Implementation Of Lung Cancer Nodule Detection Using CT scan

Ananda Babu J
Information Science Department
Malnad College Of Engineering
Hassan, Karnataka, India – 573202
abj@mcehassan.ac.in

Deepika G L
Computer Science Department
Kalpataru Institute Of Technology
Tiptur, Karnataka, India – 572201
deepikashankar66@gmail.com

Sariya Mazhar
Computer Science Department
Kalpataru Institute Of Technology
Tiptur, Karnataka, India – 572201
sariyamazhar27@gmail.com

Preeti T L
Computer Science Department
Kalpataru Institute Of Technology
Tiptur, Karnataka, India – 572201
preetitl2003@gmail.com

Pooja P
Computer Science Department
Kalpataru Institute Of Technology
Tiptur, Karnataka, India –572201
poojaprakash7026@gmail.com

Namitha C
Computer Science Department
Kalpataru Institute Of Technology
Tiptur, Karnataka, India – 572201
namithac193@gmail.com

***Abstract*— The paper focuses on enhancing the precision in detecting and measuring small lung nodules which are crucial for early diagnosis and treatment of lung cancer. Machine learning and image processing techniques are used to overcome traditional imaging techniques where the radiologists often struggle to distinguish nodules from surrounding tissues due to limited resolution in the images. This study improves small lung nodule detection using advancements in high-resolution Time - 0f-Flight, Positron Emission Tomography and resolution recovery algorithms. Techniques like Otsu thresholding, Watershed transform, and GLCM were used. Simulations evaluated nodule accuracy for sizes 4-10 mm, contrast levels 2:1 to 8:1, count levels 1%-100%, and respiratory motion amplitudes. Otsu thresholding was used for image reconstruction. Watershed transform effectively segmented foreground from background. GLCM features from CT scans enabled accurate lung cancer nodule identification using an SVM algorithm. Combining advanced imaging techniques and algorithms significantly improves the accuracy and reliability of small lung nodule detection, aiding early lung cancer diagnosis and treatment.**

Keywords*— Otsu thresholding technique, GLCM feature, Watershed, SVM Machine Learning Algorithm.

I. INTRODUCTION

The lungs are a pair of cone shaped, sponge-like organs.[1] The right lung has three lobes, and it is larger than the left lung, which has two lobes. Anatomy of lung is shown in Fig.1. Lung cancer is a disease where cells multiply abnormally and grow into a nodule. Fig.2 describes the beginning of the cancer. There are four stages of lung cancer. In stage I, the cancer is limited to the lung. In stages II and III, the cancer infects the chest (with larger and more invasive tumor classified as stage III). In the stage IV, the cancer is in both lungs or has spread to fluid around the lungs or other parts of the body.[1].

Despite advancements in medical imaging and diagnostics, early detection of lung cancer remains challenging. Existing studies highlight difficulties in identifying small nodules, distinguishing between benign and malignant growths, and accurately staging cancer using conventional methods (Wang-Jia Li et al, 2022) [3]. Furthermore, manual analysis of imaging data is time-consuming and prone to errors, necessitating more reliable and efficient diagnostic tools. The urgency of early and accurate lung cancer nodule diagnosis motivates the study and hence we are going to overcome all the above challenges. Initially to extract the Lung cancer nodules, a novel automatic methodology has been proposed, which is mainly based on the black circular neighborhood rule and image processing techniques (P.B. Bach et al) [4]. In algorithms, feature extraction is implemented. These divide the area, which is subsequently examined to look for nodules that would indicate the sickness and we have made use of CT imaging and GLCM options that aid in nodule detection. The application of Otsu's rule facilitates the determination of the tumor's size and stage (W. C. Hanna et al) [5].

This research paper consists of Introduction, Literature Survey, Methodology, Experimental Results and finally the Conclusion

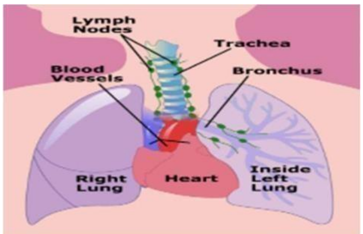


Figure1: Anatomy of Lung

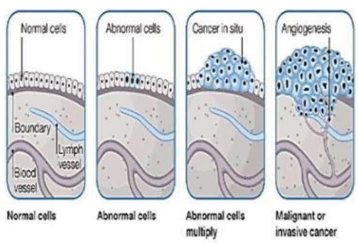


Figure 2: Beginning of Cancer

II. LITERATURE SURVEY

Paper 1: "A morphological operation-based approach for Subpleural lung nodule detection from CT image"

Authors: Rekka Mastouri, Henda Neji, Saoussen Hantous- Zannad, Nawres Khlifa

Year: 2018

Explanation: This study focuses on a method for automatically segmenting sub-pleural lung nodules from CT scans that are dependent on morphological processes. Due to the difficulty in extracting sub-pleural nodules, a computer-aided diagnosis system is therefore essential. Three processes make up the suggested system: pre- processing, initial sub-pleural lung nodule detection, and post-processing

Paper 2: "*A survey on detection of lung cancer using different image processing techniques*"

Authors: Sanjana Narvekar, Mayur Shirodhar, Tanvi Raut, Purva Vaingankar, k. M.chaman Kumar, Shailendra Aswale

Year: 2020

Explanation: The world is changing at an incredible rate, and with it, the number of cases of malignant lung cancer development. One such instance is cellular breakdown in the lungs, which has claimed the lives of many people. Positron emission tomography (PET), magnetic resonance imaging (MRI), X-ray imaging, magnetic resonance imaging (MRI), and computed tomography (CT) scans are used to detect cellular breakdown in the lungs. Comparing X-ray and PET sweeps to CT and X-ray, the former are more expensive. Compared to other imaging procedures, CT photos are preferred. The great majority of specialists choose X-rays or CT sweeps. By applying image management techniques to the image, we may decompose CT sweeps and X-ray images with greater depths to prevent such irregularities. CT.

Paper 3: "Lung Cancer Screening Using Computer-Aided Detection and Image Processing Techniques"

Authors:Anil Boddupalli; Laxman Rayala; Sai Sandeep Lingareddy; Yetra Mohan Sai Saran Reddy; Yamuna Devi M M, A. Veeraswamy

Year: 2023

Explanation: Lung cancer accounts for 11% of all deaths in India, making it one of the top causes of death. Finding the area affected by lung cancer has been easier recently because to advances in image processing techniques. Better treatment outcomes for lung cancer may arise from early detection. It is much preferred to use applied image processing techniques to evaluate CT scan data and identify lung illnesses in humans. This can also help in identifying the problem regions in a number of ways, making it possible for people to receive the right kind of healthcare support. Here, the infected lung region has been clearly identified with the application of classification algorithms such as Support Vector Machines (SVM). Further research findings on pre-processing, segmentation, and feature extraction are presented in this work

Paper 4: "Lung nodule detection based on 3D convolution neural networks"

Authors: Lei Fan, Zhaoqiang Xia, Xiaobiao Zhang, Xiaoy Feng

Year:2017

Explanation: This work suggests the use of 3D convolutional neural networks for the detection of lung nodules in lung CT scans. Lung CT images are subjectedto a combination of conventional morphological pre-processing techniques and 3D convolutional neural networks.

Paper 5:" *Segmentation and Prediction from CT Images for Detecting Lung Cancer*"

Authors: K.S Chethan, S. Vishwanath, rakshith V.Patil, K.A Vijetha

Year: 2020

Explanation: Throughout the world, cancer is among the most common medical conditions. Lung cancer is the most common type of cancer among the general population, though there are other varieties as well. One of the most deadly medical conditions worldwide, lung cancer affects people of all genders. One crucial measure that can reduce the chance of death from cancer is early detection. Our work performs lung nodule categorization by utilizing the CT scan data set of the lungs that was gathered from the websites of Kaggle in early stage. Lung nodule categorization has become more and more dependent machine learning algorithms in recent years.

III. METHODOLOGY

1. Architecture Diagram

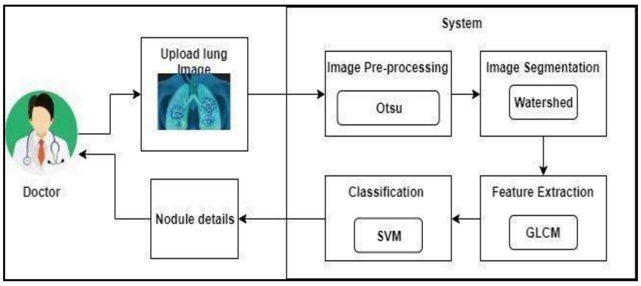


Figure3: System Architecture

The lung picture is used as an input in this system, and several approaches are applied to identify the lung nodule. Using Otsu's thresholding method, we first calculate a measure of spread for the pixel levels on each side of the threshold—that is, the pixels that fall into the foreground or background—by iterating over all conceivable threshold values. The watershed algorithm is used to filter images in preparation for image segmentation. The watershed transform is a better segmentation technique for identifying foreground objects and background locations. by using the GLCM feature, which is computed from the CT image's discovered lung nodule. Lastly, we use the SVM machine learning technique to identify lung nodules.

2. Dataset

Datasets used in lung cancer nodule detection using CT scans typically contain annotated medical images that are crucial for developing and validating algorithms for automated detection. CT Scan Images: The dataset consists of CT (Computed Tomography) scan images of the chest area of patients. These images are typically in DICOM (Digital

Imaging and Communications in Medicine) format, which is standard in medical imaging.

Annotations: Each CT scan is annotated to mark the presence and location of lung nodules. Annotations are usually provided by radiologists or medical experts who have identified and categorized the nodules based on their characteristics such as size, shape, and density.

Variety of Nodules: The dataset may include various types of nodules (e.g., solid, ground-glass opacity, part-solid) and nodules of different sizes, as these characteristics influence detection algorithms.

Size and Scope: The size of the dataset can vary widely depending on its purpose. Some datasets may include hundreds to thousands of CT scans, while others may be smaller and more focused.

DatasetLink:https://www.kaggle.com/datasets/sariyamazhar/lung-cancer-nodule-detection-dataset[12]

3. Libraries

i. OpenCV

OpenCV (Open-Source Computer Vision Library) is an open- source computer vision and machine learning *software library*

ii. Flask

A compact and light-weight Python web framework, Flask offers practical tools and capabilities that facilitate the development of Python web applications

iii. Keras

An open-source package called Keras offers an artificial neural network Python interface

iv. Matplotlib

For the Python programming language and its NumPy numerical mathematics extension, Matplotlib is a graphing library

v. NumPy

A Python package called NumPy is used to work with arrays.

vi. TensorFlow

TensorFlow is an open-source machine learning platform and framework.

4. Algorithms:

1) Otsu Threshold Algorithm:

KwIn Grayscale image I
KwOut Optimal threshold value T_{opt}
Compute grayscale histogram $H(i)$ using Eq. (1);
Compute cumulative distribution function $C(i)$ using Eq. (2);
Compute mean grayscale intensity value μ using Eq. (3);
for $T = 0$ *to 255* **do**
  Compute $P_0(T)$ and $P_1(T)$ using Eq. (5);
  Compute $m_0(T)$ and $m_1(T)$ using Eqs. (6) and (7);
  Compute between-class variance $var(T)$ using Eq. (4);
end
Find the optimal threshold value T_{opt} using Eq. (8);
Apply threshold T_{opt} to image I to obtain binary image.

2) Watershed Algorithm:

Require: $|R| = |M|$
function WATERSHED(R, M) ▹ a relief and a markers as parameters
  $PQ \leftarrow \emptyset$ ▹ the priority queue
  $bg \leftarrow 0$ ▹ value of background
  for $(i, r_i) \in R \wedge (i, m_i) \in M \wedge m_i \neq bg$ **do**
    for $(j, m_j) \in N_D(i, m_i) \wedge m_j = bg$ **do** ▹ iterate over neighbors of element (i, m_i)
      $push(r_i, i, PQ)$ ▹ push i into PQ with priority level r_i
      break
    end for
  end for
  while $|PQ| \neq 0$ **do**
    $i \leftarrow pop(PQ)$ ▹ pop an element coordinate from the priority queue
    for $(j, m_j) \in N_D(i, m_i) \wedge m_j = bg$ **do**
      $M \leftarrow (M \setminus (j, m_j)) \cup (j, m_i)$ ▹ mark an element
      $push(max(r_i, r_j), j, PQ)$
    end for
  end while
  return M
end function

3) SVM Algorithm:

Algorithm 1: SVM

1. Set $Input = (x_i, y_i)$, where $i = 1, 2, \cdots, N, x_i = R^n$ and $y_i = \{+1, -1\}$.
2. Assign $f(X) = \omega^T x_i + b = \sum_{i=1}^{N} \omega^T x_i + b = 0$
3. Minimize the QP problem as, $min\ \varphi(\omega, \xi) = \frac{1}{2}\|\omega\|^2 + C.(\sum_{i=1}^{N} \xi_i)$.
4. Calculate the dual Lagrangian multipliers as $min\ L_P = \frac{1}{2}\|\omega\|^2 - \sum_{i=1}^{N} x_i y_i(\omega x_i + b) + \sum_{i=1}^{N} x_i$.
5. Calculate the dual quadratic optimization (QP) problem as $max\ L_D = \sum_{i=1}^{N} x_i - \frac{1}{2}\sum_{i,j=1}^{N} x_i x_j\ y_i\ y_j (x_i, x_j)$.
6. Solve dual optimization problem as $\sum_{i=1}^{N} y_i x_i = 0$.
7. Output the classifier as $f(X) = sgn(\sum_{i=1}^{N} x_i y_i (x \cdot x_i) + i$.

4) GLCM Algorithm:

Begin
Initialize the temperature $T_i (i = 1, 2, \ldots, n)$;
Initialize *cmax,cmin,*and *maximum number of iterations;*
Cost=the best search agent by Eq.10;
While (l<Max number of iterations)
Update t and β
for each search agent
Update the position of the current search agent by the Eq.30;
Perform Levy flight strategy according to Eq.26;
Bring the current search agent back if it goes outside the boundaries by Eq.31;
end for
Evaluate the fitness of all agents by image thresholding with agent parameters;
Update Cost if there is a better solution;
l= l+1
end while
Return Cost as the optimal parameter for image thresholding;
End

5. Implementation:

1. Data Flow Diagrams

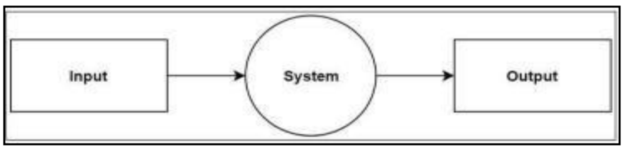


Figure:4: *Data Flow Diagrams 0*

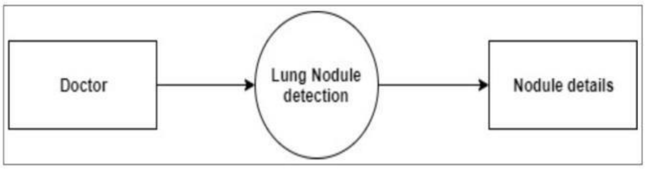


Figure 5: Data Flow Diagrams 1

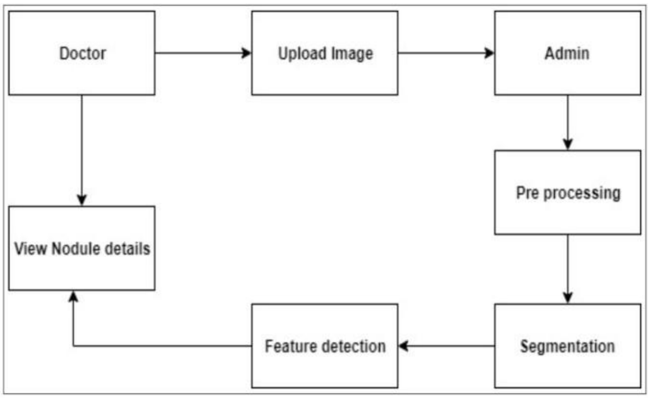


Figure 6: Data Flow Diagrams 2

2. *Software's Used*

i. *Python compiler [3.6.11]*

An application called a Python compiler transforms your human-readable Python code into a lower-level language that the computer's hardware can execute directly, usually bytecode or machine code

ii. *Visual Studio Code:*

Microsoft created Visual Studio Code, popularly known as VS Code, which is a source-code editor compatible with Windows, Linux, macOS, and web browsers. Debugging, syntax highlighting, intelligent code completion, snippets, code refactoring, and integrated Git version control are among the features.

iii. *Anaconda environment:*

A directory containing a particular set of installed Conda packages is called a Conda environment.

iv. *Installing required packages:*

Here, we're using OpenCV 4.10.0 + and the Python compiler version 3.6.11+. Moreover, SciPy and NumPy are utilized for certain computations needed for this experiment.

➢ The core Python library for large-scalemathematical computation is called NumPy.[13]

➢ SciPy is an open-source, BSD-licensed scientific library for Python that is used in science, engineering, and mathematics computation applications. [13]

3. *Models used:*

i. *COCOMO Model:*

Boehm proposed the COCOMO (Constructive Cost Estimation Model) [1981]. Boehm suggests three steps for software cost estimation: Basic COCOMO, Intermediate COCOMO and Complete COCOMO.

The project parameters can be roughly estimated using the basic COCOMO model. The following expressions yield the basic COCOMO estimate model:

$$Effort = a1*(KLOC)a2PM$$

$$Tdev = b1 \times (Effort)b2\ Months$$

Where,

1) KLOC is the estimated size of the software product expressed in Kilo Lines of Code,

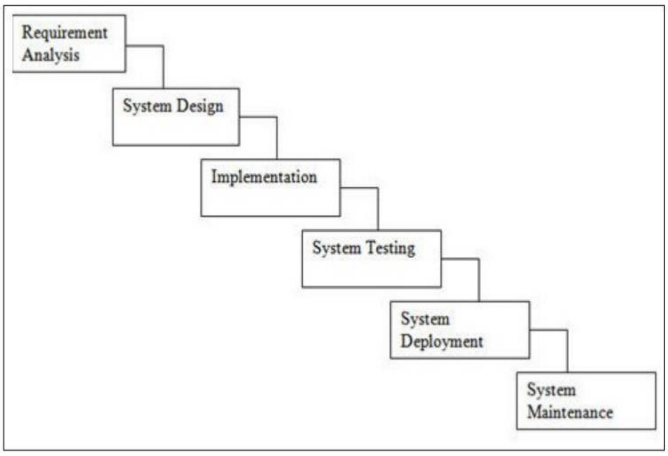
2) a1, a2, b1, b2 are constants for each category of software products,

3) Tdev is the estimated time to develop the software, expressed in months,

4) Effort is the total effort required to develop the software product, expressed in person months (PMs).

The effort estimation is expressed in units of person-months (PM). It is the area under the person-month plot. It should be carefully noted that an effort of 100 PM does not imply that 100 persons should work for 1 month nor doesit imply that 1 person should be employed for 100 months, but it denotes the area under the person-month curve.

ii. *Waterfall Model*:



4. *Proposed System:*

In this system, we have a tendency to use respiratory organ image as an input and apply some techniques to spot the nodule of the respiratory organ. Here 1st we have a tendency to use Otsu's thresholding methodology involves iterating through all the potential threshold values and shrewd a life of unfolding for the pel levels either side of the edge, i.e. the pixels that either fall in foreground or background. then that pictures are filtered for image segmentation by victimization watershed formula.

Segmentation victimization the watershed rework works higher to establish, foreground objects and background locations. By applying the GLCM feature that reason from the detected respiratory organ nodule in the CT image. and eventually, we have a tendency to apply the SVM machine learning formula for detective work nodule ofrespiratory organ.

IV. EXPERIMENTAL RESULTS

Figure 7: Home page of Application

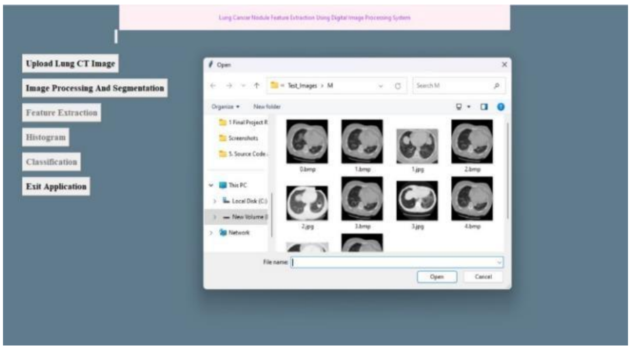


Figure 8: Receiving inputs from user

The figure 7 and figure 8 depicts a graphical user interface (GUI) of a software application titled "Lung Cancer Nodule Feature Extraction Using Digital Image Processing System." The left side of the screen has a number of buttons in a vertical alignment inside the interface. The buttons are labelled as follows, top to bottom:

*Uploading a Lung CT image

*Image Processing and Segmentation

*Feature Extraction

*Application for Histogram Classification

*Exit

The UI has a subdued blue background. The GUI elements and their arrangement in the screenshot are succinctly and clearly summarized in this explanation.

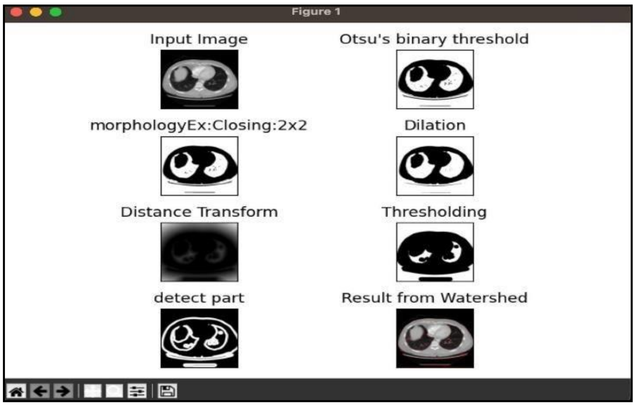


Figure 9: Image Processing

The procedures and methods shown in the snapshot are thoroughly summarized in this description.(i) The user first uploads the original grayscale lung CT scan image, which displays the lungs' cross-sectional view.(ii) Using Otsu's thresholding technique, our system computes Otsu's Binary Threshold, a binarized version of the input image that is used to differentiate between various regions by turning the image into black and white.(iii) A picture that has undergone morphological closing operation (with a 2x2 kernel), which aids in eradicating tiny black holes from the white areas.(iv) The image has now undergone dilatation, which enlarges the limits of the white zone and highlights its features.(v)Step for the computation Distance Conversion An altered picture that displays each pixel's separation from the closest zero pixel, usually utilized.

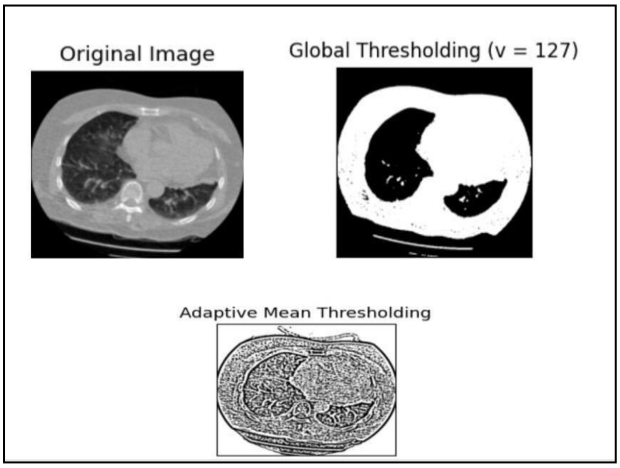


Figure 9**:** The feature extraction of the lung by GLCM

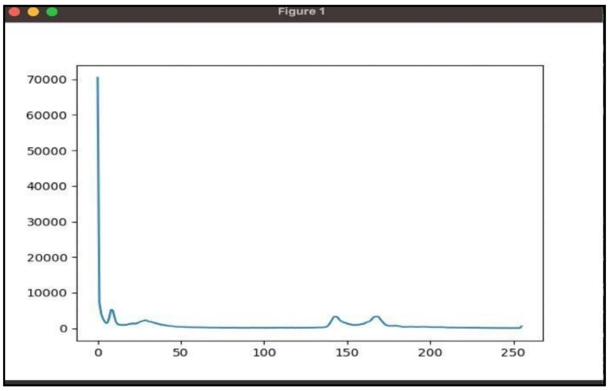


Figure 10: Histogram

This plot is a histogram of pixel intensities for a given image. The high peak at the low intensity values suggests that the image contains a large number of dark pixels. The subsequent low and relatively flat line indicates fewer occurrences of mid-range and high-intensity pixels.

An explanation of the storyline:

Y-Axis: 0 to 70,000 is the vertical axis. The frequency or count of pixel values in the image is most frequently represented by this axis.

X-Axis: 0 to 255 is the range of the horizontal axis. The grayscale values, or pixel intensity levels, of an image are generally represented by this axis.

Features of the Storyline:

A high frequency of pixels with low intensity values is shown by the plot's abrupt peak at the 0-intensity value at the beginning. As the intensity values rise, the frequency sharply decreases after the initial peak and stays quite low with just slight variations. Intensity levels range from mid to high, with a few minor peaks and troughs; however, these are much less than the first peak.

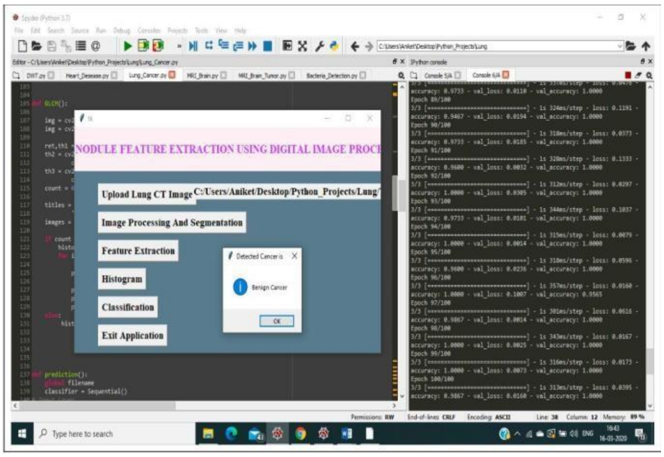


Figure 11: Malignant Cancer

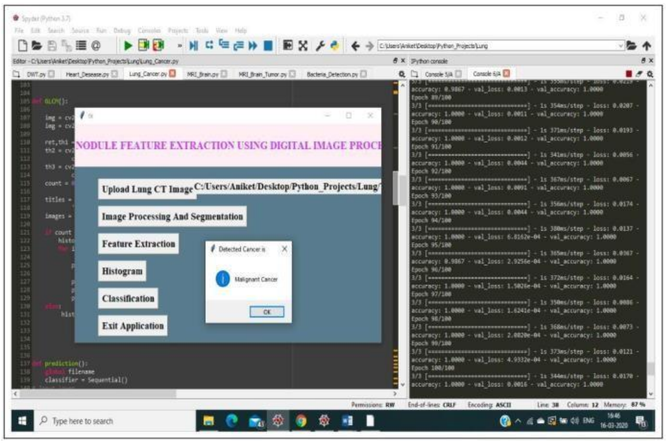


Figure 12: Benign cancer

Then the application will classify whether the cancer is malignant or benign using SVM.

Hence, we use machine learning approaches to detect lung nodules. Otsu thresholding was utilized for preprocessing, Watershed was used for segmentation, GLCM was employed for feature extraction, and SVM classification was utilized to obtain the final output.

The study's findings demonstrate that combining these advanced imaging techniques and algorithms significantly improves the accuracy and reliability of small lung nodule detection, aiding early diagnosis and treatment of lung cancer.

V. *SYSTEM REQUIREMENTS*

A. *SOFTWARE REQUIREMENTS*

- Operating System: Windows 7 and above
- Technology : Python
- IDE: Anaconda or Spider

B. *HARDWARE REQUIREMENTS*

- Hardware: Pentium Dual Core
- Speed : 2.80 GHz
- RAM: 1GB
- Hard Disk: 20 GB

VI. *CONCLUSION*

Our work highlights the viability of using low-dose PET imaging to quantify sub-centimeter nodules, with the potential to achieve measurement errors of no more than 20% based on simulation results. However, comprehensive validation utilizing clinically relevant phantoms is necessary to achieve substantial clinical application. To improve accuracy, it is crucial to follow recommendations such using respiratory motion correction techniques and using a reconstruction voxel size of 1 mm for tiny nodules. Further emphasizing the significance of thorough validation in honing these approaches for clinical use, the integration of image analysis techniques like Otsu's thresholding, Watershed segmentation, GLCM texture analysis, and SVM classification holds promise for attaining accurate nodule size measurements. It will take ongoing investigation and validation to improve these methods and increase their applicability in clinical settings.

VII. DISCUSSION

First, we upload the lung image to the system typically from medical imaging techniques such as X-rays, CT scan. Once the image is uploaded successfully pre-processing is performed using Otsu. Then we perform segmentation using Watershed algorithm followed by feature extraction which is done using GLCM. To obtain the classification of the image where the output result is either benign or malignant tumor we used SVM algorithm. This structured approach not only enhances accuracy but also ensures that each image is thoroughly examined, making the diagnostic process more reliable. By leveraging these advanced techniques, healthcare professionals can make better-informed decisions and to automate the analysis of lung images to aid in the diagnosis of lung tumors, ultimately improving patient outcomes.

REFERENCES

[1] World Health Organization (2023) Lung Cancer. https://www.who.int/news-room/fact-sheets/detail/lung-cancer

[2] SanjanaNarvekar, MayurShirodhar, TanviRaut, PurvaVaingankar, k. M.chaman Kumar, ShailendraAswale: "*A survey on dection of lung cancer using different image procseesingtechniques*"in year 2020

[3] Wang-Jia Li, Fa-Jin Lv, Yi-Wen Tan, 2 Bin-Jie Fu, and Zhi-Gang Chu- "Benign and malignant pulmonary part-solid nodules differentiation via thin-section computed tomography" Quant Imaging Med Surg. 2022 Jan; 12(1): 699–710. doi: 10.21037/qims-21-145

[4] P. B. Bach et al., "Benefits and harms of CT screening for lung cancer: A systematic review", J. Amer.Med.Assoc.,vol.307,no.22,pp.2418–2429,Jun.2012.

[5] W. C. Hanna et al., "Minimal-dose computed tomography is superior to chest X-ray for the follow-up and treatment of patients with resected lung cancer," J. ThoracicCardiovasc.Surgery,vol.147,no.1,pp.30– 35, Jan.2014.

[6] Anil Boddupalli; LaxmanRayala; SaiSandeepLingareddy; Yetra Mohan Sai Saran Reddy; Yamuna Devi M M, A. Veeraswamy "Lung Cancer Screening Using Computer-Aided Detection and Image Processing Techniques" in year 2023

[7] Rekka Mastouri, Henda Neji, Saoussen Hantous- Zannad, Nawres Khlifa, " A morpho logical operation-based approach for Subpleural lung nodule detection from CT images ", 4th Middle East Conference on Biomedical Engineering (MECBME), IEEE, 2018.

[8] D.R. Aberle et al., "Reduced lung-cancer mortality with low-dose computed tomographic screening, "New England J. Med., vol. 365, no. 5, pp. 395–409, Aug. 2011.

[9] D. Shlomi, R. Ben Avi, G. R. Balmor, A. Onn, and N. Peled, "Screening for lung cancer: Time for large-scale screening by chest computed tomography," Eur. Respiratory J., vol. 44, no. 1, pp. 217–238, Jul. 2014.

[10] M. Infante et al., "Lung cancer screening with spiral CT: Baseline results of the randomized DANTE trial," Lung Cancer, vol. 59, no. 3, pp. 355–363, Mar. 2008.

[11] Wikipedia-Informational Contents.

[12] Kaggle Dataset

[13] Python 3.11.3 documentation–conda environment [conda] - Creation of conda environments

[14] Google-Images

[15] D. S. Gierada et al., "Projected outcomes using different nodule sizes to define a positive CT lung cancer screening examination," J. Nat. Cancer Inst., vol. 106, no. 11, 2014, Art.no.dju284,doi:10.1093/jnci/dju28

[16] Manoj Kumar D P, " Machine Learning Based Crop Management: Towards Intelligent Recommendations for Crop, Fertilizer and Pesticides " Published in International Conferences in Recent Advances in Science and Engineering Technology, IEEE,2023. DOI: 10.1109/ICRASET59632.2023.10420050

[17] Manoj Kumar D P, " Hierarchical Federated Learning-Based method for Privacy Preserving in Healthcare Environment", Published in International on Evolutionary Algorithms and Soft Computing Techniques(EASCT), IEEE, 2023. DOI: 10.1109/EASCT59475.2023.1039363

[18] Manoj Kumar D P, " Quantum Squirrel Search Algorithm based Support Vector machine algorithm for Brain Tumor Classification" in Internet Technology Letters (Scopus), Wiley Online Library,(Q3 Journal).DOI: 10.1002/itl2.48

[19] Manjunatha B N, Dr. Santhosh Kumar D.R, Dr. AnandaBabu J , Manoj Kumar D P "IoT Based Smart Home Using Edge computing", Natural Volatilies and Essential Oils (NVEO) 2021;8(5):9279-9285(Scopus)

[20] Manoj Kumar D P, Dr.AnandaBabu J, Dr.Raviprakash M L, Manjunatha B N "Clustering and Detection of Liver Disease in Indian Patient Using Machine Learning Algorithms", Journal of Xidian University, ISSN No:1001-2400, Volume 15, Issue 12, 2021(Scopus),https://doi.org/10.37896/jxu15.12/029.

[21] Manoj Kumar D P , NeelamMalyadri, Srikanth M S,Dr. Ananda Babu J," A Machine Learning model for Crop and Fertilizer recommendation", in Natural Volatiles and Essentials Oils, Volume 8, Issue 5, pp. 10531-10539, December 2021.