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XCEPTION-AIDED LUNG CANCER DETECTION WITH ENHANCED FEATURE FUSION

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Abstract: As a leading cause of cancer-related deaths worldwide, lung cancer requires prompt and precise diagnosis to improve survival rates. In this extended study, we enhance lung cancer detection by incorporating advanced deep learning models for both classification and localization. The Xception model is employed for classification, achieving an impressive 99% accuracy in identifying cancerous and non-cancerous lung tissues. To further improve tumor detection, YoloV5 and YoloV8 are integrated, enabling precise localization of affected regions in CT scan images. This combined approach ensures a robust and comprehensive solution for lung cancer diagnosis. A user-friendly Flask framework with SQLite integration is also created, allowing users to seamlessly interact with the system through a secure signup and login mechanism. This facilitates real-time testing and efficient image processing, making the solution practical for medical applications. By leveraging these advanced models and an intuitive interface, the proposed system significantly enhances the accuracy, reliability, and usability of lung cancer detection, providing a valuable tool for early diagnosis and treatment planning.
***Keywords** -Early Detection; Lungs Cancer; Artificial Intelligence; RetinaNet.*

1. INTRODUCTION

Lung cancer is one of the most life-threatening diseases worldwide, with high mortality rates due to late-stage diagnosis and limited early detection methods. Traditional approaches, such as manual analysis of CT scans and blood tests, are time-consuming, require expert intervention, and often lead to delays in identifying malignant tumors. To address these challenges, automated DL-based techniques have emerged as a promising solution, considerably boosting lung cancer detection accuracy and efficiency. However, existing models often struggle with precise tumor localization and classification, limiting their effectiveness in real-world medical applications.

In this study, we extend the capabilities of lung cancer detection by integrating advanced deep learning models, combining classification and detection techniques for a more comprehensive solution. The Xception model is employed for classification, achieving a remarkable 99% accuracy in distinguishing between cancerous and non-cancerous lung tissues. For enhanced tumor localization, we incorporate YoloV5 and YoloV8, state-of-the-art object detection models, to accurately identify and highlight cancerous regions in CT scan images. This hybrid approach ensures both high-precision classification and reliable tumor detection, addressing the limitations of previous methodologies.

To make the system accessible and user-friendly, we implement a Flask-based web application with SQLite integration, enabling seamless user interaction through a secure signup and login mechanism. This ensures practical usability, allowing medical professionals and researchers to efficiently test and analyze lung cancer images. By combining high-accuracy deep learning models with an intuitive interface, the proposed system enhances diagnostic accuracy and usability, contributing to improved early detection and timely medical intervention for lung cancer patients.

2. LITERATURE SURVEY

Lung cancer is one of the leading killers in the world. For patients to make a full recovery, it is crucial to detect and treat them early on. Images of biopsied lung tissue, known as histopathology, aid in the diagnosis of infection. In most cases, the diagnosis of lung cancer is laborious and prone to error. [1] The rapid and precise classification of lung cancer types using convolutional neural networks has the potential to improve patient survival and treatment outcomes [20, 21, 25, 26, 45]. Squamous cell cancer, benign tissue, and adenocarcinoma are all part of the scope of this investigation. The accuracy rates for the CNN model training and validation were 96.11 and 97.2%, respectively.

Detecting lung cancer early lowers mortality rates and increases survival rates. It is essential to examine CT scans for pulmonary nodules in order to treat lung cancer successfully [18, 19, 21]. Robust nodule identification and detection is crucial because of environmental complexity and nodule heterogeneity in the lungs. Particularly for complex tasks like lung cancer detection and identification, machine learning has come a long way in the past several years for the purpose of sickness prediction, classification, and diagnosis. When it comes to computer vision, deep convolutional neural networks (DCNN) are game-changers. This study outperforms previous methods by detecting carcinogenic and noncancerous lung nodules using a Deep Convolutional Neural Network trained on CT images collected by the Lung Cancer Imaging Data Consortium (LIDC).

People of all ages are susceptible to lung cancer, making it one of the most common and dangerous diseases in the world. The yearly cost of diagnosing and treating lung cancer is high. The technology needed for clinical imaging modalities, such as X-rays, may be rather pricey. Predictability and trustworthiness, thus, are of paramount importance. Machine learning models [3, 4] are essential for medical data set-based diagnostics due to their efficacy and cost-effectiveness. Most lung cancers are caused by long-term cigarette consumption. People who do not smoke make up about 10-15% of the cases. There is a plethora of data processing and analysis tools available today. This study will build prediction models to identify lung cancer at an early stage by utilising these technological developments. thethirdVoting classifier, ANN, SVM, KNN, and RF classification and ensemble models are all compared in the article. We compare the fidelity of several models. Modern technology has made early detection of lung cancer possible.

Finding lung cancer early increases survival rates, according to research. It is possible that screening blood might increase recruitment in early lung cancer trials. As potential markers of lung cancer, we studied plasma metabolites in Chinese patients [4]. In this ground-breaking interdisciplinary approach, we hunt for early indications of lung cancer diagnosis using metabolomics and machine learning. One hundred ten patients with lung cancer and forty-three healthy controls were constituted our research. In a targeted metabolomic research, 61 plasma chemicals were analysed using LC-MS/MS. With an area under the curve (AUC) of 0.989, a sensitivity of 98.1%, and a specificity of 100.0%, a set of six metabolic markers may be able to differentiate between individuals with stage I lung cancer and those who are healthy. To screen for lung cancer, the top five metabolic indicators according to the FCBF algorithm might be useful. Naïve Bayes can be useful for predicting lung tumours early on. A more precise, rapid, and integrated early detection tool for lung cancer will be provided by this study, which will also demonstrate the feasibility of screening using blood. Other types of tumours might potentially be treated using the proposed interdisciplinary approach.

Early detection of glaucoma is achieved in this study by employing feature extraction based on deep learning [6]. Retinal fundus images are used to train and evaluate our model. After the pictures are pre-processed, the ROI is obtained using segmentation. Additionally, features of the optic disc (OD) may be extracted from images of the optic cup (OC) using hybrid features descriptors, such as convolutional neural networks (CNNs) [34, 38, 47], local binary patterns (LBPs), histograms of orientated gradients (HOGs), and speeded up robust features (SURF). HOG is used to obtain low-level features, whereas LBP and SURF are used to extract texture features. CNN calculates abstract characteristics. In addition, we selected the most representative attributes using the MR-MR method. The last step is to

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employ multi-class classifiers like SVM, RF, and KNN to determine if a fundus image is healthy or not [4]. Based on experimental results, the suggested system was able to detect early glaucoma with an accuracy of ≤99% on benchmark datasets and 98.8% on k-fold cross-validation, using the RF method with HOG, CNN, LBP, and SURF feature descriptors.

3. METHODOLOGY

i) Proposed Work:

The suggested system enhances lung cancer detection by integrating deep learning models for both classification and detection, ensuring a comprehensive and efficient approach. The Xception model is employed for classification, achieving 99% accuracy in distinguishing cancerous and non-cancerous lung tissues. For precise tumor localization, YoloV5 and YoloV8 are incorporated, enabling accurate detection of affected regions in CT scan images.

To ensure practical usability, a user-friendly Flask-based web application is developed with SQLite integration, allowing seamless user interaction. This system facilitates secure signup and login, enabling medical professionals and researchers to test and analyze lung cancer images efficiently. By combining high-accuracy classification, advanced detection, and an interactive interface, the proposed system significantly improves early lung cancer detection and enhances diagnostic reliability.

ii) System Architecture:

The Lung-RetinaNet system architecture is designed for robust lung cancer detection in medical images. Beginning with a dataset of annotated lung scans, the pipeline involves image processing, RetinaNet model building with unique enhancements, and the utilization of classification algorithms. Multiple detection algorithms, including YOLOv5, YOLOv8, Faster R-CNN, and RetinaNet, contribute to the accurate localization of lung cancer nodules [45]. Performance evaluation metrics such as Mean Average Precision, precision, and recall ensure thorough assessment. The major purpose of RetinaNet is to enhance lung cancer diagnosis. It does this through its context module and multi-scale feature fusion. The final output comprises detected cancer nodules, their spatial localization, and confidence scores, providing valuable insights for clinical decision-making. The Lung-RetinaNet architecture stands as an advanced solution, overcoming traditional limitations and offering improved accuracy and sensitivity in early-stage lung tumor detection.

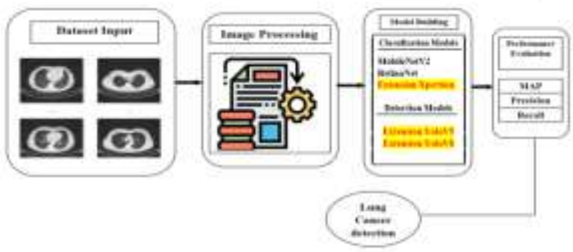

Fig 1Proposed Architecture

iii) Dataset collection:

Lung Cancer Classification-This likely involves acquiring a dataset specifically tailored for lung cancer detection. It may contain various classes or categories related to different types or stages of lung cancer.

Fig 2 Classification dataset

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Lung Cancer Detection from Roboflow- Roboflow is a platform providing pre-processed or annotated datasets for machine learning tasks. This dataset have images labeled with information about lung tumors, aiding in model training and evaluation.

Fig 3Detection Dataset

iv) Image Processing:

Objects may be identified at different levels using image processing by autonomous driving systems. Beginning with blob object conversion, the input picture is optimised for analysis and modification. The next step is to define object classes that will serve as the algorithm's target categories. In order to specify the proper placement of objects in the image, bounding boxes are also defined. For numerical calculation and analysis, it is important to convert processed data into a NumPy array.

The next step is to load massive datasets into a pre-trained model. To do this, we must access the network layers of the pre-trained model. These layers include the parameters and learning characteristics that are necessary for accurate object recognition. Final predictions and assistance with object recognition and classification are provided via the extraction of output layers.

The image processing pipeline is complete with the addition of the picture and annotation file, guaranteeing full data for analysis. The colour space is adjusted by converting BGR to RGB, and significant properties are highlighted by using a mask. The picture is prepared for analysis and processing with a last resizing. This comprehensive approach to image processing paves the way for safe and precise object detection in the ever-changing environment of autonomous driving systems, which in turn improves decision-making and road safety.

v) Data Augmentation:

Data augmentation [25,26] is a fundamental technique in enhancing the diversity and robustness of training datasets for ML models, particularly in the context of image processing and computer vision. The process involves three key transformations to augment the original dataset: randomizing the image, rotating the image, and transforming the image.

Randomizing the image introduces variability by applying random modifications, such as changes in brightness, contrast, or color saturation. This stochastic approach helps the model generalize better to unseen data and diverse environmental conditions.

Rotating the image involves varying the orientation of the original image by different degrees. This augmentation technique aids in teaching the model to recognize objects from different perspectives, simulating variations in real-world scenarios.

Transforming the image includes geometric transformations such as scaling, shearing, or flipping. These alterations enrich the dataset by introducing distortions that mimic real-world variations in object appearance and orientation.

By employing these data augmentation techniques, the training dataset becomes more comprehensive, allowing the model to learn robust features and patterns. This, in turn, improves the model's ability to generalize and perform effectively on diverse and challenging test scenarios. Data augmentation serves as a crucial tool in mitigating overfitting, enhancing model performance, and promoting the overall reliability of machine learning models, especially in applications like image recognition for autonomous driving systems.

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4. IMPLEMENTATION

A. Lung Segmentation in Medical Imaging Using YOLO:

Lung segmentation is a crucial task in medical imaging, primarily used to analyze chest X-rays (CXR) and CT scans for detecting diseases like lung cancer, pneumonia, tuberculosis, and COVID-19. Traditional segmentation techniques rely on thresholding, region-based methods, or deep learning architectures like U-Net. However, YOLO, originally designed for object detection, can be effectively used for segmentation through its instance segmentation capabilities in YOLOv8.

Why Use YOLO for Lung Segmentation?

Real-time segmentation: YOLO is optimized for high-speed inference, making it suitable for clinical applications.

End-to-end learning: Unlike traditional multi-step segmentation pipelines, YOLO detects and segments in a single pass.

Bounding box + mask output: YOLO not only provides object localization but also a segmentation mask, making it useful for identifying lung regions.

Scalability: It can handle large datasets efficiently without requiring extensive preprocessing.

Robust performance: YOLO's deep learning-based approach generalizes well to different types of lung images (X-rays, CT scans).

B. Rescaling vs. Normalization in Deep Learning

Both rescaling and normalization are data preprocessing techniques used to bring pixel values into a suitable range for deep learning models. This improves training efficiency and model performance.

1. Rescaling

Rescaling is a simple transformation that scales pixel values to a fixed range, typically [0,1] or [-1,1].

Equation for Rescaling (0 to 1)

X′=X255X' = \frac{X}{255}

• XX → Original pixel value (0 to 255)

• X′X' → Scaled pixel value (0 to 1)

☑ **Why is rescaling important?**

✔Prevents large numerical values that could slow down training.

✔ Makes the data more compatible with activation functions like sigmoid (0 to 1) or tanh (-1 to 1).

✔ Ensures all pixels contribute equally during training.

2. Normalization

Normalization adjusts the pixel values to have zero mean and unit variance, making data distribution more standard.

Equation for Normalization (Zero Mean, Unit Variance)

X′=X−μσX' = \frac{X - \mu}{\sigma}

- **μ\mu** → Mean of pixel values in dataset
- **σ\sigma** → Standard deviation of pixel values
- **X′X'** → Normalized pixel value

☑ **Why normalize?**

✔**Improves convergence speed** by making optimization easier.

✔ Helps models learn **more generalizable features**.

✔ Useful when different input features have different scales.

3. Difference Between Rescaling & Normalization

Feature	Rescaling (0 to 1)	Normalization (Zero Mean, Unit Variance)
Formula	X'=X/255X' = X / 255	X'=(X−μ)/σX' = (X - \mu) / \sigma
Output Range	[0,1] or [-1,1]	Mean = 0, Variance = 1
Use Case	Image data (CNNs)	Data with varying distributions
Effect	Compresses values	Standardizes distribution
Best for	Image preprocessing	Statistical consistency

Which One to Use?

- **Use Rescaling** → When working with **image datasets** for deep learning models like CNNs.
- **Use Normalization** → When working with **non-image datasets** or when features have very different scales.

a) Rescaling & Normalization Equations

Rescaling and normalization are **crucial** for deep learning models to ensure numerical stability and faster convergence.

Equation for Rescaling (0 to 1)

X′=X255X' = \frac{X}{255}

- **XX** → Original pixel value (0 to 255)
- **X′X'** → Scaled pixel value (0 to 1)

This ensures that all pixel values are in a small, normalized range.

Min-Max Normalisation Equation (Custom Range [a,b])

X′=a+(X−Xmin)(b−a)Xmax−XminX' = a + \frac{(X - X_{\min}) (b - a)}{X_{\max} - X_{\min}}

- **Xmin,XmaxX_{\min}, X_{\max}** → Minimum & maximum pixel values
- **a,ba, b** → Desired output range (e.g., [0,1] or [-1,1])
- **X′X'** → Normalized pixel value

For example, for range [−1,1][-1,1]:

X′=−1+(X−0)(1−(−1))255−0=X127.5−1X' = -1 + \frac{(X - 0) (1 - (-1))}{255 - 0} = \frac{X}{127.5} - 1 .

b) Lung Segmentation in Medical Imaging

The technique of segmenting the lungs from medical imaging is known as lung segmentation like X-rays (CXR) or CT scans. It is widely used in disease detection (e.g., lung cancer, pneumonia, COVID-19, tuberculosis).

Common Approaches for Lung Segmentation

i. **Thresholding-Based Segmentation**

- Converts image to binary using a threshold.
- **Equation:** I(x,y)={1,if I(x,y)>T0,otherwiseI(x, y) = \begin{cases} 1, & \text{if } I(x, y) > T \\ 0, & \text{otherwise} \end{cases}
- TT = Intensity threshold
- Works well for **clear boundaries** but fails on complex cases.

ii. **Region-Based Segmentation (Watershed, Active Contours)**

- **Equation (Active Contour Model - Level Set):** ∂ϕ∂t=−F|∇ϕ|\frac{\partial \phi}{\partial t} = -F |\nabla \phi|
- ϕ\phi = Evolving contour
- Helps detect the lung boundary more accurately.

iii. **Deep Learning-Based Segmentation (U-Net, DeepLabV3, Mask R-CNN)**

- U-Net is a widely used CNN model for medical image segmentation.
- Uses an encoder-decoder structure with skip connections.

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5. EXPERIMENTAL RESULTS

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)

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

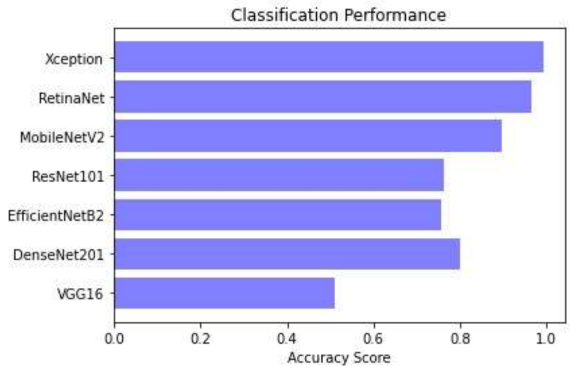

Fig 4 Accuracy comparison graph

Precision: A high level of accuracy in classifying positive instances or samples is known as precision. Accuracy is determined by applying the following formula:

Precision= TP/(TP + FP)

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

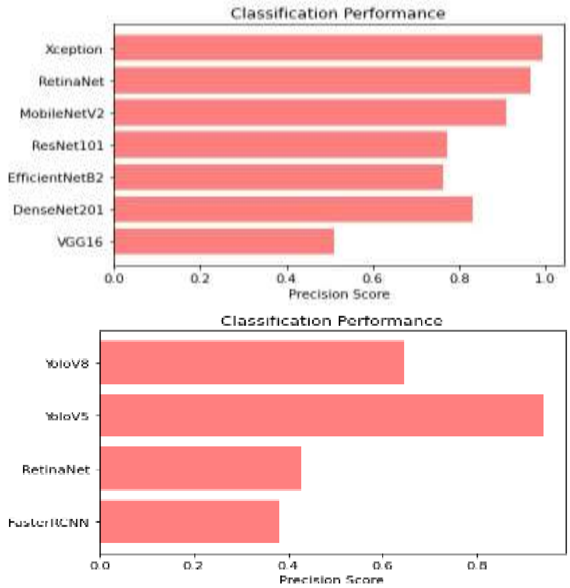

Fig 5 Precision comparison graph

Recall: The ability of a model to identify all pertinent instances of a class is assessed by machine learning recall. By comparing the number of correctly predicted positive observations to the total number of positives, it reveals how well a model captures examples of a class.

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

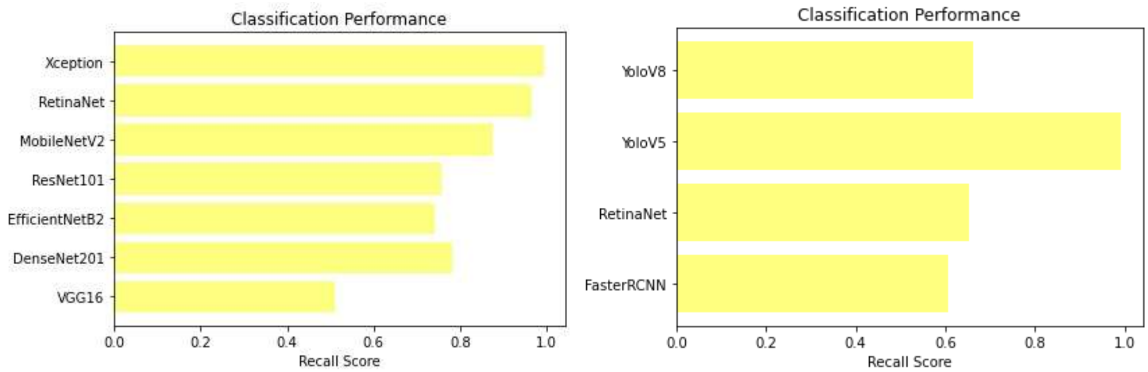

Fig 6 Recall comparison graph

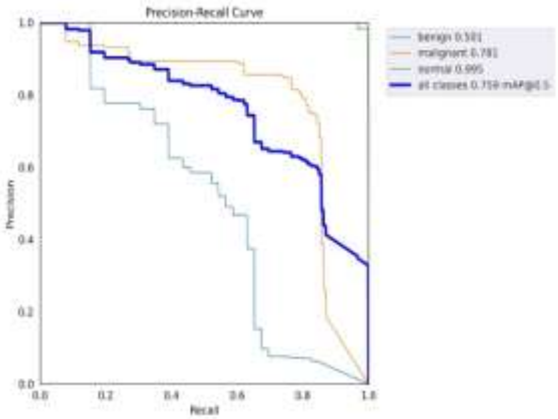

Fig 7. Precision- Recall comparison curve

mAP: Quality metric for ranking Accuracy on Average (MAP). Both the quantity and placement of pertinent recommendations are taken into account. If we take the average precision (AP) at K for all users or queries and average it out, we get MAP at K.

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

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

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

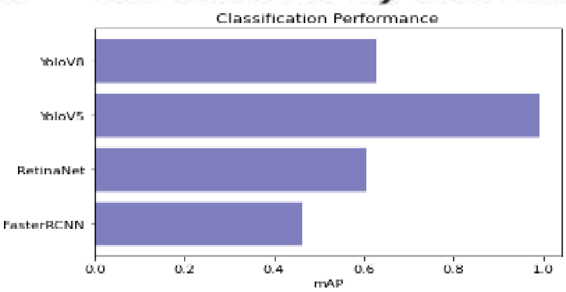

Fig 8mAP comparison graph

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.

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

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

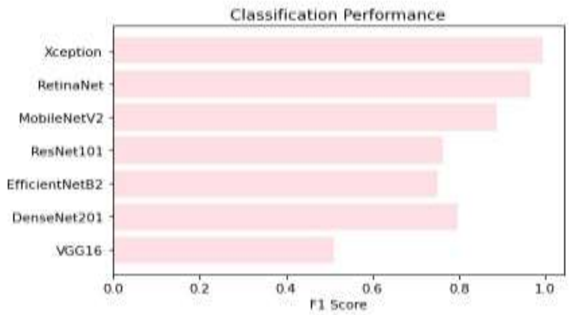

Fig 9 F1 Score comparison graph

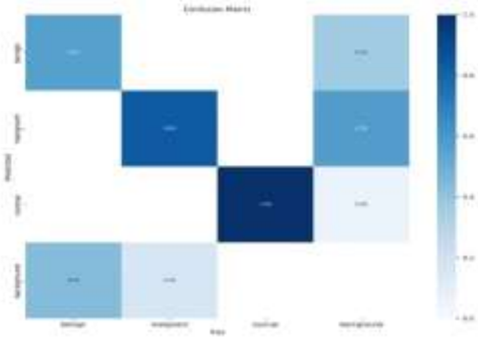

Fig 10 Confusion matrix

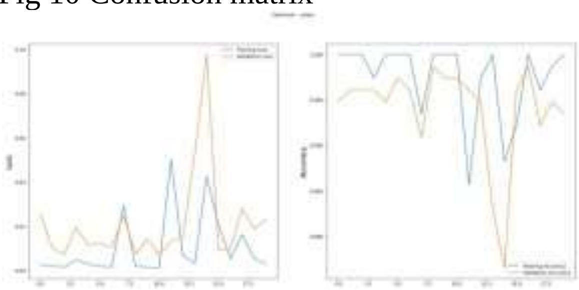

Fig 11 Accuracy-Loss graph

ML Model	Precision	Recall	mAP
FasterRCNN	0.352	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 12 Performance Evaluation table

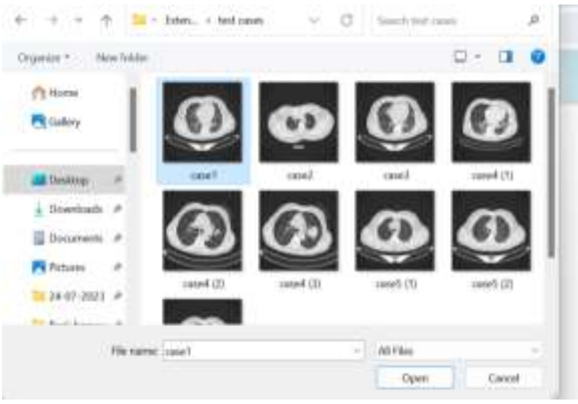

Fig 13 Input image folder

Fig 14 Upload input image

Fig 15 Predict result for given input

6. CONCLUSION

The proposed system effectively enhances lung cancer detection by integrating the Xception model for high-accuracy classification and YoloV5 and YoloV8 for precise tumor localization. With a 99% classification accuracy and advanced object detection capabilities, the system ensures reliable identification of cancerous regions in medical images. Additionally, the user-friendly Flask framework with SQLite integration provides seamless interaction, making it accessible for medical professionals and researchers. This comprehensive approach improves early diagnosis, enhances usability, and contributes to more effective lung cancer detection and treatment planning.

7. FUTURE SCOPE

The proposed system can be further improved by integrating advanced deep learning architectures, such as transformer-based models, to enhance classification and detection accuracy. Real-time processing capabilities using cloud-based deployment can make the system accessible for large-scale medical applications. Additionally, expanding the dataset with diverse medical images can improve model generalization for detecting different lung cancer types. Implementing explainable AI techniques can help medical professionals interpret the model's decisions, increasing trust and adoption. Future enhancements may also include mobile and IoT-based applications for real-time lung cancer screening in remote healthcare settings.

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