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Original scientific paper

HARNESSING DEEP LEARNING FOR LUNG CANCER DETECTION USING CT SCAN IMAGES

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Abstract. *Lung cancer persists to be considered as the primary cause of rising mortality rates worldwide with clinical projection depending upon early-stage detection. Detection at the preliminary stage is crucial for treatment of the disease also to further the prognosis process. In this study IQOTHNCCD dataset is used. An innovative model is constructed for distinguishing images into three categories. The dataset comprises of three types of images such as malignant images, benign images and normal images. Preprocessing of the images is done with intensive steps in order to remove unwanted data. Deep learning along with transfer learning have been applied to the image dataset for classifying the images into various categories. In biomedical image classification deep learning serves as the most effective technique for classification and detecting the abnormal pulmonary nodules. Techniques such as InceptionV3, ResNet50, VGG16, VGG19, MobileNetV2 are evaluated through experiment for ensuring the credibility of the designed model. Key performance indicators were used which includes accuracy, sensitivity, precision and F1 score. The results obtained through the proposed model which is the custom CNN model yielded an accuracy of 98.79%, sensitivity of 98.97%, precision of 96.6% and F1 score of 97.7%.*

Key words: *Deep Learning, Transfer Learning, Custom CNN, InceptionV3, ResNet50, VGG16, VGG19, MobilenetV2*

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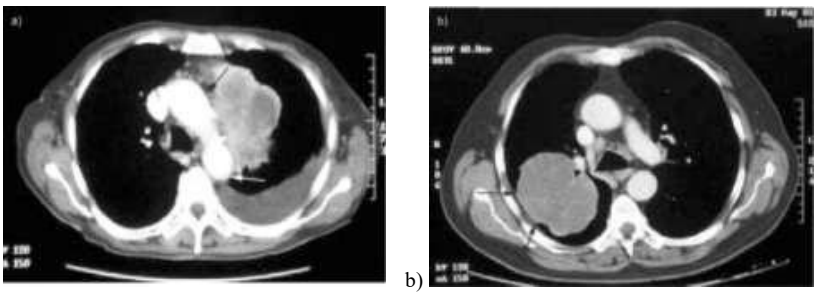
1. INTRODUCTION

Lung cancer is one of the most aggressive cancers that appears due to the uncontrolled increase in the number of cells. It is globally accepted that lung cancer is one of the most leading types of cancer and caused more deaths among the cancer patients. The lung tissues are covered by a membranous coat called pleural sac, which holds fluid called pleural fluid; this pleural fluid ensures the interplay between the outer and inner coats of the lung. This interplay leads to the development of neoplasms. Two most common types of cancerous growths associated with this disease are small cell lung carcinoma and non-small cell lung carcinoma [1]. Lung cancer constitutes one of the most perilous diseases, accounting for a mortality rate of 19.4% [2]. In the year 2024, the incidence of new cases is projected to reach 11.7% [3]. A variety of imaging modalities have been employed to identify pulmonary malignancies at the primary stage, which encompass Computed Tomography, Sputum Cytology, Chest X-ray, and Magnetic Resonance Imaging [4]. During the diagnostic process, neoplasms are systematically classified for accurate diagnosis. The predominant etiology of lung cancer is attributed to cigarette smoking; however, additional recognized risk factors include environmental air pollution and excessive alcohol consumption. Lung carcinoma that has spread to the cerebral area can manifest with decreased vision and unilateral muscular paralysis. Moreover, hemoptysis, thoracic pain, and dyspnea are also found in primary lung neoplasms [5]. Unfortunately, most diagnoses at presentation are at a late stage of the disease since no clinical manifestations occur in the earlier stages. The prognosis for survival is much improved when neoplasia is diagnosed at an earlier stage. Advanced photographic alteration techniques can greatly enhance the methodology of physical examination and diagnostic assessment. Recently, a number of scholars have been engaged in the exploration of computational learning methodologies aimed at the early identification of the life-threatening ailment known as cancer. The neural network serves an essential function in differentiating neoplastic cells from non-cancerous tissues, thereby offering a significant instrument for the formulation of supportive biomarkers in oncology. Lung tumors are categorized as either benign or malignant through the application of Convolutional Neural Networks (CNN) and transfer learning paradigms. Given that deep learning and machine learning algorithms are predominantly designed to function within specific feature space distributions, it is imperative that models are reconstructed whenever there is a modification in these feature spaces. Consequently, deep learning models necessitate a substantial volume of labeled data during the training phase. This requirement significantly complicates the development of a machine learning model for a target domain where a paucity of labeled data exists for supervised learning. Nevertheless, in particular scenarios, Transfer Learning has been shown to enhance both learning accuracy and performance. We have made use of the IQOTHNCCD lung cancer dataset and have proposed a classification methodology based on convolutional neural networks. A CNN model has been devised for this purpose. Hyperparameter optimization has also been conducted during the training of the model utilizing our dataset, employing various architectures. Effective lung cancer screenings have the potential to be life-saving interventions. The manual evaluation of screenings is often labor-intensive, financially burdensome, and not consistently precise. Deep learning, especially, has the capability to enhance the quality of screenings while simultaneously reducing associated costs. Cancer remains one of the most lethal diseases, exhibiting a high mortality rate. Lung cancer is

responsible for a significant proportion of cancer-related deaths (18% of all cancer fatalities), contributing to approximately 8.2 million deaths globally. In the year 2024, prostate, lung, and colorectal cancers are anticipated to constitute roughly 48% of all cancer diagnoses among the male population. For females, breast, lung, and colorectal cancers are projected to represent about 51% of newly diagnosed cancer cases in 2024 [6]. According to WHO the cancer rates may jump to 45 percent by 2030 [7]. Early detection is pivotal in cessation of the amplification of cancerous cells.



a) b)

Fig. 1 a) Left lobe with nodule [8]; b) Right lobe with nodule [8]

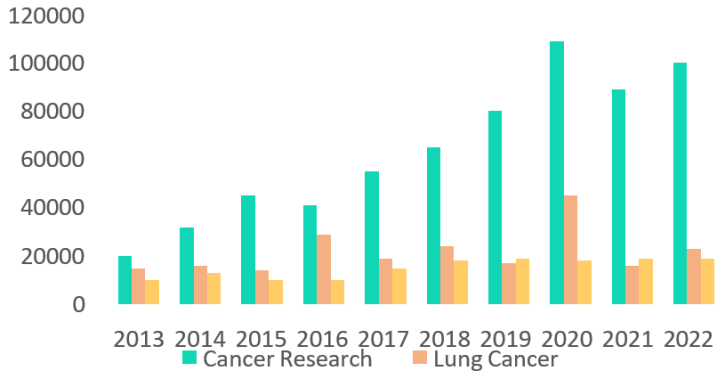


Fig. 2 Representation of research done from the year 2013 to 2022 [9]

Fig. 1a, Fig. 1b depicts the both halves of the lungs where each consists of unwanted nodule which ensures that there's presence of tumor. Whereas Fig. 2 represents the number of research work done from the year 2013 to 2022.

The article consists of introduction in Section 1, motivation of the work in Section2 followed by objective in Section3 then a survey of related works in Section 4, the elaboration of the proposed methodology and architecture of the model in Section 5, details on the dataset used along with the pre-processing steps and feature extraction in Section 6, and finally, Section 7 where the results and evaluation metrics are elaborated. Lastly, Section 8 is the conclusion section which lists the findings and future work.

2. MOTIVATION

Precise and timely identification of lung cancer is important to enhance patient prognosis since early diagnosis highly improves the possibility of effective treatment. Standard diagnosis techniques involving manual image interpretation of medical images and traditional machine learning algorithms have several limitations such as subjectivity, inter-observer variability, and poor ability to extract complicated patterns from imaging data. These constraints can lead to delayed or improper diagnoses, resulting in inappropriate or delayed treatment. Deep learning has transformed image classification tasks in recent years by making it possible to automatically extract hierarchical features directly from unprocessed image data. This has particularly found applications in lung cancer classification, where models have shown outstanding discriminative power in distinguishing between benign, malignant, and normal lung tissues. Further, CNNs can precisely detect fine changes and intricate patterns that are critical in detecting early-stage lung cancer and therefore enable quick and accurate diagnosis. Further, the versatility of CNN architectures supports adaptation to further optimize efficiency. In addition, transfer learning has proven to be a powerful method to improve model performance, particularly when there is limited labeled medical data. By using pre-trained models on large benchmark datasets and fine-tuning them on lung cancer data, transfer learning not only saves training time but also enhances accuracy. This method can help overcome the issue of limited annotated medical data while preserving high performance. As computing power further increases, advancements in deep learning algorithms are predicted to further refine both accuracy and efficiency, situating deep learning-based approaches as crucial tools for the classification and prognosis of lung cancer.

3. OBJECTIVE

In this work, the purpose is focused on the development and construction of an innovative model for classification of lung carcinoma images into benign, malignant, and normal images. The prime focus, based on the obtained capabilities of CNN and transfer learning, has been put upon classification using the medical images for lung cancer upon the IQOTH NCCD dataset. Classification results are compared with others obtained from the findings using models of Inception V3, ResNet50, and VGG16, VGG19 and MobileNetV2 in order to validate the reliability of the designed model.

4. RELATED WORKS

Anand et al. [2] applied transfer learning to improve the strength of the models. The VGG-16 and Inception V3 architecture has been chosen because of the effectiveness in feature representation and handling the complexity involved in classifying image tasks. Models were trained to classify and predict patient lungs having a tumor from preprocessed CT images. The VGG16 model's accuracy came out to be 96%. Although the model generated good results concerning lung cancer detection with deep learning, it also portrayed the challenges of large labelled datasets, biased datasets, and fine-tuning pre- trained networks into a medical image application.

Cari et al. [10] constructed a convolutional neural network model for classifying CT scan images into cancerous and non-cancerous images. The model consisted of three layers with filter size 128,256 and 512 on first layer, second layer and third layer respectively. Various combination amongst filters, batch size, dropout and epoch values were made to determine the accuracy value and hence prevent the same from overfitting. Preprocessing was carried out at the beginning step in the form of resizing, scaling and normalization. Sigmoid and ReLU activation functions were used. The accuracy of the proposed model yielded 95% along with recall and precision values with 90% and 100%.

Harshavardhan et al. [11] designed a model for distinguishing between lung cancer images and healthy images. The dataset consisted of about 2400 images. Normalization of images and image resizing were considered to be the pre-processing pipeline for clear images. Additionally for noise reduction gaussian blurring, median filtering and denoising autoencoders were used. Image augmentation was employed in order to reduce overfitting and improve generalization. Contrast enhancement techniques such as histogram equalization, adaptive histogram equalization and contrast stretching were applied for uniform pixel distribution. Feature extraction techniques such as histogram of oriented gradients and local binary patterns. The authors applied ResNet-18, VGG16, VGG19 and CNN along with gradient descent optimization method for avoiding classification error. Various performance metrics such as accuracy, precision, recall and F1-score were used to determine their performance. The results obtained from this experiment include accuracy of 96.86% for VGG19 model where as 95.45% for VGG16. ResNet18 model yielded 93.45% while CNN gave an accuracy of 91.23%.

BR et al. [12] represented a stacked neural network model for detection followed by classification of lung cancer using CT scan data. The purpose was to investigate the accuracy levels of various neural networks and establish the preliminary stage of the disease. This model is particularly meant for segmentation process. Here two different classifiers are combined for creation of a classification model. Deep learning was used for carrying out the classification task. With the help of image processing techniques feature extraction was carried out. The required feature was changed using joint one hot encoding on categorical features along with min max normalization on numerical features. The recommended methods performance was evaluated with parameters such as F1-measure, accuracy, precision, and recall. The model yielded an accuracy of 96%.

BC et al. [13] designed a lung cancer prediction system with the help of LIDC-IDRI dataset. Preprocessing techniques such as contrast limited adaptive histogram equalization, wiener filtering along with gaussian filtering and Gabor filtering were used in the study. Those methods were applied for normalization of images for accurate size and variation also for minimizing the unwanted noise which distorts the image quality. Various image enhancement methods like image scaling, color space modification and contrast enhancement were implemented. The study comprises of three types of classifiers such as K-Nearest Neighbors, Random Forest and Support Vector Machine. The results came out to be 95.06% for support vector machine whereas KNN gave an accuracy of 86.89%.

Anjum et al. [14] suggested a model comprised of EfficientNet and its other types from B0 to B7. 25,000 set of images were used for carrying out the experiment. The dataset was divided into 80% of training set, 10% of testing test and 10 % for validation set. Preprocessing of images were done for ensuring the image pixel size to be similar and even. Further horizontal flipping and augmentation were performed for expansion of dataset. For training the dataset for enhanced learning epoch size was set to 100.

Hyperparameter tuning was made in order to get the efficient values. EfficientNetB2 model yielded an accuracy of 97% with pixel of images with 260* 260. The training loss was 0.07 whereas validation loss was 0.97, also training and validation accuracy came out to be 0.97 and 0.07 respectively.

Zebua et al. [15] recommended a ResNet architecture model for classifying X-ray images into various types of lung carcinoma. Dataset was collected from Kaggle repository comprising of 1000 images. Preprocessing of the image dataset was done in order to remove unwanted data. Images were resized to 256*256 pixels for maintaining similarity. Image augmentation was performed so as to create new dataset for enhancing the variety. Horizontal and vertical flipping of images was performed. Additionally geometric transformation suitable for bending of images was inculcated. The authors trained various ResNet models such as ResNet50, ResNet101 and ResNet152.83% of accuracy was produced by ResNet50 model with 46 epochs for training the model whereas ResNet101 achieved an accuracy of 82%. The accuracy of the ResNet152 model gave an accuracy of 89% superior to other models.

Al-Shouka et al. [16] the authors have applied various methods of transfer learning that are Xception, VGG16, ResNet, MobileNetV2. Data augmentation techniques were used. The misclassification rate of Resnet was lesser than the other methods, and hence, it is efficient enough for the accurate classification of lung cancers. The accuracy came to be 94%. This might be due to the reason that the style of the feature extractor of ResNet worked well since it managed to extract efficient features of lung cancer since it has the capability to distinguish between malignant and benign tumors.

Bhola et al. [17] the data sets used were the images of the CT scan categorized under the various types of lung cancers. This work applied the architecture of EfficientNet B2 that used transfer learning and data augmentation in the preprocessing phase for training the model to realize the effectiveness of the lung cancer detection system. Results and discussion contain the result of the study implemented, that is the result covering grouping of the CT scans into adenocarcinoma, squamous cell carcinoma, large cell carcinoma, and normal lung tissue. In short, it is a result which proves that pre-training greatly enhanced accuracy, processing speed, and allowed for diagnosis of lung cancer on the pre- symptomatic level.

Ahnaf et al. [18] showcased the fact that in comparison with GLCM, the method of extracting LBP features appears to be reporting a much higher accuracy regarding lung cancer detection. Among them, the combination of the LBP feature extraction method with SVM classification resulted in an accuracy of 93%, which defined the essence of this approach in the prognosis of lung cancer. However, the method employing the GLCM feature extraction in conjunction with Gaussian Naive Bayes classification yielded a very low accuracy of merely 50%. Hence, proving that proper selection of the feature extraction and classification methods is highly essential for obtaining accurate detection of lung cancer.

Rani et al. [19] presented the fact that transfer learning is one of the most important techniques, which led models of medical image analysis learn from existing knowledge from massive datasets like ImageNet. It is classified into two stages, it is initially applied to a big labeled dataset and then fine-tuned in some particular dataset. This approach led transfer learning extract the traditional features and improve performance. Such efficiency resulted in better performance by transfer learning to address core problems associated with data and time limitations in addition to the performance of the model as

highlighted by improved models' performance during the task of lung cancer detection. Some feature extractors employed in lung cancer diagnosis included VGG-16, VGG-19, InceptionV3, and MobileNetV2. With the use of KNN and SVM supervised learning algorithms, further classifications will be made for specific classes. Performance metric such as accuracy was used to determine the performance of model. The accuracy of the model observed between 56% and 99.94%, and hence it showcased that the transfer learning was applied effectively in enhancing the overall output of deep learning models.

Ashhar et al. [20] compared different types of convolutional models which included state of the art structures such as google net, squeezenet, shuffle net, dense net, mobilenetV2 upon the LIDC-IDR dataset. Preprocessing of the images were done in order to enhance the uniformity. The images were resized to a dimension of 244*244 along with 70% of the dataset was meant for training purpose. The primary learning rate was decided to be 0.01 also other parameters such as validation frequency, epochs drop rate and momentum was set to 50, 20, 0.2, 0.9 respectively. For the determination of the models performance using accuracy, specificity, sensitivity and area under the curve was being used. Amongst the models the results obtained from google net (94.53%) was superior as compared with other architectures followed by squeeze net yielding 94.13%.

Abd Al-Ameer et al. [21] recommended a model for prediction of lung carcinoma tissue images with the help of state of the art architecture such as inception v3 along with random forest and convolutional neural network. The neural network aimed at extracting features beneficial for prediction and prognosis of the disease. For ensuring the image quality to be standardized preprocessing techniques such as normalization was applied to the images. VGG16 along with InceptionV3 models were used a feature extractor and hence acted an input to the neural network. Adam optimizer was used to decide the best learning rate. The model yielded an accuracy of 97.07% along with precision being 96.88%, recall score being 97.31%, fscore being 97.09% additionally specificity being 96.88%.

Priyadarshini et al. [31] used seven supervised machine learning classifiers were used with thorough examination. Prior to categorisation, image processing techniques are used to differentiate between benign and malignant cases. When compared to other classifiers, the MLP classifier performed better and achieved noticeably higher accuracy, indicating its potential for use in clinical settings.

Velumurugan et al. [32] proposed a model for segmentation of lung lobe and lung cancer detection are major medical imaging tasks for precise diagnosis and early treatment. The conventional approaches suffer from slow convergence and inadequate exploration. To overcome these issues, an innovative RSPO_ShCNN (Rat Swarm Political Optimizer-based Shepard Convolutional Neural Network) was introduced. RSPO was designed by integrating Rat Swarm Optimizer (RSO) and Political Optimizer (PO) to improve performance. CT scans were preprocessed through the application of a Laplacian filter, segmented using PSPNet optimized by RSPO, and nodule detection was achieved by utilizing a grid-based method. Features are extracted and classified by utilizing RSPO_ShCNN with better accuracy (94.8%), precision (92.6%), and F-measure (93.7%) compared to conventional approaches.

Sudha et al. [33] investigated about lung cancer malignant tumors which are irregular cell growths with the capability to invade nearby tissues and metastasize. Early diagnosis is crucial to enhance patient survival, but manual processing was time-consuming and error-prone, affecting accurate cancer prognosis. Current techniques are unable to detect the size, shape, and dissemination of cancer cells. To overcome these limitations, this paper suggests a Deep Learning-based Swarm Intelligence approach with CFSO (Convolutional Neural Network Fish Swarm Optimization). The approach involves three steps: pre-processing with a Wiener filter, segmentation with U-Net, and classification with CFSO to save computational cost and enhance accuracy. Performance testing reveals the model achieves 97.80% accuracy, 98.49% recall, 96.8% precision, 97.32% F1-score, and an IoU value of 0.7822, with increased efficiency and reliability. The following table 1 showcases the unitary version of the following research paper objective and findings concisely.

5. PROPOSED FRAMEWORK

This section describes the methodology for carrying out the classification process. For a custom convolutional neural network, amalgamation of various layers are required to carry out the process of classification. The architecture includes a first layer of convolutional nature with size 128 filters of 8 × 8. The layer will extract features from an input of size 224 × 224 × 3 and will pass this sequence to the following batch normalization layer; it will normalize the activations generated after applying the ReLU activation function. The second convolutional layer also employs 256 filters of size 5×5 to deduce the middle features from feature maps

Also, it's passed through batch normalization so that while training, there will be no divergence. After all these max-pooling is applied with a pool size of 3×3 so that spatial dimensions of the feature maps could be reduced as much as possible while keeping the most critical information content. The third convolutional layer is a 256-filters application with stride 1×1, using a kernel size of 3×3. In this layer, it will try to extract relatively more complex features from the input. It, too goes under batch normalization again. Besides, there are two more convolution layers, each using 256 filters, with kernel size being 1×1, and stride 1×1. They had been analyzed for finer refinement of feature representations and, after each of them, batch normalization is used so that the training dynamics do not get seriously affected by them.

The sixth convolutional layer tries to get higher-level features and follows with batch normalization by having 512 filters with a 3×3 kernel size and 1×1 stride to down sample. In order to further down sample, max- pooling layer is added with a pool size of 2×2. Its seventh, eighth, and nineth convolutional layers have 512 filters with a 3×3 kernel size and 1×1 stride to refine feature representations and also follows with batch normalization. It concludes by the addition of a max-pooling layer, which utilizes a pool size of 2×2 effectively down sampling the feature maps. It presents flattened output from previous layers at this point in time. It converts it into a one-dimensional array and then passes through two fully connected layers with 1024 units each so that the overfitting would be avoided during the training. Dropout with the rate of 0.5 is applied wherein it temporarily drops some of the units of the network. Here, this architecture is using the last layer as a fully connected one with 3 units, employing softmax activation for classification of data in appropriate classification whose equation in represented below in equation.

$$\sigma(\vec{I}) = \frac{e^{Ij}}{\sum_{j=1}^{3} e^{Ij}} \quad (1)$$

Where $\sigma()$: softmax function, $\vec{I}$: the image and eI_j: standard exponential factor of input vector [22].

Table 1 Survey of related work done

Author	Objective
Anand et al. [2]	Applied transfer learning approach for classifying images into normal or abnormal using Inceptionv3, VGG16
Cari et al. [10]	Suggested a convolutional neural network model consisting of three layers for ease of detection of lung cancer
Harshavardhan et al. [11]	Proposed a model for distinguishing between healthy lung images and diseased lung images.
BR et al. [12]	Developed a new methodology by fusing CNN and ANN classifiers in the form of a Stacked neural network.
BC et al. [13]	Designed a model for classifying images into various carcinoma categories
Anjum et al. [14]	Constructed an EfficientNet model with varying from B0 to B7 Efficient Net B2 yielding highest accuracy
Zebua et al. [15]	Demonstrated a methodology for classifying images into different cancer categories using ResNet50, Resnet101, ResNet152
Al-Shouka et al. [16]	Designed a model using transfer learning and analyzed the results with Xception, MobileNetV2, VGG16 and ResNet
Bhola et al. [17]	Articulated a model comprising of EfficientNetB2 which in return paved a way for categorizing the images into various types of lung cancer.
Ahnaf et al. [18]	Formulated a method by using feature extraction techniques such as local binary pattern and gray level covariance matrix feature with Support Vector Machine and Gaussian Naive Bayes
Rani et al. [19]	Proposed a model while implementing transfer learning which would segregate the images into cancer affected cases and unaffected cases.
Ashhar et al. [20]	Investigated various convolutional neural network model which segregated different types of images into carcinomic and non-carcinomic cases.
Abd Al-Ameer et al. [21]	Recommend a deep learning model for detection of lung cancer tissue images along with combining VGG16 and Inceptionv3 as feature extractors
Priyadarshini et al. [31]	Recommended a model for lung cancer classification out of which multilayer perceptron yielded highest accuracy.
Velumurugan et al. [32]	Presented a model which performs segmentation of images with optimized classification of images into cancerous and non cancerous.
Sudha et al. [33]	Established a model that performed segmentation of images along with optimization using deep learning architecture.

The peculiarity and quality of the concrete model are attributed to innovative application for presenting the additional convolutional layer with a kernel size of (8×8). Such a size is quite large in comparison with all conventional models. Besides, the model uses several layers, where the kernel size equals (1×1). Such dimension is not typical for frameworks of existing architectures of Convolutional Neural Network. Fig.3 represents the architecture of the proposed model.

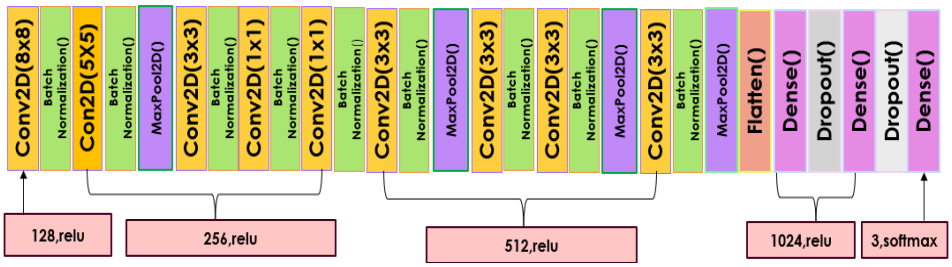


Fig. 3 Architecture of Custom Convolutional Neural network

Figure 4 illustrates the comprehensive methodology employed in the classification process. With the first step beginning with dataset loading followed by applying preprocessing techniques to refine the images. Thereafter the dataset is segregated in a ratio of 7:2:1 and further model is being trained and tested to provide classification result.

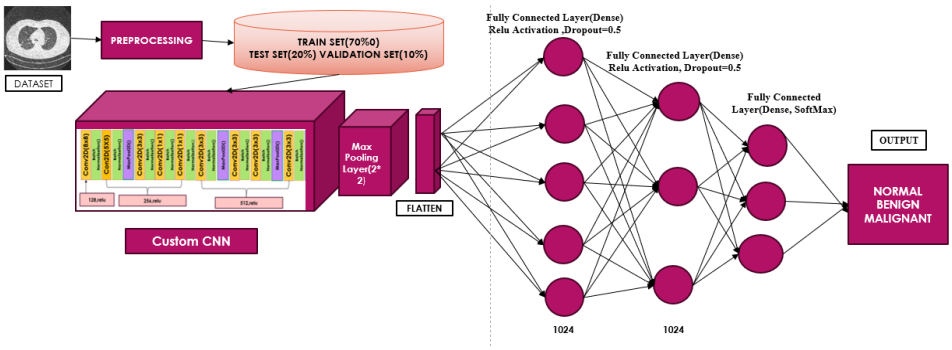


Fig. 4 Proposed methodology for carrying out lung cancer classification

Likewise, Fig. 5 depicts the architecture of VGG16 model comprising of convolutional layers stacked with pooling layer further flatten layer solves the dimensionality issue followed by fully connected layer with softmax activation function where the classification task is carried out.

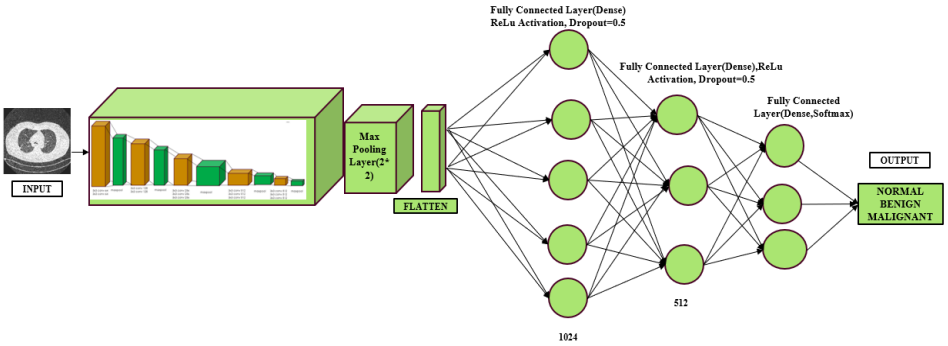


Fig. 5 Framework of VGG16 Model

Fig.6 illustrates the VGG19 model, which has additional three convolutional layers that helps to fine grain the convolution process. It also comprises of pooling layer, flatten layer and fully connected layer with relu activation. The ultimate layer aids in the process of classification in the presence of softmax function.

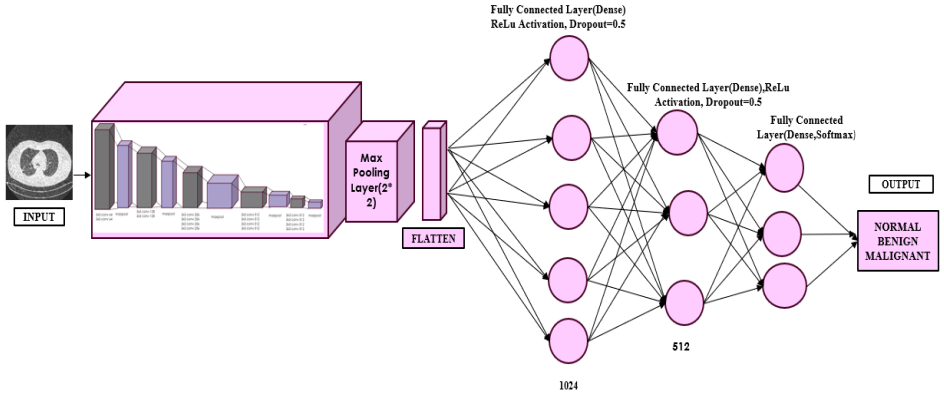


Fig. 6 Framework of VGG19 Model

The representation of the ResNet50 model is shown in Figure 7. It is composed of convolutional blocks, which are then followed by batch normalization layers with the Relu activation function, identity blocks that make the training process easier, as well as a flatten layer and a fully connected layer.

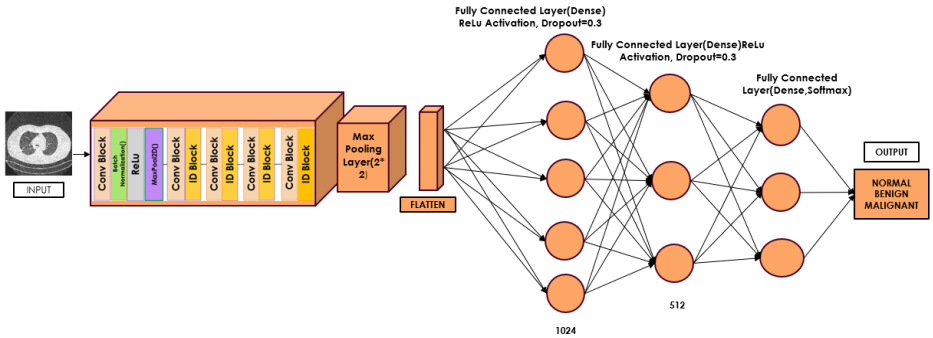


Fig. 7 Framework of ResNet50 Model

Fig. 8 portrays the InceptionV3 model that consists of inception module and an additional concatenation layer. Inception v3 effectively increases feature diversity while maintaining a reasonable computing cost by utilising concatenation. Without appreciably expanding the number of parameters, the model can learn robust representations due to the usage of different filter sizes. Concat layer amalgamates pooling layer with dropout layer and furthers the process of classification.

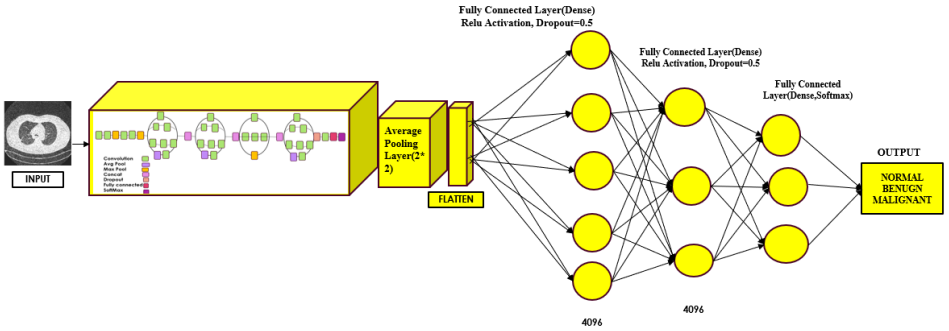


Fig. 8 Framework of Inception V3 Model

Fig.9 iconifies the MobileNetV2 model comprising of convolutional layers, pooling layers and fully connected layers with softmax activation function for multi class classification. The SoftMax layer is the last activation function utilised in the network's classification head in MobileNetV2. Its main function is to translate the raw output logits of the model into probability distributions so that predictions may be more easily interpreted.

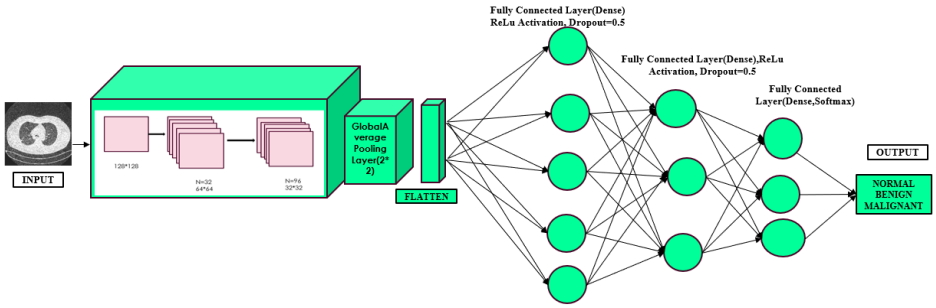


Fig. 9 Framework of MobileNetV2 Model

6. IMPLEMENTATION

6.1. Software Requirement

This section explains the procedure for undertaking the overall methodology toward the lung cancer classification task as explained in the illustration below. The experiment is undertaken through Python 3 programming language on Google Collaboratory, which further contains various relevant libraries and modules about analysis. It contains multiple frameworks that support domains like deep learning and transfer learning. The created model in Fig. 4 along with other models for classifying lung cancer was implemented on a 64-bit Windows 11 system with 16 GB of RAM The execution was carried out on Google Colaboratory, which offers access to potent cloud-based GPUs, guaranteeing effective processing and model optimisation, due to the computational needs of deep learning model training.

6.2. Dataset Used

This section gives the information of the dataset that has been used for classifying the lung cancer using CT scans. The study is carried out with the help of available CT scans that are obtained from Kaggle repository [23]. Total dataset constitutes 1097 CT images. The first class contains benign lung cancer images holding 11% that is 120 CT scan images. The second class holds 561 malignant lung cancer images holding 49%. The test set has 416 standard lung images with dimensions of 512x512 pixels, and it makes up 40% of the total dataset. In this research, 70% is devoted to training and 20% to testing while 10% to validation.

6.3. Preprocessing Technique

The proposed method indeed gives implicit pre-processing to the images coming from the computed tomography scans in classifying lung cancer. Among these include resizing and the transformation of the shear angle during the rescaling process [24]. More importantly, most of the critical techniques used at the pre-processing stage included resizing, normalization, and the use of image augmentation [25,26]. In this case, the Keras ImageDataGenerator function was used. Actually, the resizing of an image is taking the dimensions of an image to an appropriate size of dimension from the dimensions provided by the neural networks. This essentially makes uniformity throughout an entire dataset. Normalization is done in order to normalize pixel values such that they lie in normalized range between 0 and 1 or between -1 and 1, improving convergent speeds of deep learning models while again enhancing general performance [27].

6.4. Feature Extraction

The deep learning models acts as a feature extractor at each stage with different grades of features extracted varying from low level features to high level features. Deep convolutional layers are used to capture spatial hierarchies in images, making them effective for tasks requiring fine-grained feature extraction. While later layers extract more abstract, high-level properties like shapes, patterns, and objects, the early layers capture more fundamental features like edges and textures.

7. Results and Discussion

To ensure the validity of the model's various performance metrics such as accuracy, specificity, sensitivity and F1 score were used for the same. Accuracy can be defined as the correctly predicted instances out of all classes and can be mathematically represented as in equation 2 [28] where TP denotes accurately predicted positive cases, TN denotes accurately predicted negative cases, FN denotes inaccurate prediction of negative cases whereas FP denotes inaccurate prediction of positive cases.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{2}$$

Precision, also known as positive predictive value of all the samples that are actually predicted as positive from all those which would be predicted to be positive [29].

Mathematically it can be represented as in equation 3 where TP denotes accurately predicted positive cases and FP denotes inaccurate prediction of positive cases.

$$Precision = \frac{TP}{TP + FP} \tag{3}$$

Sensitivity is the count of those samples that are classified as positive and those which are actually predicted to be positive. It is also denoted as recall and is represented in equation 4 [30] where TP denotes accurately predicted positive cases and FN denotes inaccurate prediction of negative cases.

$$Sensitivity = \frac{TP}{TP + FN} \tag{4}$$

F1 score is the combination of both precision and recall which is represented in equation 5.

$$F1\ Score = \frac{2 \cdot Precision \cdot Recall}{Precision + Recall} \tag{5}$$

Table 2 demonstrates the various deep learning models trained for carrying out the classification task with different epoch sizes.

Table 2 Epoch size of various models

Model	Max Epoch
Custom CNN	10
VGG16	10
VGG19	10
Inception v3	10
ResNet 50	25
MobileNetV2	10

Table 3 demonstrates the comparative analysis of all the models which were trained individually and their scores are generated and Fig10 showcases its graphical representation. The accuracy for custom CNN model came out to be 98.79% precision is 96.6% sensitivity is 99.1% whereas f1 score came out to be 97.82%. Likewise, the accuracy for VGG16 is 88.48% followed by precision of 88.24% then sensitivity of 92% and its f1 score is 86.96%.VGG 16 performed meagerly than the custom CNN model. Due to the presence of inception modules in Inception V3, it achieved an accuracy of 95.45% with a precision of 97.37% also sensitivity of 96.52% along with f1 score of 96.94%. ResNet50 yielded an accuracy of 94.85% with 94.83% of precision also its sensitivity and f1 score came out to be 94.80% and 94.83%. VGG19 model after training accuracy came out to be 93.64% also 93.63% being its precision score accompanied by sensitivity score of 93.45% and F1 score of 93.53%. MobileNetV2 produced an accuracy of 93.64%,with precision of 92.36% along with sensitivity and f1 score of 92.13% and 92.21%.Inception V3 model performed better than ResNet50, VGG16,VGG19 and MobileNetV2. It is clear that Out of all the models custom CNN model outperformed other models.

Table 3 Competitive analysis of performance metrices for respective models

Model	Accuracy	Precision	Sensitivity	F1Score
Custom CNN	98.79%	96.6%	99.1%	97.82%
VGG16	88.48%	88.24%	92.00%	86.96%
InceptionV3	95.45%	97.37%	96.52%	96.94%
Resnet50	94.85%	94.83%	94.80%	94.83%
VGG19	93.64%	93.63%	93.45%	93.53%
MobileNetV	92.42%	92.36%	92.13%	92.21%

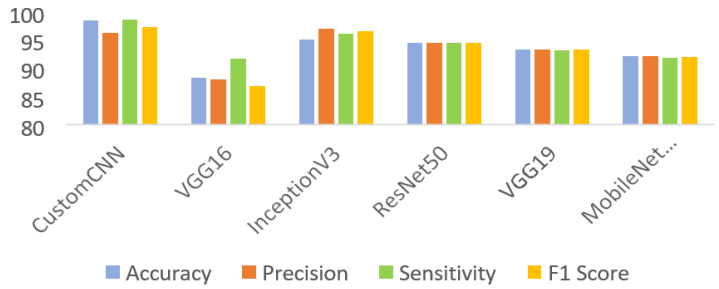


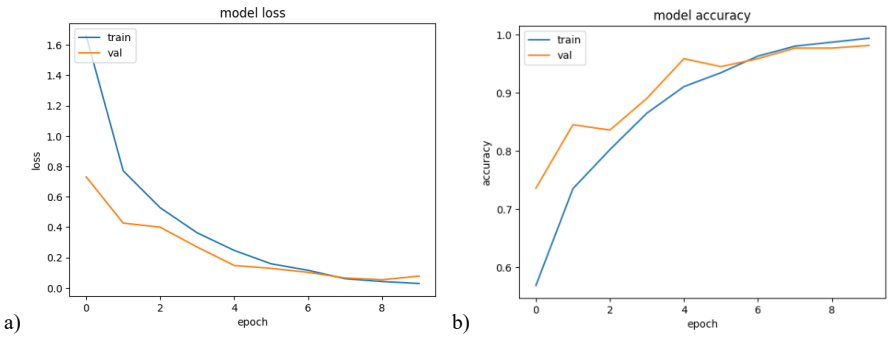
Fig. 10 Graphical Representation of performance metrics of models

Table 4 displays the performance evaluation of each model with different cases as benign, malignant and normal case. For the custom CNN model precision for malignant and benign case is similar where sensitivity of them are 98.31% and 99.15% respectively. f1 scores for benign, malignant and normal cases are 94.74%,99.15% and 99.57%.Benign case for inception V3 model achieved an accuracy of 95.45% with a precision of 97.37% along with sensitivity of 96.52% and f1 score of 96.94%. For the normal case precision score is 96.15% along with sensitivity score of 95.24% its f1 score is 95.69%. Additionally in ResNet50 model the precision, sensitivity and f1 score for benign case is 91.15%, 97.17%, 94.06% for malignant case is 97.09%, 92.59%, 94.79%for normal case is 96.49%, 94.83%, 95.65% respectively.VGG16 model yielded a precision, sensitivity and f1 score values of 88.24%, 85.71%, 86.96% for benign case 93.27%, 93.27%, 93.27% for malignant case and 96.49%, 94.83%, 95.65% for normal case. VGG19 achieved a precision, sensitivity and f1 score values of 93.75%, 96.00%, 94.86% for normal case 93.27%, 93.27%, 93.27% for malignant case 93.88%, 91.09%, 92.46% for benign case. The precision, sensitivity and f1 score for benign case of MobileNetV2 yielded 90.91%, 89.89%, 90.40% for malignant case 91.60%, 96.77%, 94.12% and for normal case 94.59%, 89.74%, 92.11% respectively.

For multi class classification task to be carried out after training the neural networks accuracy and loss curves are generated. The below figures demonstrate the training and validation accuracy and loss for various deep learning models. Fig. 11a, Fig11. b represents the training and validation loss and accuracy curves which is 0.12 and 0.98. The optimal point for custom CNN model is achieved at epoch 8 with best convergence rate.

Table 4 Accuracy, Precision, F1 score & Sensitivity values for Custom CNN, InceptionV3, Resnet50, VGG16, VGG19 & MobileNetV2 for benign, malignant & normal cases

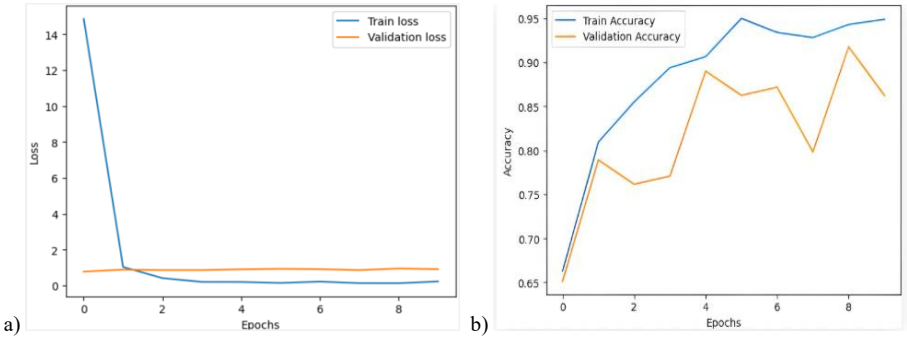
Custom CNN	Accuracy	Precision	Sensitivity	F1Score
Benign	98.79%	90%	100%	94.74%
Malignant	98.79%	100%	98.31%	99.15%
Normal	98.79%	100%	99.15%	99.57%
InceptionV3				
Benign	95.45%	97.37%	96.52%	96.94%
Malignant	95.45%	92.86%	94.55%	93.69%
Normal	95.45%	96.15%	95.24%	95.69%
VGG16				
Benign	88.48%	88.24%	85.71%	86.96%
Malignant	88.48%	82.88%	92.0%	87.20%
Normal	88.48%	94.02%	88.0%	90.91%
ResNet50				
Benign	94.85%	91.15%	97.17%	94.06%
Malignant	94.85%	97.09%	92.59%	94.79%
Normal	94.85%	96.49%	94.83%	95.65%
VGG19				
Benign	93.64%	93.88%	91.09%	92.46%
Malignant	93.64%	93.27%	93.27%	93.27%
Normal	93.64%	93.75%	96.00%	94.86%
MobileNetV2				
Benign	92.42%	90.91%	89.89%	90.40%
Malignant	92.42%	91.60%	96.77%	94.12%
Normal	92.42%	94.59%	89.74%	92.11%



a) b)

Fig. 11 a) Training & Validation Loss for Custom CNN; b) Training & Validation Accuracy for Custom CNN

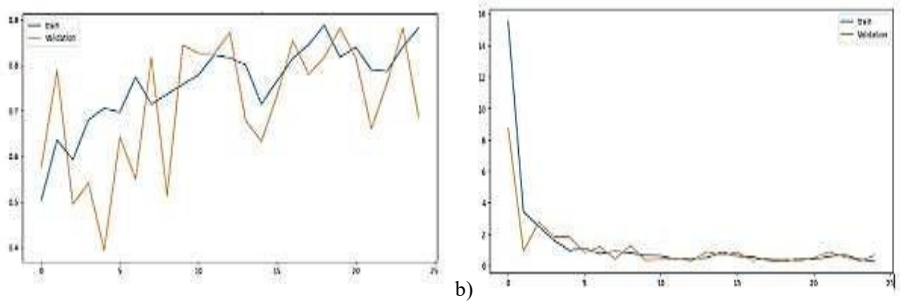
Fig. 12a illustrates the loss curve of 0.13 and Fig. 12b represents the accuracy curve of 0.95 for the InceptionV3 model.



a) b)

Fig. 12 a) Training & Validation Loss for InceptionV3; b) Training & Validation Accuracy for InceptionV3

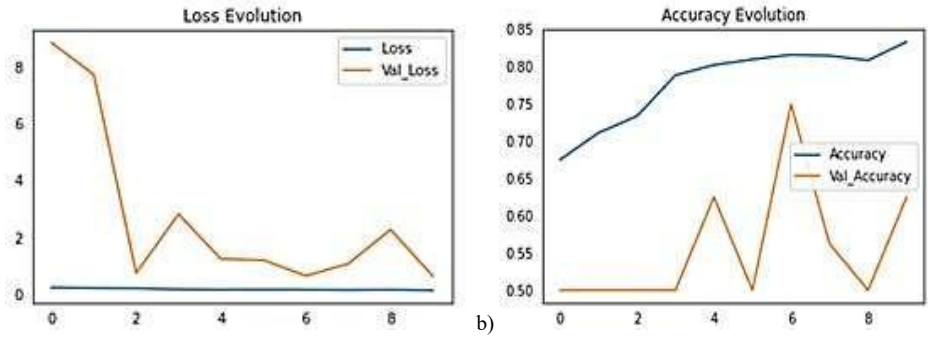
Figure 13a represents accuracy curve of 0.94 and Figure 13b represents the loss curve of 1.5 for ResNet50 model.



a) b)

Fig. 13 a) Training & Validation Accuracy for Resnet50; b) Training & Validation Loss for ResNet50

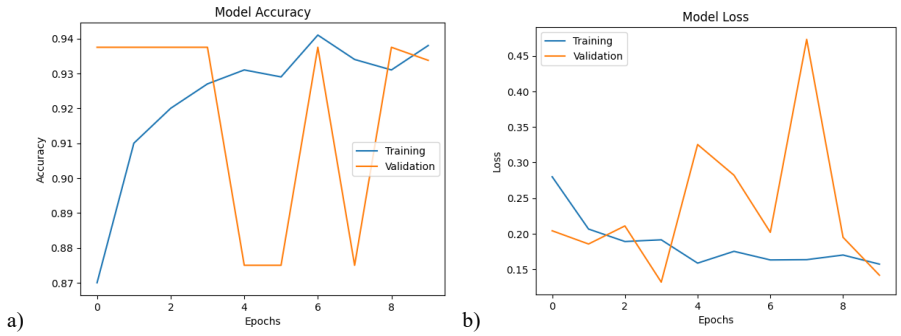
Figure 14a illustrates the loss curve of 1.2 and Figure 14b represents the accuracy curve of 0.88 for VGG16 model.



a) b)

Fig. 14 a) Training & Validation Loss for VGG16; b) Training & Validation Accuracy for VGG16

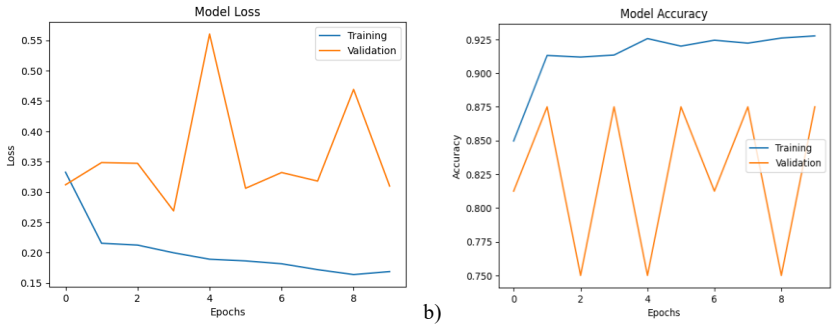
Whereas Figure 15a represents the loss curve of 0.15 and Figure15b represents accuracy curve of 0.93 for VGG19 model.



a) b)

Fig. 15 a) Training & Validation Accuracy for VGG19; b) Training & Validation Loss for VGG19

Figure 16a represents the loss curve of 0.19 and Figure16b represents accuracy curve of 0.91 for MobileNetV2 model.



a) b)

Fig. 16 a) Training & Validation loss for MobileNetV2; b) Training & Validation Accuracy for MobilenetV2

The detailed confusion matrix computation for custom CNN model, Inception V3 model, VGG16 model, ResNet50 model, VGG19 model and MobileNetV2 model is depicted in fig. 17, fig. 18 fig. 19, fig. 20, fig. 21 and fig. 22 respectively. It is used for the recognition of correctly labeled data to their respective classes and the wrongly labeled data to their respective classes. The green color in the matrix denotes the valid instances that were predicted accurately and the red color denotes the invalid cases. Most of the correct cases resides diagonally. High value on the diagonal indicates a high number of valid instances for the concerned class.

Figure17 and Figure 18 represents the distribution of various instances into true positives, true negatives, false positives and false negatives fetched after executing the custom CNN model and InceptionV3 model.

TARGET / OUTPUT	BENIGN	MALIGNANT	NORMAL	SUM
BENIGN	36 10.91%	3 0.91%	1 0.30%	40 90.00% 10.00%
MALIGNANT	0.00%	174 52.73%	0.00%	174 100.00% 0.00%
NORMAL	0.00%	0.00%	116 35.15%	116 100.00% 0.00%
SUM	36 100.00% 0.00%	177 98.31% 1.69%	117 99.15% 0.85%	326 / 330 98.79% 1.21%

Fig. 17 Confusion Matrix of Custom CNN

TARGET / OUTPUT	BENIGN	MALIGNANT	NORMAL	SUM
BENIGN	111 33.64%	2 0.61%	1 0.30%	114 97.37% 2.63%
MALIGNANT	4 1.21%	104 31.52%	4 1.21%	112 92.86% 7.14%
NORMAL	0 0.00%	4 1.21%	100 30.30%	104 96.15% 3.85%
SUM	115 96.52% 3.48%	110 94.55% 5.45%	105 95.24% 4.76%	315 / 330 95.45% 4.55%

Fig. 18 Confusion Matrix of InceptionV3

Following the execution of the VGG16 model and ResNet50 model, the representation of different instances into true positives, true negatives, false positives, and false negatives is shown in Figures 19 and 20.

TARGET / OUTPUT	BENIGN	MALIGNANT	NORMAL	SUM
BENIGN	90 27.27%	6 1.82%	6 1.82%	102 88.24% 11.76%
MALIGNANT	10 3.03%	92 27.88%	9 2.73%	111 82.88% 17.12%
NORMAL	5 1.52%	2 0.61%	110 33.33%	117 94.02% 5.98%
SUM	105 85.71% 14.29%	100 92.00% 8.00%	125 88.00% 12.00%	292 / 330 88.48% 11.52%

Fig. 19 Confusion Matrix of VGG16

TARGET / OUTPUT	BENIGN	MALIGNANT	NORMAL	SUM
BENIGN	103 31.21%	6 1.82%	4 1.21%	113 91.15% 8.85%
MALIGNANT	1 0.30%	100 30.30%	2 0.61%	103 97.09% 2.91%
NORMAL	2 0.61%	2 0.61%	110 33.33%	114 96.49% 3.51%
SUM	106 97.17% 2.83%	108 92.59% 7.41%	116 94.83% 5.17%	313 / 330 94.85% 5.15%

Fig. 20 Confusion Matrix of ResNet50

Figures 21 and 22 show how different occurrences were distributed into true positives, true negatives, false positives, and false negatives following the execution of the VGG19 and MobileNetV2 models.

TARGET / OUTPUT	BENIGN	MALIGNANT	NORMAL	SUM
BENIGN	92 27.88%	3 0.91%	3 0.91%	98 93.88% 6.12%
MALIGNANT	5 1.52%	97 29.39%	2 0.61%	104 93.27% 6.73%
NORMAL	4 1.21%	4 1.21%	120 36.36%	128 93.75% 6.25%
SUM	101 91.09% 8.91%	104 93.27% 6.73%	125 96.00% 4.00%	309 / 330 93.64% 6.36%

Fig. 21 Confusion Matrix of VGG19

TARGET / OUTPUT	BENIGN	MALIGNANT	NORMAL	SUM
BENIGN	80 24.24%	2 0.61%	6 1.82%	88 90.91% 9.09%
MALIGNANT	5 1.52%	120 36.36%	6 1.82%	131 91.60% 8.40%
NORMAL	4 1.21%	2 0.61%	105 31.82%	111 94.59% 5.41%
SUM	89 89.89% 10.11%	124 96.77% 3.23%	117 89.74% 10.26%	305 / 330 92.42% 7.58%

Fig. 22 Confusion Matrix of MobileNetV2

Table 5 demonstrates the comparative analysis of various deep learning models and other leading edge architectures with the use of diverse sets of lung cancer dataset. The proposed model has highest accuracy amongst all the other models.

The studies adopted employ various datasets like CT images, LDCT, LIDC-IDRI, LC25000, IQOTH/NCCD, and lung cancer tissue images. The models adopt various machine learning and deep learning methods like CNNs and ensemble learning techniques. Performance metrics include accuracy, sensitivity, specificity, and F-score. The performance of different studies can be tabulated as follows: Anand et al. (2022) obtained 96% accuracy in using CT images, whereas Cari et al. (2024) reported 95% accuracy with the use of CT scans, yielding 100% sensitivity and 90% specificity. Harshavardhan et al. (2024) and BR et al. (2024) both recorded accuracies of 96.86% through lung CT scans, with similarly matched sensitivity and specificity values. BC et al. (2024) used the LIDC-IDRI dataset with 95.06% accuracy, whereas Anjum et al. (2023) achieved 97.24% accuracy using the LC25000 dataset. Zebua et al. (2024) proved 89% accuracy using LDCT, whereas Al-Shouka et al. (2023) used CT scans to achieve 94% accuracy. Bhola et al. (2023) achieved 90.16% accuracy using CT scans, whereas Ahnaf et al. (2023) used the IQOTH/NCCD dataset to achieve 93% accuracy. Ashhar et al. (2020) and Abd Al-Ameer et al. (2022) achieved 94.53% and 97.09% accuracy, respectively, with the LIDC-IDRI and lung cancer tissue datasets. Priyadarshini et al. (2025) achieved 97.29% accuracy with CT scan images, whereas Velumurugan et al. (2025) achieved 94.8% accuracy with CT images, with 92.6% sensitivity and 93.7% F-score. In addition, Sudha et al. (2025) employed the LIDC-IDRI dataset and achieved a high accuracy of 97.80%, with sensitivity of 96.8% and specificity of 98.49%.The model proposed is far superior to current approaches, with excellent performance of 98.79% accuracy using the IQOTH dataset. It has a sensitivity of 96.6%, specificity of 99.1%, and F-score of 97.82%. This high performance is due to the incorporation of sophisticated optimization methods and careful image processing, and it is a powerful tool for precise lung cancer classification.

Table 5 Performance evaluation metrics of existing models

Author(s)	Methods used	Accuracy	Precision	Sensitivity	F1 Score
Anand et al. [2] (2022)	CT images	96%	-	-	-
Cari et al. [10] (2024)	CT scans	95%	100%	90%	-
Harshavardhan et al. [11] (2024)	Images of Lung CT scans	96.86%	96.86%	96.50%	96.68%
BR et al. [12] (2024)	CT scan	96%	97.37%	97.37%	
BC et al. [13] (2024)	LIDC-IDRI	95.06%	94.05%	99.01%	93.02%
Anjum et al. [14] (2023)	LC25000	97.24%	-	-	-
Zebua et al. [15] (2024)	LDCT	89%	90.0%	90.0%	89.5%
Al-Shouka et al. [16] (2023)	CT scans	94%	-	-	-
Bhola et al. [17] (2023)	CT scans	90.16%	90.16%	92.37%	90.72%
Ahnaf et al. [18] (2023)	IQOTH/NCCD	93%	94%	93%	92.5%
Ashhar et al. [20] (2020)	LIDC-IDRI	94.53%	99.06%	65.67%	86.84%
Abd Al-Ameer et al. [21] (2022)	Lung cancer tissue images	97.09%	96.89%	97.31%	97.09%
Priyadarshini et al. [31] (2025)	CT scan images	97.29%	97.23%	96.5%	96.5%
Velumurugan et al. [32] (2025)	CT images	94.8%	92.6%	-	93.7%
Sudha et al. [33] (2025)	LIDC-IDRI	97.80%	96.8%	98.49%	97.32%
Proposed Model	IQOTH	98.79%	96.6%	99.1%	97.82%

8. CONCLUSION

The demarcation of the lung nodules that have been affected strictly is necessary since this step goes a long way in making sure that the whole process of diagnosis turns out to be correct. In the study, the paper exhaustively analyzed the IQOTH lung cancer dataset with the intention of forecasting the chances of multiplication of the cancer by using designed deep learning model that present stunning results. The principal aim of this research is to construct a model that is highly efficacious at providing predictions remarkably well, going a long way to further help medical practitioners make the right decisions regarding care for patients. This custom CNN model is remarkable in a way that it achieves an accuracy as high as 98.79%, which is significantly higher than most of the other well-established architectures. Its comparative accuracy to Inception V3 was measured to be 95.45%, ResNet50 at 94.85%, VGG16 with an accuracy of 88.24%, VGG19 with an accuracy of 93.64% and MobileNetv2 with an accuracy of 92.42%. These results go a long way toward underlining the effectiveness that the custom CNN model portrays at classifying cases of those afflicted with the disease of cancer and those who are not affected by the disease. This feature of sharply classifying cases of lung cancer assumes tremendous importance because such patients at risk can be identified and subjected to timely medical interventions that would likely save their lives. As such, further segmentation would therefore be possible in a further minute detail onto the work while also allowing interplay with various other models as well. Besides this, a multi-modal approach could be included, and in combination with an ensemble technique, it can also enhance the overall effectiveness of the integration. Furthermore, as multi scale feature learning allows deep learning models to collect information across several scales from tiny nodules to huge lesions multi-scale could be a promising path. This capacity is

essential for detecting cancer in its early stages and for more accurately differentiating between benign and malignant instances.

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