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# An Optimized Tuning Based Hybrid DL Approach For Lung Cancer Classification

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Lung cancer is the second deadliest disease and the second most lethal illness because it affects the respiratory system. Numerous artificial intelligence methods have been suggested to enhance the early detection of lung cancer, including deep learning designs like 3D CNN, Inception Networks, Residual Neural Networks, and Convolutional Neural Networks. This article proposes a novel approach to use deep learning algorithms for the classification of lung cancer on CT scans. The existing methods identify cancer on ROI images, however they are not suitable for early diagnosis due to network under-fitting, overfitting, and computational complexity. To overcome this problem, this article proposed a fused VGG-16 and RESNET 50 classifier, the best choice is the recommended RMSprop tuning, which achieves over 98% accuracy in just 422ms for testing set.

**Keywords:** Lung Cancer, Deep learning, Hybrid, Fused Feature, Optimizer tuning.

## 1. Introduction

Lung cancer is the second deadliest disease and the second most lethal illness because it affects the respiratory system. Numerous artificial intelligence methods have been suggested to enhance the early detection of lung cancer, including deep learning designs like 3D CNN, Inception Networks, Residual Neural Networks, and Convolutional Neural Networks. This article proposes a novel approach to use deep learning algorithms for the classification of lung cancer on CT scans. This section summarizes those techniques which are used for the CT lung cancer classification.

In [1], the deep learning technique is proposed. While in [2], the three dimensional convolutional neural network is proposed and it achieved 0.78 Area Under Curve (AUC) for test set. In [3] also, a 3D CNN is used but it performs nodule segmentation based classification on LUNA 16 dataset. In [4] also, three dimensional with different CNN architecture is used for nodule segmentation and classification. But its performance was only around 83% for both sensitivity and specificity.

Like article 3 and 4, articles [5] and [6] also utilized the deep neural network architecture for nodule segmentation and classification. While article [7] also utilize the 3D CNN for nodule segmentation on LIDC-IDRI dataset, but it achieved 0.913 as its AUC value in nodule segmentation challenge. The traditional VGG network is improved with an additional block called COVID block to identify the respiratory problem in lungs [8]. It achieved around 95% for all three classes. A brief summary of machine learning techniques with deep and hand craft features for lung cancer classification is addressed in [9]. The transfer learning property in deep learning architectures like VGG net, RESNET and DenseNet was analysed for lung cancer classification in [10]. Among these architectures, the DenseNet-201 performed well but it also achieved only 53% as its precision value.

In [11], the transfer learning using Alexnet and the customized CNN layers were used for classification. The customized CNN performed well as compared to the Alexnet. In [12], the ensemble model with deep learning models like Alexnet, VGG, DensenNet was used. This ensemble model achieved AUC of 0.99 in Region of Interest based image. A brief summary of Lung nodule detection and classification is presented in [13] & [14]. In [15], the statistical analysis of risk factors that cause lung cancer is analysed using Artificial neural network.

In [16], the DL architectures like Mobilenet, VGG-19 and other architecture performance for lung cancer classification is performed. The hybrid combination of VGG-19 and Long Short Term Memory Neural network is used for classifying Kaggle and Luna 16 classification. This hybrid approach achieved 99% accuracy [17].

In [18], the Ebola optimization is used for finding the weights in CNN for Iraq Lung cancer classification. It performed well for normal cases only. The efficient network architecture is used for classification in [19]. In [20], the DenseNet-121 with modifications for Adenocarcinoma classification.

Based on the aforementioned techniques, the following points was not considered for the analysis in lung cancer classification:

- The overfitting or under-fitting problem in network was not discussed.
- Computational time analysis for testing set with their proposed methods also not discussed.

Hence, in this, the above two points was considered and this problem was addressed by using proper selection of tuning techniques in training the hybrid deep learning approaches.

The paper is structured in the following manner: Section 2 summarized the current techniques that are used for lung cancer classification. Section 3 highlighted the working of the proposed methodology. Section 4 presented the simulation outputs for the proposed techniques. Section 5 highlighted the proposed technique advantages and it possible future extensions.

## 2. RELATED WORKS

In this section, the current techniques that were employed for lung cancer classification either by using Iraq (ID) dataset or Kaggle Dataset (KD) is discussed.

Abdollahi (2023) utilized the Lenet-5 architecture for classifying the lung cancer using Iraq dataset [23]. In this, the Lenet-5 comprises of convolutional encoder and three fully connected layer attached to the dense network. With this network, it achieved 97.18% accuracy.

Mohamed et al., (2023) proposed a hybrid combination of Ebola search algorithm and Convolutional neural network. In this, they utilized Ebola algorithm for finding the optimal hyper parameters of CNN. With this tuned parameters, the CNN achieved 87% accuracy in ID set classification.

Pathan et al., (2024) also utilized a hybrid combination of optimization and deep learning architecture for ID set. Here, they customized the deep learning architecture with input layer size of 448 448 3. This customized DL hyper parameters like batch size, learning rate and epochs were tuned by using Sine Cosine Algorithm. This hyper-parameter tuned CNN helps to achieve 99% accuracy. But it makes higher computational time for larger sets as its input layer size is high.

Raza et al., (2023) analyzed the augmentation role and Efficient network architecture based transfer learning performance on ID set classification. Here, the augmentation helps to balance the dataset. Then, the balanced set were subjected to classification using transfer learning approach with Efficient network architecture B0, B1, B2, B3 and B4. Among these architectures, the B1 architecture performed well and achieved higher accuracy of 99.1%. Multiple augmentations were performed on smaller class sets to balance the set.

Al- Yasriy et al., (2020) utilized the Alex network for ID set classification. Here, they directly classified the 110 cases in the ID set. With their proposed Alex net architecture, they achieved 95.4%. They performed binary classification on ID set as malignant or non-malignant.

Majumder et al., (2024) proposed an ensemble deep learning approach for ID set classification. Here, they utilized Xception network and V2 version of RESNET and mobile network for base classification. The base classifier results were combined using ranking by mitscherlich function in fuzzy ranking. This proposed approach helps to achieve 99.5% accuracy in ID set.

Kareem et al., (2023) utilized the hand craft techniques like pre-processing, segmentation and feature extraction for ID set classification. But for classification they utilized Support Vector Machine with different kernel function. It achieved maximum accuracy of 89.68% on clubbed set.

## 3. PROPOSED METHODOLOGY

This paper proposed a hybrid deep learning technique with optimal tuning approach for performing Lung Cancer Classification (LCC) using CT images. The process in the proposed approach is presented in the flow chart in Figure 1.

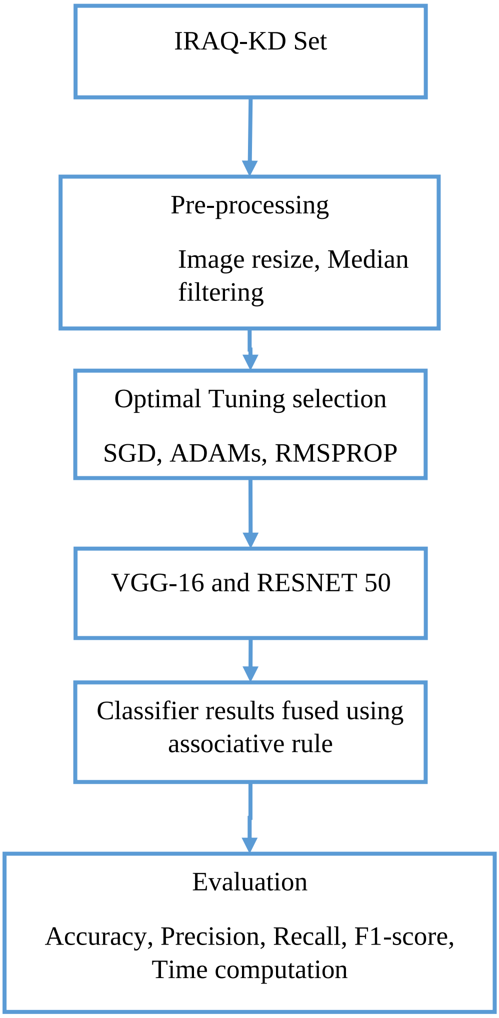



Figure 1. Hybrid DL-Flow chart for LCC

The steps in the hybrid DL-based LCC on CT images is as follows:

Step 1: Load IQ-OTH and Kaggle CT chest dataset.

Step 2: Combine both datasets into a single dataset.

Step 3: Perform Pre-process to resize and remove artefacts in the images.

Step 4: Split the dataset as training, testing and validation in the ration 0.7:0.2:0.1.

Step 5: Perform VGG-16 based training for all the optimizers.

Step 6: Perform RESNET 50 based training for all optimizers.

Step 7: Observe performance in terms of accuracy.

Step 8: Re-train the classifiers with selected optimizer.

Step 9: Combine features from both sets for fused classification.

Step 10: Re train with the combined features and test the set.

Step 11: Evaluate the fused classifier performance.

The working of each modules is presented below:

### A. INPUT DATASET

The input dataset used in this work is the CT Scan images of Lung region. Here, two datasets from Iraq set and Kaggle set was combined to form a single dataset. The Iraq dataset comprises of early stage image of Lung cancer and Kaggle chest CT dataset comprises of advanced stage of Lung cancer. The depth information of both datasets is addressed below.

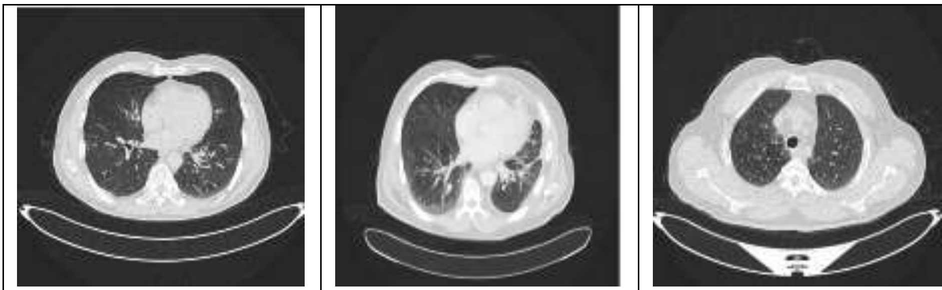
#### a. IQ-OTH/NCCD

This dataset is gathered from the Iraq Oncology Department and it contains CT scan images of both healthy and cancer patients. Totally, 1190 images were collected from 110 patients. The cancer images were further split into Benign and Malignant and its distribution is presented in the below table 1.

**Table 1. Data Distribution in IQ-OT/NCCD Dataset**

| Cases | Number of Images |
|---|---|
| Normal | 416 |
| Benign | 120 |
| Malignant | 561 |

The sample imagers in the Iraq dataset is shown in the figure.



a. Benign | b. Malignant | c. Normal

Figure ID set images

## b. KAGGLE CHEST

In this, another lung cancer dataset was taken from the Kaggle site and it contains four types CT scan images namely, Adenocarcinoma, Large cell Carcinoma, Normal and Squamous Cell Carcinoma.

### i. Adenocarcinoma

This type of cancer is found in the mucus glands and this gland are responsible for breathing. The 30% of this dataset contains ACC data. The patients with this disease shows the symptoms of coughing, hoarseness and weight loss.

### ii. Large cell Carcinoma

Large cell carcinoma is a deadly lung cancer disease as it spreads faster to other regions as compared to other types. Generally, it comprises 10-15% of non-small lung cancer disease and it cannot be easily distinguished from other types.

### iii. Squamous Cell Carcinoma

It is also a type of non-small cell cancer and it occurs in the central part or the main breathing region of the lungs. It usually occurred by the inhalation of gases during smoking.

Like Iraq dataset, the Kaggle dataset also contains normal images and its distribution of these images is given in the table 2.

**Table 2**. **Data Distribution in Chest Dataset**

| Cases | Number of Images |
|---|---|
| Normal | 215 |
| LCC | 186 |
| SCC | 260 |
| ACC | 338 |

The sample images in the kaggle chest dataset is shown in the figure.

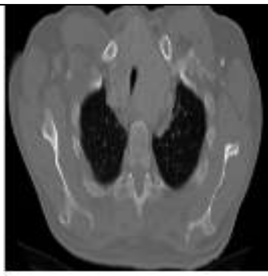
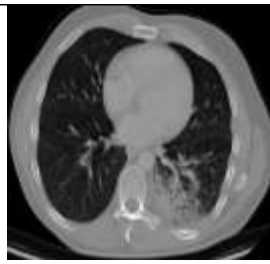
| | | | |
|---|---|---|---|
|  |  |  |  |
| ACC | LCC | SCC | Normal |

Figure KD set images

In this, both these images were combined to form a dataset that helps to analyse both early and later stage of lung cancer. This clubbed dataset was used for the analysis.

## B. PRE-PROCESSING

As images were converted from DICOM format to an image formats like JPG and JPEG, it may contain disturbance in the images. This disturbance was removed from the image using median filtering. Because median filtering is used to preserve the image edges.

Similarly, the image will be of different size and it also transform into a uniform size of 224 and 224. These process were performed on the image set to normalize the inputs for both the classifiers.

## C. TUNING TECHNIQUES

In Deep learning, the learning rate, neuron weights were adjusted for improving the classifier performance using optimizers like Stochastic Gradient Descent, Adaptive Moment Estimation and Root Mean Squared Propagation.

### a. SGD

SGD is also a type of Gradient Descent (GD) Algorithm. The Special feature of this technique is it calculates the gradient value by using a single batch of data instead of larger sets like GD algorithm. This helps to speed up the process and reduce the computational time for analysis.

This small batch set is also selected randomly from the sets and hence it named as SGD. This helps to enhance its process in the larger sets. The steps in the SGD algorithm is a s follows:

#### i. Initialize

Set the model parameters randomly from the predefined or given values. Here the model parameters denote the learning rate (α), drop-out period and neuron weights.

### ii. Parameter Definition

In this phase, the total iterations and the maximum learning rate were defined.

### iii. SGD Loop

The below process will be performed in a repeated manner either it reaches the final iterations or its final solution:

- Randomness is introduced in training set at each round of iteration.
- This randomness is used for selecting small batch of data for training.
- The gradient value is calculated from the selected batch set.
- The learning rate will be altered and this alteration is based on the sign convention of gradient value.
- At the end of each iteration, the objective function will be evaluated for gradient update.

### iv. Optimal Parameters

The optimal learning rate and other tuned parameters will be obtained at the end of its final iteration.

Another major difference between the GD and SGD algorithm is that the solution obtained in SGD will be noisier one as shown in the below figures.

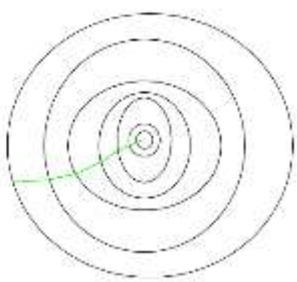


Figure 2. Path by GD for solution

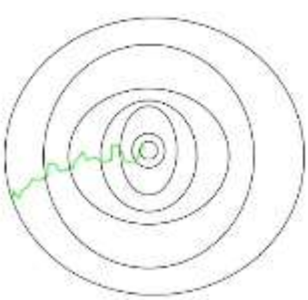


Figure 3. Path by SGD for solution.

By comparing figure 2 and 3, it can be seen that the path by SGD is noisier as compared to the GD algorithm. It is also observed that in SGD, it takes more iterations to reach its final values. Even though it takes more iterations, it overall computational time is minimum than GD algorithm.

**b. RMSprop**

RMSprop is the abbreviation of Root Mean Square Proportion algorithm. It is an advanced version of adaptive gradient algorithm. In GD and SGD, the algorithm takes more time to reach its minimal solution. To overcome this problem, in RMSprop, the learning rate were reduced in exponential form for each iteration. This reduction is based on the gradient value and its threshold. Whenever, the squared gradients are below its threshold, the learning rate will be reduced exponentially. So the learning rate reach its minimum value faster than other algorithms. The steps in the RMSprop algorithm is as follows:

**i. Initialize**

In SGD, the learning rate (α) only initialized, while in this, along with α, decay rate (γ), Stability rate (ε) and parameter setting (θ).

**ii. Squared Gradient**

Initially, the squared gradient value is set as zero for all tuning values.

**iii. RMSprop loop**

This loop repeat it process till it minimizes the learning rate with the following steps:

- Evaluate gradient value for each parameter with respect to its threshold. The gradient is calculated using the formula 1.

$$g_i = \nabla_\theta J(\theta) \qquad (1)$$

- Compute the squared gradient Value Ei.

$$E_i = \gamma E_{i-1} + (1-\gamma){g_i}^2 \qquad (2)$$

- With respect to $E_i$, update other parameters.

$$\theta_{i+1} = \theta_i - \alpha \frac{g_i}{\sqrt{E_i + \varepsilon}} \qquad (3)$$

The exponential decay parameter in this algorithm helps to enhance the solution and its solution depends on the recent gradients only and it helps to attain stable solution.

### c. ADAM

ADAM is the abbreviation of Adaptive Moment Estimation. It is also a type of gradient descent algorithm but it increases the process for acquiring solutions using a momentum. This momentum is called exponentially weighted average. This approach works well for the larger sets and also for large tuning parameters. This approach obtains better solution by combining the traditional GD with momentum and the RMSprop algorithm.

### i. Modified GD with momentum

In this, the GD algorithm is updated with the exponentially weighted average parameter (β). This modification is presented as below:

$$w_{i+1} = w_i - \alpha m_i w_i + 1 \qquad (4)$$
$$= w_i - \alpha m_i w_i$$

Here, the $m_i$ is the gradient's average at the i iteration and is given as follows:

$$m_i = \beta m_{i-1}(1 - \beta)[\partial L\, \partial w_i] m_i \qquad (5)$$

Here, the β is a constant and its value is 0.9. while the $\partial L$ is loss's derivative function and $\partial w_i$ is the weight derivative function.

This modified gradient is combined with the RMSprop algorithm and utilize two exponential decay factors and it helps to attain solutions earlier than other algorithms.

## D. CLASSIFIERS

In this, the classifiers like VGG 16 and RESNET 50 were used for the analysis. Here, the VGG 16 helps to extract deep features with their deep layers. While the RESNET 50 also extracts deep features but it removes the redundant features using their skip connections.

### a. VGG 16

Visual Geometry Group (VGG) is introduced by Oxford university and it helps to achieve 97.25% accuracy in 14 million Image dataset called Imagenet. This becomes possible with the deep features from the 16 layers of VGG network. Hence, it named as VGG-16. The layers in VGG-16 architecture is presented in the figure 4 and the number of layers is as follows:

- 16 convolutional layer blocks
- 13 individual convolutional layers (CL)
- 3 fully connected layers
- Soft-max layer
- Classification layer.

.

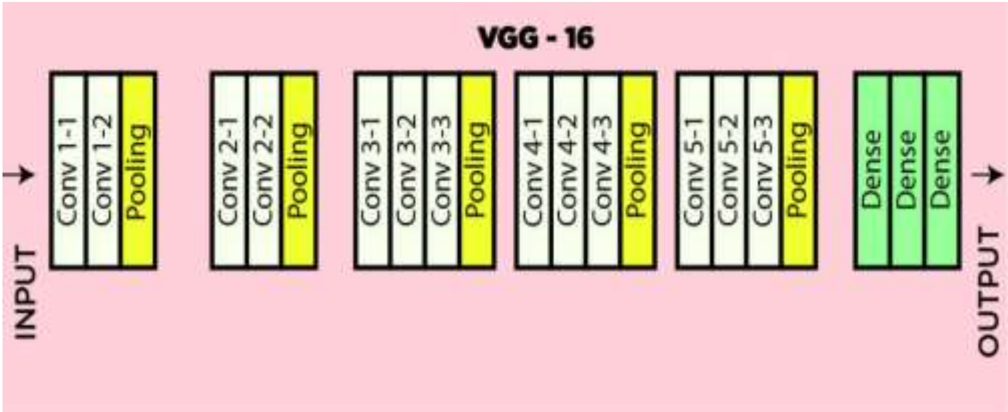



Figure 4. VGG-16

The layer distribution in VGG-16 is as follows:

Layer 1: Input image with dimensions of 224, 224 and 3.

Layer 2: In this, two convolutional layers were stacked together. In this, the CL has 64 filters and dimension of filter is 3 *3. The spatial property is preserved by using same padding.

Layer 3: Max Pooling layer is used to gather features. Here, the max pooling layer size is 2*2 with stride dimensions as 2.

Layer 4: Like layer 2 it stacks two CL layers but its filter size is 128.

Layer 5: Same as Layer 3.

Layer 6: Like Layer 2 and Layer 4, it stacks two CL layers but its filter size is 256.

Layer 7: Like Layer 6, it increases the filter size as 512 and stacks two convolutional layers.

Layer 8: Same as Layer 3.

Layer 9: Same as Layer 7 and Layer 3.

Layer 10: Flattening layer to normalize the output feature vector as 7*7*512.

Layer 11-13: Fully connected layers with ReLU function with different input and output size.

- First fully connected layer input is flattening layer output and its output size is 4096.
- Second fully connected layer input is first layer output and its output remain same as 4096.
- Third layer input is second layer output and its output is number of classes in the set.

Layer 14: Fully connected layer with number of classes.

Layer 15: Soft-max function to identify the probability of each output.

Layer 16: Final classification layer to produce the categorical output.

With this 16 layers, the deep features from the lung images were extracted and it is utilized for classification.

**b. RESNET 50**

As the layer gets deeper, the deep learning algorithm faces the accuracy saturation problem. This accuracy saturation problem is overcome by using the residual network architecture called RESNET. RESNET architecture has different types of RESNET models like RESNET-18, RESNET-32 and RESNET-50. Among these architectures, the RESNET-50 is the best architecture and it is due to the Residual Block with skip Connections and bottle neck convolutional layers.

**i. Bottleneck Convolutional Layers**

The residual block contains the bottleneck convolutional layer as shown in the figure 5.

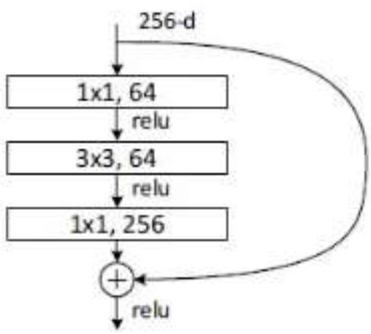



Figure 5. Residual Block

Like VGG-16, it uses three convolutional layer in a stacked format. But in this, the convolutional layer is followed by Batch Normalization and ReLU layer. Even the convolutional Layer size is minimum as follows:

- First layer uses 64 convolutional filter with size 1*1 to minimize the redundant information from the input.
- Second layer also use 64 filter with size 3*3 to preserve spatial properties.
- While third layer use 256 convolutional filter with size 1*1 to retain the original information and its connected to the Skip connection of the residual block.

The ReLu layer in the block helps to get the positive features from the image and it helps to analyse deeper patterns from the image. Here, the input feature is connected at the final layer through skip connection and it helps to analyse the input features deeply.

### ii. RESNET-50 architecture

Like other architectures, it has input layer with size 224, 224 and 3. The input layer is followed by the pre-process layer of convolutional layers. Then, fifty residual blocks were used to extract deep features and it is the reason for naming RESNET-50 architecture. Then, it followed by fully connected layer with number of classes and softmax layer. The RESNET 50 architecture with the stacked Residual blocks is shown in the Figure 6.

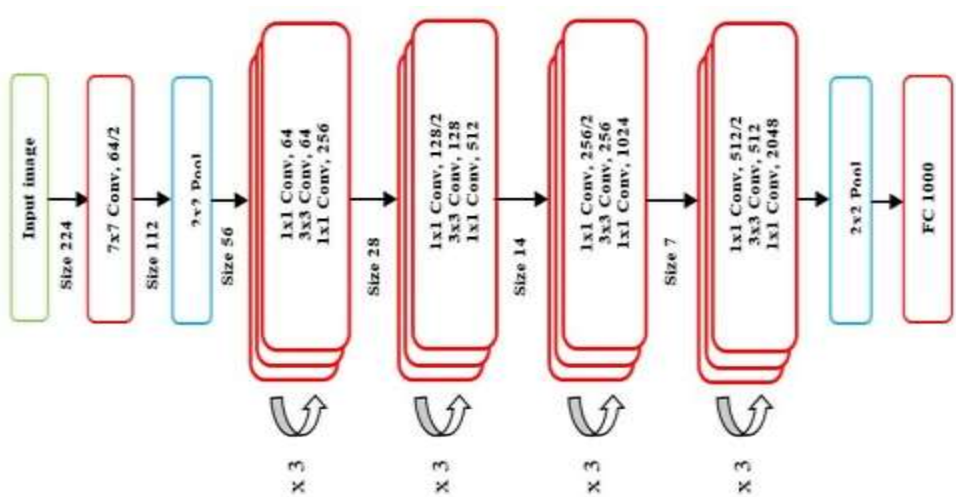



Figure 6. RESNET 50 architecture

With this RESNET-50, the deep features from lung CT image is extracted and is used for forming fused classifier with VGG-16 network.

## 4. FUSED CLASSIFIER

In this, the classifier outputs were clubbed together using the average rule on the associative rule (i.e.) adding the outputs from the classifiers.

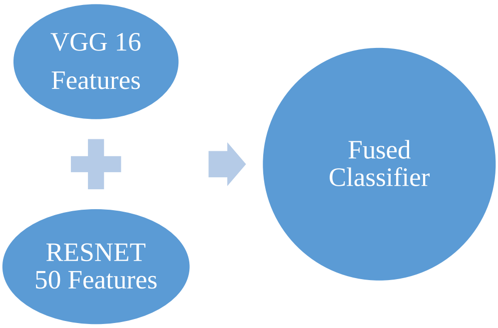



Figure 7. Fused Classifier

## 5. EVALUATION

The tested classifier performance was evaluated using Accuracy, precision, Recall, F1-score and its computational time for time analysis. From these metrics, the optimal method for tuning the classifier is proposed for an efficient Lung cancer classification

## 6. RESULTS AND DISCUSSION

With the help Google Colab application, the proposed techniques were realized in Python3 in CPU environment.

The sample input images in the clubbed dataset is presented below.

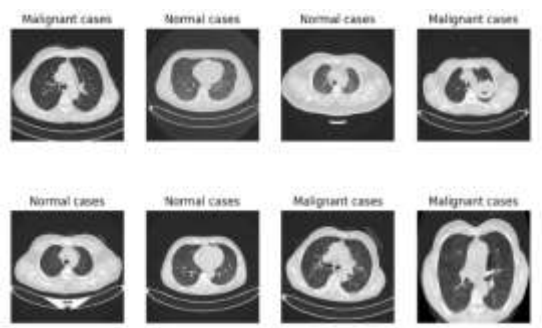



Figure 7. Sample Input images.

These datasets were processed using both the VGG-16 and RESNET 50 architectures with different tuning techniques namely SGD, ADAM and RMSprop. The output for the best tuning technique is presented below.

First, the deep features from the pre-processed dataset were used for classification by using VGG-16 network and the corresponding accuracy and loss plot of the network is shown in the below figures.

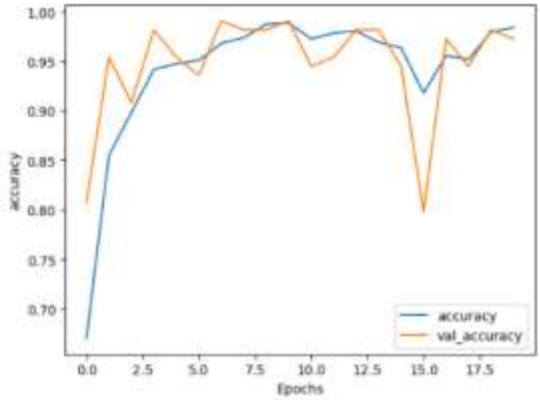



Figure 8. Accuracy Plot (VGG-16)

The VGG-16 was trained only for 20 epochs and within these 20 epochs it achieved better accuracy of 98.23 % in training and 97.25% for validation and this result is presented in the above accuracy plot.

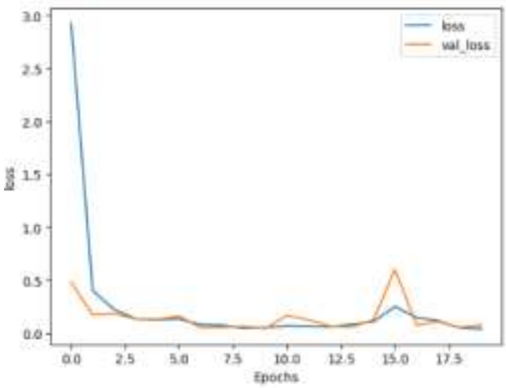



Figure 9. Loss plot (VGG-16)

Similarly, in loss also, the VGG-16 performed well by minimized its loss 3.6% for training and 7.6% for the validation set. This trained VGG-16 is used for testing and its performance on test set classification presented in the confusion chart below.

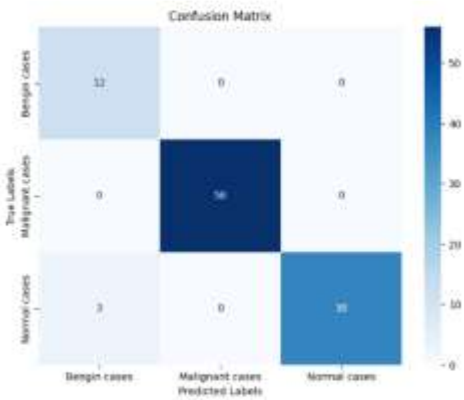



Figure 10. Confusion Chart (VGG-16)

The deep features from VGG-16 helps to identify the early stage of lung cancer with zero misclassification rate and it can be seen in the Figure. Similarly, the network performance was evaluated in terms of Accuracy, precision, recall and F1-score as shown in the figure.

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| Bengin cases | 0.80 | 1.00 | 0.89 | 12 |
| Malignant cases | 1.00 | 1.00 | 1.00 | 56 |
| Normal cases | 1.00 | 0.93 | 0.96 | 41 |
| accuracy | | | 0.97 | 109 |
| macro avg | 0.93 | 0.98 | 0.95 | 109 |
| weighted avg | 0.98 | 0.97 | 0.97 | 109 |

Figure 11. Evaluation

The VGG-16 with ADAM optimization performed well in the Lung cancer classification by achieving 97% accuracy and above 80% in precision, recall and F1-Score. This shows that the ADAM optimizer with the VGG-16 is suitable for CT based lung cancer classification.

```
Found 109 images belonging to 3 classes.
/usr/local/lib/python3.10/dist-packages/k
  self._warn_if_super_not_called()
4/4 ━━━━━━━━━━━━━━━━━━━━ 2s 320ms/step
```

Figure 12. Computational time (VGG-16)

The computational time for the testing set is around 320ms with the VGG-16. The same pre-processed dataset was tested using RESNET-50 and the corresponding performance is shown in the below figure.

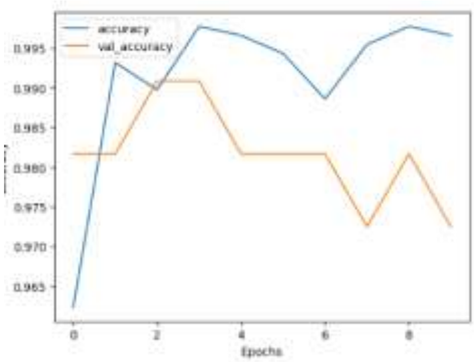



Figure 13. Accuracy Plot (RESNET-50)

Like VGG-16, the RESNET-50 is also trained with ADAM optimizer and it achieved 99% accuracy for training and 97% for validation.

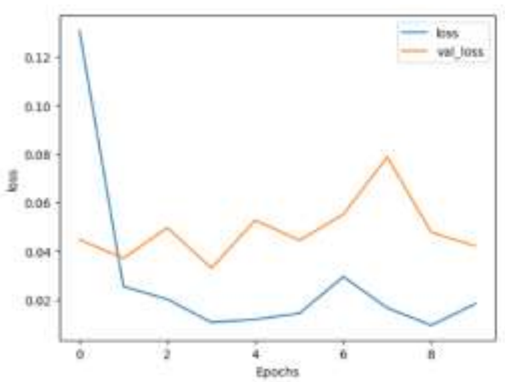



Figure 14. Loss plot (RESNET-50)

Similarly, in loss also, the RESNET-50 reduced well for the training as compared to the validation and it can be seen from the figure. With this trained RESNET-50, the test set were evaluated and it also achieved 97% accuracy and above 80% for precision, recall and F1-score.

```
Found 109 images belonging to 3 classes.
/usr/local/lib/python3.10/dist-packages/kera
  self._warn_if_super_not_called()
WARNING:tensorflow:5 out of the last 9 calls
3/4 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 0s 302ms/stepWARNIN
4/4 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 4s 488ms/step
```

Figure 15. Computational Time (RESNET-50)

In terms of computational time, the RESNET-50 utilized 488ms for testing set. But its accuracy was around only 97%.  Hence, this problem is overcome in the Fused model, In fused model, the features from VGG-16 and RESNET-50 were combined for classification and is trained using the RMSprop algorithm. The RMSprop algorithm helps to achieve higher accuracy of 98% and is shown in the below figure.

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| Bengin cases | 0.80 | 1.00 | 0.89 | 12 |
| Malignant cases | 1.00 | 1.00 | 1.00 | 56 |
| Normal cases | 1.00 | 0.93 | 0.96 | 41 |
| accuracy | | | 0.97 | 109 |
| macro avg | 0.93 | 0.98 | 0.95 | 109 |
| weighted avg | 0.98 | 0.97 | 0.97 | 109 |

Figure 16. Evaluation

In terms of individual class analysis also, the RMSprop tuning helps to achieve higher precision, recall and F1-score values of above 90% in benign and malignant as compared to normal cases. This shows that the RMSprop is best for tuning the fused model and its processing time were also analyzed for the test set and its result is presented in the below figure.

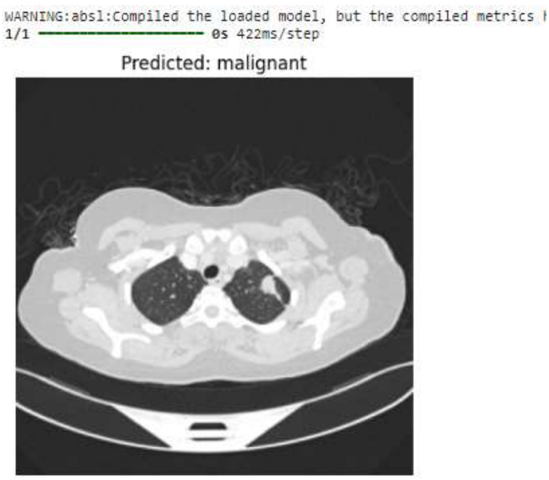



Figure 17. Fused Classifier Performance

The figure shows that the proposed method correctly identified the malignant lung cancer in 422ms.

This proves that the RMSprop tuning is best for Lung Cancer Classification using Fused classifier.

## 7. DISCUSSION

In this, the performance of various classifiers on Iraq and Kaggle dataset is discussed and its performance were compared with the proposed method.

**Table 3. Performance Comparison (ID dataset)**

| Method | Image Size | Accuracy (%) | Precision (%) | Recall (%) | F1-score (%) | Computational Time (ms) |
|---|---|---|---|---|---|---|
| **Lenet [23]** | - | 97.8 | - | - | - | - |
| **SCA-CNN [24]** | 448 | 99.0 | 93.0 | - | 92.4 | - |
| **Efficient Net B1 [25]** | 227 | 99.1 | 98.63 | 98.64 | 98.63 | - |
| **Alex Net [26]** | 227 | 98.45 | 97.10 | | 96.4 | - |
| **Ebola – CNN [18]** | 240 | 93.21 | 100 | 90.71 | 92.72 | - |
| **VGG-16 (proposed)** | 224 | 97.67 | 93 | 98 | 95 | 320 |

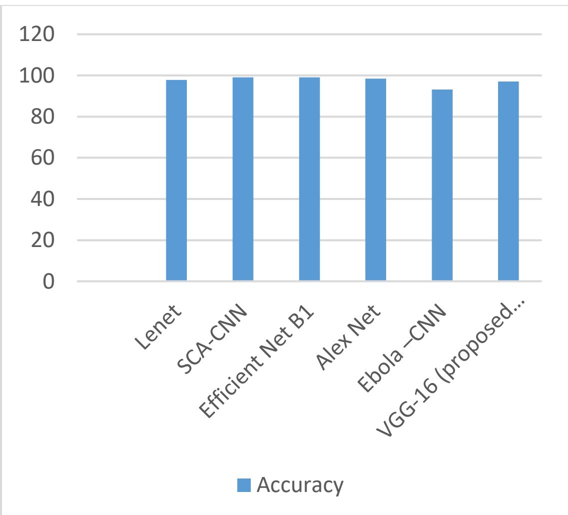



Figure Accuracy Comparison (ID-set)

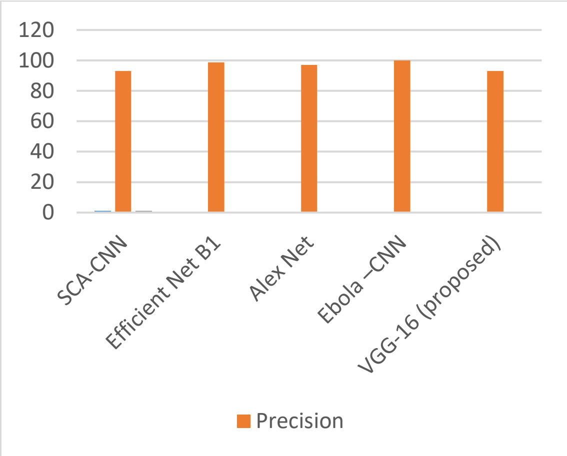



Figure Precision Comparison (ID-Set)

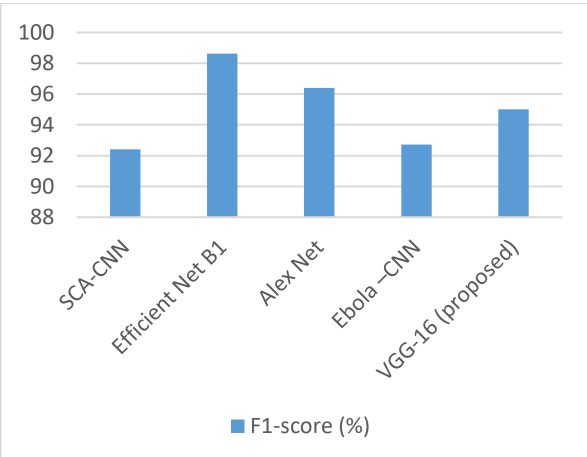



Figure F1-score Comparison (ID-set)

From the table 3 and Figures, it can be seen that the proposed VGG-16 performed superior than Ebola but it lower than other techniques. But in the proposed technique, the input size is 224 while in other network the size is greater than 224 which may help to have more spatial properties but it takes more computational time for processing. From the computational point of view and the performance, the proposed VGG-16 performed well in Iraq dataset.

**Table 4. Performance Comparison (KD set)**

| Method | Accuracy (%) | Precision (%) | Recall (%) | F1-score (%) | Computational time (ms) |
|---|---|---|---|---|---|
| **DenseNet (201) [29]** | 85.8 | 88.9 | 86.2 | 86.3 | - |

| | | | | | |
|---|---|---|---|---|---|
| **VGG 16 – Decision Tree** | 91 | 91 | 93 | 91 | - |
| **VGG-16** | 85.8 | 77 | 85.75 | 80.25 | - |
| **RESNET 50 proposed** | 97 | 97 | 97 | 97 | 488 |
| **Ensemble (ID-KD)** | 98.9 | 98 | 98 | 98 | 422 |

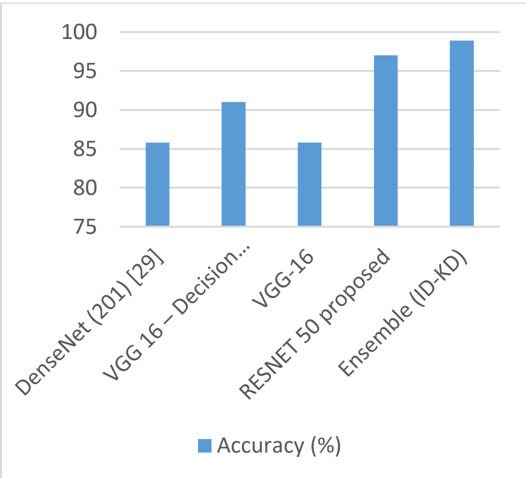



Figure Accuracy Comparison (KD-set)

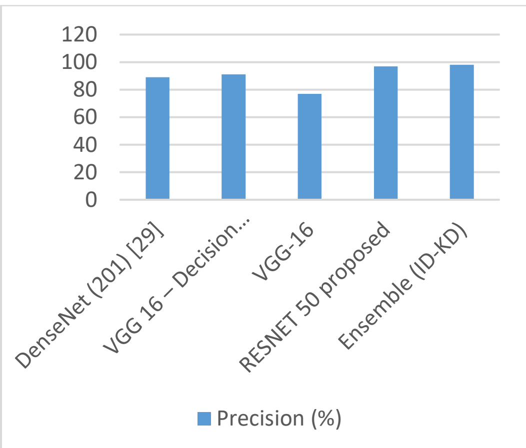



Figure Precision Comparison (KD-Set)

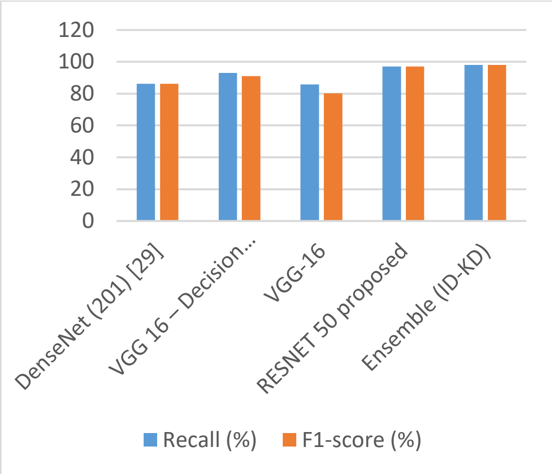



Figure Recall & F1-score Comparison (KD-set)

From the table 4 and Figures, it can be seen that the proposed RESNET 50 performed superior than other techniques. But in the proposed technique, the input size is 224 while in other network the size is greater than 224 which may help to have more spatial properties but it takes more computational time for processing. From the computational point of view and the performance, the proposed RESNET 50 and Ensemble learning performed well in both clubbed and KD set.

## 8. CONCLUSION

This paper mainly addressed the over-fitting and under-fitting problem in lung cancer classification using Deep learning techniques on CT images. To analyze this, it utilized the clubbed dataset of IQ and Kaggle chest set. This clubbed dataset was analyzed using VGG-16 and RESNET-50 using three optimizers namely ADAM, SGD and RMSprop for tuning DL weights. From these optimizers, the ADAM was initially used for training the individual classifiers and it performed well for VGG-16 as compared to RESNET-50 in terms of both classification and computational time. Because in VGG-16, it achieved higher accuracy of 97% and 320ms for testing set. While in RESNET-50, it performance were reduced below 97% for accuracy and it takes around 488ms for computation time.

Hence, this problem is overcome with the RMSprop tuning in the fused classifier and it helps to achieve accuracy around 98% and it takes only 422ms for testing. This shows that the proposed RMSprop tuning is best for the fused VGG-16 and RESNET 50 classifier. In future, the proposed technique can be analyzed further by using both texture and deep feature based classification.

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