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# Automatically Segmenting and Classifying the Lung Nodules from CT Images

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**Abstract:** Lung cancer, a widespread and potentially disastrous type of cancer, requires urgent action to prevent catastrophic consequences caused by delayed medical care. Currently, Computed Tomography (CT) scans are used to assist doctors in detecting lung nodules at an early stage. However, the accuracy of lung nodules diagnosis heavily relies on the expertise of physicians, which can lead to potential oversight of specific patients and subsequent difficulties. As a result, deep learning has emerged as a highly considered and effective method in various medical imaging fields, including lung cancer and nodules detection. In this paper, we proposed a Custom-VGG16 model to analyze CT images of lungs and accurately classify malignant lung nodules. The Custom-VGG16 model was tested using the LIDC-IDRI database to evaluate its effectiveness. The experimental results highlight the remarkable performance of the Custom-VGG16 network, achieving an accuracy rate of 95%. Furthermore, the results indicated that the Custom-VGG16 network outperforms both the VGG16 and CNN models in detecting lung nodules.

***Keywords:*** *Deep Learning, CNN, LIDC-IDRI, VGG16*

## 1. Introduction

Lung cancer is the most common form of cancer in both men and women worldwide, significantly burdening public health. In 2015, it was estimated that there were approximately 221,200 new lung cancer cases, accounting for about 13% of all cancer diagnoses. Moreover, lung cancer accounts for around 27% of all cancer-related deaths. Due to these alarming statistics, it is crucial to carefully examine and closely monitor lung nodules, especially in their early stages. Early detection plays a vital role in improving the chances of survival. Early diagnosis and prompt treatment significantly increase the chances of successfully healing lung cancer[1][9]. As a result, the first and critical step is to undergo lung cancer screening, which involves using advanced identification methods to improve patient outcomes. Different methods for diagnosing lung cancer are available, including MRI, isotope scanning, X-ray, and CT scan. X-ray chest radiography and Computer Tomography (CT) are commonly used to identify lung diseases[2][3][27][28][29]. Physicians and radiologists rely on CT images to detect diseases, visualize their structural features, describe the patterns and severity, and evaluate how the diseases progress and respond to treatment. On the other hand, Lung nodule detection is the process of identifying small masses or lesions in the lung tissue that may indicate the presence of lung cancer.

Machine learning algorithms can aid in detecting lung nodules by analyzing medical images such as X-rays, CT scans, and MRI scans. Various datasets are created to perform the research to detect lung cancer and nodule detection. The well-known dataset are LIDC-IDRI (The Lung Image Database Consortium and Image Database Resource Initiative), NLST (National Lung Screening Trial), Kaggle Data Science Bowl 2017, JSRT (Japanese Society of Radiological Technology), DDSM (Digital Database for Screening Mammography), SPIE-AAPM Lung CT Challenge, SPIE-AAPM-NCI Lung CT Challenge, etc. are available in the present scenario[5][20][30][31][33]. All the mentioned datasets are images of CT and X-ray-related images. Various stages

are there to research the image datasets using machine learning or Neural networks algorithms. Based on the model, the image dataset needs pre-processing and feature extractions before classification. Image pre-processing techniques such as Image normalization, Image denoising, Image enhancement, Image registration, Image segmentation, etc., and image feature extraction techniques SIFT, LBP, GLCM, Shape-based features, etc., are used to perform better classification[6][14][21][22][34][35].

In addition, various machine learning algorithms are used to classify lung cancer images. Machine learning algorithms are utilized to classify lung cancer based on different data types, such as medical imaging, patient records, or genetic information. Several algorithms are commonly used for this purpose. The algorithms include Logistic Regression, SVM, Random Forest, XGBoost, AdaBoost, Naive Bayes, etc. On the other hand, neural network algorithms such as CNNs, RNNs, DBNs, LSTMs, and potentially DRL have been implemented for lung

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cancer classification[16][17][24][32][37][38]. [6] have developed an innovative approach to identify lung cancer in CT scans using advanced deep learning techniques. This method involved a series of preprocessing steps to identify specific lung regions more susceptible to cancer. They extracted features by UNet and ResNet. These features are then used as input for multiple classifiers, including XGBoost and Random Forest. They have achieved an impressive accuracy rate of 84% on the LIDC-IRDI dataset. [10] have developed an advanced system for automatically predicting the prognosis of lung cancer. They created and trained two convolutional neural networks (CNN) and recurrent neural networks (RNN) models. These models are designed to identify nodules in CT scans, potential indicators of lung cancer. Convolutional neural networks are used to analyze nine specific characteristics of the identified nodules. By training the CNNs, they could evaluate the importance of these characteristics in the presence of cancer. Finally, they employed an XGBoost model to train a logistic regression that establishes a connection between the values of the identified factors and the probability of lung cancer. This model yielded an impressive accuracy rate of 82.39% in predicting lung cancer. [11] have proposed a system using MATLAB to implement image processing and machine learning techniques. The process involves preprocessing the CT image and then extracting features. The SVM algorithm has been implemented to classify the lung CT images. [21]Advanced techniques such as Optimal Deep Neural Network (ODNN) and Linear Discriminant Analysis (LDA) were used to detect lung cancer. Various features were extracted from the CT lung images and reduced their complexity. The ODNN model was applied to the CT images and further enhanced using the Modified Gravitational Search Algorithm (MGSA) to improve the accuracy of lung cancer classification. The proposed classifier achieved an overall accuracy of 94.56%.

***Contribution***

Our research focuses on identifying lung nodules, segmenting them, and classifying them based on size.

1. **Improved Nodule Detection**: By developing algorithms or models to identify lung nodules accurately, we can contribute to the early detection of potentially cancerous growths. Early detection is crucial for timely treatment and better patient outcomes.

2. **Accurate Segmentation**: Segmenting lung nodules from medical images allows for precise localization and analysis. Accurate segmentation can aid in quantifying nodule characteristics, such as size and shape, essential factors in diagnosing and monitoring lung cancer.

3. **Size-Based Classification**: Classifying lung nodules based on size can provide valuable information regarding their potential malignancy. Larger nodules indicate a higher risk of malignancy and may require immediate attention.

4. **Prognostic Value**: Size-based classification of lung nodules can also have prognostic implications. Research has shown that the size of lung nodules is associated with the risk of malignancy and patient prognosis.

***Organization***

To ensure a coherent flow, the remaining sections of this paper are organized as follows:

Section 2 provides a comprehensive literature survey, offering insights into various research papers concerning lung diseases.Section 3 delves into the methodology proposed in this study. It encompasses a detailed description of the dataset employed, the implementation steps for the Custom-VGG16 model, and architecture tables that compare VGG16 and Custom-VGG16.The complete results of the proposed model are presented in Section 4, accompanied by a comparative analysis against existing models. Subsequently, the conclusion and a discussion of future work are presented.

## 2. Liturature Survay

So many researches worked on lung cancer prediction like Song et al. [1] proposed deep neural networks to classify lung nodules as either benign or malignant using CT scans. Three different types of networks such as CNN, DNN, and SAE, were used and tested on a public database of lung nodules. The results showed that CNN performed best, correctly identifying 84.15% of nodules as benign or malignant. This suggested that CNN could learn and recognize the features distinguishing benign from malignant nodules in the CT scans. Asuntha et al.[2] developed a new algorithm called FPSOCNN to improve the efficiency of the classification of lung nodules. Researchers used a large database of thoracic CT scans called the LIDC dataset to assess the accuracy of various methods for identifying benign and malignant pulmonary nodules. This dataset contains over 1000 scans, and pulmonary nodules can appear in multiple slices of the scan. This research has achieved the 95.62% accuracy. Sori et al. [3] introduced DFD-Net technique to improve the accuracy of detecting lung cancer in CT scan images. This method involves two key steps: first, the utilization of DR-Net to reduce image noise, and then the utilization of a two-path convolutional neural network to identify cancerous regions. The researchers employed two datasets to train and validate the DFD-Net model: the Kaggle Data Science Bowl 2017 and LUNA 16. The Kaggle dataset comprised 2,101 labeled instances, where a value of 0 indicated a normal or cancer-free result, while a value of 1 indicated an abnormal or cancerous outcome. Impressively, the DFD-Net model achieved an accuracy of 87.46%. Sreekumar et al.[4] involved in analyzing CT scans to detect the lung nodules, and features are extracted using a 3D CNN model based on the C3D network architecture. The LIDC-IDRI dataset and LUNA16 grand challenge datasets are utilized to reduce false-positive results. The model can detect the location of cancerous lung nodules and highlight them in the CT scans. This model achieved an accuracy of 86% for detecting malignant nodules and anticipating their cancerous severity.

Most of the researches just concentrated on diagnosing like Cengil et al.[5] proposed a method for diagnosing lung cancer uses a popular software library called TensorFlow. The technique relies on a database called SPIE-AAPMLungX, which contains CT scan images of 70 patients. Out of these patients, 10 are used for initial training, while 60 are used for further training. In this research 3D convolutional neural network is used to classify the data. This network architecture allows for a more comprehensive analysis of the images by considering three dimensions instead of just two. It involves processing a 4D image representation, including parameters for depth, height, width, and channels. Including the "depth" dimension allows the network to examine the images more thoroughly, enabling better detection of lung cancer nodules. Bhatia et al. [6] introduced a machine-learning approach to identify lung cancer in CT scans using deep learning. Their methodology involved a series of preprocessing techniques designed to improve the visibility of lung regions, followed by feature extraction using UNet and ResNet models. In addition, the team employed an ensemble strategy to boost accuracy even further, combining multiple classifiers, including XGBoost and Random Forest. This approach achieved a noteworthy accuracy rate of 84% during testing on the LIDC-IRDI dataset.

Heuvelmans et al. [7] evaluated the effectiveness of the Lung Cancer Prediction Convolutional Neural Network (LCP-CNN), a deep learning model, in accurately classifying indeterminate nodules. The researchers trained the LCP-CNN using ultrasound (US) screening data and assigned a malignancy score to each nodule. To conduct their investigation, they utilized CT scans from the LUCINDA study, which included patients from reputable referral centers in the United Kingdom, Germany, and the Netherlands. To maintain high sensitivity, the researchers devised a test to distinguish benign nodules and identify non-cancerous ones. The study's results showcased the impressive performance of the LCP-CNN, achieving an overall accuracy rate of 94.5%.Yanfeng et al.[8] have proposed a model to identify the lung nodules in thoracic MR images utilizing deep learning techniques. Researchers employed a Faster R-CNN network with carefully optimized parameters, along with the creation of spatial three-channel inputs and transfer learning techniques. These strategies enable the network to locate regions corresponding to lung nodules precisely. To evaluate the proposed method, the researchers conducted experiments utilizing 142 T2-weighted MR scans obtained from a particular hospital. The model provided an accuracy of 85.2%.

But Qing et al.[9] introduced a new approach to detecting small-cell lung cancer using an advanced computer algorithm based on neural networks. The algorithm, known as the entropy degradation method (EDM), uses high-resolution computed tomography (CT) scans to detect the early signs of lung cancer. The study included a sample of 12 lung CT scans, half from healthy lungs, while the other half from patients diagnosed with small cell lung cancer. To train the algorithm, five scans from each group were employed, and the remaining two scans were reserved for testing. The algorithm could detect small-cell lung cancer with an impressive 77.8% accuracy. Chethan et al.[11] described an approach for analyzing CT images of the lungs. The method utilizes several techniques, including image processing, segmentation, feature extraction, and classification, to identify the left and right lungs and extract 33 features from each one. The features were then inputted into a machine learning algorithm called Support Vector Machine (SVM) for further classification. MATLAB was used to implement the system, which achieved an accuracy rate of 86.25%.

Bhandary et al. [12] developed a Deep-Learning (DL) framework to detect lung pneumonia and cancer. The framework employed two different DL methods to ensure accurate classification. The first method utilized a modified AlexNet (MAN) version to classify chest X-Ray images as usual or pneumonia cases. The second method combined handcrafted and learned features to improve the accuracy of lung cancer detection. The performance of the DL framework was evaluated using benchmark lung cancer CT images from the LIDC-IDRI dataset, achieving an impressive classification accuracy of over 97.27%. In addition, the proposed approach was also tested on lung CT images from the same dataset, using MAN with an SVM classifier, resulting in a classification accuracy of 86.47%. Moreover, by integrating the improved DL framework with the EfficientNet (EFT) architecture, comparable levels of accuracy exceeding 97.27% were achieved.

All these researches used deep learning and machine learning techniques in predicting and diagnosing lung cancer using various imaging modalities such as CT scans and MR images. In addition, they highlight the advancements in accuracy rates, ranging from 77.8% to over 97.27%, and the effectiveness of different network architectures and algorithms for lung cancer detection.

## 3. Methodology

We implemented a deep learning model that uses Convolutional Neural Networks (CNNs) to segment and detects malignant lung nodules from CT (computed tomography) images.

CT imaging is a powerful diagnostic tool that uses X-rays to produce detailed images of the body. However, the interpretation of these images can be challenging, especially when it comes to detecting minor abnormalities like lung nodules. Deep learning models have shown promising results in automating the detection process, potentially improving the accuracy and speed of diagnosis.

The implemented deep learning model takes a 512*512 input from each CT image and uses it as input to the CNN. The model architecture is illustrated in Figure 1. The model consists of multiple layers of convolutional, pooling, and activation functions. A final layer outputs a segmentation mask indicating the location and size of malignant nodules in the CT image.

### *3.1 Data set*

We employed the LIDC-IDRI dataset [36] containing lung CT images that multiple radiologists have annotated to identify malignant nodules. This dataset consists of 1018 low-dose CT images from 1010 patients, with each image annotated by four radiologists. The annotations classify each CT image into one of three categories: nodules smaller than 3mm, nodules larger than 3mm, and non-nodule samples. Examples of preprocessed lung CT images with nodules and the corresponding nodule segmentation are showcased in Figure 2 and Figure 3. The dataset comprises 62,492 images, including 40,772 nodules and 21,720 non-nodules.

To facilitate the training and evaluation of our deep learning model, we partitioned the LIDC-IDRI dataset into three distinct subsets: a training set, a testing set, and a validation set. The training set encompasses 70% of the total images, the testing set accounts for 20%, and the validation set makes up the remaining 10%. For a detailed breakdown of the sample distribution across the sets, please refer to Table 1, which illustrates the specific allocation of samples for training, testing, and validation purposes.

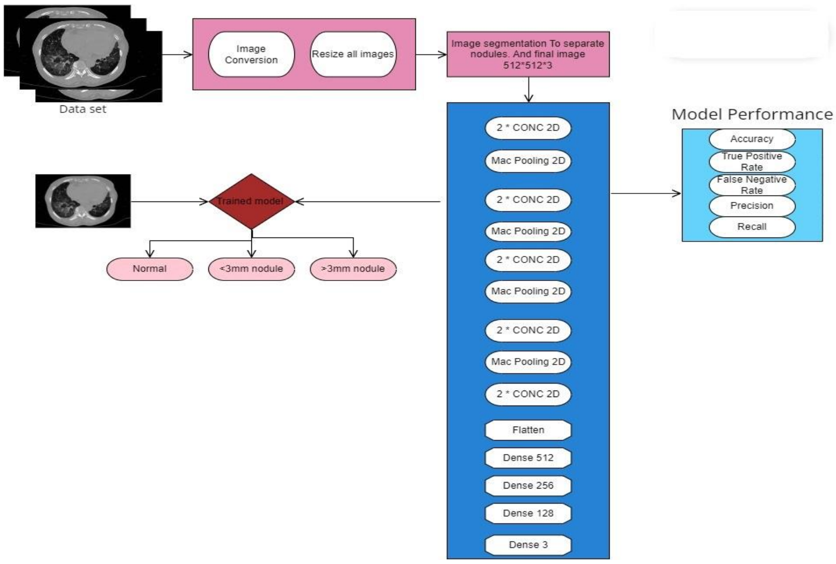


**Fig 1.** Proposed model architecture

**Table 1.** LIDC-IDRI data set for training and testing

| | **Number of samples with nodules** | **Number of samples without nodules** |
|---|---|---|
| **Training samples** | **28540** | **15204** |
| **Testing samples** | **8154** | **4348** |
| **validation** | **4077** | **2172** |

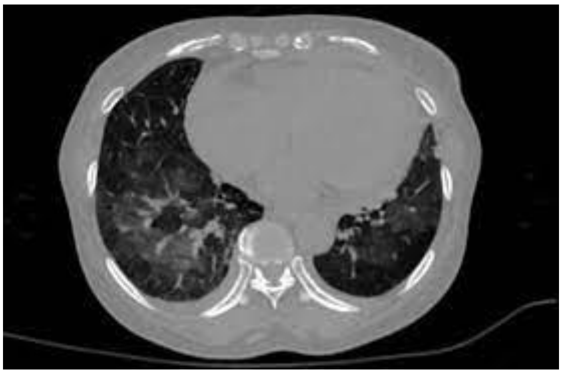

**Fig 2.** Sample lung CT image

### *3.2 Implementation*

Figure 1 presents a deep-learning model we developed to detect small nodules in CT images. Our preprocessing steps involved converting the images to grayscale and resizing them to 512*512.Next the proposed model named as Custom-VGG16 constructed as five convolution layers with max pooling to identify the nodules, followed by four fully connected dense layers. The output is obtained from the last layer, which uses a softmax activation function with dimensions of 3*1.

The Convolutional layers extracted features from the input image (I) by performing convolution operations using a set of filters (W) learned during training., This produced a set of feature maps (F). The convolution operation can be represented mathematically using equation 1.

$$f(x, y) = \sum(I * W)(x, y) \qquad (1)$$

Equation 1 defines the spatial coordinates of the feature maps as (x, y). The convolution operation (*) entails multiplying every element of the filter (W) by the corresponding element of the input image (I). The resultant products are subsequently summed to generate a singular scalar value.

$$p(x, y) = Max\_Pool(f)(x, y) \qquad (2)$$

The feature maps spatial dimensions were effectively decreased by incorporating pooling layers, which employed downsampling techniques such as max pooling. The pooling operation can be symbolically expressed as (2), where "Pool" indicates the pooling operation, and (x, y) represents the spatial coordinates of the resulting pooled feature maps.

The fully connected layers, known as dense layers, performed the final classification. First, the dense layers (3) applied linear transformations to the input, followed by activation functions such as ReLU and softmax to generate output predictions.

$$y = f(wx + b) \qquad (3)$$

Where y represents the output predictions, f denotes the activation function, W and b denote the learnable weights and biases, and X represents the input to the layer.

During training, the CNN model learned to map input images to output predictions through a process known as forward propagation. Then, the model's predictions were compared to the ground truth labels using a loss function (4), such as cross-entropy, for classification.

$$loss(y_{true}, y_{pred}) = \frac{1}{m} - \sum_{c=1}^{C}(y_c \log(p_c)) \qquad (4)$$

where Y_true represents the ground truth labels, Y_pred denotes the model's predictions, and Loss denotes the specific loss function used. C represents the number of classes, $y_c$ represents the ground truth label for class c, and $p_c$ represents the predicted probability for class c.

In Table 2, we specify the key hyperparameters used in our model. A learning rate of 0.001 was chosen as it is commonly used for training Custom-VGG16 model. To prevent overfitting, we implemented a dropout rate of 0.03, meaning that 3% of the parameters were randomly dropped during each training iteration. We used the popular Adam optimizer algorithm for training our neural network, as it adapts the learning rate over time. Finally, we employed the ReLU and Softmax activation functions widely used in CNNs. Table 3 will illustrates the number of parameters trained in each layer for existing VGG16 and Table 4 illustrates the number of parameters trained in each layer in proposed Custom-VGG16 model.

**Table 2**. Hyperparameters tuned for Custom-VGG16

| **Parameters** | **values** |
|---|---|
| Learning rate | 0.001 |
| Batch size | 32 |
| CNN dense layers | 4 |
| CONV 2D layers | 5 |
| Number of epochs | 100 |
| Activation | Relu, softmax |
| Optimizer | Adam |
| Drop out | 0.50 |
| Loss | Categorical cross entropy |

**Table 3.** Number of parameters trained in each layer of VGG16

| **Layer (type)** | **Output Shape** | **Param #** |
|---|---|---|
| input_1 (InputLayer) | 768, 768, 3 | 0 |
| block1_conv1 (Conv2D) | 768, 768, 64 | 1792 |
| block1_conv2 (Conv2D) | 768, 768, 64 | 36928 |
| block1_pool (MaxPooling2D) | 384, 384, 64 | 0 |
| block2_conv1 (Conv2D) | 384, 384, 128 | 73856 |
| block2_conv2 (Conv2D) | 384, 384, 128 | 147584 |
| block2_pool (MaxPooling2D) | 192, 192, 128 | 0 |
| block3_conv1 (Conv2D) | 192, 192, 256 | 295168 |
| block3_conv2 (Conv2D) | 192, 192, 256 | 590080 |
| block3_conv3 (Conv2D) | 192, 192, 256 | 590080 |
| block3_pool (MaxPooling2D) | 96, 96, 256 | 0 |
| block4_conv1 (Conv2D) | 96, 96, 512 | 1180160 |
| block4_conv2 (Conv2D) | 96, 96, 512 | 2359808 |
| block4_conv3 (Conv2D) | 96, 96, 512 | 2359808 |
| block5_pool (MaxPooling2D) | 48, 48, 512 | 0 |
| block5_conv1 (Conv2D) | 48, 48, 512 | 2359808 |
| block5_conv2 (Conv2D) | 48, 48, 512 | 2359808 |
| block5_conv3 (Conv2D) | 48, 48, 512 | 2359808 |
| block5_pool (MaxPooling2D) | 24, 24, 512 | 0 |
| flatten (Flatten) | 294912 | 0 |
| dense (Dense) | 1024 | 301990912 |
| dense_1 (Dense) | 512 | 524800 |
| dense_2 (Dense) | 256 | 131328 |
| dense_3 (Dense) | 128 | 32896 |
| dense_4 (Dense) | 3 | 387 |

**Table 4.** Number of parameters trained in each layer in proposed Custom-VGG16

| Layer (type) | Output Shape | Param # |
|---|---|---|
| input | 768, 768, 3 | 0 |
| batch_normalization_2 | 768, 768, 3 | 12 |
| Conv2D | 768, 768, 64 | 1792 |
| Conv2D | 768, 768, 64 | 36928 |
| MaxPooling 2D | 384, 384, 64 | 0 |
| Conv2D | 384, 384, 128 | 73856 |
| Conv2D | 384, 384, 128 | 147584 |
| MaxPooling 2D | 192, 192, 128 | 0 |
| Drop_out | 192, 192, 128 | 0 |
| Conv2D | 192, 192, 256 | 295168 |
| Conv2D | 192, 192, 256 | 295168 |
| MaxPooling 2D | 96, 96, 256 | 0 |
| Conv2D | 96, 96, 256 | 590080 |
| Conv2D | 96, 96, 256 | 590080 |
| Conv2D | 96, 96, 256 | 590080 |
| MaxPooling 2D | 48, 48, 256 | 0 |
| Dropout | 48, 48, 256 | 0 |
| Conv2D | 48, 48, 512 | 1180160 |
| Conv2D | 48, 48, 512 | 2359808 |
| Conv2D | 48, 48, 512 | 2359808 |
| MaxPooling 2D | 24, 24, 512 | 0 |
| Flatten | 294912 | 0 |
| Dense | 512 | 150995456 |
| Dense | 256 | 131328 |
| Dense | 128 | 32896 |
| Dense | 3 | 387 |

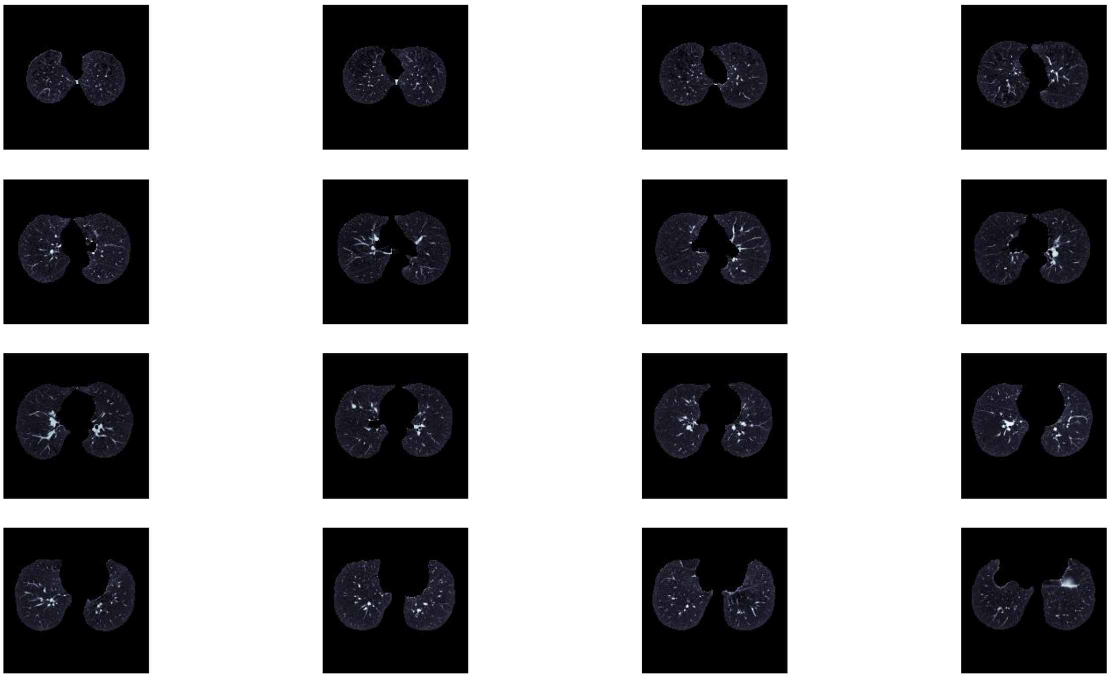

**Fig 3**. Segmented nodules from CT image

## 4. Result Analysis

Our approach is segmenting and classifying lung nodules using the LIDC-IDRI Kaggle dataset. The dataset contains three classes of CT images, like no nodule, <3mm nodule size, and >3mm nodule size images. We implemented a Custom-VGG16 deep learning and trained the model for 100 epochs while tuning the hyperparameters and achieving an accuracy of 0.95. In addition, our model performed well in classifying true positive and false negative values, an essential aspect of classification accuracy. In our proposed model we reduced the number of parameters.

The models had high true positive and false negative values, indicating that the model was well-fitted from Figure 3. However, our model emphasized the importance of evaluating the model's overall performance on a validation set to ensure it fits the training data. Figure 4 shows that our model's training and validation loss consistently reduced epoch by epoch, and the accuracy of the model increased up to 100 epochs, indicating that the model was learning and improving as it continued to train.

The evaluation metrics for the Custom-VGG16 model are presented in Table 5. These metrics encompass precision, recall, and F1-score for each class. Precision gauges the model's accuracy in identifying true positives within the predicted positives, while recall measures its ability to correctly identify true positives among all actual positives. The F1-score offers a balanced assessment of the model's performance by calculating the harmonic mean of precision and recall. The consistent values of precision, recall, and F1-score across different classes indicate the model's stability, without showing favouritism towards any particular class. Additionally, our model surpasses all recommended models, including the standard VGG16, as demonstrated in the provided comparison. The confusion matrix of our proposed model is illustrated in Figure 5. The Figure 6 presented true positive and false positive rate graph and Table 6 illustrate the Comparison of results of proposed model and prescribed models.

**Table 5**. Proposed Custom-VGG16 model results

| | Precision | recall | F1-score | Support |
|---|---|---|---|---|
| 0 | 0.87 | 0.98 | 0.93 | 1000 |
| 1 | 1.00 | 1.00 | 1.00 | 1000 |
| 2 | 0.98 | 0.86 | 0.92 | 1000 |
| Accuracy | | | 0.95 | 3000 |
| Macro avg | 0.95 | 0.95 | 0.95 | 3000 |
| Weighted Avg | 0.95 | 0.95 | 0.95 | 3000 |

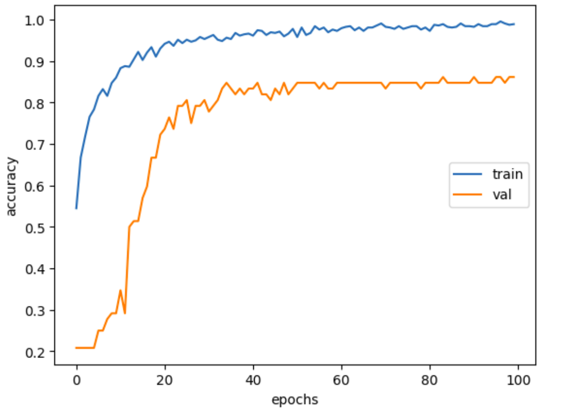


**Fig 4.** training and validation accuracy of proposed model

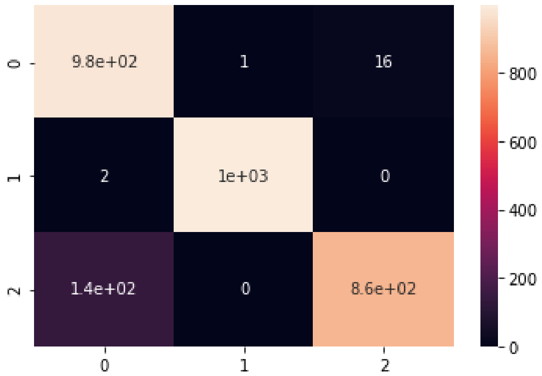


**Fig 5.** confusion matrix of proposed model

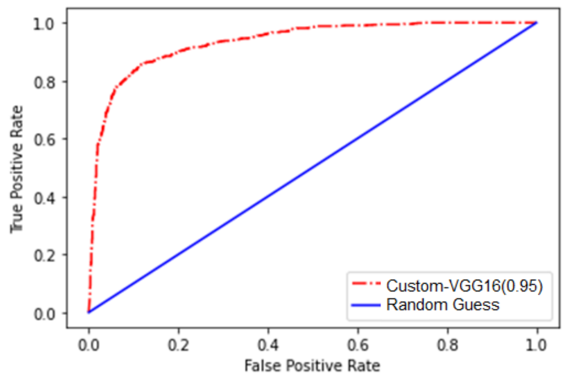


**Fig 6.** True positive and false positive rate graph

**Table 6.** Comparison of results of proposed model and prescribed models

| Reference | Dataset | Area of Implementation | Model | Accuracy |
|---|---|---|---|---|
| [1] | LIDC-IDRI | Lung Nodules | CNN | 84.15 |
| [2] | LIDC data | Lung Nodules | Fuzzy particle swarm optimization convolution neural network (FPSOCNN) | 95.62 Worked on Two Classes |
| [3] | Kaggle Data Science Bowl 2017 challenge (KDSB) and LUNA 16 | Lung Nodules | DFD-Net | 87.4 |
| [4] | LIDC-IDRI and LUNA16 | Lung Nodules | 3D CNN model | 86 |
| [5] | SPIE-AAPM-LungX data. | Lung Nodules | 3D CNN model | |
| [6] | LIDC-IDRI dataset. | Lung Cancer | Random Forest and XGBoost classifier. | 84 |
| [10] | LIDC-IDRI | Lung Cancer | CNN,RNN | 82.39 |
| [11] | DICOM lung CT images | Lung Cancer | SVM | 86.25 |
| [12] | LIDC-IDRI | Lung Abnormality | modified AlexNet | 97.27 Worked on Two Classes |
| [13] | ELCAP | Lung Nodule | Custom CNN | 91.7 |
| [15] | Lung CT-Diagnosis database | Lung Tumor | Enhanced Capsule Networks (ECN) | 96.41 Worked on Two Classes |
| [18] | LIDC-IDRI | Malignant Lung cancer | AlexNet | 93.20 |
| [19] | (LIDC), NDSB | Lung Nodule | 3D-CNN model | 86 |

| | | | | | |
|---|---|---|---|---|---|
| [23] | JSRT | Lung Cancer | SVM,ANN | 82.43 | |
| [25] | LIDC | Lung Nodule | Multi-Scene Deep Learning Framework (MSDLF) | 98.7 | Worked on Two Classes |
| [26] | JSRT | Lung Cancer | CNN | 84.02 | |
| Executed model | LIDC-IDRI | Lung Nodule identification | VGG16 | 89.40 | |
| **Proposed model*** | **LIDC-IDRI** | **Lung nodule identification** | **3D-CNN Custome VGG16 model** | **95.00** | |

## 5. Conclusion

Our research mainly aims to identify cancerous lung nodules in lung images and classify lung cancer according to its severity. Advanced Deep Learning techniques are employed to locate cancerous lung nodules accurately. The proposed approach utilizes a Custom-VGG16 method, effectively classifying the images and detecting the lung nodules from lung CT images. In this research LIDC-IDRI dataset has been executed as the input dataset. Notably, this model has achieved an impressive accuracy rate of 93.5% in classifying nodules in lung CT images.

Future research efforts will focus on further improving the classification performance of nodules and optimizing the proposed model. Additionally, there are plans to add more datasets related to lung cancer to concentrate on various parameters and assign grades to images based on the level of malignancy of nodules. This advancement holds significant value in diagnosing and treating lung cancer in clinical applications.

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