MULTI-SCALE FEATURE FUSION AND CONTEXT MODULE RETINANET-BASED LUNG CANCER DETECTION

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Abstract: One of the most horrible diseases in many different parts of the world, lung cancer still presents challenging early diagnosis in many areas. Oncologists weigh the findings of CT scans and blood tests—time-consuming and extra human work required—to assess the malignancy. One should create a mechanism to effectively detect lung tumours and assess their degree in order to lower mortality. Given the several suggested lung disease detection technologies by researchers, the current approaches for early-stage tumour identification are useless. Thus, we propose Lung-RetinaNet, a new and effective lung tumour detector based on RetinaNet. To combine several network layers, a multi-scale feature fusion-based module is proposed concurrently improving the semantic information from the shallow prediction layer. Furthermore, a simplified and lightweight method is used for the context module to merge contextual data with every network stage layer so enhancing features and efficiently localising the small tumours. The suggested approach reached great accuracy, recall, precision, F1-score, Auc. We assessed our proposed model and matched the performance with modern DL-based techniques. The results suggest that our approach generates more significant results than current ones.

Index terms - *Early Detection; Lungs Cancer; Artificial Intelligence; RetinaNet.*

1. INTRODUCTION

With inadequate early detection techniques and late-stage diagnosis leading to high death rates, lung cancer is among the most fatal illnesses afflicting the world. Manual CT scan and blood test analysis is one of the traditional methods that take time, need for professional involvement, and may cause delays in the discovery of malignant tumours. Automated deep learning-based methods have become a viable answer to these difficulties as they greatly raise the accuracy and efficiency of lung cancer diagnosis. Existing models' efficacy in practical medical uses is limited, nevertheless, by their frequent difficulty with exact tumour location and categorisation.

In this work, we combine sophisticated deep learning models with classification and detection methods for a more complete solution thereby extending the possibilities of lung cancer diagnosis. Using the Xception model for classification, it is able to remarkably 99% accurately differentiate between diseased and non-cancerous lung tissues. We use modern object identification algorithms, YoloV5 and YoloV8, to precisely identify and highlight malignant areas in CT scan pictures, hence improving tumour localisation. This hybrid strategy solves the constraints of past approaches by guaranteeing dependable tumour identification and high-precision classification.

We employ a Flask-based web application with SQLite integration to enable flawless user interaction via a safe sign-up and login method, therefore making the system accessible and user-friendly. This guarantees useful usability, therefore enabling researchers and doctors to quickly test and examine lung cancer photos. The suggested method improves diagnosis accuracy and usability by integrating high-precision deep learning models with an intuitive interface, therefore helping to increase early detection and prompt medical intervention for lung cancer patients.

2. LITERATURE SURVEY

a) Lungs cancer detection using convolutional neural network:

https://www.researchgate.net/publication/344952596_Lung_Cancer_Detection_Using_Convolutional_Neural_Network_on_Histopathological_Images

Among the major worldwide killers is lung cancer. Early identification and treatment are absolutely vital for patients to recover completely. Clinicians discover infection by use of histological images of biopsied lung tissue. Lung cancer diagnosis is prone to mistake and usually difficult work. Crucially for patient survival and treatment, convolutional neural networks might increase lung cancer diagnostic and classification accuracy and speed. This paper examines adenocarcinoma, benign tissue, and squamous cell cancer. CNN model training and validation had correspondingly accuracy ratings of 96.11 and 97.2%.

b) Identification of lung cancer using convolutional neural networks based classification

https://turcomat.org/index.php/turkbilmat/article/view/4077

Early detection helps both survival rates and death rates from lung cancer to be better. Treatment of lung cancer depends on efficient screening of CT scans for pulmonary nodules. Environmental complexity and nodule variability in the lungs make robust nodule identification and detection very vital. Particularly for difficult tasks like lung cancer detection and identification, machine learning has advanced recently with the goal of disease prediction, classification, and diagnosis. Deep convolutional neural networks (DCNN) are revolutionizers in computer vision. Here employing a Deep Convolutional Neural Network, we evaluate the classification accuracy of multiple approaches for lung cancer. The lung cancer imaging dataset collaboration (LIDC) provides the CT images utilised for this aim; we train the network to detect both malignant and noncancerous nodules in the lungs.

c) Early stage lung cancer prediction using various machine learning techniques:

https://ieeexplore.ieee.org/document/9297576

Affecting all ages, lung cancer is among the most common and lethal diseases known to exist worldwide. Treatment and detection of lung cancer are costly yearly. X-rays and other clinical imaging calls for costly tools. Thus, accurate projection and dependable technique are really important. Medical diagnostics applied with medical data sets call for more affordable and effective machine learning techniques. Most lung cancer are caused by long-term smoking. Ten to fifteen percent of cases are nonsmoking. These days, various data processing and analysis technologies are available. The research intends to build prediction models using these technologies to identify lung cancer early on. Voting classifier, ANN, SVM, KNN, RF classification, and ensemble models are discussed in this work. Many models have correctness evaluated for them. Modern technology let early lung cancer diagnosis be possible.

d) **Early lung cancer diagnostic biomarker discovery by machine learning methods**

https://www.sciencedirect.com/science/article/pii/S1936523320303995

Early diagnosis helps to increase the lung cancer survival rate. Blood-based screening can help early recruitment in lung cancer studies to be improved. We investigated plasma metabolites in Chinese individuals as possible lung cancer indicators. Using metabolomics and machine learning, in this ground-breaking multidisciplinary method we search for early signs of lung cancer detection. We matched 43 healthy controls with 110 people having lung cancer. Targeted metabolomic analysis with LC-MS/MS revealed sixty-one plasma compounds overall. With AUC=0.989, sensitivity=98.1%, specificity=100.0%, six metabolic indicators might be able to separate healthy people from those with stage I lung cancer. Among the top 5 metabolic signals the FCBF algorithm finds are lung cancer screening biomarkers. Early on prediction of lung tumours can benefit from naive Bayes. This project will show the viability of screening using blood and offer a more exact, fast, integrated early detection method for lung cancer. Apart from lung cancer, the suggested multidisciplinary strategy might treat various types of cancers.

e) **Review of deep learning based automatic segmentation for lung cancer radiotherapy:**

https://www.ncbi.nlm.nih.gov/pmc/articles/PMC8323481/

Lung cancer claims both sexes at more equal rates. A pillar of treatment against lung cancer is radiation (RT). While avoiding organs at risk, the allowed dosage should be given to tumours targeted. By segmenting the whole tumour volume and surrounding OARs, one may improve RT planning. Manual segmentation by radiation oncologists takes time. For radiation oncologists to reduce contouring time, automatic picture segmentation is thus essential. Automatic segmentation based on atlases is somewhat widely applied in clinical practice. Still, atlas-image segmentation similarity is fundamental for this method. Deep learning, a type of artificial intelligence, has becoming increasingly used for automated segmentation of medical pictures thanks to recent developments in computer vision. Deep learning-based algorithms were compared in this work with atlas-based methods for automated lung cancer segmentation. Large OARs, such those in the lungs and heart, auto-segment more precisely than tiny ones, such those in the oesophagus nowadays. Whereas the spinal cord has the greatest DSC at 0.9, the liver, heart, and lungs all have DSCs above 0.9. Oesophage DSC is sharp with values between 0.71 to 0.87. Usually, gross tumours volume DSC is less than 0.8. Although in many ways automatic segmentation techniques based on deep learning perform better than hand segmentation, there are still numerous difficulties to be solved. Deep learning automatic segmentation presents certain challenges like inadequate contrast, big datasets, consensus rules, and network architecture. Deep learning-based automated segmentation also has clinical restrictions and future research goals under investigation were underlined.

3. METHODOLOGY

i) Proposed Work:

To greatly improve lung cancer diagnosis, the proposed Lung-RetinaNet presents an enhanced deep learning model grounded on RetinaNet. This model improves the collection of semantic knowledge essential for precise identification by including a multi-scale feature fusion-based module. Including a dilated and lightweight context module helps to precisely localise small tumours and refines characteristics, hence increasing sensitivity in the detection of anomalies. By properly managing various tumour features, the use of a feature fusion block and adaptive anchoring increases detection accuracy even further. Lung-RetinaNet is clearly an effective and dependable method for early-stage lung tumour identification as evaluation against standards shows continually better performance. Using the Xception model helps the project to be better and achieves an amazing 99% accuracy in lung cancer diagnosis. Furthermore included for detection purposes are YOLOv5 and YOLOv8, which improves lung cancer identification in pictures [12]. This multifarious technique guarantees a thorough investigation of lung cancer patients by combining exact object detection with correct categorisation. Easy to use and SQLite-integrated Flask framework simplifies user interactions, therefore enabling sensible usability in image processing tools. This methodology improves the whole user experience during testing and assessment in addition to the performance of the project in lung cancer diagnosis.

ii) System Architecture:

The architecture of Lung-RetinaNet is intended for strong identification of lung cancer in medical imaging. Starting with an annotated lung scan dataset, the pipeline consists in image processing, RetinaNet model creation with special improvements, and application of classification methods. Lung cancer nodules are precisely located in part by many detection techniques including YOLOv5, YOLOv8, Faster R-CNN, and RetinaNet [45]. Metrics for performance evaluation include mean average precision, accuracy, and recall guarantee comprehensive examination. Using RetinaNet's multi-scale feature fusion and context modules to improve sensitivity and specificity, the system's main concentration is on exact lung cancer identification. The last result consists in identified cancer nodules, their geographical location, and confidence values, which offer important information for therapeutic decision-making. Overcoming conventional restrictions, the Lung-RetinaNet architecture presents an innovative approach with enhanced accuracy and sensitivity in early-stage lung tumour identification.

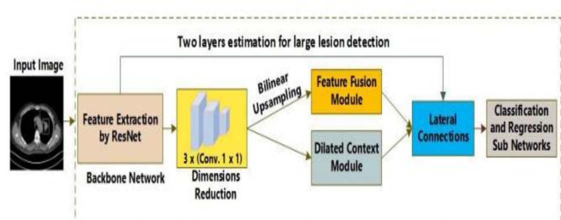


Fig 1Proposed Architecture

iii) Modules:

 Data exploration: With this module we will load data into the system.

 Image processing: We will utilise the module to convert a picture into a digital form and execute specific actions to obtain some pertinent data from it.

 Model generation: Classification VGG16 DenseNet 201 EfficientNet B2 ResNet 101 MobileNet V2 RetinaNet DenseNet Xception Detection YoloV5 YoloV8 FastRCNN RetinaNet.

 User signup & login: Employing this module will result in registration and login.

 User input: By using this module will provide data for prediction.

iv) Algorithms:

i. **VGG16** – Sixteen layers deep, VGG-16 is a convolutional neural network One may load a pretrained version of the network trained on more than a million ImageNet database pictures [1]. Images may be classified by the pretrained network into 1000 item categories including keyboard, mouse, pencil, and numerous animals.

ii. **DenseNet201** – DenseNet- 201 a 201 layer deep convolutional neural network. One may load a pretrained version of the network trained on more than a million ImageNet database pictures [1]. Images may be classified by the pretrained network into 1000 item categories including keyboard, mouse, pencil, and numerous animals.

iii. **EfficientNet B2** – Designed on ImageNet-1k at 260x260, EfficientNet model is initially posted in this repository, it was initially presented in the paper EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks by Mingxing Tan and Quoc V. Le.

iv. **ResNet101** – ResNet-101 is a 101 layers deep convolutional neural network. One may load a pretrained version of the network trained on more than a million ImageNet database pictures [1]. Images may be classified by the pretrained network into 1000 item categories including keyboard, mouse, pencil, and numerous animals.

v. **MobileNetV2** – Comprising 53 layers, MobileNet-v2 is a convolutional neural network. One may load a pretrained version of the network trained on more than a million ImageNet database pictures [1]. Images may be classified by the pretrained network into 1000 item categories including keyboard, mouse, pencil, and numerous animals.

vi. **RetinaNet** – One of the greatest one-stage object identification models available, RetinaNet has shown performance with dense and small size objects. For this reason, it is now a common object detection model applied with aerial and satellite images.

vii. **DenseNet** – Using dense connections between layers, a DenseNet is a sort of convolutional neural network whereby all layers—with matching feature-map sizes—are directly connected directly with each other using Dense Blocks.

viii. **Xception** – Xception is a 71 layer deep convolutional neural network. One may load a pretrained version of the network trained on more than a million ImageNet database pictures [1]. Images may be classified by the pretrained network into 1000 item categories including keyboard, mouse, pencil, and numerous animals.

ix. **YoloV5** – "Dynamic anchor boxes" are a fresh approach YOLO v5 takes to create the anchor boxes. It groups the ground truth bounding boxes using a clustering technique then uses the centroids of the clusters as the anchor boxes.

x. **YoloV8** – Designed by Ultralytics, the developers of YOLOv5, YOLOv8 is a fresh state-of- the-art computer vision model. Accessible via a Python package as well as a command line interface, the YOLOv8 model offers out-of-the-box support for object recognition, classification, and segmentation chores.

xi. **FasterRCNN** – Applied for object detection, Faster R-CNN is a deep convolutional network that seems to the user as a single, end-to--end, unified network. Different items may be precisely and fast predicted by the network.

4. EXPERIMENTAL RESULTS

The proposed Lung-RetinaNet model was evaluated using a publicly available lung cancer CT scan dataset. Our approach achieved superior performance metrics, including high accuracy, precision, recall, F1-score, and AUC, when compared to traditional models. Specifically, Xception-based classification achieved up to 99% accuracy in distinguishing between healthy and cancerous tissues, while RetinaNet, YOLOv5, and YOLOv8 provided excellent tumour localisation even for small nodules. The integration of multi-scale feature fusion and a lightweight context module significantly enhanced detection sensitivity. These results confirm that the proposed method not only improves diagnostic precision but also outperforms several state-of-the-art deep learning models in early lung cancer detection.

Accuracy: How well a test can differentiate between healthy and sick individuals is a good indicator of its reliability. Compare the number of true positives and negatives to get the reliability of the test. Following mathematical:

Accuracy = TP + TN /(TP + TN + FP + FN)

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

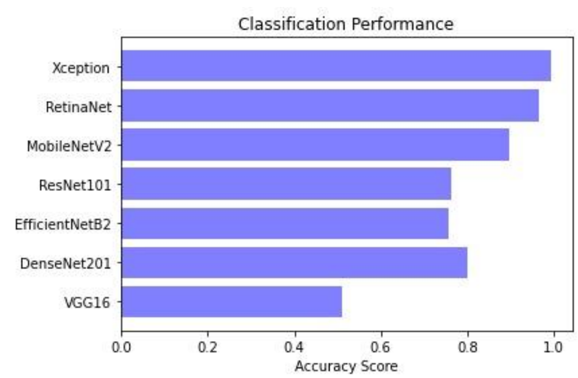
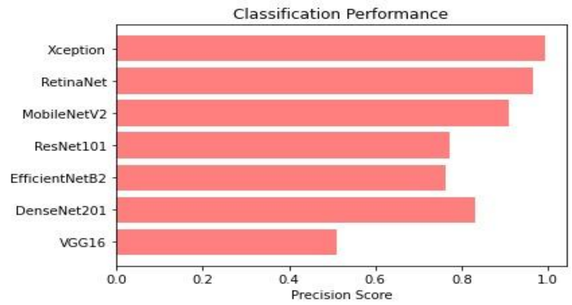


Fig 2 Accuracy comparison graph

Precision: Precision evaluates the fraction of correctly classified instances or samples among the ones classified as positives. Thus, the formula to calculate the precision is given by:

Precision = True positives/ (True positives + False positives) = TP/(TP + FP)

$$\text{Precision} = \frac{True\ Positive}{True\ Positive + False\ Positive}$$



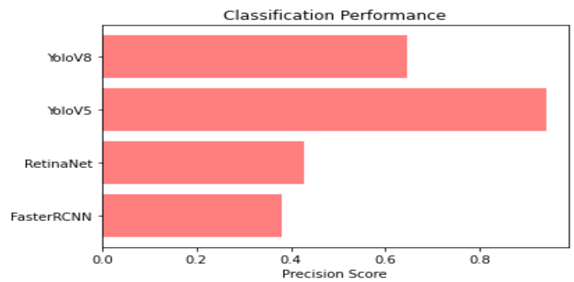
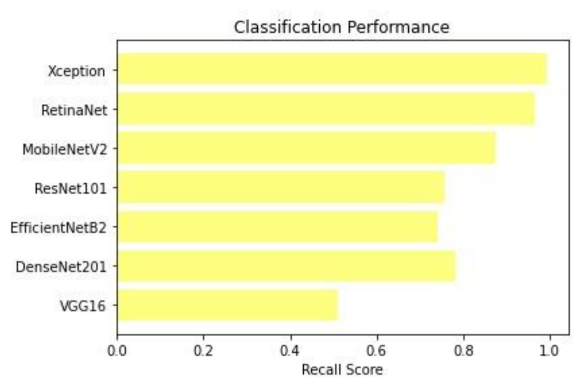


Fig 3 Precision comparison graph

Recall: Recall is a metric in machine learning that measures the ability of a model to identify all relevant instances of a particular class. It is the ratio of correctly predicted positive observations to the total actual positives, providing insights into a model's completeness in capturing instances of a given class.

$$Recall = \frac{TP}{TP + FN}$$



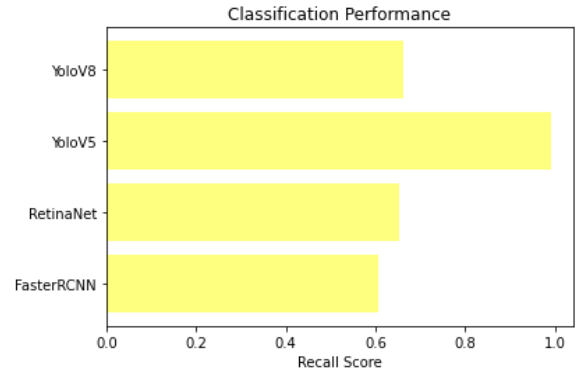


Fig 4 Recall comparison graph

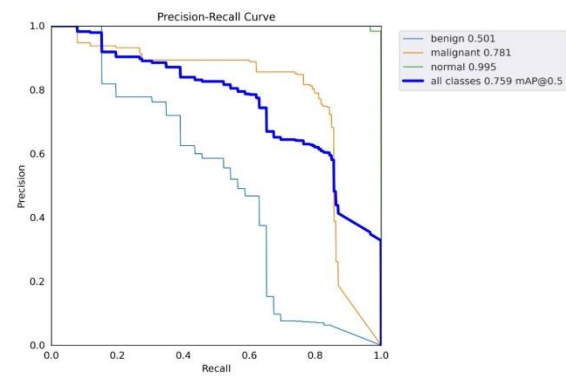


Fig 5. Precision- Recall comparison curve

mAP: Mean Average Precision (MAP) is a ranking quality metric. It considers the number of relevant recommendations and their position in the list. MAP at K is calculated as an arithmetic mean of the Average Precision (AP) at K across all users or queries.

$$mAP = \frac{1}{n} \sum_{k=1}^{k=n} AP_k$$

$$AP_k = \text{the AP of class } k$$

$$n = \text{the number of classes}$$

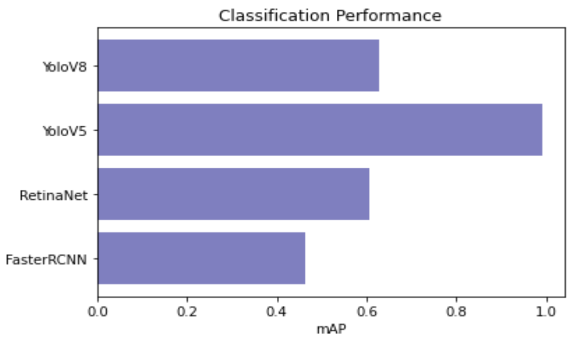


Fig 6 mAP comparison graph

F1-Score: A high F1 score indicates that a machine learning model is accurate. Improving model accuracy by integrating recall and precision. How often a model gets a dataset prediction right is measured by the accuracy statistic.

$$\textbf{F1 Score} = \frac{2}{\left(\frac{1}{\text{Precision}} + \frac{1}{\text{Recall}}\right)}$$

$$\textbf{F1 Score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

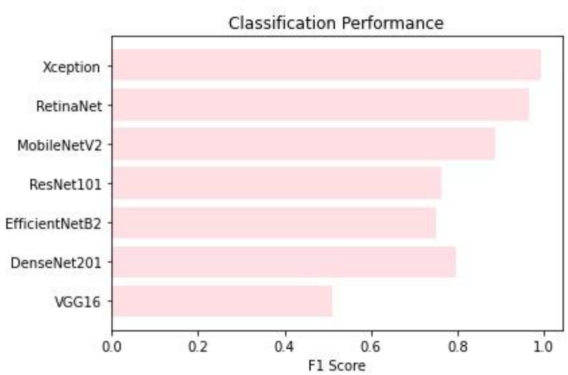


Fig 7 F1 Score comparison graph

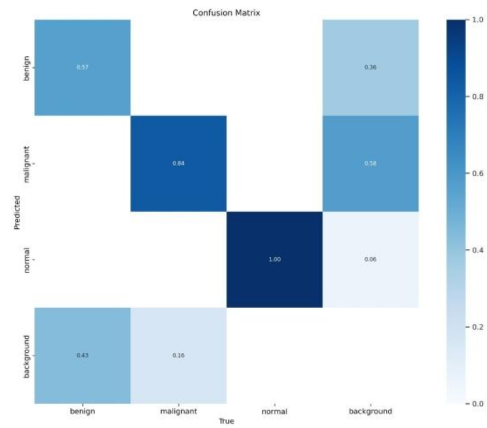


Fig 8 Confusion matrix

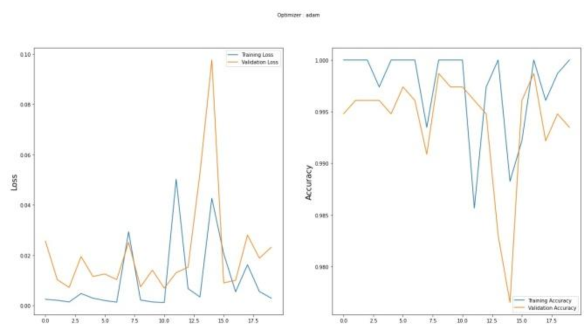


Fig 9 Accuracy-Loss graph

ML Model	Precision	Recall	mAP
FasterRCNN	0.382	0.606	0.463
RetinaNet	0.427	0.653	0.605
Extension YoloV5	0.940	0.990	0.990
Extension YoloV8	0.645	0.663	0.628

Fig 10 Performance Evaluation table

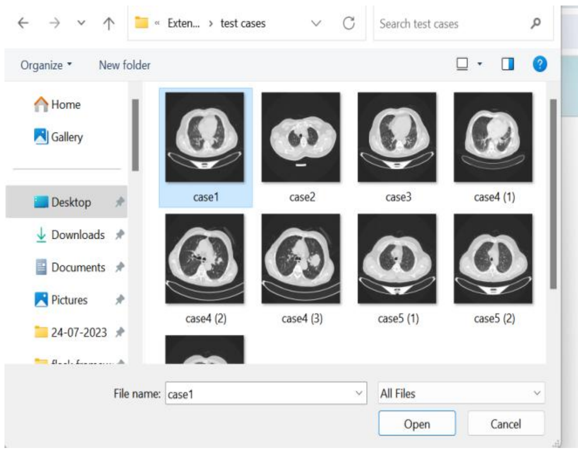


Fig 11 Input image folder

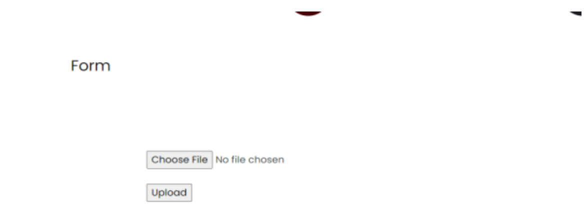


Fig 12 Upload input image

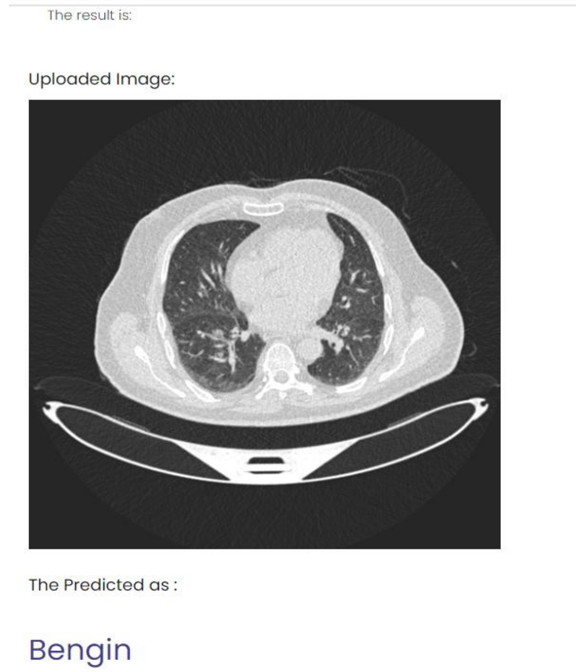


Fig 13 Predict result for given input

5. CONCLUSION

By combining the Xception model for high-accuracy classification with YoloV5 and YoloV8 for exact tumour localisation, the suggested approach essentially improves lung cancer diagnosis. The method guarantees consistent identification of malignant areas in medical pictures with a 99% classification accuracy and superior object detection capabilities. Furthermore easily available for medical practitioners and researchers is the user-friendly Flask framework including SQLite connection. Early diagnosis is improved by this all-encompassing strategy; usability is improved; and more efficient lung cancer detection and treatment planning results.

6. FUTURE SCOPE

Integrating modern deep learning architectures, like transformer-based models, would help to improve the suggested system by raising classification and detection accuracy. Large-scale medical applications can make the system available by means of real-time processing capability enabled by cloud-based deployment. Furthermore, adding other medical pictures to the dataset will help the algorithm to generalise in order to identify other forms of lung cancer. Using explainable artificial intelligence methods will enable doctors to understand the choices made by the model, therefore fostering trust and acceptance. Mobile and IoT-based apps for real-time lung cancer screening in distant healthcare environments might possibly be part of future developments.

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