Different highlights are identified during highlight extraction in order to restrict the questionable areas. Territory, eccentricity, circularity, and fractal measurement are extricated shape features. Surface features like mean, fluctuation, vitality, and entropy were used. Finally, the grouping stage makes use of Support Vector Machine (SVM) computation. For both the test and the train, 79% accuracy was achieved. (D. P. Kaucha, 2017)

This approach offered very few methods for detecting harmful cells in lung CT scans. The goal of that paper is to identify the problematic cells and provide more precise results by employing various division techniques, such as thresholding and watershed division. A limit value is established in thresholding to keep the foundation and the object of enthusiasm apart. The pixel has a place with the article if its value is more significant than the limit value; else, it is out of sight. The thresholding approach can then be used to separate the area of interest. The article and the foundation are separated in the watershed division using a variety of markers, including outside markers associated with the foundation and inner markers associated with the object of interest. It is a simple, quick, and intuitive tactic. The analysis shows that the watershed division approach is more accurate (85.27%) than the thresholding approach (81.24%). (T. Sowmiya and colleagues, 2014)

Thakare demonstrated the various image processing techniques used to diagnose lung conditions. The Median Filter methodology is employed in their intended approach to commotion evacuation and upgrading. The best thing about the middle channel is that it removes noise without obstructing the view. It is used to remove salt and pepper noise from the image while preserving the locations' edges. Gabor channels are used in the improvement stage because they produce better results than rapid fourier and autoupgrade. The purpose of this paper is to identify the tumour at an early stage. Images of CT filters are captured for informational purposes. The component extraction step of later image processing determines the image's territory, border, and unconventionality. The information is arranged using a calculation called a Bolster Vector Machine. The above-mentioned highlights aid in determining the tumor's size, which in turn helps determine the stage of the malignant growth. (T. Sowmiya and colleagues, 2014)

This technique suggested a paradigm for identifying lung malignant growths based on CAD. EDM (EntropyDegradation Method), a neural system-based computation, is suggested in their framework to differentiate SCLC (small cell lung disease) from CT scan images. The National Cancer Institute provided the lung CT filter images used for preparation and testing. Five sweeps are selected at random from each gathering to get the 10. model. Some photos are referred to as group 0, while those with SCLC are called bunch 1. The starting phase location of lung illness is suggested in this paper. (D. P. Kaucha et al., 2017)

Using image processing, CT scan images from several crisis centres are used to reveal lung-dangerous developments. To suggest a plan utilising MATLAB, research was done on noise decline channels, thresholding, watershed division, and feature extraction. After being improved and smoothed, the data images were then separated using marker-controlled watershed division. Zone, edge, and flightiness were eliminated from the dataset, and the

Maximum Edge classifier was used to create the game plan. (R. Y. Bharati et al., 2019)

They suggested using the dynamic vector quantisation technique to create a new system called CADe (PC upheld acknowledgement) for quick and flexible distinguishing proof of the aspiratory handles in the data CTchannel images. The elevated level VQ is utilised to divide lung territory after providing a more distinct separation of the lungs from chest volume. The disclosure and division of INCs were positively impacted by the low level VQ. Using rule-based filtering tasks in conjunction with a segment-based help vector with a machining classifier produced fake positive decreasing. 205 datasets from the publicly accessible online LIDC (Lung Image Database Consortium) database were used to validate this method. At an expressness of 4 FPs/analyze, the logical marker finally reaches 82.7% affectability of the CADe system. (Sammouda, R., and Taher, F. 2011)

They brought up the fact that lung cancer, one of the most dangerous diseases in the world, typically spreads internally due to aberrant cell development of lung tissues. It's interesting to note that if the malignant growth is detected early, the patient's chances of survival can be increased. This essay revolves around the startling concepts of information mining that are applied to predict the causes of lung illness. Furthermore, the Ant Colony Optimisation (ACO) approach has been swiftly explained. The malady expectancy estimation of the infection under investigation should be increased or decreased using this strategy. In order to produce rules and order the reasons behind the tumour, this study focusses on organising information digging and ACO techniques. It also provides the basic framework for deciphering the clinical conclusion. In 2013, M. New Begin et al. In order to determine if a patient's condition is normal or unbalanced, the authors of this research developed a robotised demonstration framework for the early detection and prediction of lung malignant development endurance using a neural system classifier. Histogram evening out is applied to images during the pre-handling phase. Highlights are separated using GLCM, followed by PCA and the binarization technique. The WEKA information mining tool was used to display the results on 909 CT images of different classifiers. (Miah, M. B. A. & Yousuf, M. A. 2015)

Here, designers primarily focus on significant mass improvement, and the concealment of foundation is achieved by adjusting the parameters of the suggested change work in the predetermined go. Manually examining the sputum samples is time-consuming, inaccurate, and requires a focused, prepared person to avoid suggestive errors. The outcomes of the division will be used as a foundation for a Computer-Aided Diagnosis (CAD) framework for early disease detection, increasing the patient's chances of endurance. The authors of this research suggested using the Gabor channel to enhance clinical images. Overall, it's a great improvement tool for clinical images. (Vishu K. and others, 2016)

By analyzing LUNGCT images, they developed a programmable CAD framework for the early detection of lung malignant development. First, removing the lung regions from the CT image using a few image preparation techniques, such as Weiner channel, disintegration, and bit picture cutting. The extraction process uses bit plane cutting techniques to convert the CT image into a paired image. Following extraction, the district developing division computation is used to split the separated lung sections. Malignant growth knobs were ordered using a rule-based approach. A set of guidelines was developed based on the extracted highlights, and a demonstration marker achieved 80% accuracy. (D. Sharma and others, 2017)

Powered by many testing datasets in the domains of PC vision and clinical imaging, semantic division is a functional examination domain where DCNNs are used to exclusively arrange every pixel in the image. Before the deep learning revolution, the standard AI method typically relied on nearby features that were used to automatically characterise pixels. Many models have been proposed in the last few years that show Twelve

better for division and acknowledgement tasks. However, creating deep models is challenging due to the disappearing slope problem, which is resolved by implementing modern enactment capabilities, such as Exponential Linear Units (ELU) or Rectified Linear Units (ReLU). He et al. have presented a profound leftover model that overcomes this problem by encouraging the preparation process through character planning. (R. Y. Bhaerao, 2019)

Similarly, CNNs that develop division methods based on FCN perform better than those that use standard picture division. Random engineering, a computationally advanced model with approximately 134.5M system boundaries, is one of the picture fix-based models. This methodology's primary drawback is the widespread use of endless pixel cover and related convolutions. Intermittent neural networks (RNN), which are calibrated on incredibly large datasets, have improved the display of FCN. One of the most advanced performance methods is semantic image division using Deep Lab. SegNet is divided into two sections: the comparing interpreting system uses pixelwise grouping layers, and the encoding system is a 13-layer VGG16 arrangement. This paper's main focus is on how the decoder upsamples its lower goal input, which includes maps. Later, in 2015, a better version of SegNet known as Bayesian SegNet was put forth. PC vision software are used to study the vast majority of these designs. In any event, certain profound learning models have been specifically developed for the clinical picture division, taking into consideration difficulties of class lopsidedness and inadequate knowledge (Bhaskar, N. A 2018).

"U-Net" is regarded as one of the very earliest and most well-known approaches for semantic clinical picture division. Fig. shows a graph of the fundamental U-Net model. 2. Convolutional encoding and disentangling units are the two main components of the system, according to the structure. The two components of the system execute the fundamental convolution tasks after ReLU enactment. The encoding unit uses 2×2 max-pooling tasks for down-examining. The convolution translate (speaking to up-convolution, or de-convolution) tasks are carried out to up-test the component maps during the interpretation stage. Component maps were harvested and duplicated from the encoding unit to the unravelling unit using the very first version of U-Net. A few division assignment preferences are provided by the U-Net model. Firstly, this model considers the simultaneous use of global area and setting. Second, it provides better division assignment execution and requires less test preparations. Third, division maps are legitimately delivered by a start-to-finish pipeline, which processes the entire picture in the forward pass. In contrast to fix-based division draws, this ensures U-Net jelly the entire setting of the info pictures, which is a considerable amount of flexibility (Fan, L., et al., 2017).

In the interim, a number of U-Net model modifications have been put forth, including a very simple version of U-Net for CNN-based medical imaging data division. Two changes are made to U-Net's original structure in this model: first, a variety of division maps and forward component maps are added (component astute) from one system component to the next. Finally, summing (component insightful) is carried out outside of the encoding and disentangling units. The element maps are extracted from different layers of encoding and deciphering units. Although there was no benefit to using a summary of highlights during the testing phase, the authors indicate promising execution improvement during preparation with improved union compared with U-Net. In any event, this concept illustrated how summation affects a system's display. In 2016, a profound shape-conscious system called Deep Contour Aware Networks (DCAN) was proposed, which can extract staggered relevant highlights using a various levelled design for exact organ division of histology pictures and shows awesome execution for division. The significance of skipped associations for biomedical picture division tasks has been experimentally assessed with U-Net and other systems. In addition, Nabla-Net, a deep convolutional architecture resembling a burrow, was put forth for division in 2017. (V. An. Gajdhane and L. M. Deshpande, 2014)

IMAGING MODALITIES

The features of cancer are identified using imaging techniques. By visualizing modalities, we can view the vital organs without having to open them. With the use of various modalities, the interior of every organ in the body can be examined in three dimensions. The most often used modalities nowadays are ultrasound, computerized tomography (CT) scanners, magnetic resonance imaging (MRI), and medication. With a CT scan, detailed pictures of any organ in the body can be obtained. A computer is connected to a CT scanner, which is known to as an X-ray machine. The CT scanners function is to demand a collection of organ images. The patient has no pain while using the CT scanner to easily identify the body's unhealthy areas. Images of any organ in the body Sound waves were employed in ultrasound. Ultrasound waves are used to examine the body and detect discomfort and swelling in pregnant women. Ultrasound is safer and non-invasive because it doesn't use radiation. Common imaging technique that made use of strong magnetic flux and radio waves. According to Aarthipoornima (2017), magnetic resonance imaging (MRI) is also used to examine internal body organs, joints, medulla spinals, brain, breast, heart, bones, and veins.

Lungs Computerized tomography (CT)

One of the most serious malignancies in the world today is lung cancer, and the most widely used method for screening for lung cancer is contrast-enhanced computerised tomography (CT).

One of the simplest methods for tumour identification is the handling and analysis of clinical images. In the past, intrusive methods have been used to analyse any condition, such as cancer or tumours. In spite of this, modern clinical imaging suggests non-invasive methods for tumour analysis. Although deformable models and other algorithms offer great accuracy in liver segmentation in CT images, their use in magnetic resonance imaging (MRI) is challenging. As a result, there aren't many studies that use these techniques for MRIs of this type.Cancer has various causes, many of which can be avoided. For instance, data from 2014 indicated that smoking cigarettes causes the deaths of approximately 480,000 people in the United States each year

DATA SET LUNA16

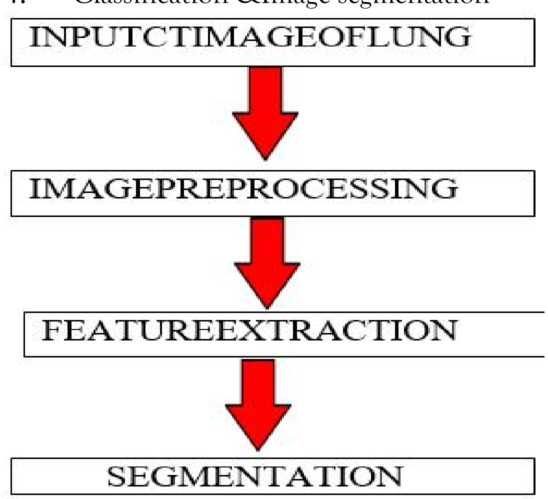
We make use of the publicly available LIDC/IDRI data set. Sweeps with a cut thickness more than 2.5 mm were forbidden. A total of 888 CT scans are included. There are ten compressed envelopes in this collection. The subset0.zip file was utilised. There are 260 patients' data in this entire collection. This dataset includes additional explanations and a different layout of the images from the LIDC/IDRI collection. This site provides access to the LIDC/IDRI dataset. LIDCIDRI (https://wiki.cancerimagingarchive.net/show/Public). Both training and testing are done using this dataset.

2. PROPOSED METHODOLOGY

There are some important steps discussed here with details: 1. First of all input the CT scan image of lung. 2. The first step performs pre-processing on the LUNA 16 training datasets. Different pre-
Images .It reduced the gray picture level to a binary image. The algorithms functions by presuming two sets of pixel in the picture after abi-model histogram. Then applied the waters hed transform. The basic aim of this technique segment the image when the twor
applied on data. Horizontally and vertically rotate the pictures. 3. Then we can extract the specified features using the U-Net model. Best features are extracted during this way. Convolution and max pooling layers are involved for this purpose.4. Now classification and segmentation is done using the U-Net model

General Flow of Methodology:

1. Input CT SCAN image of lung
2. Preprocessing of images
3. Feature Extraction
4. Classification &Image segmentation



Input CT SCAN image of lung

First of all we input CT scan image of the lung

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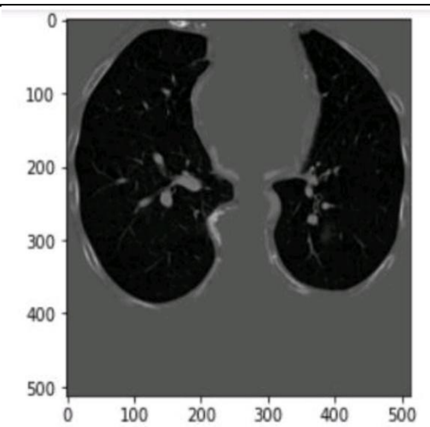

Fig 2.1

Image preprocessing

Preprocessing is the next step in improving the quality of the raw CT picture; some procedures are carried out on the image during this process, which enhance specific details and data; therefore, some operations are beneficial. Limiting The OTsu technique uses a clustering to automatically execute picture thresholding, turning the greyscale image into a binary one. The technique assumes two groups of pixels in the image, following a bi-model histogram. First, determine the ideal threshold value for splitting the two courses; pixel intensities must be array-stored for this to work. The threshold value and variance are computed using the total mean 20.

Watershed Transform

A watershed is a binary image or transformation that is defined in greyscale. This technique's primary goal is to segment the image when the edges of the two regions of interest are near to one another. Finding basins for catchment or watershed mountain sides is how the seafloor transformations operate. It handles it as though it were a surface with corresponding light pixels. High altitudes and a gloomy image are the results of low elevations. Figure 3.4 below displays the watershed transform's output image.

Data Augmentation

Picture information growth is used to expand the preparation dataset in order to improve the presentation and expertise of the model to sum up. Various growth methods, such as flipping, presenting commotion, picture improvement, and pivot, are being used by experts; however, many of these procedures alter the pixel's power values in unique images, and some of them also require altering the pixel values in comparing pivot at 208. To keep the specific picture pixel values and related information unchanged, we simply used non-intrusive preprocessing techniques.

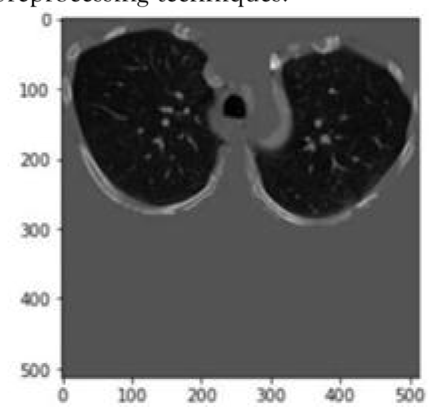

Fig 3.1(a): Input Image of Augmentation

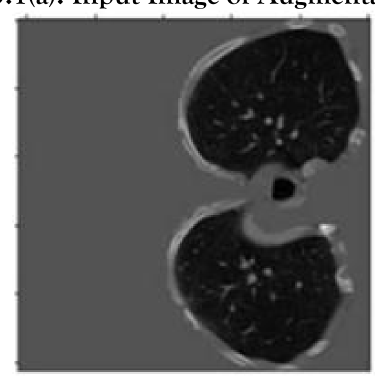

Fig 3.1(b): After Image Augmentation

Training

Different parameters are set for best weight is learning when we train our model. Input image size, Optimizer, Learning Rates, Loss, Batch size these all parameters are set

1. Input size: In training the input size of lung image is 256, 256,

Optimizer: The Adam was utilised in optimisation. Adam is a technique for adaptive learning rate optimisation created especially for deep neural network training. As an alternative to the traditional stochastic gradient descent process, it can be used to iteratively update the network weights depending on training data. Adams determines each student's unique learning rate based on various factors. Its name comes from adaptive moment estimation, which explains why

Adam adjusts the learning rates for each neural network weight by estimating the first and second moments of the gradient.

1. **Learning Rate:**

When we train the model we set learning rate LR 0.0001.In an optimization algorithm the training rate may be a tuning parameter in an algorithm that identify the step size at eachiteration while moving toward a minimum of a loss function. In setting a learning rate, there's a trade-off between the speed of convergence and overshooting.

2. **Loss:**

Binary cross Entropy Loss used in it, also known as sigmoid cross Entropy loss. It is a cross Entropy loss plus sigmoid activation. Not similar to softmax loss it is independent for eachvector component, it means that the loss calculated for every convolutional neural networkoutput vector component is not affected by others component values.

3. **Batch Size:**

The batch size is 16.The batch size are the number of processed samples before the model is updated. The size of a batch must be more then or equivalent to one and not exactly or equivalent to the number of samples in the trained dataset.

Feature extraction

Using a formal approach to classify the pattern is made simple by feature extraction. because it explains the relevant shape information that a pattern has. Feature extraction is a unique kind of dimensionality reduction in image processing and pattern recognition.

Feature extraction can be a dimensionality discount method that reduces an initial set of statistics to more manageable chunks for processing. There may be a great number of variables that require a great deal of processing power as a result of those enormous information units. For feature extraction, we employ UNet. In this technique, nice features are extracted.

The 1/2 inside the u-net structure serves as the encoder. To continuously encode the complete image into function representations at various special levels, it can be a pre-trained form of network, such as convolution blocks, followed by a maxpool down sampling.

Segmentation

A technique for dividing a digital image into multiple parts is called image segmentation. Pixels or super pixels match in the case of image segments. Segmentation is accomplished by simplifying the representation of a picture, or by making it easier to analyse parts of interest rather than the entire segmented 3D image. The best candidates for the cancer nodules were selected and placed in little boxes. To identify these best nodule candidates, as determined by LUNA16 data, a modified U-NET was trained. A popular CNN architecture for biomedical image segmentation is U-NET. If each pixel has a value between 0 and 1, which indicates the probability that the pixel belongs to a nodule, the model is trained to produce 269 form pictures. To do this, one of the final UNET layer's softmaxes is taken from the slice-like mark. U-Net inputs, ground truth, and a patient's segmented tumour result from the LUNA16 are corresponding.

GENERAL MODEL UNET

We used UNet model for classification and segmentation because of a lot of its advantages. In UNet to classify all pixels into one class softmax applied on the subsequent image which is surveyed bycross-entropyloss function in UNet architecture. The decoder aim is to semantically project the discriminative features (lower firmness) knowledgeable by encoder to urge a dense classification.

The decoder is the last a large portion of the encoder onto the pixel space (higher goal) the Segments speak to articles or parts of items, and include sets of pixels, or super-pixels. Division includes disconnecting an obvious contribution to parts to rearrange picture examination. Picture division sorts pixels into bigger parts ,dispensing with the need to consider singular pixels units of perception. Its design has an encoder network followed by a decoder organization. The encoder is that the 1/2 inside its own organization. It generally might be a pre-prepared characterization organization. Apply convolution blocks overviewed by a maxpool down testing to encode the information picture into include portrayals at various levels. 26

U-NET was initially settled and utilized for the most part for characterization and division of biomedical pictures. The design can be regularly observed as an organization of encoders followed by an organization of decoders. The decoder mirrors the design's subsequent half. The point is to extend the discriminative highlights (lower goal) learned by the encoder semantically onto the pixel space (higher goal) to accomplish a thick grouping. The decoder is made out of testing and connection joined by typical cycle of convolution. U-NET engineering is assortment of convolutionary encoding and disentangling units that takes the information picture and create the division include maps with separate to pixel classes.

Fig 3.5 shows the UNet design chart.

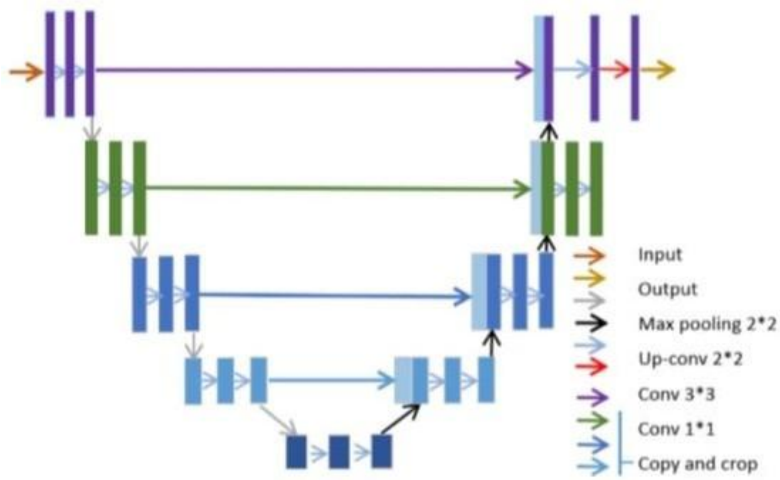

Fig. U-NET Architecture

2. RESULTSAND ANALYSIS

All the given volumes in the LUNA 16 dataset training used in the proposed system, in which 888 images are used for training dataset, for testing purpose 269 images are used. UNET model are used to segment out the tumor. Each image size is 256, 256, 1 batch size is 16 and for training we set epochs value is 20.

Lungs Cancer Detection and Segmentation Results and Explanation

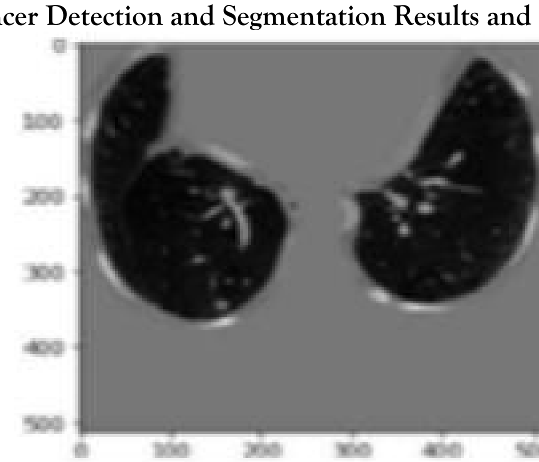

Fig 4.1(a) Image 1 of Lungs

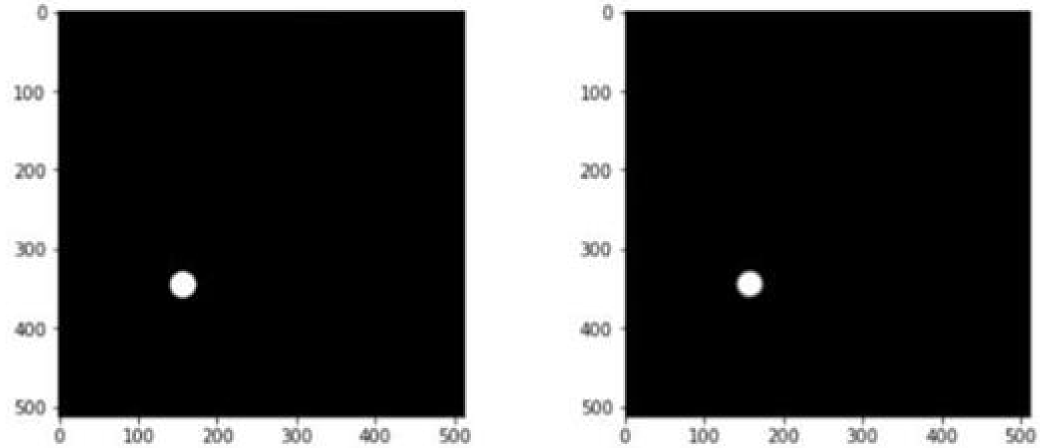

Fig 4.1(b) left side ground truth 4.1(c) Right side predicted tumor image

The above image 4.1(a) shows the test image of lung tumor .Left side Fig 4.1(b) shows ground truth Right side Fig 4.1(c) shows predicted Tumor image .We set different Epoch values for better results.

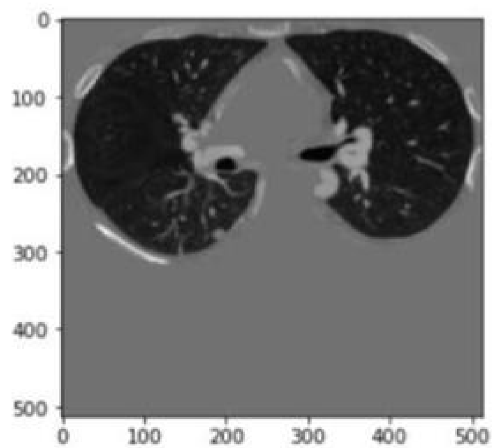

Fig 4.2 CT image of Lungs

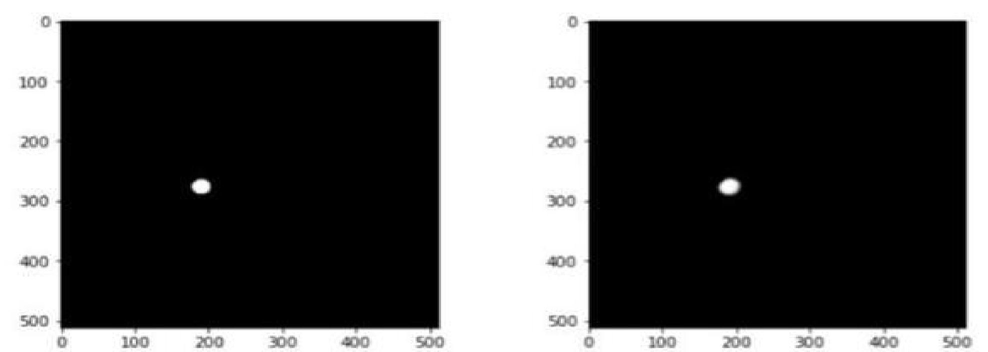

Fig 4.2 (b) left side ground truth 4.2(c) Right side predicted tumor image

The above image 4.2 (a) shows the test image of lung tumor. Left side Fig 4.2(b) shows ground truth Right side Fig 4.2(c) shows predicted Tumor image.

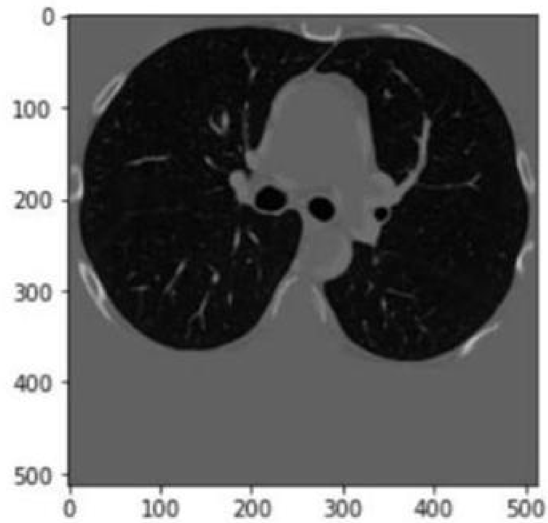

Fig 4.3(a) CT image of Lungs

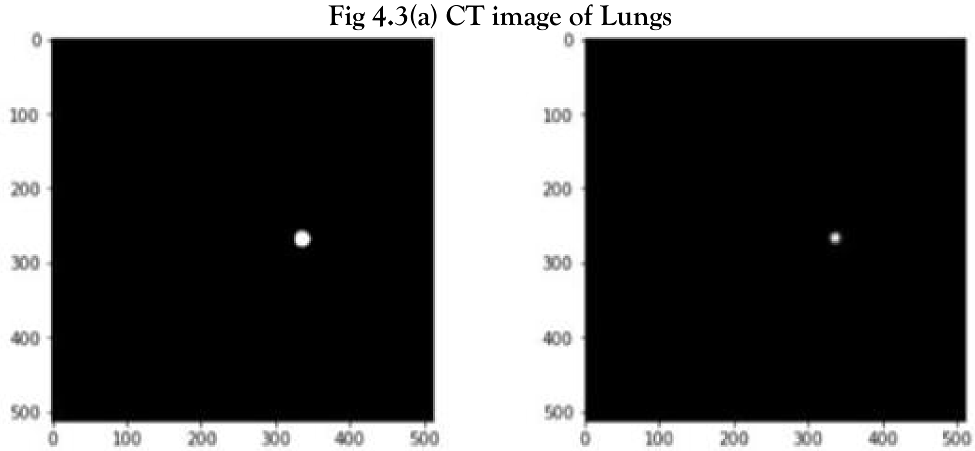

Fig 4.3 (b) left side ground truth 4.3(c) Right side predicted tumor image

The above image 4.3 (a) shows the test image of lung tumor. Left side Fig 4.3(b) shows ground truth Right side Fig 4.3(c) shows predicted Tumor image.

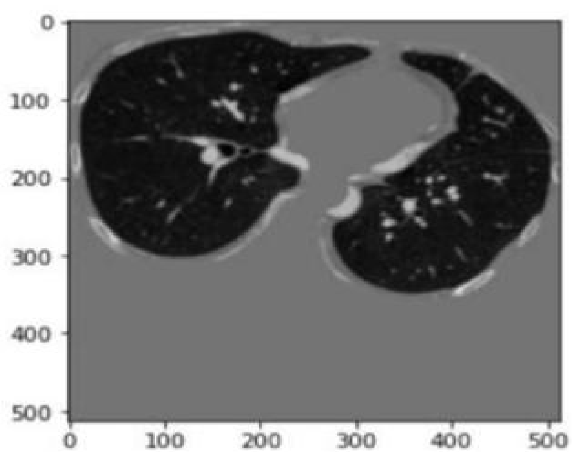

Fig 4.4(a) CT image of Lungs

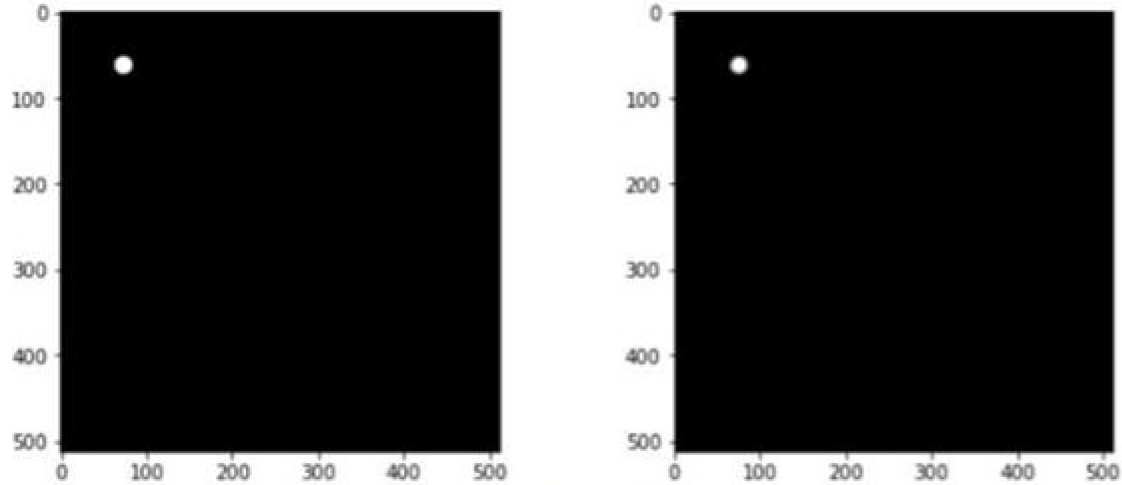

Fig 4.4(b) left side ground truth 4.4(c) Right side predicted tumor image

The above image 4.4 (a) shows the test image of lung tumor. Left side Fig 4.4(b) shows ground truth Right side Fig 4.4(c) shows predicted Tumor image.

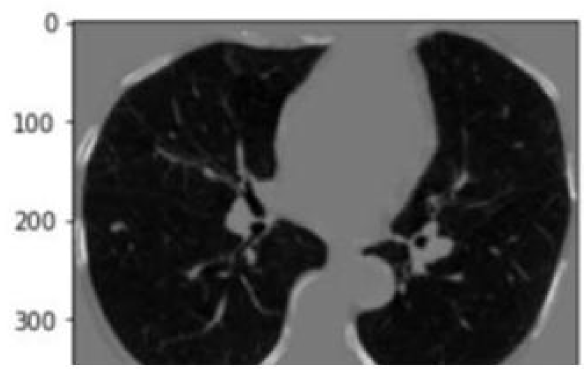

Fig 4.5(a) CT image of Lungs

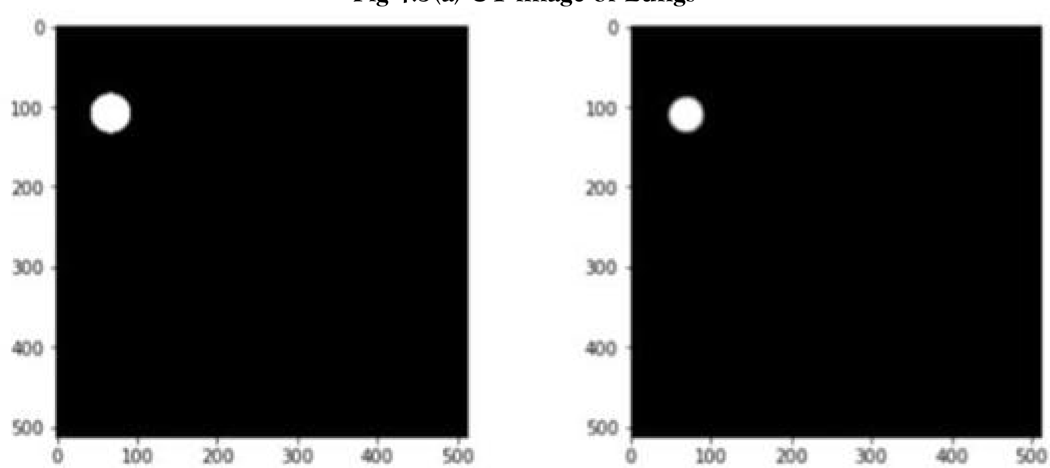

Fig 4.5(b) left side ground truth 4.5(c) Right side predicted tumor image

The above image 4.5 (a) shows the test image of lung tumor. Left side Fig 4.5(b) shows ground truth Right side Fig 4.5(c) shows predicted Tumor image.

LUNG NODULE ANALYSIS LUNA 16 PRDICTION RESULTS & PERFORMANCE EVALUATION PARAMETERS

Table: Result estimation

Pixel Accuracy	99.87335205078125%
True Positive Accuracy	100.0%
Dice Coefficient	0.851520572450805
IOU Score	0.7496739%

CONCLUSION

One of the most serious and pervasive diseases that poses a significant public health concern is lung cancer, which has a high fatality rate. UNET architecture is used to identify lung tumours. This model is used to identify patients' lung tumours.rate. In order to get a fully computerised diagnosis method for lung tumour identification, appropriate lung tumour segmentation from CT, MRI, and X-ray is utilised. By adopting computer tools for tumour segmentation, radiologists can save precious time thanks to advancements in technology and data availability. Our primary objective in this thesis work is to use the U-Net model to separate lung tumours from CT data. We used the 260-patient LUNA 16 dataset to train and evaluate our model. We create a deep convolutional neural network (CNN) for this suggested system.

REFERENCES

Ada, R. K. (2013). Early detection and prediction of lung cancer survival using neural network classifier .International Journal of Application or Innovation in Engineering and Management (IJAIEM) , 2(6) .

Al-Tarawneh, M. S. (2012). Lungcancerdetection using image processing techniques. Leonardo Electronic Journal of Practices and Technologies, 11(21), 14758.

Bar, Y. Diamant , I., Wolf, L., Lieberman, S., Konen, E., & Greenspan, H. (2015, April). Chest pathology detection using deep learning with non-medical training. In 2015 IEEE 12th international symposium on biomedical imaging (ISBI) (pp. 294-297). IEEE.

Bhalerao, R. Y., Jani, H. P., Gaitonde, R. K., &Raut, V. (2019, March). A novel approach for detection of Lung Cancer using Digital Image Processing and Convolution Neural Networks. In 2019 5th International Conference on Advanced Computing & Communication Systems (ICACCS) (pp. 577-583). IEEE.

Bhalerao, R. Y., Jani, H. P., Gaitonde, R. K., &Raut, V. (2019, March). A novel approach for detection of Lung Cancer using Digital Image Processing and Convolution Neural Networks. In 2019 5th International Conference on Advanced Computing & Communication Systems (ICACCS) (pp. 577-583). IEEE.

Bhalerao, R. Y., Jani, H. P., Gaitonde, R. K., &Raut, V. (2019, March). A novel approach for detection of Lung Cancer using Digital Image Processing and Convolution Neural Networks. In 2019 5th International Conference on Advanced Computing & Communication Systems (ICACCS) (pp. 577-583). IEEE.

Bhaskar,N.A(2018)SurveyonEarlyDetectionandPredictionofLungCancer.IJTIMES), June-2018.41

Chaudhary,A.,&Singh,S.S.(2012).LungcancerdetectiononCTimagesbyusingimage processing. In 2012 International Conference on Computing Sciences (pp. 142-146). IEEE.

Fan, L., Xia, Z., Zhang, X., & Feng, X. (2017, October). Lung nodule detection based on 3D convolutional neural networks. In 2017 International Conference on the Frontiers and Advances in Data Science (FADS) (pp. 7-10). IEEE.

Gajdhane, V. A., & Deshpande, L. M. (2014). Detection of lung cancer stages on CT scanimages by using various image processing techniques. IOSR Journal of Computer Engineering (IOSR-JCE), 16(5)28-35.

Golan, R., Jacob, C., &Denzinger, J. (2016, July). Lung nodule detection in CT images using deep convolutional neural networks. In 2016 International Joint Conference on Neural Networks (IJCNN) (pp. 243-250). IEEE.

Gupta, A., Saar, T., Martens, O., &Moullec, Y. L. (2018). Automatic detection of multisize pulmonary nodules in CT images: Large-scale validation of the false-positive reduction step. Medical physics, 45(3), 1135-1149.

Han,H., Li, L.,Han, F., Song,B.,Moore,W.,&Liang, Z. (2014). Fastandadaptivedetectionof pulmonarynodules in thoracic CT images using a hierarchical vector quantization scheme. IEEE journal of biomedical and health informatics, 19(2), 648-659.

Kaucha, D. P., Prasad, P. W. C., Alsadoon, A., Elchouemi, A., &Sreedharan, S. (2017, September). Early detection of lung cancer using SVM classifier in biomedical imageprocessing. In 2017 IEEE International Conference on Power, Control, Signals and Instrumentation Engineering (ICPCSI) (pp. 3143-3148). IEEE.

Miah, M. B. A., &Yousuf, M. A. (2015, May). Detection of lung cancer from CT image using image processing and neural network. In 2015 International conference on electrical engineering and information communication technology (ICEEICT) (pp. 1-6). ieee.

Priya, S. S., & Ramamurthy, B. (2018). Lung cancer detection using image processing techniques. Research Journal of Pharmacy and Technology, 11(5), 2045-2049.

Rao, P., Pereira, N. A., & Srinivasan, R. (2016, December). Convolutional neural networks forlungcancerscreeningincomputedtomography(CT)scans.In20162ndInternationalConference on Contemporary Computing and Informatics (IC3I) (pp. 489-493). IEEE.

Ravindranath,K.,&Somashekar,K.(2017,December). Earlydetectionoflungcancerby noduleextraction—Asurvey.In2017InternationalConferenceonElectrical,Electronics, Communication, Computer, and Optimization Techniques (ICEECCOT) (pp. 1-4). IEEE.

Rendon-Gonzalez,E.,&Ponomaryov,V.(2016,June).AutomaticLungnodulesegmentation and classification in CT images based on SVM. In 2016 9th International Kharkiv SymposiumonPhysics andEngineeringofMicrowaves, Millimeterand SubmillimeterWaves(MSMW)(pp. 1-4). IEEE.

Sharma, D., & Jindal, G. (2011). Identifying lung cancer using image processing techniques. In International Conference on Computational Techniques and Artificial Intelligence (ICCTAI) (Vol. 17, pp. 872-880).

Sowmiya, T., Gopi, M., Begin, M., &Robinson, L. T. (2014). Optimization of lungcancer using modern data mining techniques. International Journal of Engineering Research, 3(5), 309-314.

Suk, H. I., Lee, S. W., Shen, D., & Alzheimer's Disease Neuroimaging Initiative. (2014). Hierarchical feature representation and multimodal fusion with deep learning for AD/MCI diagnosis. NeuroImage, 101, 569-582.

Sun,W.,Zheng,B.,&Qian,W.(2016,March).Computeraidedlungcancerdiagnosiswithdeep learning algorithms. In Medical imaging 2016: computer-aided diagnosis (Vol. 9785, p.97850Z). International Society for Optics and Photonics.

Taher, F., & Sammouda, R. (2011, February). Lung cancer detection by using artificial neural network and fuzzy clustering methods. In 2011 IEEE GCC Conference and Exhibition (GCC) (pp. 295-298). IEEE.

Tan, J., Huo, Y., Liang, Z., & Li, L. (2017). A comparison study on the effect of false positive reduction in deep learning based detection for juxtapleural lung nodules: CNN VS DNN. In Proceedings of the Symposium on Modeling and Simulation in Medicine (pp. 1-8).

Wu, Q., & Zhao, W. (2017). Small-cell lung cancer detection using a supervised machine learning algorithm. In 2017 International Symposium on Computer Science and Intelligent Controls (ISCSIC) (pp. 88-91). IEEE.

Xu, Y., Mo, T., Feng, Q., Zhong, P., Lai, M., Eric, I., & Chang, C. (2014, May). Deep learningof feature representation with multiple instance learning for medical image analysis. In 2014 IEEE international conference on acoustics, speech and signal processing (ICASSP) (pp. 1626- 1630). IEEE.

Zhou, T., Lu, H., Zhang, J., & Shi, H. (2016). Pulmonarynodule detection model based on SVM and CT image feature-level fusion with rough sets. BioMed research international, 2016.

Patil, B. G., &Jain, S. N. (2014). Cancer cells detection usingdigital image processingmethods. International Journal of Latest Trends in Engineering and Technology (IJLTET), 3(4), 45-49.