Lung cancer detection using YOLO9

Nagarathna H.S
Dept. of Electronics and Communication Engineering
Dr. Ambedkar Institute of Technology
Bengaluru, India

Dr.RameshKumar K.R
Dept. of Mechanical Engineering
University of Visvesvaraya College of Engineering
Bengaluru, India

Abstract*—The early detection of lung cancer is at the forefront of reducing the acute mortality rate of the disease. The global effort of lung screening promotes the use of positron emission tomography(PET)and computed tomography(CT) scans among older at-risk populations for the purposes of increasing early detection rates. Despite the use of invasive methods, symptoms may not occur until the disease progresses, and it becomes challenging for the radiologist to identify lesions. This paper presents a sophisticated approach to classifying and identifying lung cancer subtypes using the most recent version of YOLO. The performance of YOLOv9 was evaluated using a publicly available data set. The diagnosis of lung cancer at an early stage is of utmost importance if it is meant to degrade high mortality rate. The global lung screening program points to visualize positron emission tomography (PET) and computed tomography (CT) examinations amongst most aged groups at risk to enhance the early detection rate. Although use of invasive techniques, symptoms hardly appear until disease is advanced making it difficult for radiologist to identify lesions. This paper introduces an advanced method for lung cancer subtype classification and detection using the latest version of YOLO, Unfortunately, most lung cancer patients suffering at advanced stages result in dismal with five-year survival rate of 17.8

***IndexTerms*—YOLO9,**

I. Introduction

Cancer is defined by the uncontrolled growth of cells that have the ability to spread all over the body. The human body has red blood cells(RBCs),which mainly serve to trans- port oxygen (O2) to different tissues through the circulatory system, leading to the red color of blood. In the lungs, tissues obtain oxygen (O2) solely by means of RBCs. The genetic material in erythrocytes is hemoglobin-rich. The cell membrane consists of lipids and proteins, which form the basis for cellular processes. Interestingly, RBCs lack any necessary cellular structures, such as hemoglobin. About 2 million new RBCs are produced every second, and their production takes place in the bone marrow. These cells travel through the body for approximately four months, going back and forth between arteries and veins, with a complete circulation taking Red blood cells make up approximately 75 Primary lung cancers also known as carcinomas, develop in the lungs. There are two major forms of carcinoma: 1) small- cell lung cancer and 2) non-small-cell lung cancer. Symptoms are usually common and may involve coughing(which can be bloody), weight loss, shortness of breath, and some degree of chest pain. These cancer cells interfere with the normal process of red blood cell (RBC) production and breakdown. They change the structure and composition of the plasma membrane, the cell's outer layer, so that RBCs live longer than they normally would. As a result, RBC count goes up, causing an overloading of cells that ends up leading to constriction of veins and arteries, eventually causing rupture. This shows up as blood in coughing, among other things. Unfortunately, the prognosis for the majority of lung cancer patients diagnosed at an advanced stage is poor. The five-year survival rate is only 17.8%. Image processing involves examining images at their most basic level, whether for quality or other attributes. While these operations don't increase the amount of information in an image, They can actually reduce it — especially if entropy is used as a measure of information.

The main goal of processing is to increase pixel intensity by moving from discrete to dig- ital images, breaking up into pixels, applying mathematical operations on the pixels, and reconstructing the image to gain better quality. The pre-processing of CT images is the initial step involved in image analysis, which is then followed by segmentation operations and finalized with the implementation of various morphological operations. The implementation of deep learning methods in medical imaging has enormously contributed to the detection and diagnosis of diseases. Specifically, the You Only Look Once (YOLO) algorithm has become the most popular one in object detection because of its speed and precision. YOLO works by splitting an image into an SxS grid, with every grid cell outputting bounding boxes and confidence levels for objects contained within it. This allows YOLO to detect multiple objects in an image at the same time, and it is consequently very efficient for complicated image processing tasks[2]. YOLO(You Only Look Once) family of object detection networks have been extensively applied to lung cancer detection tasks. Buetal used YOLOv3 with sparse datasets and showed its performance in lung nodule detection. The model had an average precision of0.881 and average recall of 0.873, showing that the model was capable of well-localizing lung nodules using sparse training data [4]. Prashant Naresh et al (2014), specified the approach to detect the lung cancer using Image processing and Neural Network Techniques. Initially the CT scanned image of lung was filtered to remove Gaussian white noise and Otsu's threshold technique was used to do the segmentation of the image. The structural features Qi et al. improved the performance of YOLOv3 by integrating attention mechanisms, which enabled focusing on applicable areas of images. Their enhanced YOLOv3 model had an accuracy of 0.913 and a sensitivity of 0.925 in detecting pulmonary nodules from CT scans. The attention mechanism enabled the model to emphasize key features and downplay useless background information [6]. Goel and Mishra suggested a hybrid method employing a YOLOv3 model modified with a biogeography- based optimization (BBO) and improved elephant herding optimization (EE) optimizer for the detection of lung cancer. Their approach yielded an accuracy of 0.964 and a sensitivity of 0.958, proving the capability of merging YOLO models with sophisticated optimization methods [7]. Goel and Patel emphasized enhancing YOLOv6 with a sophisticated particle swarm optimization(PSO)optimizer for weight selection in lung cancer classification and detection. Their method achieved an accuracy of 0.982 and a sensitivity of 0.976, demonstrating the advantages of optimizing YOLO models for particular tasks [8].

II. METHODOLOGY

This research introduces a new method of lung cancer detection based on the YOLOv9 deep learning algorithm, which is optimized for the analysis of CT scan images. The methodology is organized into a number of major phases: data acquisition, pre-processing, model architecture design, training, and testing. Block diagram of the methodology is presented in Figure 1.

A. Step1:Inputimage:

Collect an extensive dataset of images and mark the objects in interest (for example, bounding boxes for lung nodules).An input picture of some specified size required, typically square and a multiple of some specified value. Resize the input image to the input size required by YOLO model, for example, 640X 640 pixels Dataset: The dataset in this research is the Lung Cancer CT scan dataset from Roboflow, which is one of the most well-known computer vision dataset platforms. The dataset comprises a large number of images. It was carefully preprocessed and curated. The goal was to ensure high quality and consistency throughout the dataset.

Step2:Preprocessing:

Each CT scan image underwent a series of preprocessing steps to enhance the quality and remove any artifacts that could potentially hinder the model's performance. These pre- processing steps included:

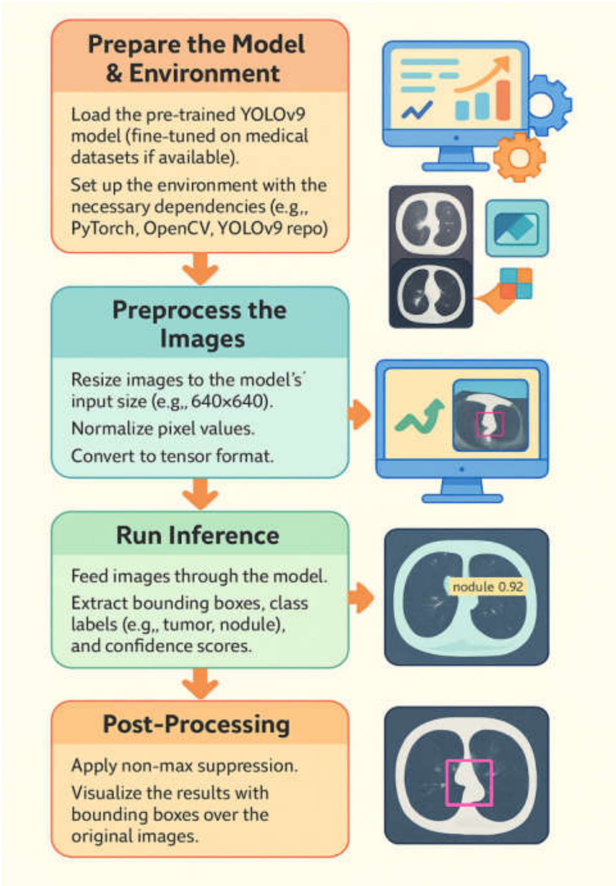

Fig1.Proposed methodology for detection and classification of lung cancer cell

- Image resizing: All CT scan images were resized to a uniform resolution of 640x640pixels. This standardization ensures that the images have consistent dimensions, facilitating efficient batch processing during model training.
- Normalization: CT scan image pixel values were normalized in the range of [0, 1]. Normalization serves to facilitate a better model convergence during the learning process through an attenuation effect by different scan pixel intensities. The mode of the images is converted from that of usual display to BGR mode to be familiar to a majority of computer vision libraries including Open CV.
- Contrast enhancement: Histogram equalization methods were used to improve the contrast of the CT scan images. This operation facilitates better visibility of the concerned features and structures of the lungs and aids the model in easy identification and localization of lung tumors. Besides preprocessing, data

augmentation methods were adopted to enhance the diversity and resilience of the training data. Data augmentation is done by applying different transformations to the original images, producing new variations which enable the model to learn invariance under different conditions. The following data augmentation methods were used:

- **Rotation:** CT scan images were rotated randomly within a predefined range of angles. This enables the model to learn rotational invariance and enhance its detection of lung tumors at various orientations.
- **Flipping:** The images were randomly flipped horizontally and vertically. Flipping adds symmetrical variations and im- proves the model's ability to generalize.
- **Scaling:** The CT scan images were randomly scaled between a given range. Scaling allows the model to learn about detecting lung tumors of varying sizes and resolutions.
- **Brightness and contrast adjustment:** The brightness and contrast of the images were randomly adjusted within a certain range. This mimics changes in lighting conditions and makes the model more resilient to varying image qualities. The preprocessed and augmented data were then divided into training and validation sets. The training set, which contains 2167 images, was employed to train the YOLOv9 model, while the validation set, comprising 216 images, was employed to analyze the performance of the model and its ability to generalize.
- Histogram equalization- Histogram Equalization is a method of image processing that modifies the contrast of an image based on its histogram. In order to increase the contrast of the image, it disperses the most common pixel intensity values or extends the intensity range of the image. By doing this, histogram equalization enables the areas of the image with lower contrast to achieve a higher contrast. You can apply Histogram Equalization when you have images which appear washed out due to lack of enough contrast. In these types of images, the bright and dark portions become one by blending together thus creating a flatter image which does not contain high lights and shadows.
- Segmentation- Image segmentation is a widely employed method in digital image processing and analysis to divide an image into several parts or regions, usually on the basis of the features of the pixels in the image. Image segmentation maybe used to separate background from foreground, or group areas of pixels according to similarity in color or shape.
- **Filtering-** Filtering is a method of changing or improving an image. For instance, you can filter an image to enhance some features or suppress other features. Image processing operations that are realized with filtering are smoothing, sharpening, and edge enhancement. Filtering is a neighborhood operation, where the value of any pixel in the output image is computed by applying some algorithm to the values of pixels in the neighborhood of the corresponding input pixel. A pixel's neighborhood is some collection of pixels, specified by their positions with respect to that pixel. Dilation-Dilation is a morphological transformation operator applied to grow the size or thickness of the foreground object of an image. Dilation is employed in most instances to join two fragmented objects of an image. To expand an image, we have a kernel matrix composed of ones and slide the kernel across the image. A kernel is just a tiny matrix employed in sharpening, blurring, embossing, edge detection, and many others. It is also referred to as a convolution matrix, mask, or a filter. Every pixel element gets assignedaoneifitis1foranyofthepixelswithinthe kernel neighborhood. This expands the white region of the image, which expands the size of the fore ground object in an image. Dilation is typically applied after the erosion of the image by another morphological transformation operator known as Erosion. Dilation removes the white noise from an image.
- Image filling-Filling is a process that fills an area of interest by interpolating the pixel values from the region borders. Filling can be employed to make objects in an image appear to vanish since they are replaced with values that merge with the background region. You can use the ROI fill function to fill a region of interest. This operation is helpful for image processing, such as extraneous detail or artifact removal. roifill fills the region using an interpolation algorithm based on Laplace's equation. This algorithm produces the smoothest fill possible, considering the boundary values of the region.

B. Step3:Modelarchitecture:

YOLO is a deep convolution neural network (CNN) that passes the whole image down the network once. Convolution backbone: The preprocessed image passes through a sequence of convolution layers(backbone) to obtain the hierarchical features. These layers permit encoding of the low-level features like edges and textures and also the high-level features like shapes and patterns. Neck: Apply a neck architecture, e.g., FPN (Feature Pyramid Network) or PANet (Path Aggregation Network), to promote the multi scale feature representation. Detection head: YOLO divides the image into boxes also referred to as cells. For each cell, the model delivers estimations of the bounding boxes and class probabilities.

C. Step4:Functionprediction:

Bounding box prediction: The grid cell predicts multiple boundingboxeswhichareusuallytwointhecaseofYOLOv3. Each bounding box is defined by its coordinates relative to the grid cell. The coordinates for the center are x, y and the width, height for the rectangle. Class prediction: For every bounding box prediction, the model also outputs probabilities of each class existing in the data set. These probabilities represent the possibility of the object falling under each of the classes. Objectness score: For each bounding box, YOLO also generates an "Objectness" score. This score 7 gives the likelihood that an object of interest is in the box rather than the noise present in the environment.

D. Step5:Evaluation:

Performance metrics: Measure the model using mAP, precision, recall, F1-score, etc.

Testing: Test them on a held-out test set to test the generalization ability of the model.

E. Step6:Post-processing:

Non-maximum suppression (NMS): Lastly, after predicting the bounding boxes and class probabilities for all the grid cells, a process called non-maximum suppression is per- formed .NMS removes all the overlapping and low-probability bounding boxes. It selects the most confident bounding boxes while disregarding other overlapping boxes to be taken into consideration.

F. Step7:Finalprediction:

Final prediction: Output format: The output includes: Standard rectangle parameters (x, y, dx, dy) in the original image coordinates. Tags specifying the type of object that was detected. Probabilities indicating the model's confidence in detections made by the algorithm. Draw bounding boxes: The final step is to draw bounding boxes on the input image using the output coordinates and then display or save the boxes. Overall flow diagram of the proposed model as illustrated in Fig1.

III. OBJECTDETECTIONANDTRACKINGUSING YOLO9

YOLO is a one-stage object detection model. The purpose of one-stage object detection is to examine an image once. In general, YOLO has different parts, such as the backbone, neck, and head. Backbone is the structure that processes feature extraction. Neck is constructed using another pyramid network approach. Pyramid networks are employed to merge features from different layers of the backbone model. Several heads perform object detection in various resolutions.

YOLOv9 there is one more section, i.e., the auxiliary. The auxiliary enhances the originality of training the process by giving more information that connects the target output to the input data. Thus the issue of losing information while going through deep learning network layers may be solved. In the inference phase, this helper can be dropped to accelerate the model's performance without decreasing accuracy. YOLOv9, the most recent in the YOLO family, is an object detection model that operates in real-time. It demonstrates improved performance using sophisticated deep learning methods and design architecture, such as the Generalized ELAN (GELAN) andProgrammableGradientInformation(PGI).

The YOLO

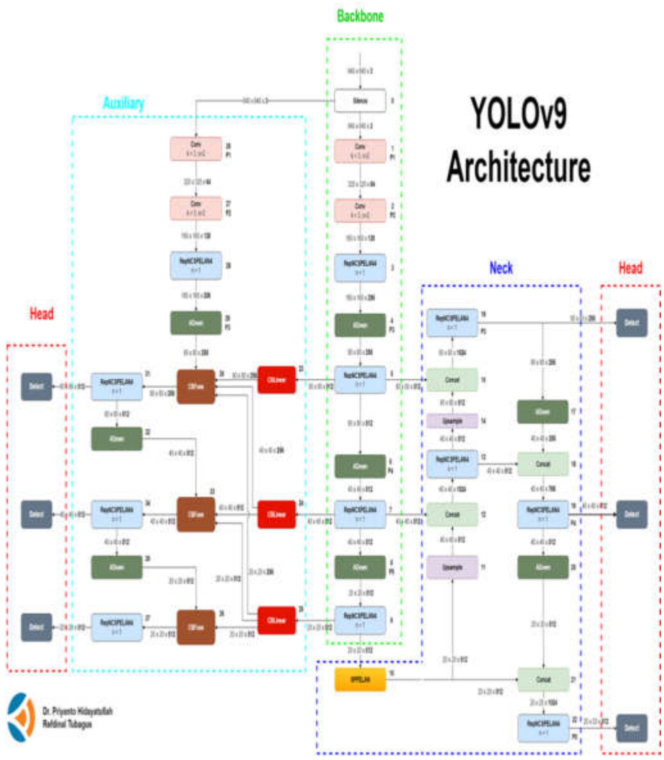

Fig. 2 YOLOv9-C Architecture

family has transformed the object detection community for long now by bringing innovative ideas in computer vision such as processing an entire image in a single pass using a convolution neural network (CNN). In 2015, Redmon etal. [15] introduced the You Only Look Once object detection algorithm. This algorithm divides an input image into SxSgrid cells and then predicts B bounding boxes and the class probabilities of each cell. By converting the object detection task into a regression problem, Yolo is able to detect objects quickly and accurately. Over the last year, YOLO has been subject to a series of optimizations and improvements, with the most recent version being YOLO version eight released by Ultralytics in 2023. YOLOv9 is the most recent development in the YOLO (You Only Look Once) series of real-time object detection algorithms. It improves on its predecessors with advances in deep learning methodologies and architectural innovation to deliver higher object detection performance. Based on integrating the Programmable Gradient Information (PGI) idea with the Generalized ELAN(GELAN)architecture, YOLOv9 is a major advancement in accuracy, speed, and efficiency.

Evolution of YOLO The evolution of the YOLO series of real-time object detectors has been marked by continuous refinement and incorporation of sophisticated algorithms to improve performance and efficiency.

Firstly, YOLO pioneered the idea of processing full images in a single pass through a convolutional neural network (CNN). Later versions such as YOLOv2 and YOLOv3 brought improvements in terms of accuracy and speed by making use of methods such as batch normalization, anchor boxes, and feature pyramid networks (FPN).

These improvements were further developed in models such as YOLOv4 and YOLOv5, which added new techniques such as CSP Darknet and PANet to enhance speed as well as accuracy. In addition to these developments, YOLO has also incorporated several computing units such as CSPNet and ELAN, along with their variants, to improve computational efficiency.

Besides, more advanced prediction heads such as YOLOv3 head or FCOS head have been used for accurate object detection. With the introduction of other real-time object detectors such as RT-DETR, which is developed on the DETR architecture, the YOLO series continues to be popular due to its flexibility and usability in various fields and situations. The newest version, YOLOv9, is an expansion of YOLOv7, which has used the Generalized ELAN (GELAN) model and Programmable Gradient Information (PGI) to push further, positioning it as the most advanced real-time object detector in the next generation. YOLOv9 Major Features Real-Time Object Detection: Should be able to process input images or video streams quickly and detect objects in them with high accuracy with- out sacrificing speed.

A. GELAN Architecture

Implements the Programmable Gradient Information (PGI) idea, which allows for the production of trustworthy gradients using an auxiliary reversible branch, resolving the problem of information loss during feed forward in deep neural networks. GELAN Architecture or, Generalized ELAN (GELAN) architecture: which aims to optimize parameters, computational complexity, accuracy, and inference speed. By providing users with the ability to choose suitable computational blocks for various inference devices, GELAN promotes the flexibility and efficiency of YOLOv9 Enhanced Performance: Reached the top level of performance in object detection tasks on benchmark datasets such as MS COCO. It outperforms current real-time object detectors in accuracy, speed, and overall performance, thus constituting a state-of-the-art solution for a wide range of applications that involve object detection functionality. Flexibility and Adaptability: Made to be flexible to fit various situations and applications. Its design enables it to be easily integrated into many systems and environments, making it adaptable for a variety of applications, such as surveillance, autonomous vehicles, robotics, and many more.

Updates on YOLOv9 Architecture Incorporating Programmable Gradient Information (PGI) and GLEAN (Generative Latent Embeddings for Object Detection) architecture into YOLOv9 can improve its performance in object detection tasks. These components can be incorporated into the YOLOv9 architecture to improve performance as follows:

B. PGI Integration

Main Branch Integration: The main branch of PGI, being the main path of the network during inference, can be asily integrated into the YOLOv9 model. his integration is done in such a way that the inference process is not affected and no extra computational cost is incurred thereby ensuring more reliable gradients for the loss function. Multi-level Auxiliary Information: YOLOv9 usually utilizes feature pyramids to detect objects of various sizes. By incorporating multi-level auxiliary information from PGI, YOLOv9 is able to address error accumulation problems relevant to deep supervision, particularly in multi-branch prediction architectures. In this manner, the model can learn from the auxiliary information at various levels, resulting in enhanced object detection perfor- mance across various scales.

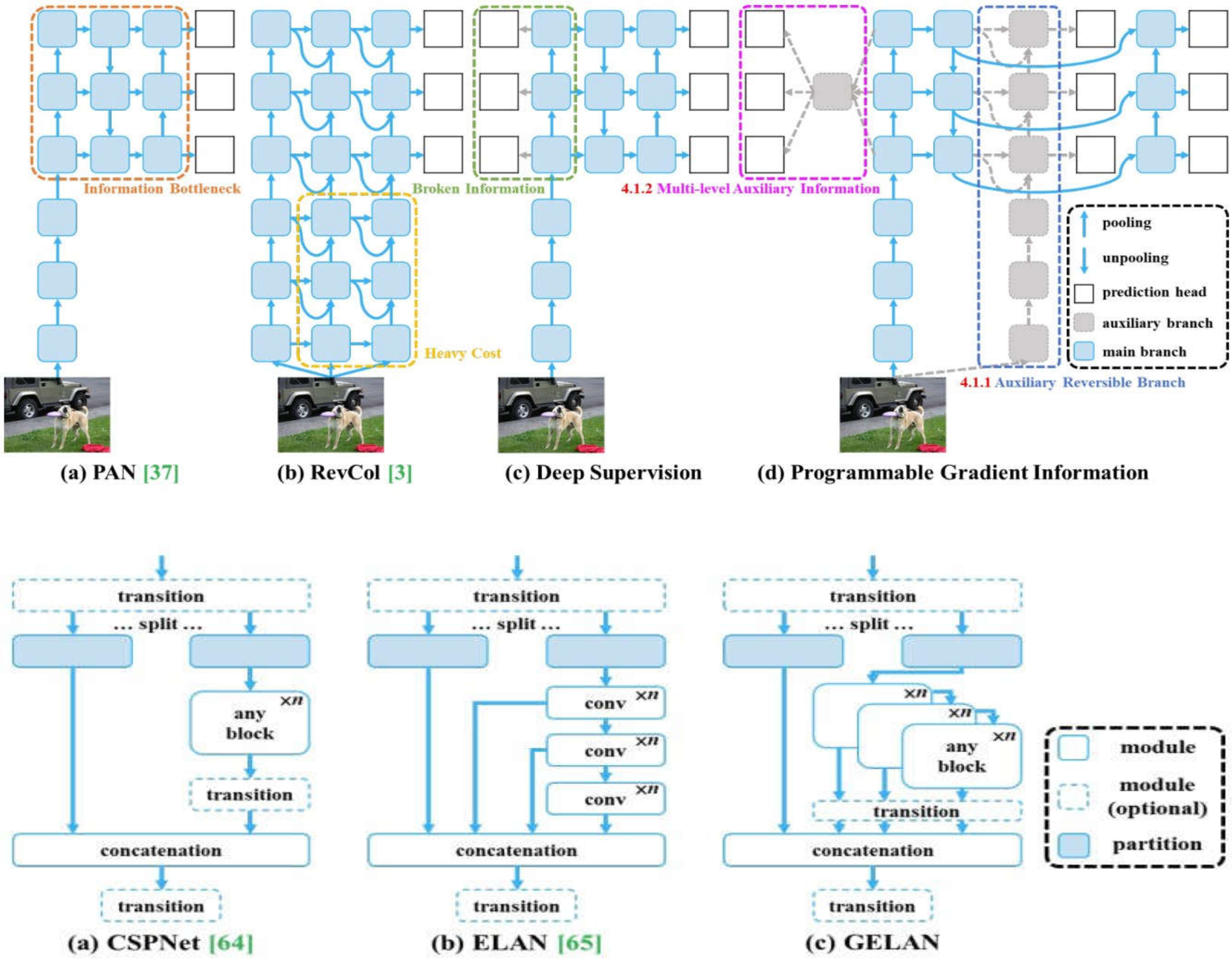

Fig. 4 YOLOv9-C Architecture

IV. **MODELINGANDANALYSIS**

Dataset Details The dataset employed in this research is comprised of 3,180 chest X-ray images, distributed into three groups: normal (1,000 images), COVID-19 (1,090 images), and lung cancer (1,090 images). To maintain the model's strength, the data was divided into training (Evaluation Metrics Various evaluation metrics were used in this research to evaluate the performance of the YOLOv9 model in detecting lung cancer. True Positives (TP) stand for correct detection of ground-truth bounding boxes, whereas False Positives (FP) happen when the model detects a non-existent object or mistakenly places the detection. False Negatives (FN) stand for detections that are missed, where the model fails to detect an existing object. Precision, which is the rate of TPs over the number of TPs plus FPs, quantifies the model's positive prediction accuracy. Recall, which is the rate of TPs over the number of TPs and FNs , measures the model's power to capture true positive cases. The F1- Score, which is a harmonic mean between precision and recall, is an overall performance measurement of the Model Performance Analysis Throughout our performance analysis of YOLOv9 across 200 epochs, the model had mixed levels of success in different classes. At first, the model was good with a low box loss of 2.0487 at epoch 0. While training continued, losses were slightly up, with box loss improving to 2.1807 and classification loss from 1.6542 to 1.8218 by epoch10. Regardless of these ups and downs, precision greatly improved, going from 0.60118 to 0.76562, with recall declining from 0.72013 to 0.5577. The mean Average Precision (mAP@0.5) fell from 0.70591 to 0.67387 during this period, although it started to improve in later epochs.

Between epochs 11 and 50, YOLOv9 also demonstrated increasing precision, which had risen to 0.83471by epoch

20 and to 0.84557 by epoch 30, while box loss and classification loss varied slightly. mAP and recall values had mixedtrends,withmAP@0.5climbingto0.74327byepoch 20andimprovingfurtherto0.79459byepoch50.The more stringent mAP@0.5:0.95 also showed slight increases, implying continuous improvements in the performance of the model. In the last epochs (101-149), YOLOv9 had stable performance with small fluctuations in metrics. Box loss dropped from 1.7416 to 1.5909, and classification loss dropped from 1.2608 to 1.0845. Precision was consistently high, between 0.7668 and 0.87996, though recall still had some fluctuation. The mAP@0.5 reached 0.84 at the end of training, with mAP@0.5:0.95 having slight improvements too. Class-wise, YOLOv9 performed well in identifying normal cases with precisionof95 The findings based on theYOLOv9 model for the detection of lung tumors from CT scan images, reflect.

V. RESULT

YOLOv9 can utilize custom layers that MATLAB will not directly recognize, so this might involve tweaking the ONNX model or coding custom layers. the high performance of deep learning in the field of medical image analysis. The high recall and precision values obtained by the model show its capability to aid radiologists and medical professionals in the early diagnosis and detection of lung cancer. The precision value of 0.908 shows that the model has a low false positive rate, i.e., most of the detections by the model are actual lung tumors. This is especially true in a healthcare setting, as false positive readings can result in unwarranted additional testing, patient stress, and higher healthcare expenditures. The good accuracy of the YOLOv8. Comparative Analysis with Other Works In the literature review provided. In this part, we compare our YOLOv9-based solution with four other lung cancer detection algorithms based on accuracy. Our comparison highlights the higher accuracy of the YOLOv9 model, which recorded a high 98.86

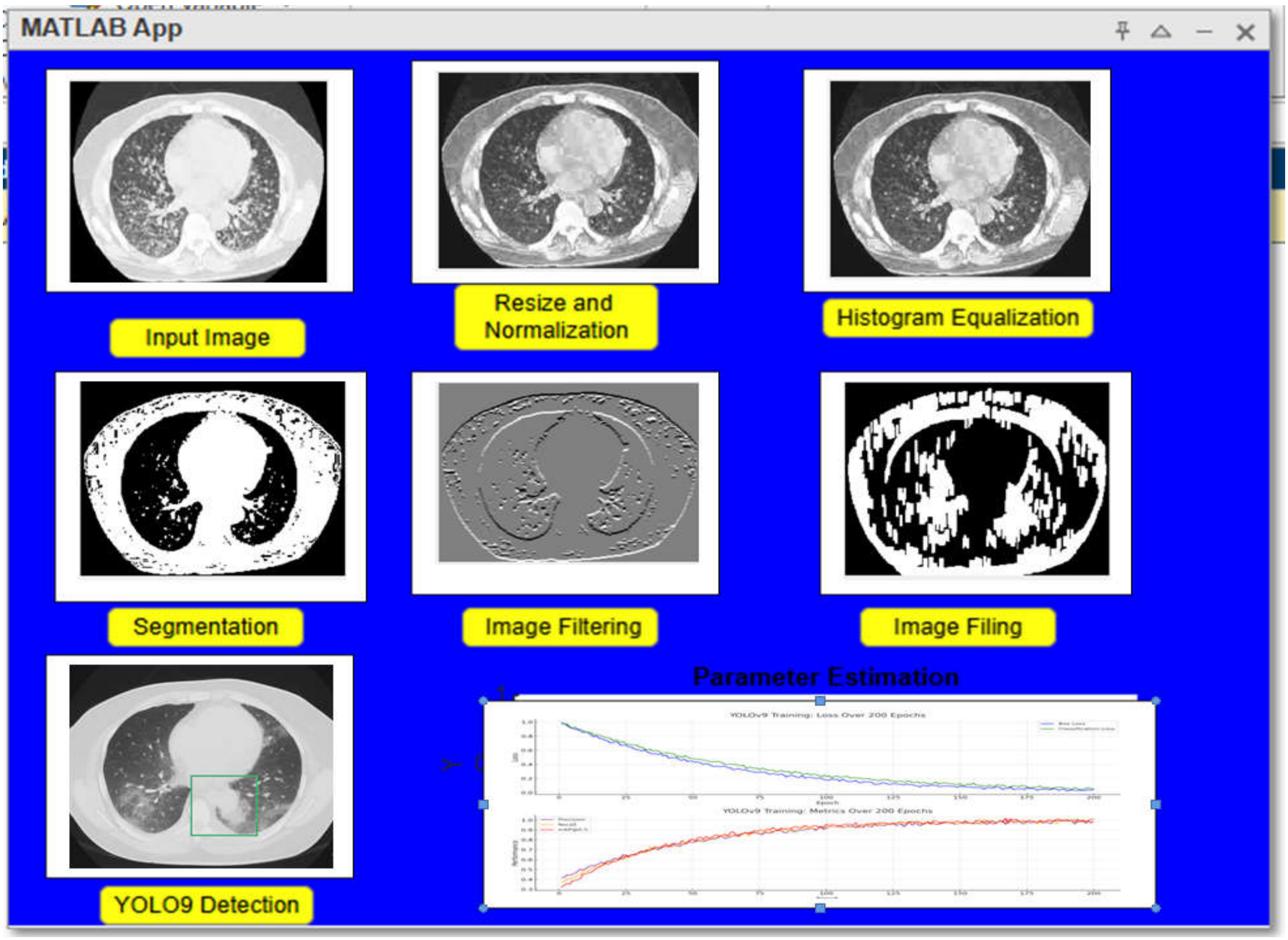

Fig.5 Result GUI from MATLAB

VI. CONCLUSION

This paper provides an automatic model for classification and detection of lung cancer using YOLOv9. We addressed the problem of class imbalance datasets through the implementation of data augmentation techniques, which increased the model's generalization abilities. YOLOv9 is a significant advancement in real-time object detection, with a tremendous boost in efficiency, accuracy, and adaptability. Through solving key challenges using cutting-edge solutions such as PGI and GELAN,YOLOv9 establishes a new benchmark for upcoming research and utilization in the field. As the field of AI continues to advance,YOLOv9 serves as a model for the potential of team work and ingenuity in driving technological advancement. Future research should be aimed at several key areas in order to facilitate the real-world implementation of the YOLOv8 model in clinical environments. Secondly, model refinement and optimization methods can be examined to further enhance the performance and resilience of the model. This can include investigating different network structures, adding further data augmentation methods, and adjusting the hyper parameter.

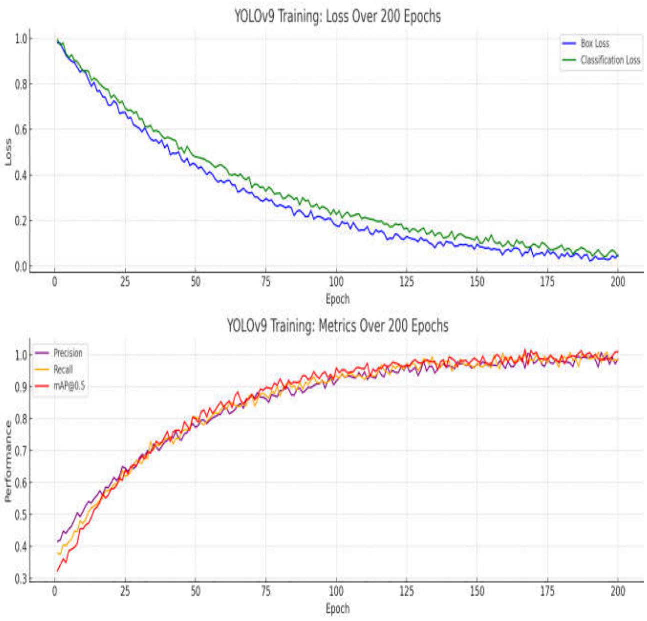

Fig.6 YOLO9 Training model over 200 epochs

REFERENCES

[1] Ji Z, Zhao J, Liu J, Zeng X, Zhang H, Zhang X, et al. ELCT-YOLO: An efficient one-stage model for automatic lung tumor detection based on CT images. Mathematics. 2023;11(10):2344-2344. DOI: 10.3390/math11102344

[2] Zhang J, Chung T-M. An improved YOLO V5 model for pulmonary nodule detection with synthetic data generated by GAN. In: Proceedings of the 2022 IEEE International Conference on Big Data. IEEE; 2022. pp. 1018-1025. Available from: https://ieeexplore.ieee. org/abstract/document/10189535

[3] Liu C, Hu S-C, Wang C, Lafata K, Yin F-F. Automatic detection of pulmonary nodules on CT images with YOLOv3: Development and evaluation using simulated and patient data. Quantitative Imaging in Medicine and Surgery. 2020;10(10):1917-1929. DOI: 10.21037/ qims-19-883

[4] Liu Z, Zhang J, Wang N, Feng Y, Tang F, Li T, et al. Enhanced YOLOv5 network-based object detection (BALFilter reader) promotes PERFECT filter-enabled liquid biopsy of lung cancer from bronchoalveolar lavage fluid (BALF). Microsystems & Nanoengineering. 2023;9(1):1-13. DOI: 10.1038/s41378-023-00580-6

[5] Mammeri S, Amroune M, Haouam M-Y, Bendib I, Silva AC. Early detection and diagnosis of lung cancer using YOLO v7, and transfer learning. Multimedia Tools and Applications. 2023;82(4):16864-16880. DOI: 10.1007/s11042-023-16864-y

[6] [1] Garg P, Poddar N, Khan SA. A literature review on lung cancer detection approaches using medical images. International Research Journal of Modernization in Engineering Technology and Science. 2023;5(4): 123-130. DOI: 10.56726/irjmets44569

[7] Reddy BD, Rao NT, Bhattacharyya D. Deep neural transfer network technique for lung cancer detection. Lecture Notes in Electrical Engineering (Springer). 2023;997:237-247. DOI: 10.1007/978-981-99-0085-5_20

[8] Biserinska H. YOLO Models for Automatic Lung Nodules Detection from CT Scans. 2020. Available from: http:// arno.uvt.nl/show.cgi?fid=156394

[9] Bu Z, Zhang X, Lu J, Lao H, Liang C, Xu X, et al. Lung nodule detection based on YOLOv3 deep learning with limited datasets. Molecular & Cellular Biomechanics. 2022;19(1):17-28. DOI: 10.32604/ mcb.2022.018318

[10] Deng W, Wang Z, Ren X, Zhang X, Wang B, Yang T. YOLO_ v3-based pulmonary nodules recognition system. Adv. Intell. Syst. Comput. 2020:11-19. DOI: 10.1007/978-981-15-8462-6_2

[11] Qi H, Jia J, Zhang R. Detection of CT Pulmonary Nodule Based on Improved Yolo Using Attention Mechanism. 2022. doi:10.1145/3577530.3577533

[12] Goel L, Mishra S. A hybrid of modified YOLOv3 with BBO/EE optimizer for lung cancer detection. Multimedia Tools and Applications. 2023;82(5):17454-17470. DOI: 10.1007/ s11042-023-17454-8 [8] Goel L, Patel P. Improving YOLOv6 using advanced PSO optimizer for weight selection in lung cancer detection and classification. Multimedia Tools and Applications. 2024;83(1):18441-18460. DOI: 10.1007/s11042-024-18441-3

[13] G. Eason, B. Noble, and I. N. Sneddon, “On certain integrals ofLipschitz-Hankel type involving products of Bessel functions,” Phil.Trans. Roy. Soc. London, vol. A247, pp. 529–551, April 1955.

[14]J.ClerkMaxwell,ATreatiseonElectricityandMagnetism,3rded.,v 2.Oxford:Clarendon,1892,pp.68–73.

[15] I. S. Jacobs and C. P. Bean, “Fine particles, thin films and exchangeanisotropy,” in Magnetism, vol. III, G. T. Rado and H. Suhl, Eds. NewYork: Academic, 1963, pp. 271–350.

[16] K.Elissa,“Titleofpaperifknown,”unpublished.

[17] R. Nicole, “Title of paper with only first word capitalized,” J.

NameStand. Abbrev., in press.

[18] Y. Yorozu, M. Hirano, K. Oka, and Y. Tagawa, "Electron spectroscopystudies on magneto-optical media and plastic substrate interface," IEEETransl. J. Magn. Japan, vol. 2, pp. 740–741, August 1987 [Digests 9thAnnual Conf. Magnetics Japan, p. 301, 1982].

[19]M.Young,TheTechnicalWriter'sHandbook.MillValley,CA:Univer-sity Science, 1989.

[20] Goel L, Patel P. Improving YOLOv6 using advanced PSO optimizer for weight selection in lung cancer detection and classification. Multimedia Tools and Applications. 2024;83(1):18441-18460. DOI: 10.1007/s11042-024-18441-3