IMENet: A Deep Learning Model for Lung Cancer Detection Using Multiple Architectures

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Abstract

In the modern era of artificial intelligence and medical imaging, accurate and efficient lung cancer detection remains a critical challenge. The increasing availability of large-scale medical imaging datasets has facilitated the development of AI-driven techniques for early diagnosis. The research creates IMENet as a deep learning framework by combining InceptionV3 with MobileNetV3Large and EfficientNetB7 to achieve superior features extraction and classification results. Trainings and evaluations of the model happen using data from the LUNA16 subset of LIDC/IDRI's public database. The preprocessing starts with Discrete Wavelet Transform that reduces noise then moves to Contrast Limited Adaptive Histogram Equalization and contrast stretching for intensity correction before using log transformation to enhance low intensity values. The training and testing phases contain ratios of 80:20 split after applying Synthetic Minority Over-sampling Technique (SMOTE) to correct class imbalance. The optimization of the IMENet model uses the Adam optimizer with an optimization rate of 0.00001 while implementing batches of 200 data points during 100 training epochs. Superior performance classification abilities of the model become apparent through the evaluation metrics which include accuracy, precision, recall, F1-score, sensitivity and specificity. The generated model reaches 95.5% accuracy which exceeds the performance of CNN and SVM-CNN and RF+CNN traditional models. IMENet stands out in lung cancer detection effectiveness thus showing promise for clinical medical applications. For future advancement the model will be expanded to analyze multiple categories and will implement AI interpretation methods and needs performance adjustments to achieve real-time medical diagnosis capabilities.

Keywords: Artificial Intelligence, Deep Learning, Hybrid Learning, Image Processing, Lung cancer Detection.

1. Introduction

Lung cancer (LC) stands as a worldwide leading threat to human life because it results in substantial cancer mortality rates. The worldwide statistics show lung cancer emerges as a major cause of death because patients receive late-stage diagnoses combined with its disease progression[1]. Lung cancer stands as the primary fatal cancer worldwide based on its high incidence of 2.09 million new cases which resulted in 1.76 million deaths in 2018[2]. This disease occurs frequently throughout the world while leading to high death statistics worldwide. LC remains symptomless at diagnosis whereas its early manifestations are generally mild. The disease frequently receives diagnosis when it has progressed too far[3]. Late recognition of medical symptoms apart from lowering chances of long-term survival also decreases treatment effectiveness. NSCLC and SCLC are the two standard classifications of LC which phys

icians categorize the disease into. The NSCLC type encompasses two main subgroups including lung squamous cell carcinoma (LUSC) alongside lung adenocarcinoma (LUAD). The detailed differentiation between LUSC, LUAD, and SCLC plays a crucial function because it determines LC prognosis differently than benign and malignant classifications. The proper classification of LC during primary diagnostic evaluation leads to enhanced treatment results which ultimately improves patient survival chances. In clinical practice PET and CT operate as widely used non-invasive imaging methods which help healthcare professionals diagnose specific lung conditions[4].

Artificial intelligence draws massive attention in medical fields through its ability to analyze medical pictures both for diagnostic assessments and predictive analyses. Radiologists need good image quality alongside strong interpretation abilities to properly read medical images[5]. The human ability to interpret images remains restricted by several factors including noise combined with fatigue and aberrations among others. These issues have resolved through technological advances in imaging technology and intelligent computer systems. The field of radiology utilizes artificial intelligence to tackle multiple clinical responsibilities including risk assessment, disease detection and prognosis, medical diagnosis, treatment response monitoring and extensive scale ailment identification. These advances depend primarily on machine learning along with deep learning technology[6]. Machine learning as an AI branch uses past facts to generate predictions. Through analysis of input data machine learning systems transform data meaningfully to reveal knowledge patterns and productive system representations. Deep learning represents a subset of machine learning that is composed of multiple processing layers for computational computation.

The goal of this research paper is to study multiple AI-driven image processing approaches for lung cancer detection while evaluating their effectiveness and precision along with their potential real-world implementation. The research analysis examines multiple AI frameworks such as convolutional neural networks (CNNs), support vector machines (SVMs) and combined AI solutions alongside their corresponding benefits and weakness points. This research investigates the impact of preprocessing techniques including noise reduction and contrast enhancement and edge detection on image quality for improved cancer detection accuracy. The study also examines ways through which AI decreases both false positive and false negative results which boosts diagnostic reliability rates.

To address the challenges in lung cancer detection, this research proposes an AI-driven image processing framework that enhances diagnostic accuracy and efficiency. The study integrates advanced image preprocessing techniques, robust feature selection, precise segmentation methods, and deep learning-based classification models to improve lung nodule detection. By leveraging Discrete Wavelet Transform (DWT) for noise reduction, Adaptive Histogram Equalization (AHE) for contrast enhancement, and transfer learning for classification, the proposed approach aims to minimize false positives and false negatives in lung cancer diagnosis. The research also introduces a performance evaluation methodology based on accuracy, precision, recall, and F1-score to ensure clinical applicability. Here are the key contributions of the study:

- Develops an advanced noise reduction algorithm using Discrete Wavelet Transform (DWT) to improve the clarity of Low-Dose Computed Tomography (LDCT) images for better feature extraction.
- Enhances image contrast and visibility through Adaptive Histogram Equalization (AHE), Contrast Stretching, and Log Transformation, optimizing image quality for accurate lung nodule detection.
- Proposes a novel lung region segmentation algorithm that accurately identifies and isolates lung nodules for precise analysis.
- Introduces a transfer learning-based classification model that improves the sensitivity and specificity of lung nodule classification, distinguishing between benign and malignant cases.
- Evaluates the Computer-Aided Diagnosis (CADx) system using accuracy, precision, recall, and F1-score, ensuring reliability and effectiveness in real-world clinical applications.

The following work is organised as follows: Section I presents an overview of the issue, including the study objective, motivation, rationale, novelty, and major contributions. Sections II and III provide the literature study on this subject and outline the recommended technique, detailing each step. Section IV presents the experimental findings and discussion of the implemented AI models, accompanied by a comparative analysis. Section V presents the conclusion and outlines further work.

2. Literature Review

This section provides a literature review of existing lung cancer detection studies to explore the methods, problems and solutions.

Srivastava, Mishra and Chauhan [2024] propose a convolutional Neural Network and pretrained convolutional neural networks (CNN) architectures - VGG-16, InceptionV3, and EfficientNetB0 which is based on Transfer learning is used for the task of lung cancer detection. The photos in the dataset are separated into test, validation, and training sets. During training, they use data augmentation approaches to make the models more resilient and broadly applicable. Model performance is evaluated using accuracy and loss metrics on the test set. The results demonstrate the effectiveness of the transfer learning based model, with EfficientNetB0 achieving the highest accuracy of 94% on the test set. This work demonstrates how deep learning models may be used to diagnose and classify chest CT scan pictures, which could lead to better lung cancer treatment and detection outcomes[7].

Hisam and Hisam [2021] propose a different deep learning-based models such as DarkNet-53 (the backbone of YOLO-v3), ResNet50, and VGG19 were applied to classify CT images of patients having Corona Virus disease (COVID-19) or lung cancer. Each model's performance is presented, analyzed, and compared. The dataset used in the study came from two different sources, the large-scale CT dataset for lung cancer diagnoses (Lung-PET -CT-Dx) for lung cancer CT images while International COVID-19 Open Radiology Dataset (RICORD) for COVID-19 CT images. As a result, DarkNet-53 overperformed other models by achieving 100% accuracy. While the accuracies for ResNet and VGG19 were 80% and 77% respectively[8].

In this study, propose a CAD system which uses deep features extracted from an auto encoder to classify lung nodules as either malignant or benign. They use 4303 instances containing 4323 nodules from the National Cancer Institute (NCI) Lung Image Database Consortium (LIDC) dataset to obtain an overall accuracy of 75.01% with a sensitivity of 83.35% and false positive of 0.39/patient over a 10 fold cross validation[9].

In this article, they proposed a deep learning model based on Convolutional Neural Network (CNN) framework for the early detection of lung cancer using CT scan images. They also have analyzed other models for instance Inception V3, Xception, and ResNet-50 models to compare with our proposed model. They compared our models with each other considering the metrics of accuracy, Area Under Curve (AUC), recall, and loss. After evaluating the model's performance, they observed that CNN outperformed other models and has been shown to be promising compared to traditional methods. It achieved an accuracy of 92%, AUC of 98.21%, recall of 91.72%, and loss of 0.328[10].

Kamatagi, Jacob and Balagangadhar [2024] presents a deep learning framework combining a convolutional neural network (CNN) and a support vector machine (SVM) for lung cancer diagnosis. The model uses data divided into six groups: 250 images in the training set and 150 images in the test set. The work includes preliminary data and development using the Keras image data generator, VGG-16 architecture, high-level rules, and SVM classifier training with labels and vectors. The model achieves 90% accuracy with 85% selection impact and 75% cross-validation flexibility using VGG-16 and SVM hybrid classifier[11].

Ghazipour et al. [2023] propose a patient-specific model based on Deep Convolutional and Recurrent Neural Networks to track a treated tumor over time making a two-year post-treatment survival time prediction. They use a cohort of data from Wake Forest University that consists of pre and post radiation-treated lung cancer patients with a wide range of follow-up scans. They train our model with these data and demonstrate that our patient specific model can predict two-year survival outcome with an ROC-AUC score of 0.718 on our hold-out test set[12].

In this work, Abugabah, Mehmood and Shahid [2023] proposes three types of data samples such as Lung adenocarcinoma (Lung a), lung squamous cell carcinoma (Lung scc), and lung benign (Lung b) have been taken and implemented models, namely Group-I, II, III with frozen layers and baseline algorithms as VGG-19. To check the validity of the proposed models on lung samples and attain the best classification accuracy on Lung scc vs. Lung b 97.53%, also discriminate between Lung a vs. Lung b testing accuracy 92.59%. In contrast, the remaining Lung scc vs. Lung a attained 89.30%. Finally, a comparison to other studies demonstrating the suggested model superiority over state-of-the-art models in testing accuracy[13].

In this work, Wang and Chakraborty [2019] proposed an automatic lung cancer prognosis system. The system has 3 steps : (1) In the first step, they trained two models, one based on convolutional neural network (CNN), and the other recurrent neural network (RNN), to detect nodules in CT scan. (2) In the second step, convolutional neural networks (CNN) are trained to evaluate the value of nine morphological features of nodules. (3) In the final step, logistic regression between values of features and cancer probability is trained using XGBoost model. In addition, they give an analysis of which features are important for cancer prediction. Overall, they achieved 82.39% accuracy for lung cancer prediction. By logistic regression analysis, they find that features of diameter, spiculation and lobulation are useful for reducing false positive[14].

Prasanna et al. [2023] present a novel approach based on deep hybrid learning for classifying lung lesions. In this study, they explore multiple memory-efficient and hybrid deep neural network (DNN) architectures for image processing. Our proposed hybrid DNN significantly outperforms the current state-of-the-art, achieving an impressive accuracy of 95.21%, all while maintaining a balanced trade-off between specificity and sensitivity. The primary focus of this research is to differentiate between CT scans of patients who have early-stage lung cancer and those who do not. This is achieved by utilizing binary classification networks, including standard CNN, SqueezeNet, and MobileNet[15]. The following Table I provide a comprehensive summary of these related works discussed below.

TABLE I. Summary of Related Work on Lung Cancer Detection

Ref	Methodology	Performance	Limitations	Future Work

[7]	CNN architectures (VGG-16, InceptionV3, EfficientNetB0) using transfer learning	EfficientNetB0 achieved 94% accuracy	Limited dataset scope	Expanding dataset and testing more architectures
[8]	DarkNet-53 (YOLO-v3), ResNet50, VGG19 on CT images	DarkNet-53 achieved 100% accuracy, ResNet50: 80%, VGG19: 77%	Dataset from two sources may introduce bias	Further model optimization and testing on diverse datasets
[9]	Extracted deep features using an autoencoder to classify lung nodules as malignant or benign. Used 10-fold cross-validation on the LIDC dataset with logistic regression analysis for final predictions.	75.01% accuracy, sensitivity: 83.35%	Moderate accuracy with some false positives	Improving feature extraction and classification methods
[10]	CNN, InceptionV3, Xception, ResNet-50	CNN achieved 92% accuracy, AUC: 98.21%, recall: 91.72%	Limited generalizability	Implementing more robust validation strategies
[11]	Combined CNN (VGG-16) with an SVM classifier for lung cancer classification. Used high-level rules and trained the SVM with image feature vectors. Applied the Keras image data generator for preprocessing.	90% accuracy	Small dataset (250 training, 150 test images)	Expanding dataset size and improving feature selection
12]	Deep CNN + RNN for tumor tracking over time	ROC-AUC: 0.718	Moderate accuracy, limited post-treatment data	Extending study period and adding more patient data
[13]	ResNet, MobileNetV2, Xception, VGG16	ResNet achieved 94% accuracy, testing loss: 0.16	Limited dataset variety	Exploring ensemble models for better robustness
[14]	Developed a three-step system combining CNN, RNN, and XGBoost to detect nodules, analyze morphological features, and predict lung cancer probability. Used logistic regression for final prediction analysis.	82.39% accuracy	Feature extraction limitations	Enhancing feature selection and reducing false positives
[15]	Hybrid DNN, CNN, SqueezeNet, MobileNet	95.21% accuracy	Balancing sensitivity and specificity	Exploring other hybrid architectures

3. Research Methodology

The proposed methodology for efficient lung cancer detection begins with the collection of the LUNA16 dataset from the publicly available LIDC/IDRI database. The data undergoes preprocessing, where images are read, resized to 224×224 pixels, and converted to grayscale. Discrete Wavelet Transform (DWT) is applied to reduce noise by removing high-frequency detail coefficients. Contrast Limited Adaptive Histogram Equalization (CLAHE) enhances local contrast, followed by contrast stretching to normalize intensity distribution within the 2nd and 98th percentiles. A log transformation amplifies lower intensity values to improve overall contrast. The images are then converted back to RGB format, and corresponding cancerous or non-cancerous labels are stored for model training. To address class imbalance, SMOTE oversampling is employed, and data is split into training and testing sets with an 80:20 ratio. Labels are converted to categorical format using one-hot encoding. The hybrid IMENet model, consisting of InceptionV3, MobileNetV3Large, and EfficientNetB7, is developed for binary classification. The model's performance is evaluated using various metrics such as confusion matrix, accuracy, precision, recall, F1-score, sensitivity, and specificity. Finally, the proposed approach is compared with existing studies to highlight its novelty. The following figure 1 presents a proposed system flowchart for the lung cancer detection.

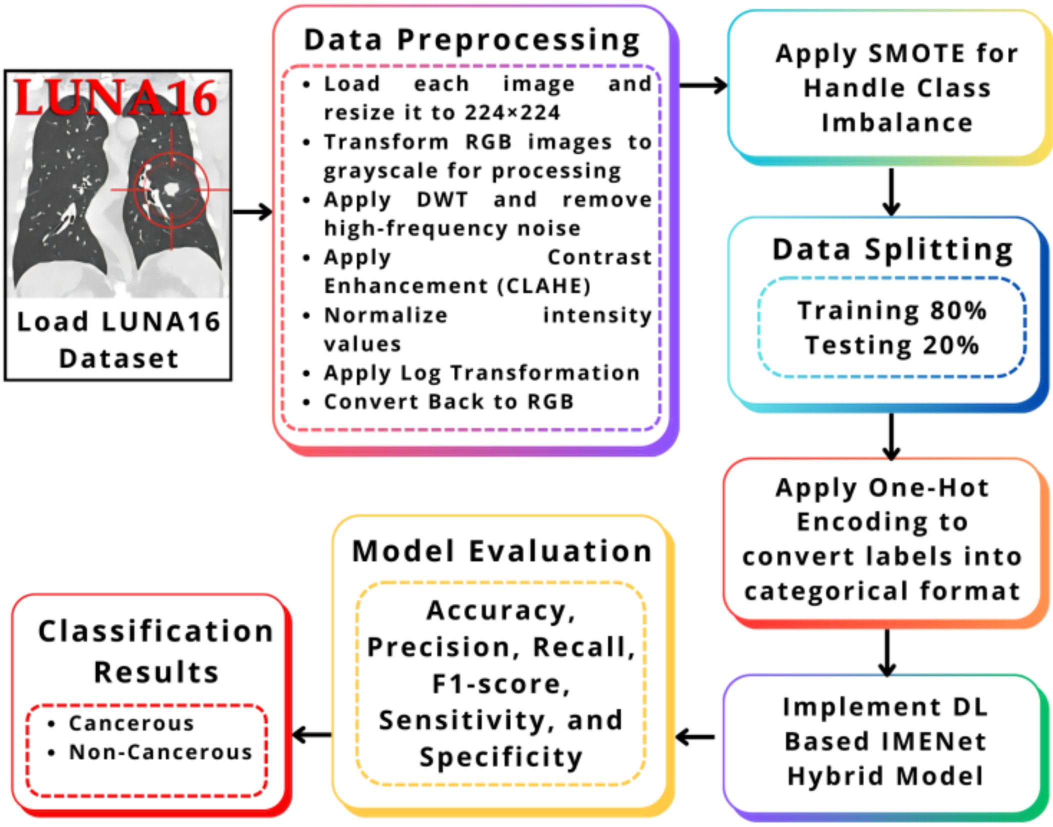

Fig. 1. Proposed System Flowchart for Lung Cancer Detection

1.1. Dataset Description

The LUNA16 dataset[16] extracted from LIDC/IDRI provides 20,094 CT scan images in DICOM format with resolution 512 × 512 × Z which establishes Z (depth) ranging between 100 to 400 slices per scan. The dataset excludes CT scans that have individual scan slice thickness larger than 2.5 millimeters. The four radiology experts who evaluated patient scans determined nodule presence. Those nodules which obtained marking agreement from three radiologists or larger than 3 mm in size were labeled as reference standards. The dataset contains information about 1,186 lung nodules through their location data and size measurements as well as the identification of cancerous or non-cancerous nodules to help researchers detect lung nodules. The following figure 2 provides the sample images of LUNA16 dataset.

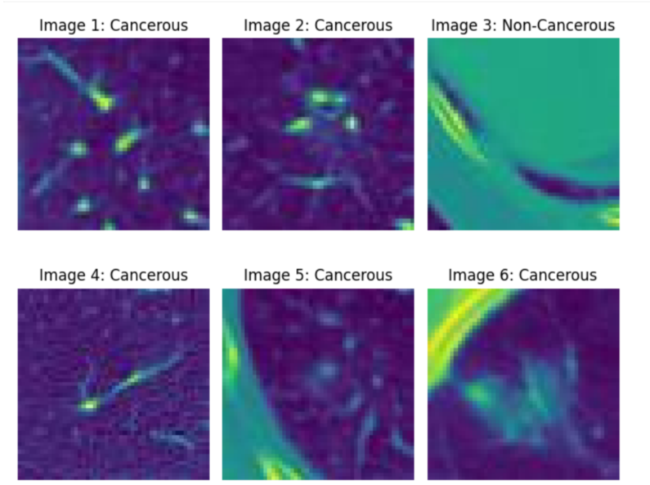

Fig. 2. Sample Images of LUNA16 Dataset

1.2. *Data Preprocessing*

The data preprocessing pipeline within this study applies multiple enhancement techniques to prepare lung images for their classification as cancerous or non-cancerous. All images undergo a series of initial steps before processing which includes reading while also applying resizing to 224×224 pixels alongside conversion to grayscale. Noise reduction occurs through Discrete Wavelet Transform (DWT) application which removes high-frequency detail coefficients before the reconstruction process. The system applies Contrast Limited Adaptive Histogram Equalization (CLAHE) to improve unique contrast features thus enhancing feature visibility. The normalization of intensity distribution occurs through contrast stretching which adjusts pixel values between the 2nd and 98th percentile values. A log transformation increases lower intensity values before better theoretical contrast levels are achieved. The image conversion from grayscale back to RGB happens at the end of preprocessing since it creates proper inputs for the model. The preprocessed images are combined with their cancerous or non-cancerous labels which will be used later during model training. The systematic preprocessing technique shapes the dataset into a form that improves both feature extraction quality and classification results.

1.3. *Visualisation Results after preprocessing*

To find out the hidden insights from the large amount of data is essential in machine learning. This section provides the exploratory data analysis of the proposed LUNA16 dataset to the relevance of this study.

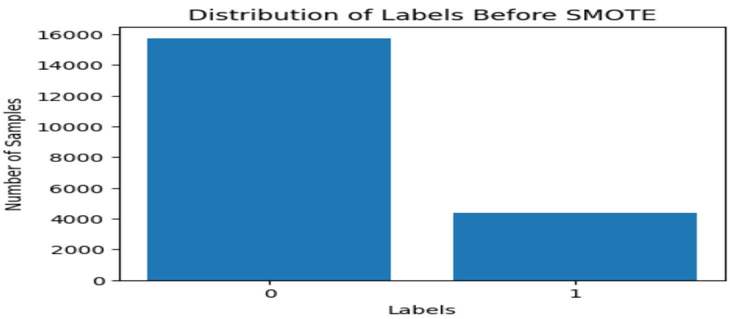

Fig. 3. Count Plot for Distribution of Labels Before Apply SMOTE on LUNA16 Dataset

The distribution of labels in the LUNA16 dataset appears as shown in Figure 3 before Synthetic Minority Oversampling Technique (SMOTE) application. The dataset displays a class imbalance scenario because label 0 contains approximately 15,800 instances while the number of label 1 instances remains below 4,400. The minority class contains 4,400 samples while the substantial majority class consists of 15,800 samples which demonstrates a significant population discrepancy. The initial class inequality demonstrates the necessity for SMOTE and similar methods to resolve minority class scarcity to enhance machine learning model functionality.

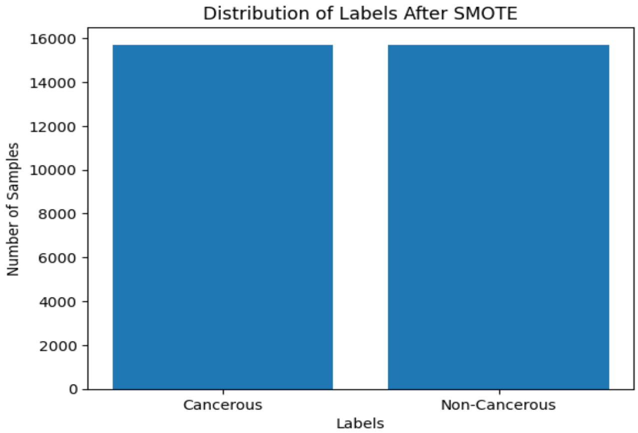

Fig. 4. Count Plot for Distribution of Labels After Apply SMOTE on LUNA16 Dataset

Figure 4 presents the label distribution outcomes after applying SMOTE on LUNA16. The dataset achieves balanced class distribution after SMOTE processing so that "Cancerous" contains 15,783 samples yet "Non-Cancerous" also contains 15,783 samples. The equal distribution of samples between the two classes makes the training process more effective by resolving the initial unbalanced nature of the original dataset.

1.4. Deep Learning Model

This section presents the overview of the proposed deep learning based models that has been utilised to build an efficient lung cancer detection system.

1) InceptionV3

InceptionV3 is a deep convolutional neural network architecture designed for image classification. Developed by Google, it improves computational efficiency using factorized convolutions, asymmetric kernels, and label smoothing[17] This model combines 48 layers to create improved features from less model parameters. The model stands out because it optimizes resource usage through its small convolutional factorization technique. Each InceptionV3 layer submits multiple filters to the input data before joining the resultant outputs. Different views of the same data provide the model with an effective mechanism to recognize both cross-channel relationships and spatial correlations.

2) MobileNetV3Large

MobileNetV3 is a neural network architecture designed for mobile and edge devices with limited computational resources. The MobileNet series reaches its third version by prioritizing model efficiency as well as speed and accuracy performance. MobileNetV3-Large and MobileNetV3-Small forms part of this architecture which brings together resource-saving elements with lightweight inverted residuals[18]. This study used MobileNetV3-Large variant. This neural network maintains high efficiency because it operates on mobile and edge systems and achieves performance-speed trade-offs between accuracy and processing requirements. Its design includes depthwise separable convolutions with squeeze-and-excitation modules and hard-swish activation that boosts its performance capabilities[1]. The architecture design using Neural Architecture Search (NAS) leads MobileNetV3 to excel in image classification and object detection despite its low latency and reduced computational requirements. There are many applications of this model because its decreased FLOPs and parameter count enables real-time processing for mobile vision tasks as well as embedded AI systems and augmented reality solutions.

3) EfficientNetB7

EfficientNetB7 represents the largest model within the EfficientNet family since it delivers superior accuracy at the expense of greater computational needs. With more layers combined with wider layers and accessing high-resolution inputs EfficientNetB7 operates. EfficientNetB7 uses compound scaling for balancing its model size against performance to minimize parameter counts and computational requirements without affecting interpretive capability[19]. EfficientNetB7 decreases computation complexity by incorporating efficient architectural building blocks. The model architecture consists of squeeze-and-excitation blocks together with depthwise separable convolutions as well as Swish activation functions. NAS automatically explored different design spaces to identify maximum-performing architectures which led to the discovery of EfficientNetB7's design. The application of EfficientNetB7 requires hefty processing resources since it enables precision tasks like fine-grained image classification along with medical and satellite image processing but demands increased computation.

4) **Proposed Hybrid IMENet (InceptionV3-MobileNetV3Large-EfficientNetB7) Model**

This research presents IMENet as a deep learning model for lung cancer detection that integrates InceptionV3 with MobileNetV3Large and EfficientNetB7 which have been pre-trained on ImageNet data. The three models first remove their complete fully connected layers while applying GAP to the extracted features before uniting the processed information into one combined tensor. The processing of the concatenated feature tensor occurs through a fully connected layer with 1024 units followed by BatchNormalization, Dropout and finishes with a Dense layer for binary classification through a softmax-activated layer. The preservation of pre-trained model representations is ensured by freezing all layers so newly added layers become the only trainable components. The model optimization process employed Adam optimization with a learning rate value of 0.00001 to minimize binary cross-entropy loss through 100 epochs using a batch size of 200. A comprehensive evaluation of classification effectiveness relies on accuracy, precision, recall, F1-score and sensitivity along with specificity. IMENet improves feature extraction through multiple high-performance architecture integration thereby increasing both accuracy and reliability of lung cancer detection.

1.5. Model Evaluation

In this study, to evaluate the proposed hybrid IMENet model performance, used confusion matrix, accuracy, precision, recall, f1-score sensitivity, and specificity etc.

- Accuracy: The performance evaluation metric known as Accuracy serves as an essential tool for both machine learning and statistics when solving classification problems. Accuracy evaluates the success rate of trained parameters by counting correct observations among all observations. It is calculate by following formula in eq (1).

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \ldots\ldots (1)$$

- Precision: The precision measurement method enables evaluation of machine learning models through calculation of true positive cases against their combined total with true and false positives. The equation to calculate the precision is defined as eq (2).

$$Precision = \frac{TP}{TP + FP} \ldots. (2)$$

- Recall or Sensitivity: The performance assessment of machine learning models heavily relies on the recall measure which works as a sensitivity indicator. The measurement evaluates how well the model identifies every positive sample in its input data. A ratio determines recall where true positives count against the summation of true positives combined with false negatives. The formula to calculate recall is as follows eq (3).

$$Recall = \frac{TP}{TP + FN} \ldots\ldots\ldots (3)$$

- F1-Score: The F1-score operates as a performance assessment metric for binary classification statistical analysis. The computation of F1-score involves dividing the combined value of precision and recall with twice their product. A harmonic mean between accuracy and recall represents the F1-score. Performance scores in F1 range from zero to one with zero representing the lowest achievement and one indicating maximal achievement. The formula to calculate f1-score is as follows eq (4).

$$F1 - Score = \frac{2 * (Precision * Recall)}{Precision + Recall} \ldots (4)$$

According to these measures evaluate the performance of develop system for lung cancer detection.

1.6. Proposed Algorithm steps

Here's a stepwise breakdown of the proposed algorithm for efficient AI-driven lung cancer detection:

Step1. Data Analysis and Preprocessing

- Load LUNA16 dataset and resize images to 224×224 pixels.
- Convert to grayscale, apply DWT for noise reduction, CLAHE for contrast enhancement, and log transformation.
- Convert images back to RGB format and store labels (cancerous/non-cancerous).

Step2. Exploratory Data Analysis (EDA)

- Analyze class distribution to understand the balance between cancerous and non-cancerous cases.
- Visualize image intensity distributions to assess contrast and brightness variations.

Step3. Data Balancing & Splitting

- Apply SMOTE to handle class imbalance.
- Split data into 80% training and 20% testing.

- Convert labels to one-hot encoding for model compatibility

Step4. Model Building

- Define the IMENet hybrid model
  - Use InceptionV3, MobileNetV3Large, and EfficientNetB7 as feature extractors.
  - Apply Global Average Pooling (GAP) and concatenate extracted features.
  - Add a fully connected layer (1024 units), BatchNormalization, Dropout, and softmax activation.
  - Freeze pretrained layers, train only new layers.

Step5. Model Compilation

- Use binary cross-entropy loss and Adam optimizer (learning rate = 0.00001).

Step6. Model Training

- Train with batch size 200 for 100 epochs with early stopping.

Step7. Performance Visualization

- Visualize the training process by plotting the learning curve to monitor model performance over epochs.

Step9. Model Evaluation

- Evaluate the model's effectiveness using various performance metrics, such as accuracy, precision, recall, and F1-score, sensitivity, and specificity.
- Analyze confusion matrix and compare against CNN, SVM-CNN, and RF+CNN models.

Step9. Analyze Model Prediction

- Analyze the model prediction by testing unseen data.

By following these steps, the proposed algorithm aims to improve lung cancer detection through a robust hybrid model that leverages the strengths of deep learning techniques.

4 Results Analysis And Discussion

This section discusses the proposed model's experimental outcomes and its performance in lung cancer detection. To obtain these results study utilised a Dell PC equipped with Windows 11 operating system with 500 GB SSD and 32 GB RAM, NVIDIA GeForce RTX 4080 GPU and various Python library such as numpy, pandas matplotlib, seaborn etc. The following figures and tables shows the output results of proposed system for lung cancer detection or classification.

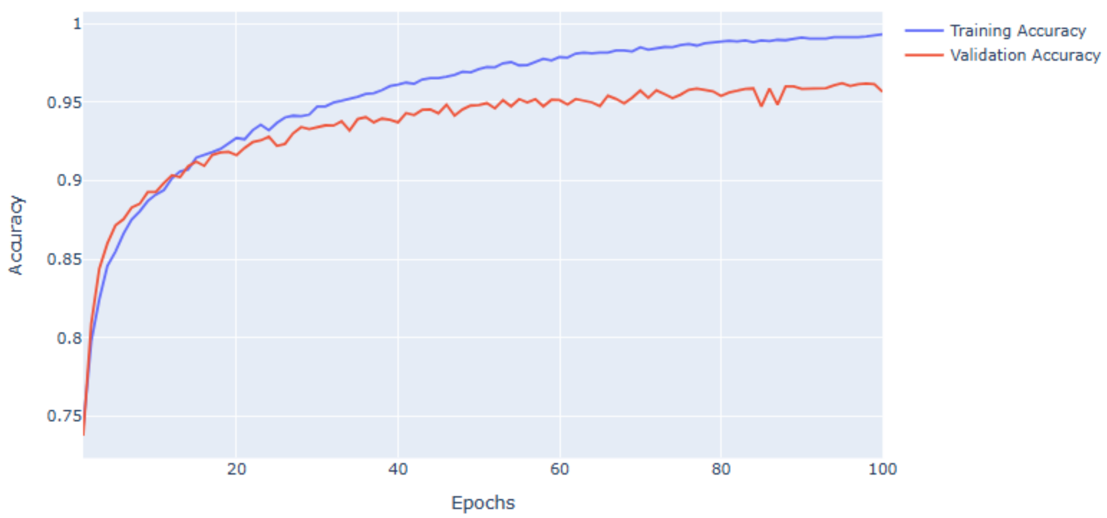

Fig. 5. Line Graph for Hybrid Model Training and Testing Accuracy on LUNA16 Dataset

During 100 epochs of training on the LUNA16 dataset the hybrid model shows its performance through Figure 5. The blue line representing training accuracy increases gradually until reaching 99.8% which demonstrates the model has mastered the training data information. Model generalization capabilities are revealed through the validation accuracy reaching 95.5% (red line). The performance and learning curve of the model are clearly displayed through this graph which proves its potential to make accurate predictions on LUNA16 database data.

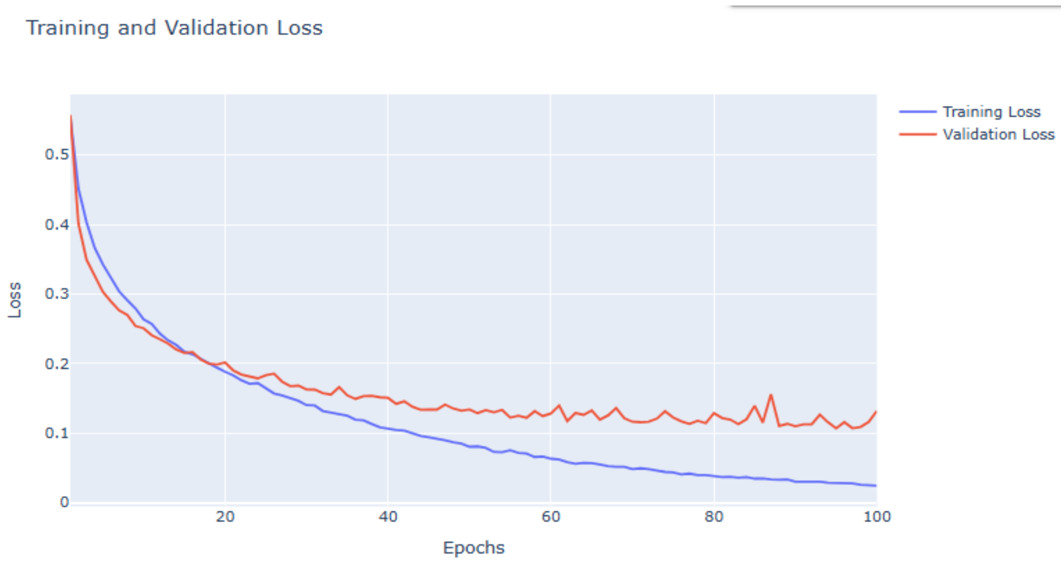

Fig. 6. Line Graph for Hybrid Model Training and Testing Losses on LUNA16 Dataset

Figure 6 illustrates the training and validation loss of a hybrid model on the LUNA16 dataset over 100 epochs. The training loss (blue line) steadily decreases to 0.008 by the 100th epoch, indicating the model's strong ability to fit the training data. The validation loss (red line) also decreases initially, but plateaus and stabilizes at 0.132 after around 20 epochs, suggesting good generalization performance on unseen data. This graph effectively demonstrates the model's learning behavior, achieving low loss values on both training and validation sets, with a slightly higher loss on validation indicating a small degree of overfitting.

```
Classification Report For Testing:
              precision    recall  f1-score   support

           0       0.99      0.93      0.96      3323
           1       0.93      0.99      0.96      2961

    accuracy                           0.96      6284
   macro avg       0.96      0.96      0.96      6284
weighted avg       0.96      0.96      0.96      6284
```

Fig. 7. Classification Report of Hybrid Model for Lungs Cancer Detection

Figure 7 shows the classification report for lung cancer detection using a hybrid model on the LUNA16 dataset. Class 0 achieved 0.99 precision, 0.93 recall, and 0.96 F1-score. Class 1 obtained 0.93 precision, 0.99 recall, and 0.96 F1-score. The overall accuracy was 0.96. All metrics demonstrate strong performance for both classes, indicating the model's effectiveness in detecting lung cancer.

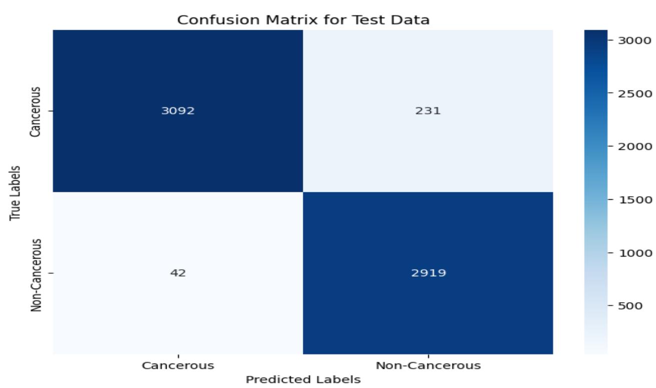

Fig. 8. Confusion Matrix of Proposed Hybrid Model on LUNA16 Dataset for Lungs Cancer Detection

Figure 8 displays the confusion matrix for a hybrid model's lung cancer detection performance on the LUNA16 dataset. The matrix reveals that the model correctly classified 3092 cancerous cases as cancerous (True Positives) and 2919 non-cancerous cases as non-cancerous (True Negatives). It also shows misclassifications, with 231 cancerous cases incorrectly identified as non-cancerous (False Negatives) and 42 non-cancerous cases wrongly classified as cancerous (False Positives). This visualization provides a comprehensive overview of the model's performance in terms of correct and incorrect classifications across both classes.

TABLE II. Performance Metrics of Proposed Hybrid IMENet Model for Lung Cancer Detection

Evaluation Metrics	Training Results	Testing Results
Accuracy	99.8	95.5
Precision	99.9	95.7
Recall	99.9	95.7
F1-Score	99.9	95.7
Sensitivity	100.00	93.0
Specificity	99.7	98.5

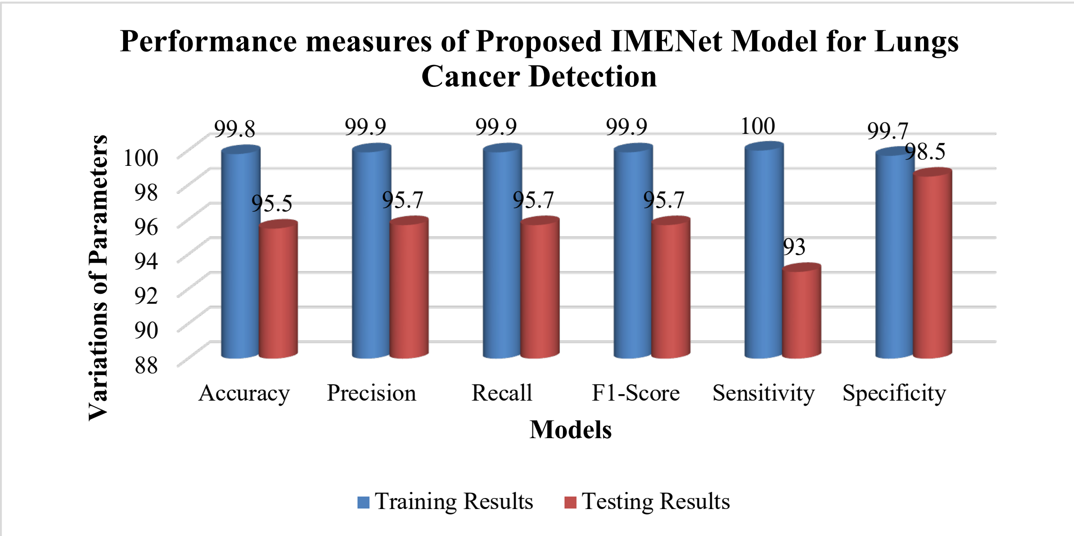

Fig. 9. Performance Bar Graph of Classification Metrics of Proposed Hybrid IMENet Model for Lung Cancer Detection

Figure 9 displays evaluation outcomes from the proposed IMENet model during lung cancer detection through six performance indicators namely Accuracy and Precision and Recall and F1-Score and Sensitivity and Specificity. The graph shows how each performance metric performs between training blue bars) and testing (red bars) in a direct evaluation of different assessment measures. Near perfect results were achieved from the training process with Accuracy at 99.8% and Precision at 99.9%, Recall at 99.9%, F1-Score at 99.9%, Sensitivity at 100% and Specificity at 99.7%. Testing results show high levels of metric achievement as the data demonstrates Accuracy (95.5%) combined with Precision (95.7%) and Recall (95.7%), F1-Score (95.7%), Sensitivity (93%) and Specificity (98.5%). This visualization highlights the model's overall effectiveness in lung cancer detection while also showcasing the slight drop in performance when transitioning from training data to unseen testing data.

TABLE III. Comparison between existing and proposed models for Lung Cancer Detection

Performance Measures	Proposed IMENet	SVM+CNN[20]	TL-based CNN[21]	CNN[20]	RF+CNN[20]
Accuracy	95.5	94	88.41	92	90
Precision	95.7	95	73.48	93	91.5
Recall	95.7	94.5	85.38	86	90
F1-Score	95.7	94.5	78.83	89	90

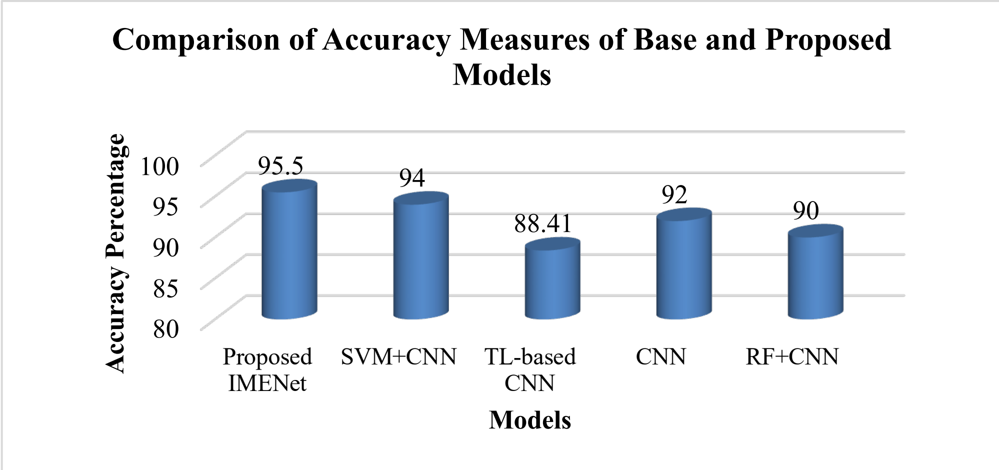

Fig. 10. Comparative Analysis of Accuracy Metrics of Base and Proposed Models for Lungs Cancer Detection

The above-mentioned Table III and Figure 10 presents a comparative bar graph illustrating the accuracy of existing and proposed models evaluated on the LUNA16 dataset. The y-axis represents the accuracy in percentage, and the x-axis denotes the different models. The proposed IMENet model achieves the highest accuracy of 95.5%, significantly outperforming the other models. SVM-CNN reaches 94%, while CNN achieves 92%. RF+CNN demonstrates an accuracy of 90%, and the TL-based CNN shows the lowest accuracy among the compared models at 88.41%. This visualization effectively showcases the superior performance of the proposed IMENet model in lung cancer detection.

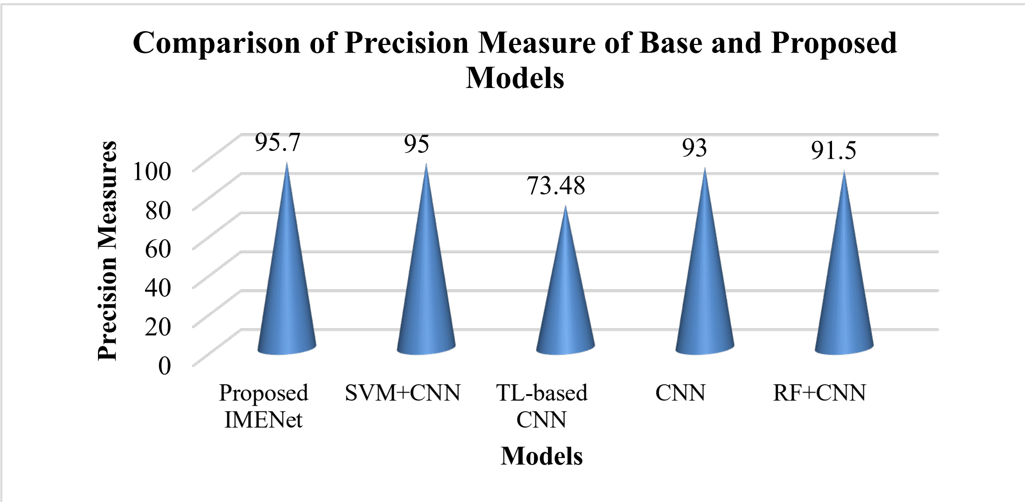

Fig. 11. Comparative Analysis of Precision Metrics of Base and Proposed Models for Lungs Cancer Detection

The above-mentioned Table III and Figure 11 show a comparative bar graph illustrating the precision of existing and proposed models evaluated on the LUNA16 dataset. The y-axis represents the precision in percentage, and the x-axis denotes the different models. The proposed IMENet model achieves the highest precision of 95.7%, significantly outperforming the other models. SVM-CNN reaches 95%, while CNN achieves 93%. RF+CNN demonstrates an precision of 91.5%, and the TL-based CNN shows the lowest precision among the compared models at 73.48%. This visualization effectively showcases the superior performance of the proposed IMENet model in lung cancer detection.

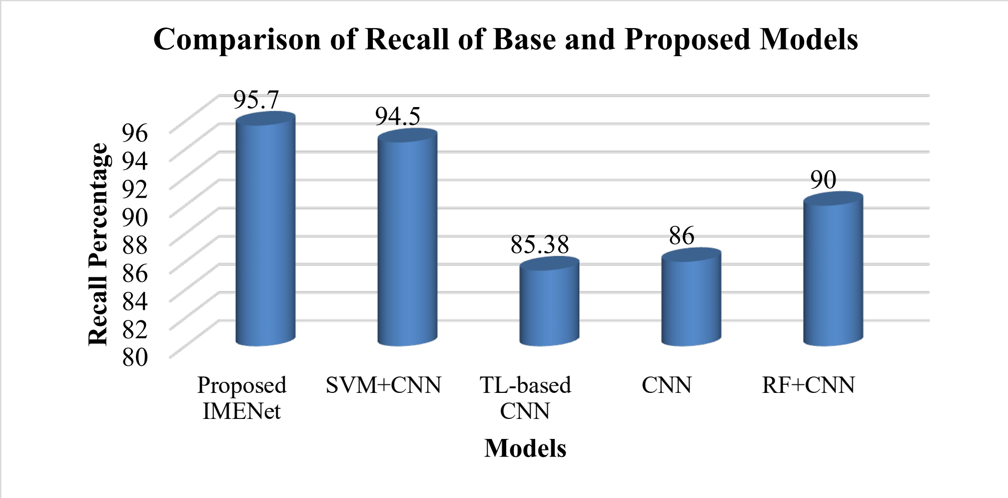

Fig. 12. Comparative Recall of Accuracy Metrics of Base and Proposed Models for Lungs Cancer Detection

The above-mentioned Table III and Figure 12 show a comparative bar graph illustrating the recall of existing and proposed models evaluated on the LUNA16 dataset. The y-axis represents the recall in percentage, and the x-axis denotes the different models. The proposed IMENet model achieves the highest recall of 95.7%, significantly outperforming the other models. SVM-CNN reaches 94.5%, while CNN achieves 86%. RF+CNN demonstrates an recall of 90%, and the TL-based CNN shows the lowest recall among the compared models at 85.38%. This visualization effectively showcases the superior performance of the proposed IMENet model in lung cancer detection.

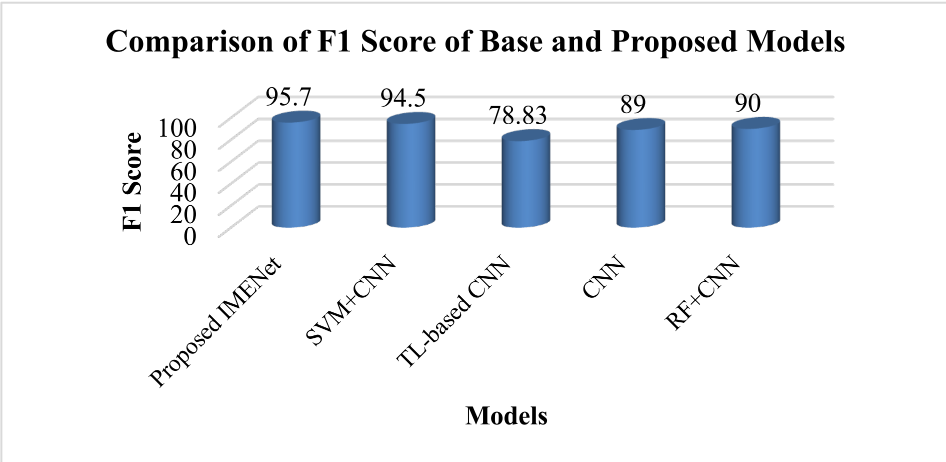

Fig. 13. Comparative Analysis of F1-score Metrics of Base and Proposed Models for Lungs Cancer Detection

The above-mentioned Table III and Figure 13 show a comparative bar graph illustrating the f1-score of existing and proposed models evaluated on the LUNA16 dataset. The y-axis represents the f1-score in percentage, and the x-axis denotes the different models. The proposed IMENet model achieves the highest f1-score of 95.7%, significantly outperforming the other models. SVM-CNN reaches 94.5%, while CNN achieves 89%. RF+CNN demonstrates an f1-score of 90%, and the TL-based CNN shows the lowest f1-score among the compared models at 78.83%. This visualization effectively showcases the superior performance of the proposed IMENet model in lung cancer detection.

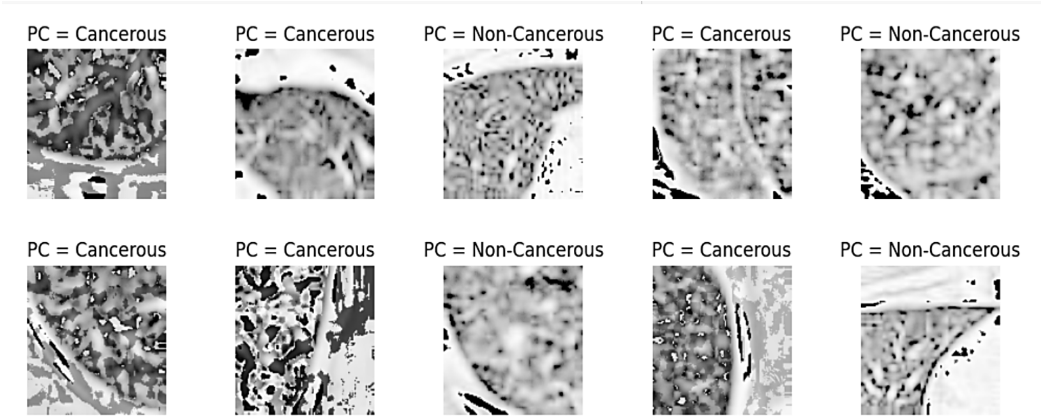

Fig. 14. Prediction Images of Proposed IMENet Model for LUNA16

Figure 14 shows the prediction images of the proposed IMENet model for lungs cancer detection. The model provides the correct prediction as shows in the output images. Each image is correctly labeled as cancerous and non-cancerous.

5 Conclusion and Recommendations

Overall, the combination of InceptionV3 MobileNetV3Large and EfficientNetB7 in the proposed IMENet model establishes superior performance in detecting lung cancer than alternative models while achieving enhanced accuracy and precision and recall rates and F1-score values. The multiple image preprocessing steps which include DWT along with CLAHE coupled with contrast stretching and log transformation produced enhanced image quality that enhanced feature extraction together with classification outcomes. SMOTE combined with the hybrid deep learning approach enables the model to improve diagnostic reliability by effectively reducing false positive and negative rates from class unbalance. Automatic medical imaging detection techniques powered by AI show tremendous value as a strong and efficient system for detecting lung cancer at an early stage. The proposed model requires future development to support multiple stage lung cancer classification for creating a more precise diagnostic system. Medical professionals gain better understanding of the decision-making procedure through explainable AI processes that improve model interpretability. The model requires additional optimization for real-time clinical use in computer-aided diagnosis systems which can enhance deployment within healthcare environments. The accuracy and generalizability of the model can improve through expansion of the patient data to include diverse demographics and implementation of three-dimensional CT scan research. AI improvements and deep learning advancements will help the proposed detection system transform lung cancer diagnostics to provide better and quicker medical assistance.

AUTHOR STATEMENTS:

Ethical Approval:

Any studies of human participants or analysis of animals are not carried in the conducted research. It is based entirely on publicly available imaging datasets (LUNA16) for experimental evaluation.

Conflict of Interest:

Another thing that the authors assert lacks any conflicting financial or personal relations that could have been involved in doing the work done, or in the article that they present in the paper.

Acknowledgement

The authors would wish to mention the contributors to the LUNA16 dataset for providing open access to medical imaging data, which served as the foundation for this research.

Author Contributions

Each of the authors has equally assisted in the design, experiment, analysis, and writing of the study. Both authors make consent on the final manuscript version.

Funding Information

No specific grants given by the funding agencies either in the government, corporate or non-financial sectors supported the study.

Data Availability Statement

The dataset of the proposed study (LUNA16) is found openly in the internet [https://luna16.grand-challenge.org/Data/]. Nevertheless, the corresponding author will also provide any other processed or experimented data in aid of this research on reasonable demand.

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