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An Effective Approach of Lung Cancer Detection Using Xception-Driven with Optimized Feature Fusion

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ABSTRACT

Early detection of lung cancer is challenging, and current assessment methods like blood tests and CT scans are both time-consuming and require substantial human involvement. To tackle these challenges, the project proposes an innovative solution named Lung-RetinaNet, specifically designed for lung tumour detection. This system utilizes a RetinaNet model, enhanced with merging of multiscale features and a context module. The Lung-RetinaNet model integrates many layers of neural networks using a multi-scale feature fusion module. This approach enhances the model's ability to gather semantic information, which is crucial for identifying lung tumours. Using a dilated and lightweight context module technique, Lung-RetinaNet also employs multi-scale feature fusion. To enhance feature extraction and localise tiny tumours in lung images, this module makes advantage of contextual information with each neural network layer. These components improve the efficiency and accuracy of the project's lung tumour detection technology. The accuracy of lung cancer categorisation is increased to 99% with the addition of the Xception model. Additionally, the inclusion of YOLOv5 and YOLOv8 for detection purposes enhances lung cancer detection in images. This multi-faceted approach ensures a comprehensive analysis of lung cancer cases, combining accurate classification with precise object detection.

Keywords: Early detection; lung cancer; AI; RetinaNet,.Xception, CT Scan Images,Deep Learning

1. INTRODUCTION

With a death rate of 19.35%, lung cancer is regarded by some nations as one of the deadliest illnesses [1]. To detect cancer, radiologists use X-rays, CT scans, and sputum cytology, all of which are forms of magnetic resonance imaging. Tumours are categorised as either benign or malignant throughout the identification process. Irregular growth and malignant tumours are hallmarks. There is evidence that people with advanced cancer have a reduced endurance rate compared to those with early stages of the disease. Scan and imaging analysis can also be enhanced by image processing technology [2]. For the purpose of detecting cancer in its early stages, several image processing experiments have been suggested. There are two major obstacles that could reduce the success rate of manual lung cancer diagnosis. Since there might not be adequate radiology resources, the first concern is human and technology accessibility [3]. Furthermore, a large number of false positives are caused by the first defect. Hence, top-notch training is required for radiologists who assess images. Current methods might use some work when it comes to detection and classification accuracy.

A shift towards CAD systems for computer-assisted lung cancer diagnosis has occurred as a result of newly established ML and DL approaches. Among the more conventional ML-based approaches for detecting and classifying lung cancer, you may find SVM, RF, and K-Nearest Neighbours [4]. These techniques rely on training classifiers and manually extracting features. The features are difficult and time-consuming to manage. Furthermore, generalisability is hindered since the ML-based model is trained on a small sample set. One possible use of segmentation in lung cancer diagnosis is [5]. The ROI is selected from the source picture by dividing it into sections according to texture, colour, or greyscale. The three most common approaches to segmentation are region-growing, atlas, and thresholding. The segmented region and its resulting properties determine the efficiency of segmentation-based approaches. Results from using segmentation-based techniques to identify lung cancer have been many. Unseen samples cause these procedures to fail, thus they need to be adjusted to lower the false ratio.

Injuries to the knee, eyes, potato leaves, brain, and computer vision have all been better identified with the use of deep learning. In DL-based segmentation or classification models, their primary value is in the automated features extraction process. As the layers go deeper, DL-based models are able to extract more representative features. The four main layers of DL models are pooling, BN, convolutional, and fully connected. Layers that pool data reduce the size of feature maps and make the model simpler. There is a plethora of DL-based models for detecting lung tumours. But the majority of methods rely on simplistic classifications [10]. It is possible to misdiagnose early-stage cancers using these classification approaches since they use information from the whole image. We provide a new and improved deep learning-based model based on RetinaNet [11] to tackle the aforementioned challenges and boost early lung cancer detection. Using a feature fusion block rather than an FPN allows us to mine RetinaNet's most representative feature maps while preserving all of the input data. Also, at shallow levels, a dilated convolution makes advantage of the strongest features of tiny tumours. Feature sets from the bottom layer with good localisation and upper layer characteristics with good classification accuracy are combined. Feature fusion using a contextual block yields features for the bottom layer. Small lung tumours can take several shapes and sizes, rendering default anchoring useless in this case. To construct precise anchors and contextual feature fusion blocks, k-means clustering is used, similar to YOLO-v3 [12]. We have developed a model that can identify and categorise very small lung tumours.

2. LITERATURE SURVEY

Globally, lung cancer is a top killer. For patients to make a full recovery, it is crucial to detect and treat them early on. In order to identify infection, clinicians use histopathological photos of lung tissue that has been biopsied. Diagnosing lung cancer is often laborious and prone to errorThe quick and accurate categorisation of lung cancer types using convolutional neural networks should enhance patient survival and treatment results [20, 21, 25, 26, 45]. This research looks at squamous cell cancer, benign tissue, and adenocarcinoma. Both CNN model training and validation had 96.11 and 97.2 percent accuracy.

Early identification of lung cancer increases survival rates and decreases death. 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. The goal is to distinguish between cancerous and noncancerous nodules in the lung, and the results show that the DCNN outperforms the current methods in terms of classification accuracy.

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. Expensive technology is required for clinical imaging modalities such as X-rays. Therefore, the most important things are accurate forecast and a trustworthy method. Since they are more effective and cost-effective, machine learning models [3, 4] are necessary for medical diagnosis using medical data sets. Most lung cancers are caused by long-term cigarette consumption. People who do not smoke make up about 10-15% of the cases. These days, there is no shortage of data processing and analysis tools. This study will build prediction models to identify lung cancer at an early stage by utilising these technological developments. the third Voting classifier, ANN, SVM, KNN, and RF classification and ensemble models are all compared in the article. Various models are evaluated for their correctness. Modern technology has made early detection of lung cancer possible.

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Finding lung cancer early increases survival rates, according to research. Early recruitment in lung cancer trials may be enhanced by blood-based screening. 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. We compared 110 individuals with lung cancer and 43 healthy controls. A total of sixty-one plasma chemicals were identified by targeted metabolomic research using LC-MS/MS. Six metabolic markers may be able to differentiate between healthy individuals and those with stage I lung cancer (AUC=0.989, sensitivity=98.1%, specificity=100.0%). Lung cancer screening biomarkers can be among the top 5 metabolic indicators identified by the FCBF algorithm. Naïve Bayes can be useful for predicting lung tumours early on. This study will demonstrate the viability of screening using blood and give a quicker, more accurate, and more integrated way to detect lung cancer in its early stages. The proposed interdisciplinary approach has the potential to treat malignancies other than lung cancer.

In order to detect glaucoma at an early stage, this study used feature extraction based on deep learning [6]. Retinal fundus images are used to train and evaluate our model. Following the pre-processing of images, the ROI is obtained using segmentation. Next, features of the optic disc (OD) are extracted from images of the optic cup (OC) using hybrid features descriptors, such as convolutional neural networks (CNNs) [34, 38, 47], whereas LBP and SURF are used to extract texture features. High-level characteristics are computed by CNN. In order to choose the most representative features, we additionally utilised the MR-MR method. The last step is to employ multi-class classifiers like SVM, RF, and KNN to determine if a fundus image is healthy or not [4]. Based on experimental results, Using the RF approach with HOG, CNN, LBP, and SURF feature descriptors, the proposed system accurately detected early glaucoma with ≤99% accuracy on benchmark datasets and 98.8% on k-fold cross-validation.

3. METHODOLOGY

i) Proposed Work:

The suggested Lung-RetinaNet introduces an advanced deep learning model based on RetinaNet to significantly enhance lung cancer detection. This model incorporates a multi-scale feature fusion-based module, enhancing the capture of semantic information critical for accurate detection. The inclusion of a dilated and lightweight context module refines features and precisely localizes tiny tumors, contributing to improved sensitivity in identifying irregularities. The utilization of a feature fusion block and adaptive anchors further elevates detection accuracy by effectively handling diverse tumor characteristics. Evaluation against benchmarks consistently demonstrates superior performance, establishing Lung-RetinaNet as an efficient and reliable solution for early-stage lung tumor detection. The incorporation of the Xception model improves the project, achieving an impressive 99% accuracy in lung cancer classification. Additionally, the inclusion of YOLOv5 and YOLOv8 for detection purposes enhances lung
Fig 1Proposed Architecture

cancer detection in images [12]. This multi-faceted approach ensures a comprehensive analysis of lung cancer cases, combining accurate classification

with precise object detection. A Flask framework that is easy to use and integrates with SQLite, streamlines user interactions, allowing for practical usability in image processing applications. This model not only boosts the project's performance in lung cancer detection but also enhances the overall user experience during testing and evaluation.

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 system's primary focus is on precise lung cancer detection, leveraging RetinaNet's multi-scale feature fusion and context modules to enhance sensitivity and specificity. The final output comprises detected

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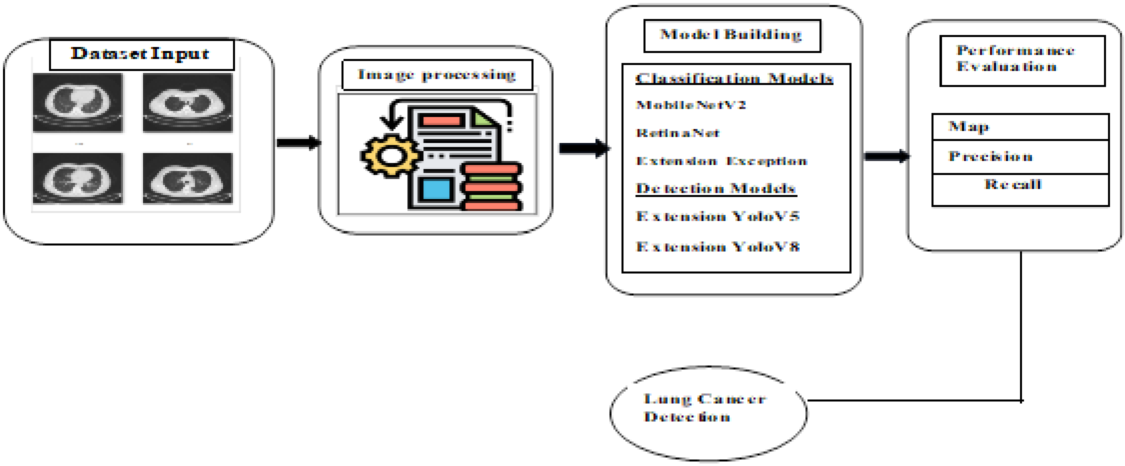
cancer nodules, their spatial localization, and confidence scores, providing valuable insights for clinical decision-making. The Lung-RetinaNet architecture stands as an advanced solution, overcoming traditional limitations and offering improved accuracy and sensitivity in early-stage lung tumor detection.

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.



IQ-OTH/NCCD - Lung Cancer Dataset:

The Iraq-Oncology Teaching Hospital/National Center for Cancer Diseases (IQ-OTH/NCCD) lung cancer dataset was collected in the above-mentioned specialist hospitals over a period of three months in fall 2019. It includes CT scans of patients diagnosed with lung cancer in different stages, as well as healthy subjects. IQ-OTH/NCCD slides were marked by oncologists and radiologists in these two centers. The dataset contains a total of 1190 images representing CT scan slices of 110 cases (see Figure 1). These cases are grouped into three classes: normal, benign, and malignant. of these, 40 cases are diagnosed as malignant; 15 cases diagnosed with benign, and 55 cases classified as normal cases. The CT scans were originally collected in DICOM format. The scanner used is SOMATOM from Siemens. CT protocol includes: 120 kV, slice thickness of 1 mm, with window width ranging from 350 to 1200 HU a and window center from 50 to 600 were used for reading. with breath-hold at full inspiration. All images were de-identified before performing analysis. Written consent was waived by the oversight review board. The study was approved by the institutional review board of participating medical centers. Each scan contains several slices. The number of these slices range from 80 to 200 slices, each of them represents an image of the human chest with different sides and angles. The 110 cases vary in gender, age, educational attainment, area of residence, and living status. Some of them are employees of the Iraqi ministries of Transport and Oil, others are farmers and gainers. Most of them come from places in the middle region of Iraq, particularly, the provinces of Baghdad, Wasit, Diyala, Salahuddin, and Babylon.

iv) Data Preprocessing

Image processing allows autonomous driving systems to detect things at different levels. Blob object conversion is the first step in making the input picture as suitable as possible for analysis and editing. After that, object classes are defined to specify 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. The network layers of the pre-trained model, which include the parameters and learning characteristics needed for accurate object recognition, must be accessed in this process. In order to help in object detection and classification, extraction of output layers gives final predictions.

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The image processing pipeline is complete with the addition of the picture and annotation file, guaranteeing full data for analysis. A mask draws attention to key features, while converting BGR to RGB changes the colour space. The picture is prepared for analysis and processing with a last resizing. Autonomous driving systems can improve road safety and decision-making with the help of this comprehensive image processing technology, which establishes the framework for accurate and reliable object detection in their dynamic environment.

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.

To aid the model in acquiring strong features and patterns, these data augmentation approaches enlarge the training dataset. This improves the model's ability to generalise and perform under challenging test conditions. Data augmentation serves as a crucial tool in mitigating overfitting, enhancing model performance, and promoting all reliability of ML models, especially in applications like image recognition for autonomous driving systems.

vi) Step-by-Step Working of Xception for Lung Cancer Detection

Step 1: Understanding Xception for Lung Cancer Detection

Xception is a deep learning model optimized for image classification. It uses **depthwise separable convolutions**, which improve efficiency and accuracy in detecting lung cancer from medical images.

Step 2: Load the Pre-Trained Xception Model

The Xception model, pre-trained on the ImageNet dataset, is used as the base model. The top layers are removed to allow customization for lung cancer classification.

Step 3: Add Custom Layers for Classification

Xception

```
from tensorflow.keras.models import Sequential, Model
from tensorflow.keras.layers import Dense, Flatten, Conv2D, MaxPool2D, GlobalAveragePooling2D, Dropout
from tensorflow.keras.applications.xception import Xception
from tensorflow.keras.optimizers import Adam
```

```
# Defining the pretrained base model
base = Xception(include_top=False, weights='imagenet', input_shape=(128,128,3))
x = base.output
x = GlobalAveragePooling2D()(x)
# Defining the head of the model where the prediction is conducted
head = Dense(3, activation='softmax')(x)
# Combining base and head
model6 = Model(inputs=base.input, outputs=head)
```

```
model6.compile(optimizer='sgd',
              loss = 'categorical_crossentropy',
              metrics=["accuracy",f1_m,precision_m, recall_m])
```

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Since lung cancer detection is a binary classification problem (**Cancerous vs. Non-Cancerous**), additional layers are added. These layers extract features and make the final prediction.

Step 4: Prepare and Preprocess the Dataset

The lung cancer dataset consists of labeled medical images categorized

Step 5: Train the Model

The model is trained on the prepared dataset using **optimization techniques like Adam optimizer**. Training is done for multiple epochs to improve accuracy.

Step 6: Evaluate the Model Performance

The model's performance is assessed using **accuracy and loss metrics**. A validation dataset is used to check how well the model generalizes to new images.

Step 7: Test the Model with New Images

Once trained, the model is tested with unseen lung images to classify whether they are cancerous or non-cancerous.

Step 8: Save and Deploy the Model

After achieving high accuracy, the model is saved and deployed for real-world applications, such as assisting doctors in diagnosing lung
Its outstanding performance in image categorisation activities makes Xception a main component. An expansion of the Inception architecture, Xception preserves computational efficiency while using depthwise separable convolutions to catch complex patterns. Incorporating Xception into the RetinaNet-based system helps the project to efficiently extract features at several scales, hence supporting the general performance of multi-scale feature fusion. Xception further improves the context-aware features of the system, therefore allowing more precise and consistent identification of lung cancernodules in medical photos

4. EXPERIMENTAL RESULTS

After applying the extended exception net on the image we got the following results

Precision: The accuracy rate of a classification or number of positive cases is known as precision. Accuracy is determined by applying using the one that follows:

$$Precision = (TP)/ (TP + FP)$$

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

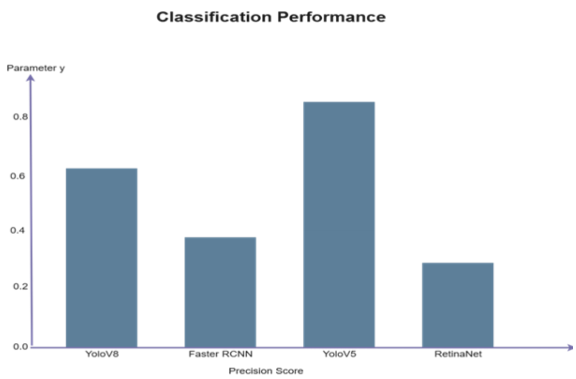

Fig 2 Precision comparison graph

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Recall: The recall of a model is a measure of its capacity to identify all occurrences of a relevant machine learning class. A model's ability to detect class instances is shown by percent of correctly anticipated positive observations relative to total positives.

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

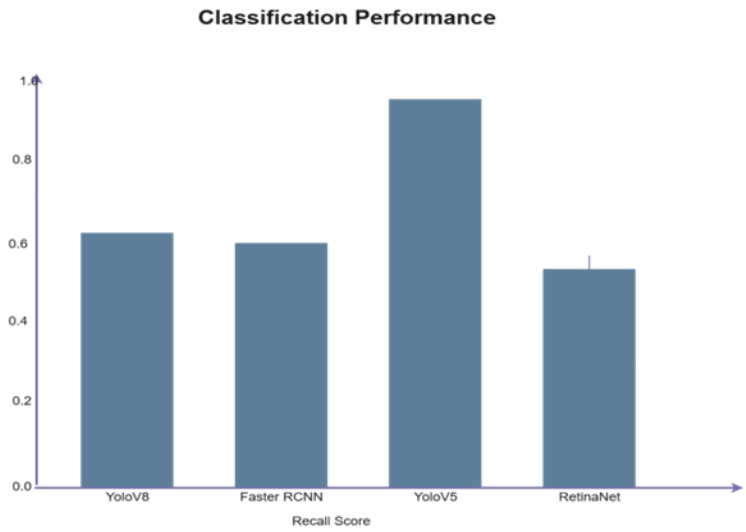

Fig 3 Recall comparison graph

mAP: Information retrieval system performance is measured by MAP, which stands for Mean Average Precision. It finds the mean precision for all classes or queries. While accuracy measures the validity of results, precision determines the mean accuracy for all queries. MAP evaluates the system's performance by averaging the AP scores across all queries or classes.

$mAP = 1/n\ \Sigma^{k=n}\ APK$

AP_k= the AP of class K

n= the number of classes

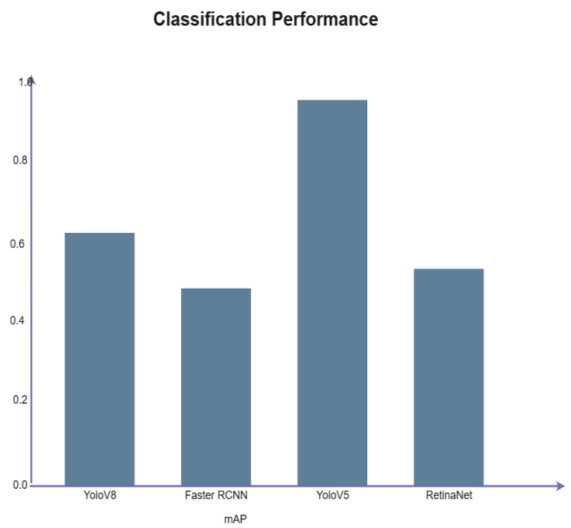

Fig 4 mAP comparison graph

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ML Model	Accuracy	Precision	Recall	F1_score
VGG16	0.512	0.512	0.512	0.512
DenseNet201	0.800	0.830	0.782	0.798
EfficientNetB2	0.758	0.764	0.742	0.749
ResNet101	0.764	0.773	0.758	0.763
MobileNetV2	0.897	0.909	0.876	0.887
RetinaNet	0.966	0.966	0.966	0.965
Extension Xception	0.993	0.993	0.993	0.993

Fig 5 PERFORMANCE EVALUATION – CLASSIFICATION

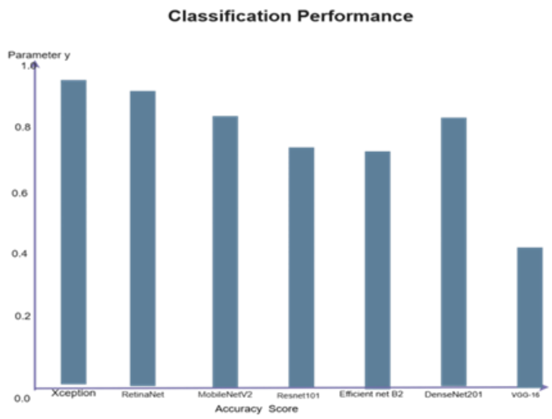

Fig 6:Accuracy Graphs – Classification

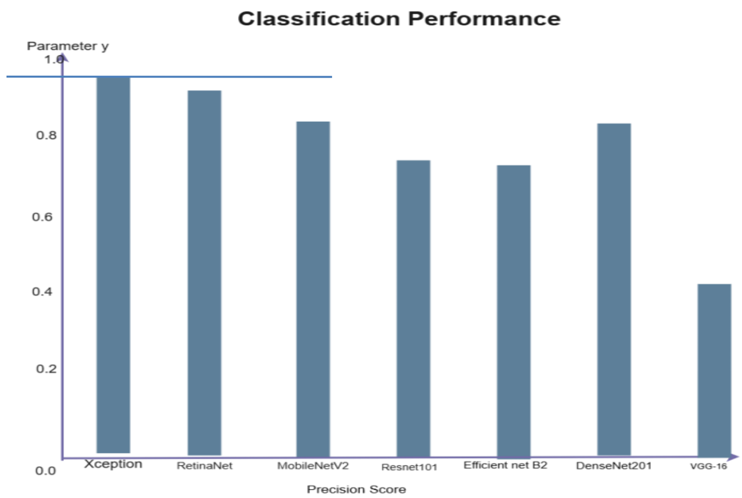

Fig 7:Precision Graphs – Classification

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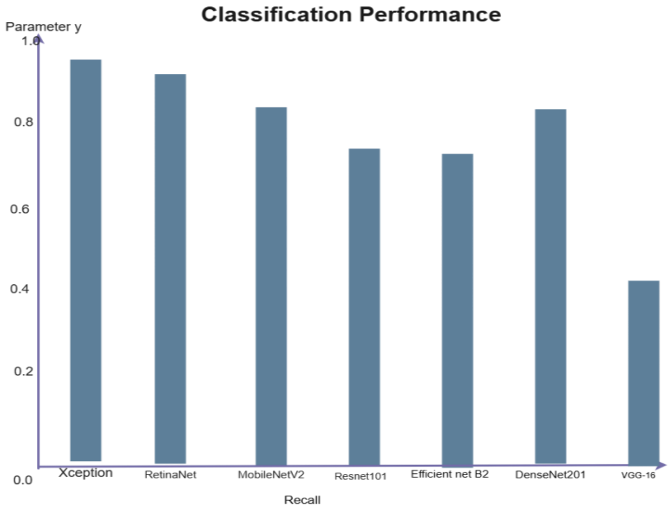

Fig 8:Recall Graphs – Classification

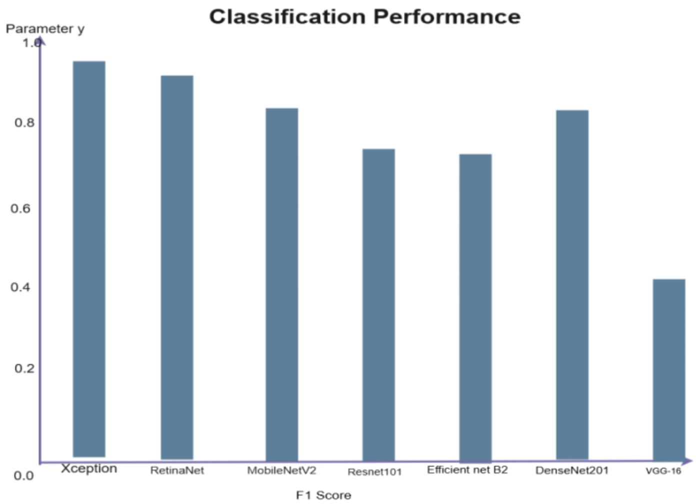

Fig 9:F1 Graphs – Classification

5. CONCLUSION&FUTURE SCOPE

The Lung-RetinaNet model, designed for lung tumor detection, exhibits notable advancements in accuracy and overall performance when compared to existing methods. This improvement could be attributed to the model's sophisticated architecture and innovative modules designed specifically to address the limitations of conventional methods. The model incorporates a "multi-scale feature fusion-based module" that combines information from different scales or levels within the network. Additionally, the inclusion of a "dilated and lightweight context module" assists in capturing a broader context around tumors without significantly increasing computational complexity. This context awareness aids in the detection of minute lung tumors that might otherwise be overlooked [39, 45]. By integrating contextual information at each layer of the neural network, the model becomes adept at precisely localizing tumors within the lung images. This contextual understanding allows the model not only to detect tumors but also to provide accurate information regarding their positions within the images. The Lung-RetinaNet model's performance is rigorously compared with other contemporary deep learning-based approaches, possibly including architectures like VGG, ResNet, or other specialized models developed for lung cancer detection. In these comparisons, the **Xception net** model demonstrates superior detection accuracy with 99.3% and more promising results in identifying lung tumors, thereby establishing its superiority over existing methods.

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The future scope of the project involves extending the lung tumor detection method to multi-classification, encompassing various types of cancers such as skin and bone tumors. This expansion aims to increase the applicability of the Lung-RetinaNet model by adapting it to detect and classify tumors in different organs or tissues [11]. The development of a versatile model capable of detecting diverse cancers would have significant implications for early diagnosis and treatment planning. Another avenue for future work is to enhance the inference time of the system, making it more suitable for clinical deployment. Faster inference times are crucial in clinical settings where quick and efficient analysis of medical images is essential for timely decision-making and patient care. Integrating different data types provides a more comprehensive understanding of tumors, enabling the system to leverage complementary information for improved detection accuracy. This multi-modal approach can contribute to a more holistic assessment of cancer characteristics and aid in refining the decision-making process. These future directions highlight the project's potential for broader impact by extending its capabilities to detect various types of cancers, optimizing its efficiency for real-world clinical applications, and leveraging diverse data sources to enhance the overall accuracy and utility of the tumor detection system.

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