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Performance analysis of lung cancer detection and classification using efficientNet: a deep learning model

Priya A[1] **· Shyamala Bharathi P**[1]

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Abstract
Lung cancer is one among the serious critical diseases worldwide. According to World Health Organisation (WHO), there are about 7.6 million death cases annually worldwide because of lung tumor and its accurate diagnosis of disease also crucial. Moreover, humanity related to cancer is projected to begin to grow to about 17 million worldwide in 2030. Computed tomography (CT) scans may offer valuable information in the lung disorders diagnosis across multiple imaging modalities. Discovering early stage lung cancer is the best way to treat it. In this proposed research, a deep learning based pre-trained model called EfficientNet with convolution neural networks for the classifications of lung cancer using the CT images. The CT lung images are gathered from The Cancer Imaging Archive database. By using these images the proposed model is evaluated and validated with the performance analysis. The goal is to identify lung cancer using CT images, that can be useful in determining that the patient is affected by cancer or not. The performance metrics used in this work are accuracy, sensitivity, specificity, precision and f1-score and the results obtained are compared with existing techniques for validation. The method achieved 99.28% training accuracy for training and 98.03% accuracy for training. Overall the efficiency of the proposed model is better than other compared techniques.

Keywords Lung cancer · EfficientNet · CNN · CT images · Deep learning · Cancer detection and classification

1 Introduction

Lung tumor is one of world's major causes of death for both women and men, with an increasing number of about five million fatalities a year. CT scans provide useful informations for the diagnoses of lung disorders. The goal is to distinguish cancerous lung images

✉ Priya A
priyaanbazhagan1912@gmail.com

Shyamala Bharathi P
shyamalabharathip.sse@saveetha.com

[1] Department of Electronics Communication and Engineering, Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences, Chennai, Tamil Nadu, India

from the input CT images given and to describe lung cancer and its intensity. This study uses a pre-trained Deep Learning technique to diagnose lung cancer [1].

Nowadays, cancer has been the most general causes of mortality for young people in the country. Lung tumor, stomach cancer, breast tumor, and prostate cancer were among the most commonly recognized cancers in both women and men that lead to significant difficulties or, in most situations, to death, if not identified at initial stages. Human body cancer is an abnormal cell growth. There are 19 different sorts of cancer which might affect a healthy person. Lung cancer has the largest mortality rate for any of these tumors. About 1.7 million deaths from this disease are reported every year [2]. Adequate separation between benign and cancerous small to medium scale 5–15 mm of CT pulmonary nodule was a concern for radiologists [3]. Early diagnosis of lung cancer is a major feature and a road to healing. Generally, X-rays, CT scans, MRIs, and other techniques may be diagnosed. Artificial neural network has already been widely used in this research and is now improved with generalization efficiency, including the training of several algorithms and the convergence of their predictions [4].

Lung cancer general visualization is not effective, as experts are always not able to recognize the affected area until entering the benign level. Five-year survival was approximately 54 percent for early lung cancer, which was confined to the lungs, but just about 4 percent in the aggressive form of untreatable lung cancer.

The risk of lung tumor grows with the cigarettes smoked over a period of time; researchers prefer to take this risk over a long period of experience of smoking. A small part of lung cancer occurs in patients who do not have known risk factors for the disease. A portion of them may be well at odd periods where there may be no outside justification to do so. In general, patient undergoes CT or X-ray or MRI scan to diagnose premature lung development in order to investigate lung cancer. In this case, the highly sensitive CT can detect minor anomalies that could be tumors.

Early diagnosis: Diagnosing lung cancer at early stage could result in adequate care options and a much higher chance of survival. However, only 16% of patients are diagnosed at an early stage when the disorder is typically treatable [5].

In this pandemic situation of COVID-19, this suggested model could help diagnose lung infection caused by the COVID-19 virus and could be used to classify the disparity between the COVID-19 infected lungs and the normal lungs [6, 7].

This study introduces a novel approach utilising deep learning based pre-trained model called EfficientNet with CNN for the classifications of lung cancer using the CT image. The CT lung images are gathered from The Cancer Imaging Archive database. Our novel approach combines comprehensive performance analysis and cutting-edge deep learning techniques to provide lung cancer diagnosis with exceptional accuracy and dependability. This study offers a reliable and efficient model for early diagnosis and treatment of lung cancer, which advances medical diagnostics and its risks in human health. Section II discusses the related work done on the lung cancer detection using different modules and techniques so far. Section III briefly discusses the suggested technique, section IV discusses performance analysis of suggested model and section V ends with discussion of conclusion.

1.1 Related works

Asuntha and Andy Srinivasan have suggested a fuzzy-PSO-CNN (FPSO-CNN) methodology for the diagnosis and classification of lung cancer. Various extraction methods have been used for extracting features like geometric, texture, intensity, and volumetric feature. The FPSO algorithm was utilized to choose the best feature derived from the models, and the FPSO-CNN model of deep learning was utilized to distinguish cancer regions from the extracted features. The results can be enhanced by upgrading the optimization model [1].

Gur Amrit Pal Singh, P. K. Gupta used various methods to recognize lung cancer. The proposed method first processed these images with image recognition methods, and then more supervised learning methods were utilized for the classification. Here, the features of texture were extracted together with statistical feature and gave different features to the classifier. Various classifiers such as k-nearest neighbor, SVM, decision trees, multinomial naive bayes, random forest, stochastic gradient descent, and multi-layer perceptron classification model were utilized. The results obtained show that the accuracy of the MLP classifier was higher than other classifiers [2].

Marjolein A. Heuvelmans et al. presented the lung cancer prediction CNN that was trained on U.S. screening results, on the isolated data set of indeterminate nodule in a European multi-centre study, to rule-out benign nodule retaining the higher sensitivity to lung cancers. LCP-CNN was trained to produce the malignancy rate for all nodules utilizing CT images from U.S. NLST and validate on CT scans found in patients in the Early Lung Cancer Diagnosis Using AI and Big Data (LUCINDA) analysis. The benign nodule rule-out test was predefined to recognize benign nodule while retaining the higher sensitivity, by computing the malignancy scores thresholds that achieved minimum 99 percent sensitivity on NLST results. Overall output was analyzed using the AUC [3].

Divyesh Bhatnagar et al. presented a classification model for the identification of abnormal and normal lung cancer diagnosis using PCA and GLCM techniques. Using the PCA algorithm, the images were evaluated and processed and, using the GLCM technique, preprocessing and extraction of features was performed and the classification process was carried out using the neural network technique. The performance achieved can be improved by introducing new methods and by strengthening the implementation of training and testing [4].

Lakshmanaprabu S.K et al. proposed an automatic diagnostic system for classifying the CT lung images. Images of CT were studied with the aid of Linear Discriminate Analysis and Optimal Deep Neural Networks. Deep features were derived from the CT images and hence the dimensionality of the features was decreased by the LDR to identify lung nodule as benign or malignant. The ODNN was added to CT image and hence optimized by the Modified Gravitational Searching algorithm to classify the classification of lung tumour [5].

He Yang et al. applied a deep learning CNN model for the classifications of thoracic CT images of lung. The architecture of CNN and precision of the classification of the initial images of nodules of lung have been applied. For understanding features of the lung nodules, new datasets were generated on basis of a mixture of artificial geometric nodules and certain transformations of original images, and also stochastic nodule shape model. Simplistic geometric nodules have been shown to be unable to capture the essential features of lung nodules [8].

Siddharth Bhatia et al. suggested a deep residual learning method to diagnose lung cancer from CT scans. A series of pre-processing techniques has been outlined to identify lung segments susceptible for cancers and extract feature utilizing the U-Net and ResNet model. The collection of features has been fed into various classifiers, viz. XGBoost and RF, as well as individual prediction, was combined for estimating the probability of the CT scans being malignant [9].

Suren Makaju et al. reviewed the many computer-aided approaches, analyzed the best current approach, defined its shortcomings and disadvantages, and then proposed a novel approach with enhancements to best current approach. The system utilized was for lung cancer identification methods to be analyzed and classified based on their accuracy rate. The strategies were evaluated at all stages and the overall limitations, disadvantages were noted [10].

Mohamed Shakeel et al. presented a model for diagnoses of lung cancer using enhanced profuse clustering and DL instantaneously trained NN. This research was proposed to rise the quality of the image of the lung and to detect lung cancer by minimizing misclassification. The noises exist in the images were removed by using the weighted means histogram equalizations solution, which eliminated noises from the images, and also enhanced image quality by using the IPC technique for the segmentation of the infected region. Multiple spectral features were obtained from the regions concerned. These were tested by using a deep learning neural network that was instantly trained for prediction of lung cancer.

Goran Jakimovski and Danco Davcev used CT scanned images for training the double convolution Deep Neural Network (CDNN) and the standard CDNN. These techniques have been checked against images of lung tumor to establish the level of Tx cancer at which these techniques would identify the likelihood of lung cancers. The first move was to pre-classifying the CT images from the first data set hence the CDNN training could be centered. Next, a double CDNN with max pooling was developed to do more in-depth search. At last, CT scan of various Tx levels of lung cancer were used to assess Tx level at which CDNN could diagnose risk of lung cancer.

Asuntha and Andy Srinivasan's fuzzy-PSO-CNN (FPSO-CNN), which uses fuzzy logic, PSO, and CNNs for lung cancer diagnosis is one example of prior research. By using supervised learning and image recognition, Gur Amrit Pal Singh and P. K. Gupta demonstrated the accuracy of the MLP classifier. A CNN with great sensitivity for screening out benign nodules was proposed by Marjolein A. Heuvelmans et al. Divyesh Bhatnagar et al. diagnosed atypical lung carcinoma using GLCM and PCA. Linear Discriminate Analysis and Optimal Deep Neural Networks were used by Lakshmanaprabu S.K. et al. to construct an autonomous diagnostic system. Using a CNN model, He Yang et al. classified thoracic CT images by emphasizing crucial nodule traits. In order to diagnose lung cancer using CT scans, Siddharth Bhatia et al. developed a deep learning technique that combines the U-Net and ResNet models. Suren Makaju et al. examined computer-aided methods and suggested improvements for the detection of lung cancer.

1.2 Proposed methodology

The development of a CNN facilitates the advancement of deep learning, from the initial layers of convolution, pooling layers, and fully connected layers, consisting of the basic networks like AlexNet, LeNet, and VGG-16, to ResNet, GoogleNet and Inception, through expanding the system depths and increasing channel's size of network to make the network more dynamic, enhancing the resolutions of image data will also provide fine-grained features better. These activities not just increase the network identification accuracy but additionally boost the issue that the measuring process of the gradient explosions specification is very large. ResNet model that skips link would absolutely bypass gradient explosions; MobileNet uses point-wise convolution and depth-wise convolutions to minimize network parameter and increase training efficiencies; SENet sets different weight based on the failure of network training in order to produce great outputs in training model. The EfficientNet has incorporated the features of the above networks by fixing the required composite ratio coefficients to match the distance, resolution, and depth of the network so that the improved model efficiency can be obtained by extending the network's three dimensions. The formula for the estimation of the coefficients of composite proportions is as follows:

$$\begin{cases} depth : d = \alpha^{\phi} \\ width : w = \beta^{\phi} \quad s.t. \alpha \bullet \beta^2 \bullet \gamma^2 \approx 2 \\ resolution : r = \gamma^{\phi} \end{cases}$$

here $\alpha \geq 1$, $\beta \geq 1$, $\gamma \geq 1$, w, d, r could be utilized for measuring the depth of the network, widths and resolutions coefficients, the defined values of ϕ could be utilized to calculate the sum of efficient resource extensions model, constants α, β, γ shall be utilized to provide the resources to the network width, depths and three-dimensional resolutions. Based on the analysis, the Efficientnet-B0 network parameter is tabulated in the Table 1, and the optimum network coefficients is: $\alpha = 1.2$, $\beta = 1.1$, $\gamma = 1.15$.

The feasibility of the model scaling idea described above depends heavily on the baseline networks. To overcome this, the new simple networks was built utilizing the Automated Machine Learning (AutoML) MNAS system, which systematically search for the CNN model which optimized both efficiency and precision (in FLOPS). The baseline network was known as EfficientNet and its architecture is seen in Fig. 1.

The initial discovery was that this baseline model consists of continuous blocks MBConv1, MBConv3, and MBConv6. There are simply various forms of MBConv blocks. The second finding was that total channel within each block was expanded or increased (by a large numbers of filters). The final finding was the inverted residual relations among the model's narrow layers.

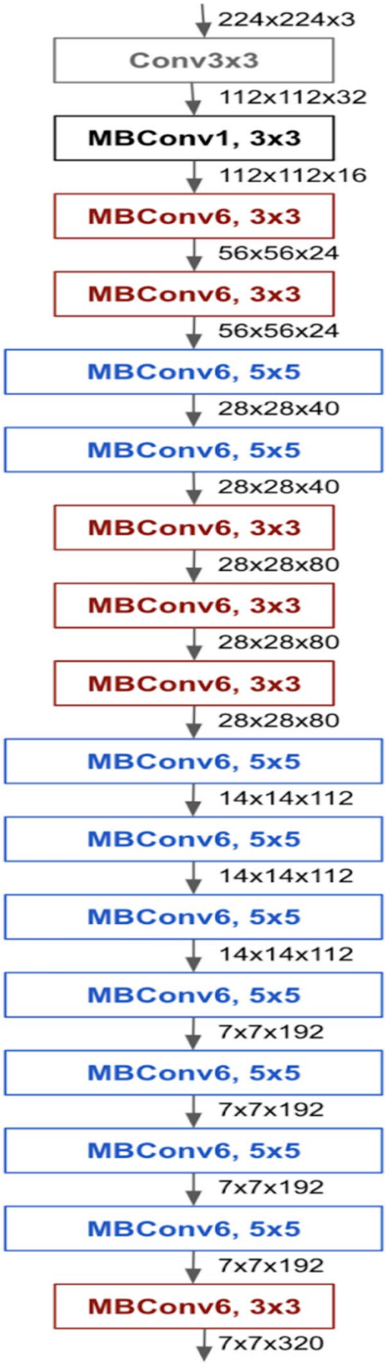
A ConvNet Layer i could be expressed as the function: $Y_i = \mathcal{F}_i(X_i)$, here $\mathcal{F}_i$ denotes operator, Y_i was the output tensor, X_i was the input tensor, with tensors shape $\langle H_i, W_i, C_i \rangle^1$, here H_i and W_i were spatial dimensions and C_i was the dimension of the channel. A ConvNet N could be expressed by

$$N = {}_{i=1\ldots s} \odot \mathcal{F}_i^{L_i}(X_{\langle H_i, W_i, C_i \rangle})$$

Table 1 Network Parameters of EfficientNet-B0 Model [18]

Stage I	Operator $\mathscr{F}i$	Resolution $\boldsymbol{Hi} \times \boldsymbol{Wi}$	Channels $\boldsymbol{Ci}$	Layers $\boldsymbol{Li}$
1	Conv 3×3	224×224	32	1
2	MBConv1, k3×3	112×112	16	1
3	MBConv6, k3×3	112×112	24	2
4	MBConv6, k5×5	56×56	40	2
5	MBConv6, k3×3	28×28	80	3
6	MBConv6, k5×5	28×28	112	3
7	MBConv6, k5×5	14×14	192	4
8	MBConv6, k3×3	7×7	320	1
9	Conv1×1& Pooling& FC	7×7	1280	1

Fig. 1 Architecture of EfficientNet-B0 Model [17]



here $\mathcal{F}_i^{L_i}$ indicates layer $\mathcal{F}_i$ was repeated L_i times in stage i, $\langle H_i, W_i, C_i \rangle$ represents the shape of the input tensor X of layer i.

A key component of the EfficientNet architecture that derives from MobileNet's ideas is the Mobile inverted bottleneck convolution (MBConv) [15, 19]. It uses depth-wise separable convolutions, applying point-wise and depth-wise convolution layers in turn. By employing depth-wise convolutions to initially capture spatial information and point-wise convolutions to integrate features across channels, this technique improves computing efficiency. Furthermore, MBConv incorporates ideas from MobileNet-V2, like linear bottlenecks and inverted residual connections. The network may use skip connections more efficiently thanks to inverted residual connections, which promote gradient flow and feature propagation. By avoiding feature compression, linear bottlenecks contribute to the preservation of the network's information richness. All things considered, MBConv improves feature extraction and representation, which helps the EfficientNet framework perform better on different tasks, like object detection and image classification [21, 22].

In both deep learning and machine learning systems, a huge number of labels and data are required, but it is challenging for the large data set to be sorted out for certain purposes, and data collection is time-consuming and laborious. Since the network's model parameters are not learned from start to finish, the models testing was typically quicker than the training of a new model. Transfer learning is part of semi-supervised learning that could decrease the reliance on tag data once the data set was limited. It could be due to the strong generalization capabilities that render it resilien [16, 20].

In this research, the approach used in the experiments was to freeze the prior convolutional layers and pooling layer's parameters, in particular, the model parameters files loaded on ImageNet dataset was pre-trained for configuring new networks [13]. The transition pre-training model is performed out on new tasks and parameters of complete connecting layers and Softmax layers are configured in conjunction with parameters tuning approach such that configuration of network might be adapted to new classification tasks, thereby speeding and improving the performance of learning of the model and improving generalization capacity. The transfer learning approach of the research can be seen in Fig. 2, which utilizes model generated by ImageNet data set of 1000 category images and then transfers it to lung cancer identification and classification tasks [11, 12, 14].

1.3 Performance analysis

The analysis of performance of the suggested deep learning based pre-trained EfficientNet with CNN model is evaluated with the help of the dataset. The proposed method is validated concerning the attributes like accuracy, recall, f-measure, precision and specificity. Comparison analysis is also done for the introduced model. The results are compared to existing DL methods used in the process of CNN classification like VGG-19, Inception, ResNet 152v2, and Squeeze Net models. All these evaluation experiments are tested and done on MATLAB toolbox called the 2019a Simulink. The whole dataset is divided as 75% for training and 25% for testing for the process of analysis of performance.

1.4 Dataset description

The dataset of CT lung images is obtained from The Cancer Imaging Archive (TCIA) database, which includes images collected from National Cancer Institute Tumor Analysis

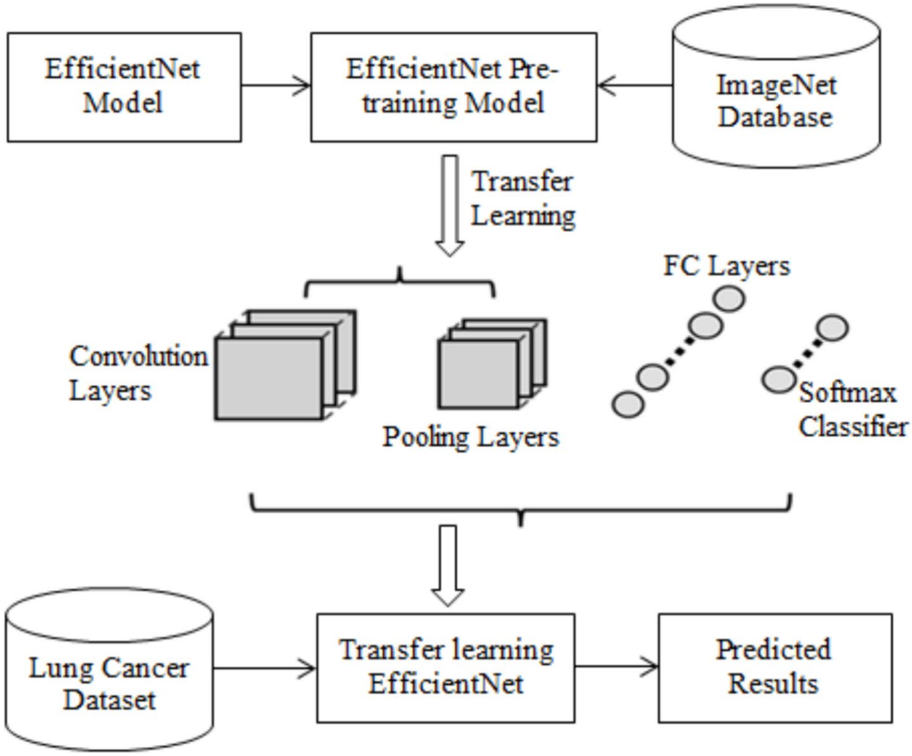


Fig. 2 Proposed Model

Consortium Lung Cohort. Patient characteristics are cross-referenced with genetic, proteomic, and clinical data using CT lung scans from the Cancer Imaging Archive (CIA) collection, which includes information from National Cancer Institute Tumor Analysis Consortium Lung Cohort. The images captured are preserved in a DICOM file. A total of

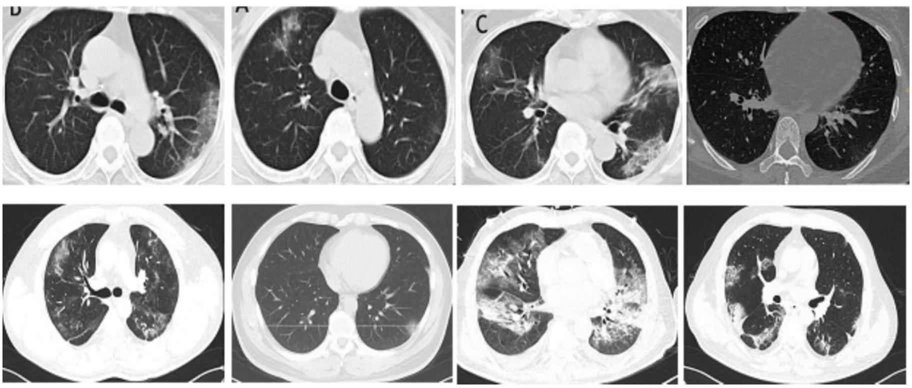


Fig. 3 Sample Images from Dataset

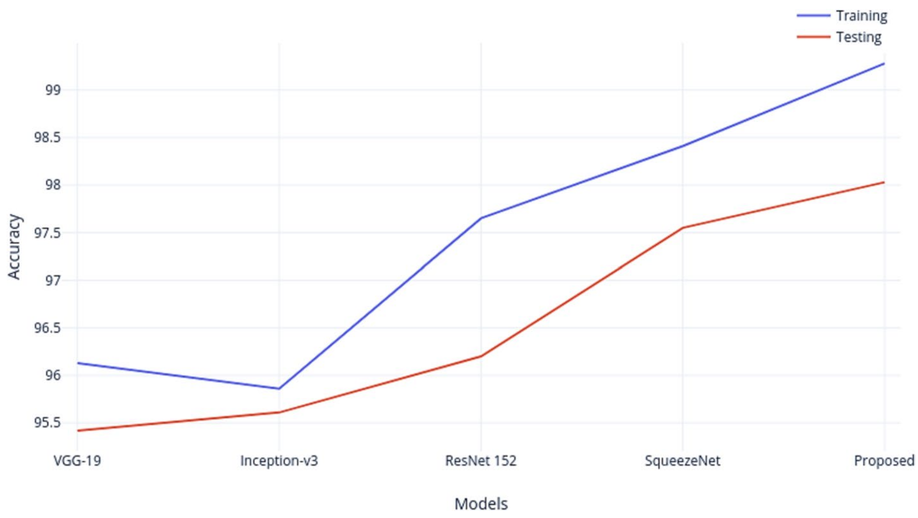


Fig. 4 Graphical Plot of Accuracy

Table 2 Performance Evaluation of Accuracy

Models	Training	Testing
VGG-19	96.13	95.42
Inception-v3	95.86	95.61
ResNet 152	97.65	96.20
SqueezeNet	98.41	97.55
Proposed	99.28	98.03

5043 images are used for the study of lung cancer in various 48-series patients. Out of the 5043 images, 3000 images are chosen and, among 3000 images, 1750 images are used in training, and 1250 images for testing. CT lung radiography images utilized medical image processing methods to detect cellular alterations indicative of lung cancer, providing the foundation for an accurate forecast. Sample images of the lung cancer dataset are represented in Fig. 3.

1.5 Performance metrics

The metrics to analyse the performance used in this work are accuracy, specificity, sensitivity, f1-score, and precision. The true positive, true negative, false positive, and false negative are properly analysed for estimating the model's outcome.

- **TP:** Count of correct predictions in cancer infected images.
- **FP:** Count of incorrect predictions in cancer infected images.
- **TN:** Count of correct predictions in the uninfected cancer images.
- **FN:** The number of incorrect predictions in uninfected cancer images.

Table 3 Performance Evaluation of Sensitivity

Models	Training	Testing
VGG-19	96.48	95.60
Inception-v3	95.90	95.78
ResNet 152	96.82	96.33
SqueezeNet	98.53	97.69
Proposed	99.45	98.26

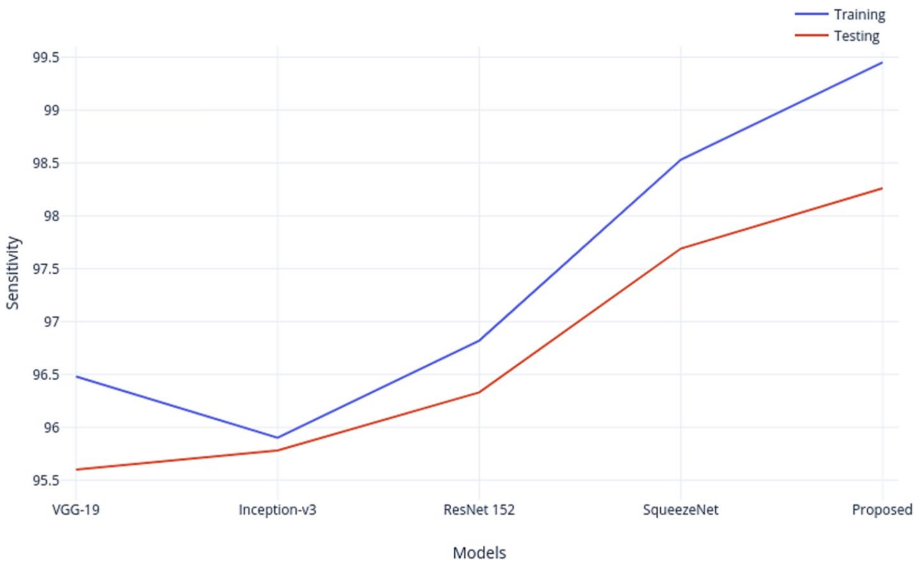


Fig. 5 Graphical Plot of Sensitivity

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

Accuracy is the primary metric of the model to estimate the performance of the model and the results of the accuracy is shown in Fig. 4. This is mostly used to estimate when the positive class and the negative class both are important equally. As it is seen in Table 2 the suggested model got a better classification rate of accuracy in both the dataset of training and testing for classification of images of lung cancer. The proposed model achieved a 99% of accuracy for training that is 0.8% to a 3.42% enhanced while comparing to the existing techniques. For the process of testing the introduced method got a 98.03 of accuracy that is 0.45 to a 2.6% enhanced performance while comparing to the existing methods. Here the Table 3 shows the evaluation performance of the metric called sensitivity.

$$\text{Sensitivity} = \frac{TP}{TP + FN}$$

Table 4 Performance Evaluation of Specificity

Models	Training	Testing
VGG-19	95.24	94.67
Inception-v3	94.95	94.02
ResNet 152	97.18	96.35
SqueezeNet	97.80	96.49
Proposed	98.72	97.11

Another metric for performance evaluation is sensitivity this sensitivity metric can also be called as recall. It can be measured as the ratio of correctly predicted positive evaluation of the overall positive predictive values. If the recall value is lower then it shows that many numbers of values of false negative affected the classifier. The model has got 99.45 rate of sensitivity in the process of training that shows an improvement of 0.9% to 3.5% enhancement while comparing to the other models. And it has got 98.03% accuracy for testing that is 0.5% to a 2.6% more performance while comparing to the available model that is shown in Fig. 5. The Table 4 shows the evaluation of the metric specificity.

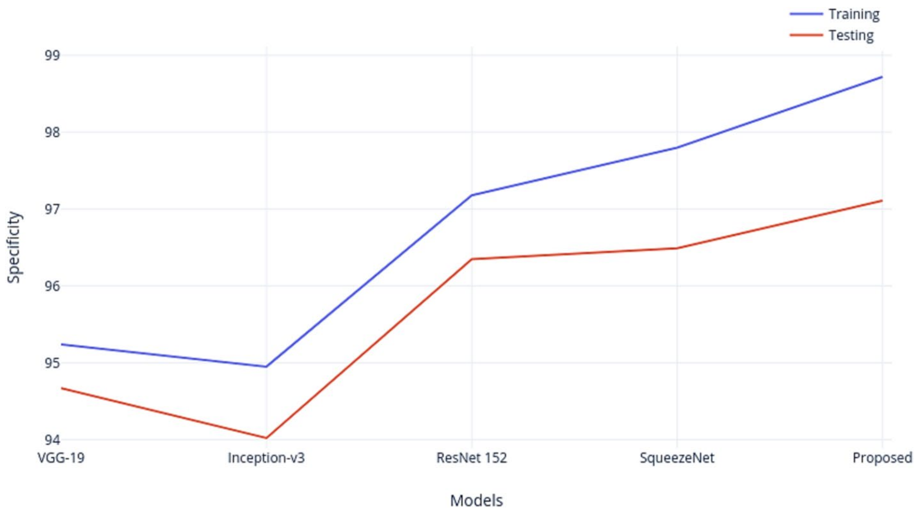


Fig. 6 Graphical Plot of Specificity

Table 5 Performance Evaluation of Precision

Models	Training	Testing
VGG-19	95.80	94.26
Inception-v3	95.12	93.92
ResNet 152	96.28	95.49
SqueezeNet	97.35	96.17
Proposed	98.71	97.50

Fig. 7 Graphical Plot of Precision

Table 6 Performance Evaluation of F1-Score

Models	Training	Testing
VGG-19	95.52	94.09
Inception-v3	95.79	93.45
ResNet 152	96.35	95.10
SqueezeNet	97.77	95.99
Proposed	98.40	97.78

$$\text{Specificity} = \frac{TN}{TN + FP}$$

Here, specificity can be defined as the prediction that the healthy cases do not have disease. The percentage of cases/subject/patients with no illness will be tested as negative. Proposed method has got 98.72% specificity for the process of training, that is 0.9% to 3.7% enhancement comparing to existing techniques. The specificity in testing is 97.11%, that is 0.6% to 3.09% increased performance than other models was shown in Fig. 6. Table 5 shows Performance Evaluation of Precision.

$$\text{Precision} = \frac{TP}{TP + FP}$$

Precision can be defined as positive predictive value. It can be measure as the cumulative predictive positive value of observations of correctly predicted positive values. If the precision value is lower, then it indicates that a large number of false positives are affected the model of classification. The model has got an 98.72% precision in the process of training, that is 1.3% to 3.6% enhanced while comparing to other techniques.

Fig. 8 Graphical Plot of F1-Score

The precision rate in the process of testing is 97.11%, that is 1.3% to 3.5% enhanced performance while comparing to the existing models was shown in Fig. 7. Table 6 depicts Performance evaluation of FI-Score.

$$\text{F1 score} = \frac{2 \times Precision \times Sensitivity}{Precision + Sensitivity}$$

The F1-score measures the accuracy of test and it is the weighted harmonic mean of precision of test and sensitivity. The f1-score is then used in managing the problem of distribution with accuracy. When the data set has imbalance classes, it was useful. The proposed model has got 98.71% F1-score in training, that is 0.6% to 2.8% enhanced while comparing to existing techniques and in testing f1-score is 97.50%, that is 1.8% to 4.3% improved performance than the existing models that was shown in Fig. 8.

2 Discussion

We present a coherent summary of the comparative analysis by addressing the disjointed discourse on the baseline model and its integration with the suggested methodology. The suggested EfficientNet-based model is compared to the conventional benchmark models, such as VGG-19, Inception-v3, ResNet 152, and SqueezeNet, based on performance measures. The study shows the improved performance of the EfficientNet model across multiple evaluation parameters by methodically evaluating accuracy, precision, recall, specificity, and F1-score. In both the stages of training and testing, the proposed approach consistently performs better than these baseline models, demonstrating its effectiveness in categorizing lung cancer photos. Compared to other well-known architectures of DL, this integration in the discussion section offers a comprehensive viewpoint on how the EfficientNet framework improves classification accuracy. Furthermore, explanations for why some models like Inception-v3 perform worse can be provided, providing a more comprehensive grasp of the advantages and disadvantages of various approaches. Readers will be able to understand the importance of implementing the EfficientNet model and how deep learning techniques might advance lung cancer diagnosis through this thorough presentation.

3 Conclusion

In this work, a prediction model for detection of lung cancer model using the techniques of deep learning is introduced. Here in the suggested DL model, the lung cancer dataset is used for evaluating processes from the cancer imaging archive database. 75% of data were used in the process of training and 25% of the data is used in testing. For detection and classification, the EfficientNet-B0 model was implemented in this research along with CNN. The CNN method is used in classification of the images for detection of glaucoma. The goal of this model is to identify lung cancer using images of CT, that will be useful in determining that if the patient is affected by cancer or not affected. The model achieved 99.28% accuracy for training, which is 0.8% to 3.42% improved compared with other techniques. The testing accuracy is 98.03%, that is 0.4% to 2.6% improved performance while comparing to the other models. Here, by the comparison of all models like VGG-19, Inception-v3, ResNet 152, and SqueezeNet, the suggested model has obtained better performance in both the process of training and testing. The model which got least performance is Inception-v3 and SqueezeNet has performance that is closer to the suggested model. In future, this proposed method can be used for other different medical image classification and disease prediction by implementing related datasets. U-Net segmentation model can be used for additional implementation for the enhancement of performance.

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Author contributions All authors are contributed equally to this work.

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Data availability Data sharing not applicable to this article as no datasets were generated or analyzed during the current study.

Declarations

Ethics approval and consent to participate No participation of humans takes place in this implementation process.

Human and animal rights No violation of Human and Animal Rights is involved.

Conflict of interest Conflict of Interest is not applicable in this work.

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