AI Based Multi Detection and Classification Method for Lung Cancer and Pneumonia using Deep Learning with VGG19 & YOLO V8 ILF on X-Ray Images

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Abstract. To propose a new AI based multi-classification model to detect lung nodules and pneumonia with an enhanced image localization framework. The model employs deep learning techniques to learn the deep features from X-ray images to isolate the affected regions in order to boost the detection and classification accuracy. This new system is developed using the ENN classifier VGG19 and an image localization framework YOLO V8 to detect the potential regions affected by lung cancer or pneumonia for robust classification. EHARQ is the error recovery method during the image acquisition phase and ensemble learning for post-processing validation on the isolated regions to check for low confidence scores. A multi-centric dataset is used to evaluate the performance of the proposed model. This research work utilizes X-ray images taken from Kaggle, which contain 5856 JPEG images, which have three labels, health, lung cancer and pneumonia, under the male and female categories. 70% of the data are used for training, and 30% are used for testing and validation purposes. The performance is measured using MATLAB, where the results are compared with existing baseline approaches such as EfficientNet-B0, Resnet-50, and 3D-DLCNN models. The suggested model enhances the performance rate of detection and classification with proven results. The ENN classifier with YOLO V8 yields 97.3% accuracy, 98.7% precision, 97.3% recall, 98.8% F1 score, 0.93 TPR and 0.07 FPR under AUC-ROC which outperforms the prevailing EfficientNet-B0, Resnet-50, and 3D-DLCNN models. Robust discrimination of lung cancer, pneumonia, and healthy classes using deep learning and ILF methods, which helps the clinical experts treat the disease at an early stage. The model overcomes the shortcomings of the existing classifiers in terms of image localization and disease classification.

Keywords: Deep Learning, Classification, Image Processing, ENN Classifier, Localization, YOLO V8, Pneumonia

1 Introduction

Respiratory diseases are most common in today's lifestyle, particularly above 40, where they cause significant challenges for humans to fight against the disease due to uncontrolled lung tissues, which leads to lung cancer, which increases cancer-related deaths. Pneumonia is caused by bacteria and fungi that affect the respiratory system and lead to lung infection. The symptoms are non-specific, so it has to be treated carefully to avoid severe spreads. Early detection and diagnosis of these diseases is crucial for better treatment and to increase survival rates. Various state-of-the-art supervised and unsupervised models have been identified to detect lung cancer and pneumonia at an early stage with the help of real-world radiograph images. Though the models perform well, few drawbacks are identified, such as high FPR and FNR rates, deep feature extraction, responding to large-scale datasets, lack of robustness, etc., which are taken as research gaps for the proposed work. As those models operate with a black-box method, it's hard for clinicians to adopt the latest technologies. To improve patient outcomes and reduce healthcare costs, the new AI-based deep learning ENN classifier VGG19 with YOLO V8 is proposed to detect and classify lung cancer at an early stage to diagnose and avoid causes of lung damage. Two potential neural network models along with computational loss functions are employed in this model to enhance accuracy, true positive rate, and robustness in terms of deep feature extraction and classification.

2 Related Work

CXR images are used in deep learning architecture to train the CNN model [1] where multiple blocks are created to extract the features. The model used FCN for classification purposes and attained superior performance. The only drawback of the model is that it follows the black-box technique, where healthcare practitioners are not able to trust and adapt to the non-linear structure, which leads to misclassification and false positive rates. A detailed review [2] was carried out on lung cancer prediction, classification, and deep segmentation using meta-analysis of 154 research articles and categorized based on accuracy, modality, and trust methods. The target class for prediction & classification in the proposed study is clearly showcased in the work. More than 30 patients are evaluated under the COVID-19 and pneumonia groups, where the length of stay was recorded to check whether the patients have lung cancer or not. NSCLC [3] patients are thoroughly monitored to check the morbidity rate to record the substantial data. A transfer learning lung classification model [4] was proposed using DenseNet-201 architecture by employing multi-class CT images. Deep belief networks, along with Gabor filters, are used to categorize the features and pass them to the network layers for robust detection and classification.

The accuracy is attained at 89%, where it lacks robustness in terms of multi-layer prediction and multi-layer analysis. QoS enhanced IWDARP [5] was proposed to optimize the feature selection techniques in order to reduce dimensionality. The process helps to study to record the intrinsic features in the given input. The EffNet model for classification using CTS [6] images was introduced to demonstrate the performance of the target class where ROC is balanced in all iterations in both small and large scale data. The model acts as an automated diagnosis system, which overcomes all the machine learning methods. The only limitation of this model is that it won't record 3D and high-pixel images to record deep features for classification analysis. A multi classification process was carried out by the researchers to predict lung nodules and their abnormalities using chest X-rays. The X-AI [7] concept is utilized to perform the decision-making process and to record the morphological changes in the chest x-ray input image to boost the accuracy to the maximum level.

Deep learning architectures such as Resnet-50 and EfficientNet-B0 [8] for multi centric classification to predict lung abnormalities were proposed by authors to boost the classification performance. 40 epochs with a batch size of 32 were carried out to train the model to extract multiple spots and isolate them for efficient classification of abnormalities in the scanned region. Optimization technique and two-step machine learning methods [9-10] to diagnose the pneumonia and COVID-19 cases using CT images where PCC is employed to highlight the efficiency followed by NB, RF, KNNs, and DT were used. This model focused only on optimization of CT images, which outperforms in training and validation. The MF-MAN [11] technique detects minor lung cells to isolate the critical regions to identify the cancer cells after masking the ROIs, and the same is passed as input to classification layers to record changes in pattern. The only drawback is that the process slows down during the iteration of large-scale data. A feature optimization and CNN-based 3D classification and monitoring approach [12-13] were attempted by the researchers where lung nodules are detected to create different blocks for multiple iterations. All the iterations are processed with maximum batch size data to boost the true positive rates in a robust manner. The model works well with a few limitations, like computational complexity, clinical data validation, etc. RAB-CRP and LC screening, diagnosis and treatment model [14-15] help healthcare researchers use population-based genetic algorithms for efficient feature detection and network architectures for screening, prediction, classification, and type of treatment methods to record the dynamic results of all patients.

This model works on all types of lung cancer and pneumonia patients for consultancy and the initial phase. An automated detection & classification of pneumonia using DM-TLA with focal loss [16] in X-ray images helps experts to reduce the dimensionality in the image and pass it to multi-centric network architecture layers to generate the deep features in order to segregate the changes recorded for efficient masking to perform the classification task. A 3D-DLCNN [17] deep learning architecture was proposed to analyze the severity level using the PET CT-DICOM dataset to perform multi classification tasks. Error detection techniques are imposed to validate the classification and low confidence scores to detect the lung nodules and severity ratio in a dynamic manner. The accuracy and TPR are achieved up to 94%, which is relatively higher than other machine learning models. The drawback of this model is computational complexity and the collection of 3D data from the clinical repository. Deep CNN with GRU approach and CNN for early detection [18–19] for lung tumor detection using multiclass layers help to reduce the false detection scores. A two-stage cascaded DL model [20] for pneumonia classification was proposed to minimize the FPR and maximize the discrimination power of the CAD system. Various LC detection models, such as swarm optimization [21-23], SVM and neural networks [22-23], hybrid deep learning models and Heart disease diagnosing using M-PCA [24-25], were proposed with minor shortcomings in terms of localization, complexity, deployment issues, black-box adaptability, etc. The main objectives of the suggested ENN classifier VGG19 with YOLO V8 model are: i) identification of ROIs using neural network model; ii) enhancing detection and classification accuracy; iii) deep x-ray image localization; iv) dynamic usage of large-scale multiclass dataset; v) 19-layer pooling for efficient classification using VGG19; vi) minimizing false ratio, etc.

3 Methodology

The suggested AI-based ENN classifier VGG19 with YOLO V8 mainly focuses on robust classification and detection of lung cancer and pneumonia. Kaggle LC large-scale dataset is used for this research study, which has high-definition X-ray images. The new model is applied to an X-ray image to identify the relevant features like entropy, GLCM, shape features, canny edges, intensity, histograms, morphological changes, colour, infiltration, FD features, etc. to predict the ROI to perform detection and classification. EHARQ and ensemble learning loss functions are applied during pre-processing and post-result validation to boost the accuracy level. YOLO V8 localizes the patterns from the X-ray image and isolates the complete morphological changes to pass into the VGG19 neural network ENN classifier for deep analysis for efficient multi-classification. Relevant regions are captured in all the pooling layers to enhance the prediction and classification tasks. The results are compared with the existing approaches such as EfficientNet-B0 [8], Resnet-50 [8], and 3D-DLCNN [17].

The new approach utilizes two powerful neural network deep learning architectures, 1) YOLO V8 and 2) ENN classifier VGG19. The major steps for detection & classification as follows,

- Data segmentation for detection and classification
- Increasing input image quality using loss function
- Localization of image to extract ROIs
- Classification of disease into three different categories
- Validation of results using deep learning method

Once the data is split into training and testing, the ROIs are isolated using bounding boxes and class probabilities. The output of first network architecture YOLO is derived by the formula,

$$YOLO_{output} = \{(x_i, y_j, w_i, h_j, p)\} \quad (1)$$

where, $x_i \; and \; y_j$ shows the center coordinates of the bounding box, $w_i \; and \; h_j$ represents the width and height, and p is class probability. The localized ROIs are passed into the VGG19 pooling layers to capture the intricate patterns followed by ReLU and softmax activation. The maximum patches with intricate values are identified in various layers are given below.

- Patch 1: W_1 connected layers and $X_{dropout}$
- Patch 2: W_2 connected layers and $X_{dropout}$
- Patch 3: W_3 connected layers and $X_{dropout}$

where, the layer attains the final extraction process and masks the image for robust classification of lung cancer and pneumonia. The RGB color is used to bifurcate the isolated regions in the multi-pooling connected layers of VGG19. The canny edge detection is carried out with the help of formula,

$$C_{Edge}(x, y) = \sqrt{G_x(x, y)^2 + G_y(x, y)^2} \quad (2)$$

where, $G_x and \; G_y$ are the gradients in the edge directions $x \; and \; y$. Once the edges are detected the ENN network model works with roulette wheel selection method as an alternative if the user wants to stop the iteration. Iterations are run with batch size, where it can be 10 or 20 based on the target image classification probability value. The GLCM is calculated using the formula,

$$GLCM_{contrast} = \; (i - j) * P(i, j) \quad (3)$$

where, $i \; and \; j$ are the value position marked by the model. The step by step process of ENN classifier VGG19 with YOLO V8 is as follows.

Step 1. Load the Kaggle LC large scale dataset (X-LC 1)
Step 2. Apply EHARQ to enhance the image quality by performing error detection
Step 3. Split the datasets into training and testing (80% and 20%)
Step 4. Localize the ROIs using YOLO V8 which is initial pre-processing of raw X-ray image
Step 5. Record the isolated regions for further analysis
Step 6. Employ VGG19 model to extract intricate patterns to discriminate the variations between healthy lung tissue, lung cancer, and pneumonia
Step 7. Features are passed to FCL to classify the labels
Step 8. Apply softmax function to identify dropouts and validate the weights
Step 9. Validate the results using ensemble learning

3.1 Data Attainment, Pre-processing and Image Localization

The Kaggle LC clinical dataset is used for this research work, which includes 5956 X-ray images under three classifications such as healthy, lung cancer, and pneumonia. The pixel size of X-ray images is 512x512 with evident segmentations. Various attribute values are recorded by clinical experts in order to use the data for further research. Figure 1 clearly shows the sample X-ray of the lung cancer and pneumonia image, which is used for pre-processing, segmentation, and classification. The attributes of the images captured by the experts and recorded in the dataset. Kaggle LC dataset is one of the large-scale datasets where the patient records consist of lung biopsy details, histopathological details, tumor location with x and y coordinate bounding boxes, and slices interval ratio, etc.

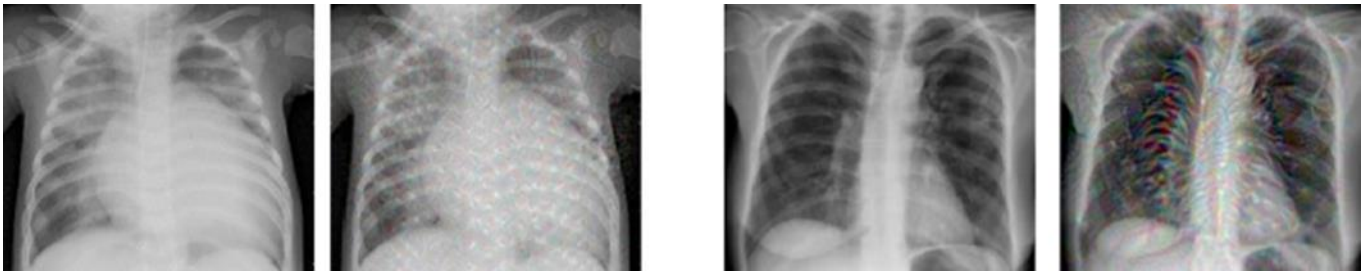

Fig. 1 Pneumonia - Left Side / Lung Cancer - Right Side

The localization and segmentation of the input image is carried out with the help of the YOLO V8 model, which suits best for large-scale datasets, to segment and mask in a robust manner. The major deviations are isolated from the input X-ray image and masked for further processing into VGG-19 pooling layers. 4099 images are used for training, and 1757 images are used for testing purposes.

3.2 ENN Classifier VGG19 for Multi Classification

Measuring In order to perform multi-classification, VGG19 pre-trained architecture is used in this new approach specifically to classify lung nodules, pneumonia, and healthy classes. VGG19 has inbuilt 19 layers with a deep neural network structure that extracts multiple features from the input LC X-ray image. The intrinsic and suspicious patterns are isolated with the help of linear activation function. The image passed into all layers, where the layer captured the deep structure to mask the image. The ReLU setup activation function is derived using the below equation,

$$F(x) = \text{ReLU}\,(W * x + b) \tag{4}$$

where, F(x) is activation function, W represents max pooling weights and x,b denotes the input pooling layer functions. The network capabilities are utilized for deep segmentation and classification. In order to reduce the spatial dimensions and to hold the isolated features, fully connected pooling layers are used. The multi-classification is achieved by softmax function, where the highest probability is selected by the model for the final classification of healthy, lung cancer, and pneumonia. The results of the probability distribution are recorded for each iteration to perform activation and softmax functions to enhance the robustness of the new AI-based approach. The following are the necessary steps carried out to perform multi-classification process.

- The ENN VGG19 resizes the input kaggle X-ray image to 224x224 pixels according to pre-trained specifications.
- Deep features like edges, textures, abnormalities, and colours are extracted.
- Spatial dimensions are reduced with the help of VGG19 max pooling layers.
- The feature recorded maps are reduced into multi flattened vectors.
- FVs are connected to the pooling layer to perform transformation followed by ReLU activation.
- Masking the binary vectors and preventing overfitting is done.
- The output of L1 is connected to L2, followed by an activation function.
- Reduce the overfitting and the output of L2 is then connected to L3 to perform multi-classification.
- The last layer is connected with the softmax function to perform multiple tasks and generate the classification probabilities.
- The class with the highest probability in L3 is selected as the final prediction.

3.3 ENN Classifier with YOLO V8 Architecture Diagram

The proposed AI-based architecture is a disease classification system that detects lung nodules and pneumonia by utilizing deep learning neural networks and localization techniques. Figure 2 portrays the new approach begins with an input X-ray raw image data from the Kaggle LC dataset. Initial pre-checking is done using the loss function called the enhanced HARQ method to boost the quality of the X-ray and better input to process without any noise or errors. The LC Kaggle dataset was split into two, where 80% is used for training and 20% for testing and validation. The input is processed through YOLO V8 for image localization, which detects intrinsic lung patterns and ROIs within a given input X-ray image and helps to isolate suspicious spots that may specify the presence of disease. The ROIs are processed through the ENN classifier VGG19 neural network model to pass with deep layers to extract multiple features to enhance the classification accuracy. Once the disease is classified, the ensembled method is deployed for post-validation checks to verify the low confidence scores for rectification. The model classifies the C-ray to 3 different classes, such as healthy, lung cancer, and pneumonia.

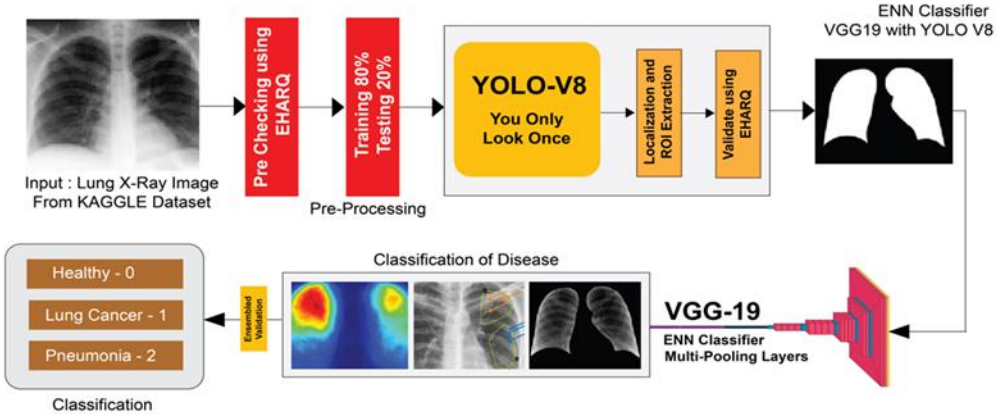

Fig. 2 ENN VGG19 with YOLO V8 Architecture Diagram

3.4 EHARQ and Ensembled Learning for Pre & Post Validation

To ensure consistency and accuracy of the suggested AI-based approach, EHARQ and the ensemble learning method are utilized as a loss function in terms of error detection and correction both for input and output. The cyclic redundancy checks are carried out by the system, which can be performed by the formula.

$$Cyclic_{Check} = Remainder\ (\frac{Data}{Generator}) \quad (5)$$

The variance, low confidence scores, and bias are minimized by the ensemble learning method, which leads to the most reliable prediction. This is done for validation purposes post-classification by the system. The robustness and accuracy are maximized, where the method checks the YOLO V8 and VGG19 results and validates for quality and consistency. The error checks are done for all the iterations with the given batch size of input data.

3.5 Confusion Matrix - True Label Predictions

As multiple classes are portrayed by the model with 3x3 matrix, it is performed to showcase healthy, lung cancer, and pneumonia. A heat map is generated to display the number of predictions for each class in the total which is shown in Figure 3. Error analysis is also measured using matrix values.

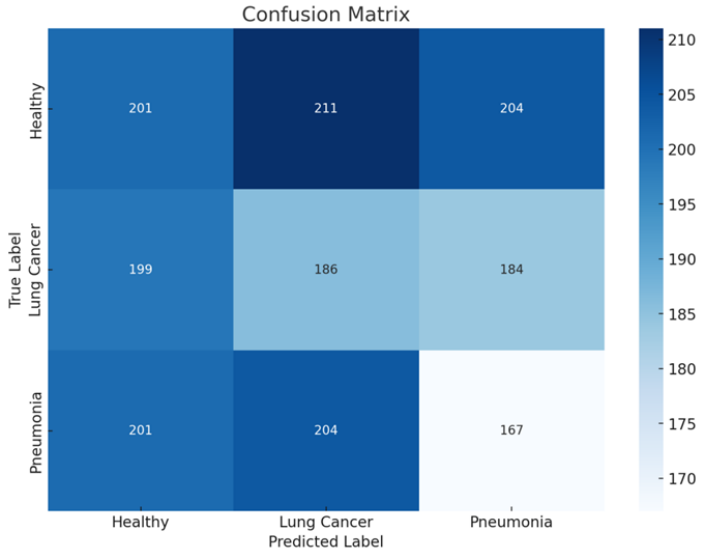

Fig. 3 3x 3 Confusion Matrixes

3.6 ENN Classifier VGG19 with YOLO V8

1. **Input:** KAGGLE Lung X-ray Image dataset
2. **Begin**: Load the X-Ray Image Dataset $data.KaggleLC$
3. **Initial Processing**

$$yolo\_v8 = load\_yolo\_v8\_model()$$
$$vgg19 = load\_vgg19\_model()$$

$detected_{regions} = ()$
$classified_{results} = ()$

4. **Localize using YOLO V8**

$for\ image\ in\ images$
$regions\_of\_interest\ =\ yolo\_v8.detect(image)$
$detected\_regions.append(regions\_of\_interest)$

5. **Classify using ENN VGG19**

$for\ region\ in\ regions\_of\_interest$
$classification\ =\ vgg19.classify(region)$
$classified_{results}.append((region, classification))$
$Segmented_{Disc}, Segmented_{Cup} = ResNet\_Segmentation(Fundus\_Images)$

6. **Apply Error Recovery - HARQ**

$harq\_results = apply\_harq(classified\_results + recovered\_results)$

7. **Validation of Results**

$final_{results} = ()$
$ensemble_{model} = load_{ensemble_{model()}}$
$final_{classification} == ensemble_{model}.validate(result)$
$final\_results.append(final_{classification})$

8. Generate **LC&P Results (0,1,2)**
9. **Output:** Lung Cancer or Pneumonia detection & classification
10. **End**

3.7 Performance Evaluation Metrics

The ENN classifier with the VGG19 and YOLO V8 models is mainly focused on lung cancer and pneumonia detection and classification. The major localization tasks are carried out by the YOLO V8 model. The comparative analysis is done using MATLAB software to assess the performance of the suggested model in terms of performance evaluation metrics such as accuracy, precision, Fscore, recall, and AUC-ROC. The analysis is compared against the baseline models such as EfficientNet-B0 [8], Resnet-50 [8], and 3D-DLCNN [17]. Multiple iterations are carried out to evaluate the new model in order to showcase the robust detection and classification.

The following are the performance metrics and formulas used in this research work for detailed analysis.

$$\boldsymbol{Accuracy} = \frac{(TPR+TNR)}{(TPR+TNR+FPR+FNR)} \times 100 \quad (6)$$

$$\boldsymbol{True\ Positive\ Rate} = \frac{TPR}{(TPR+FNR)} \quad (7)$$

$$\boldsymbol{False\ Positve\ Rate} = \frac{FPR}{(TNR+FPR)} \quad (8)$$

$$\boldsymbol{Precision}\ \frac{TPR}{(TPR+FPR)} \times 100 \quad (9)$$

$$\boldsymbol{Recall} = \frac{TPR}{(TPR+FNR)}\ \text{x}100 \quad (10)$$

$$\boldsymbol{F-Measure} = \frac{2*(Precision*Recall)}{(Precision+Recall)} \quad (11)$$

$$\boldsymbol{MCC} = \frac{T_1}{\sqrt{T_2 \times T_3 \times T_4 \times T_5}} \times 100 \quad (12)$$

where, $\boldsymbol{LCP}\ defines\ Lung\ Cancer\ and\ Pneumonia\ Detection$ and the distinct mathematical expression of the combined metrics are derived using, $T_1 = (TPR \times TNR - FPR \times FNR)$, $T_2 = (TPR + FPR)$, $T_3 = (TPR + FNR)$, $T_4 = (TNR + FPR)$, and $T_5 = (TNR + FNR)$.

- **Accuracy:** The overall predictions and classifications made by the new ENN classifier VGG19 with YOLO V8 model. It is the balanced ratio of correctly classified and predicted instances from the dataset used.
- **F-Score Analysis:** To maintain perfect balance between precision and recall, the F1 score is measured in order to provide a vocal mean against the predicted and total number of images used.
- **Precision:** Positive prediction values are measured against the total number. It gives clear predicted results on the number of cases correctly predicted as +ve out of the number of actual positive instances.
- **AUC-ROC:** The AUC-ROC assesses the true positive and false positive (1-specificity), which calculates the total number of TPR and FPR against the number of iterations by the model with a specific batch size.

- **Recall:** It is calculated to measure the performance of sensitivity, which shows how the proposed ENN model spots the positive cases. The ability is measured by how the model captures as many as positive cases against the total number of samples.

4. Results and Findings

This section shows the findings of the proposed ENN classifier VGG19 with YOLO V8. The performance metrics are discussed as how the new model overcomes the limitations of the existing model in a robust manner. The model is compared against EfficientNet-B0 [8], Resnet-50 [8], and 3D-DLCNN [17]. The outstanding results show the performance of image localization, deep segmentation, classification, and iterative improvement processes. Identification of errors in the pre-processing stage helps the model minimize the errors, and the ensemble model validates the results generated by the system. Out of 5856 X-ray images, 4099 are used for training and 1757 are used for testing and validation. Figure 4-8 shows the graphical representation of the model's performance with the X axis as the model and the Y axis as the percentage value.

4.1 Accuracy Analysis

The accuracy analysis is portrayed in Figure 4. Due to deep segmentation and pretrained weights, the model isolates the infected part from the X-ray image and detects the disease in a robust manner. The regions are isolated to measure the accuracy level of prediction and classification. Threshold range is set for all iterations as per the matrix performed. The intrinsic features are extracted for deep analysis to achieve the promising results. The results of the proposed model are compared against existing methods such as EfficientNet-B0 [8], Resnet-50 [8], and 3D-DLCNN [17]. 97.34% accuracy is achieved as per the number of corrected samples predicted out of total samples given as input under various iterations is clearly shown in Table 1.

Table 1: P&C Accuracy - comparative analysis

Metrics / Models	Resnet-50 [8]	EfficientNet-B0 [8]	3D-DLCNN [17]	**ENN with VGG19 & YOLO V8 (Proposed)**
Accuracy (It-1)	78.20	82.17	88.12	**95.87**
Accuracy (It-N)	80.40	84.36	91.40	**97.34**

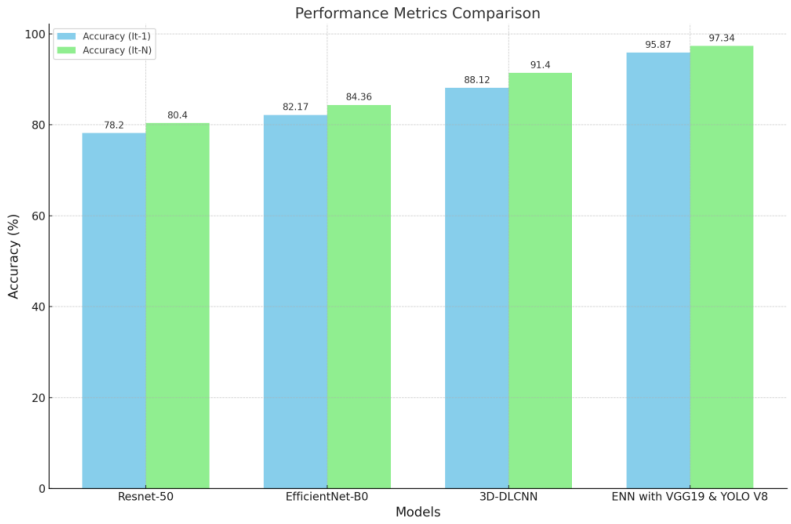

Fig. 4 Accuracy

4.2 Precision Analysis

As the model combines VGG19 with YOLO V8, real-time localization is done precisely where most of the relevant areas are deeply analyzed. Comparative analysis of precision is shown in Figure 5. This targeted approach minimizes the chances of misclassification, and its deep convolutional layers allow robust detection and classification of lung cancer, pneumonia, and

healthy labels. Due to error checking before pre-processing and post-result validation by HARQ & ensembled model, 98.70% precision is achieved, which is high compared to earlier approaches and the same is shown in Table 2.

Table 2: P&C Precision comparative analysis

Metrics / Models	Resnet-50 [8]	EfficientNet-B0 [8]	3D-DLCNN [17]	ENN with VGG19 & YOLO V8 (Proposed)
Precision (It-1)	79.37	84.92	89.42	96.10
Precision (It-N)	81.26	87.50	91.30	98.70

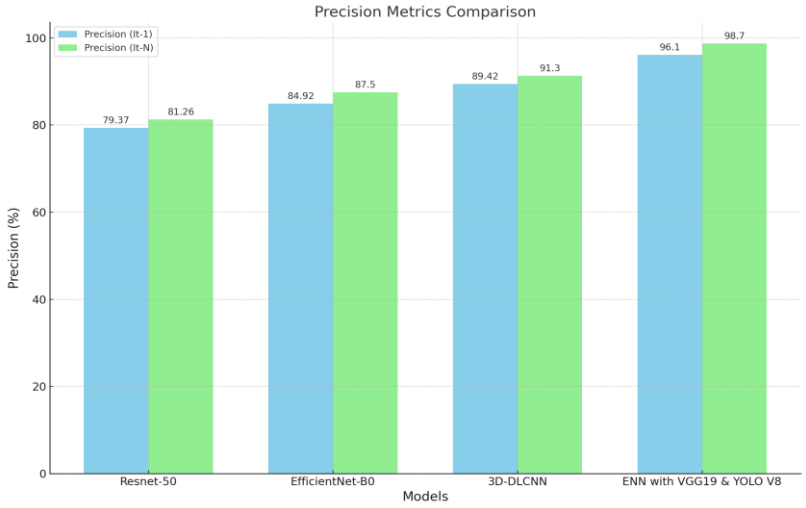

Fig.5 Precision

4.3 Recall Analysis

Figure 6 shows the recall rate of the proposed ENN classifier model. The model has the ability to capture the true positive cases by localizing the suspicious cases with YOLO V8. The intricate patterns associated with lung cancer and pneumonia is isolated by VGG19, which enhances the prediction and classification. The ensemble learning boosts the recall as it reduces the false positives due to the post-validation process. The input quality is boosted by HARQ to remove errors during the initial stage itself. Precise localization, deep learning, and isolating ROIs significantly enhance the recall rate in the new model. Table 3 shows the comparative analysis in which 97.32% is achieved by the ENN VGG19 with YOLO V8 model, marks the dominant one among all other models.

Table 3: P&C Recall comparative analysis

Metrics / Models	Resnet-50 [8]	EfficientNet-B0 [8]	3D-DLCNN [17]	**ENN with VGG19 & YOLO V8 (Proposed)**
Recall (It-1)	77.10	79.57	87.12	**94.56**
Recall (It-N)	73.65	83.46	90.20	**97.32**

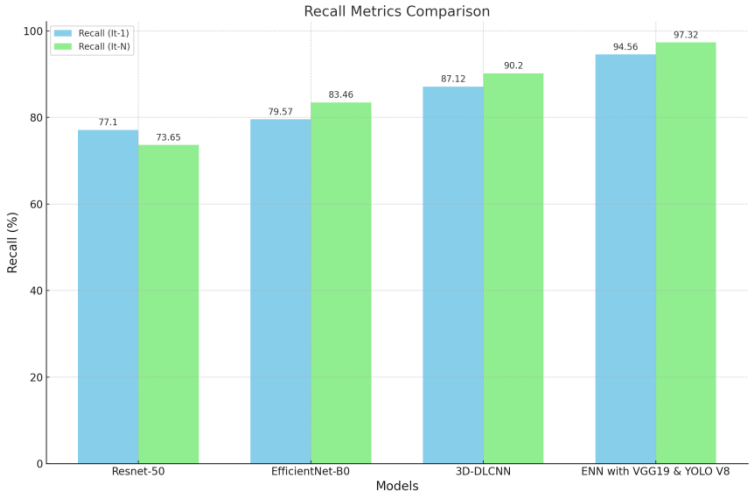

Fig.6 Recall

4.4 AUC-ROC Analysis

Figure 7 highlights the TPR and FPR performance under the AUC-ROC curve. The model is pre-trained on a comprehensive Kaggle lung X-ray dataset, which shows different cases and conditions. The model is generalized with efficient training of 4099 images with unseen data to improve the discrimination power. The predicted values are used to measure true positive rate and false positive rate. Different threshold levels are maintained during the training and testing process for continuous iterations to increase the performance. Table 4 shows the promising results with 93.02% TPR and 7.19% FPR in the final iteration, which is better compared to the earlier deep learning approaches.

Table 4: P&C AUC-ROC comparative analysis

Metrics / Models	Resnet-50 [8]	EfficientNet-B0 [8]	3D-DLCNN [17]	**ENN with VGG19 & YOLO V8 (Proposed)**
TPR	71.25	78.17	89.12	**93.02**
FPR	21.36	17.52	15.74	**07.19**

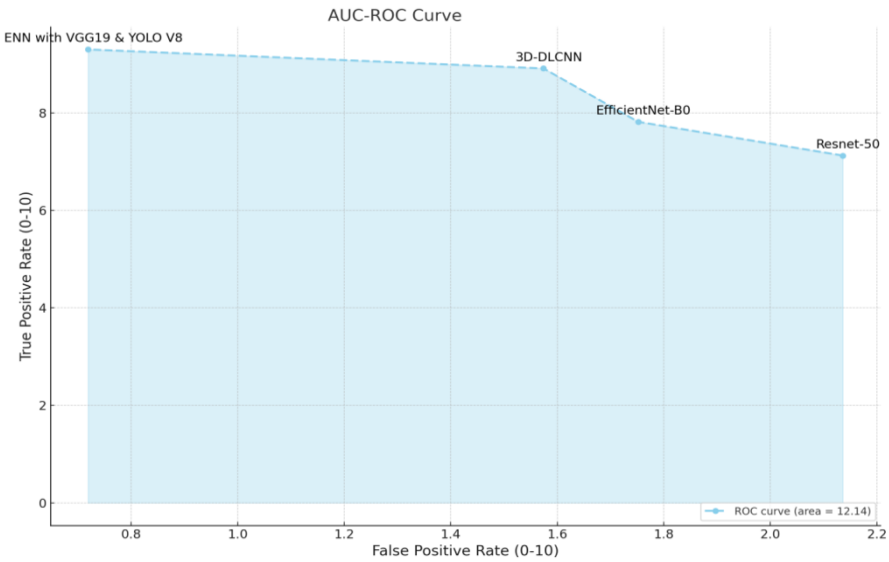

Fig 7. AUC-ROC

4.5 F-Score Analysis

Figure 8 illustrates the F-score comparative analysis of the proposed ENN classifier VGG19 with the YOLO V8 deep learning model. Due to robust training on a multi-centric dataset, the pattern recognition power has drastically boosted in all levels, starting from segmentation to classification. The risk of misclassification is reduced where the input quality of an X-ray image is boosted by the error handling method. Also, the low confidence scores are validated, and measures are taken with the ensemble method.

98.82% F-score is achieved, which is significantly high compared to the other models such as EfficientNet-B0 [8], Resnet-50 [8], and 3D-DLCNN [17] is showcased in Table 5.

Table 5: P&C F-Score comparative analysis

Metrics / Models	Resnet-50 [8]	EfficientNet-B0 [8]	3D-DLCNN [17]	**ENN with VGG19 & YOLO V8 (Proposed)**
F-Score (It-1)	75.24	78.89	86.12	**96.51**
F-Score (It-N)	76.41	83.46	88.59	**98.82**

Fig 8. AUC-ROC

5. Conclusion

In this research work, an AI-based lung cancer and pneumonia prediction and classification model is presented to support clinical experts with the help of a deep learning model called the ENN classifier with YOLO V8. The ENN classifier is a neural network-based VGG19 model that detects the lung nodules and classifies them based on the score and threshold level. Preprocessing and segmentation are done to extract the relevant features to detect and classify the disease in a robust manner. A multi-centric Kaggle dataset that contains X-ray images is used for training, testing, and validation purposes. ENN with the YOLO V8 model is applied to an X-ray image, where YOLO V8 detects the localized regions, followed by classification done through the pretrained VGG19 model in order to give the optimum result with three labels: healthy, lung cancer, and pneumonia. EHARQ and ensemble learning methods are additionally employed as pre- and post-processing validation to ensure high accuracy. More than 10 epochs with batch sizes of 20 are carried out to assess the performance of the newly proposed model. Minimum and maximum threshold levels are applied to figure out the classification. The model shows proven results by detecting and classifying the disease in a robust manner with the help of effective localization of ROIs. With YOLO V8, the ENN classifier achieved 97.3% accuracy, 98.7% precision, 97.3% recall, 0.93 TPR and 0.9 FPR under balanced AUC-ROC and 98.8% F1 score. The new model outperforms the baseline versions such as EfficientNet-B0, Resnet-50, and 3D-DLCNN in terms of image localization and accuracy. Though the model attains high accuracy, it has minor limitations such as variations based on image quality, computational complexity, segmentation challenges, preprocessing dependencies, etc. This model may be enhanced for 3D images using AI-based finite and automata models to enhance the robustness.

6. References

1. Goram Mufarah M. Alshmrani, Qiang Ni, Richard Jiang, Haris Pervaiz, Nada M. Elshennawy, “A deep learning architecture for multi-class lung diseases classification using chest X-ray (CXR) images”. Alexandria Engineering Journal, vol 64, , pp. 923-935, (2023)
2. Anirudh Atmakuru, Subrata Chakraborty, Oliver Faust, Massimo Salvi, Prabal Datta Barua, Filippo Molinari, U.R. Acharya, Nusrat Homaira, “Deep learning in radiology for lung cancer diagnostics: A systematic review of classification, segmentation, and predictive modeling techniques”, Expert Systems with Applications, 255, Part B, 124665, (2024).
3. Baris Hekimoglu, Muhammet Ali Beyoglu, “Early outcomes of lung resections in non-small cell lung cancer after COVID-19 pneumonia, Asian Journal of Surgery”, vol 45, issue, pp.1553-1558. (2022). Available From: https://doi.org/10.1016/j.asjsur.2022.04.080
4. G. Mohandass, G. Hari Krishnan, D. Selvaraj, C. Sridhathan,” Lung Cancer Classification using Optimized Attention-based Convolutional Neural Network with DenseNet-201 Transfer Learning Model on CT image, Biomedical Signal Processing and Control”, 95, Part B,, 106330, pp.1746-8094. (2024). Available From: https://doi.org/10.1016/j.bspc.2024.106330
5. Nithyanandh S and Jaiganesh V. “Quality of service enabled intelligent water drop algorithm based routing protocol for dynamic link failure detection in wireless sensor network. Indian Journal of Science and Technology”, 13(16), 1641-1647, (2020). Available From: https://doi.org/10.17485/IJST/v13i16.19
6. Rehan Raza, Fatima Zulfiqar, Muhammad Owais Khan, Muhammad Arif, Atif Alvi, Muhammad Aksam Iftikhar, Tanvir Alam, .”Lung-EffNet: Lung cancer classification using EfficientNet from CT-scan images, Engineering Applications of Artificial Intelligence”, 126, Part B, 106902, 2023. Available From: https://doi.org/10.1016/j.engappai.2023.106902
7. Aryan Nikul Patel, Ramalingam Murugan, Gautam Srivastava, Praveen Kumar Reddy Maddikunta, Gokul Yenduri, Thippa Reddy Gadekallu, Rajeswari Chengoden, “An explainable transfer learning framework for multi-classification of lung diseases in chest X-rays, Alexandria Engineering Journal”, 98, 328-343, (2024).
8. Kajal Kansal, Tej Bahadur Chandra, Akansha Singh, “ResNet-50 vs. EfficientNet-B0: Multi-Centric Classification of Various Lung Abnormalities Using Deep Learning, Procedia Computer Science”, 235, 2024, 70-80 (2024)
9. Omprakash S, Megala D, Karthikeyan MP. “Energy Aware Adaptive Sleep Scheduling and Secured Data Transmission Protocol to enhance QoS in IoT Networks using Improvised Firefly Bio-Inspired Algorithm (EAP-IFBA). Indian Journal of Science and Technology”, 16(34), 2753-2766, 2023. Available From: https://doi.org/10.17485/IJST/v16i34.1706
10. Pegah Moradi Khaniabadi, Yassine Bouchareb, Humoud Al-Dhuhli, Isaac Shiri, Faiza Al-Kindi, Bita Moradi Khaniabadi, Habib Zaidi, Arman Rahmim, “Two-step machine learning to diagnose and predict involvement of lungs in COVID-19 and pneumonia using CT radiomics”, Computers in Biology and Medicine, 150, 106165, (2022).
11. Hanguang Xiao, Qiyuan Liu, Li Li, “MFMANet: Multi-feature Multi-attention Network for efficient subtype classification on non-small cell lung cancer CT images, Biomedical Signal Processing and Control”, 84, (2023), 104768. Available From: https://doi.org/10.1016/j.bspc.2023.104768
12. Nithyanandh S and Jaiganesh V. “Interrogation of Dynamic Node Link Failure by Utilizing Bio Inspired Techniques to Enhance Quality of Service in Wireless Sensor Networks”, Shodhganga, 400513, (2020). Available From: http://hdl.handle.net/10603/400513
13. Unai Muñoz-Aseguinolaza, Izaro Fernandez-Iriondo, Itsaso Rodríguez-Moreno, Naiara Aginako, Basilio Sierra, Convolutional neural network-based classification and monitoring models for lung cancer detection: 3D perspective approach, Heliyon, 9 (11), e21203, (2023). Available From: https://doi.org/10.1016/j.heliyon.2023.e21203
14. Jaiganesh V. “Reconnaissance Artificial Bee Colony Routing Protocol to Detect Dynamic Link Failure in Wireless Sensor Network. International Journal of Scientific & Technology Research”, 10(10), 3244–3251, (2019)
15. Bingqing Long, Zeng Xiong, Manzo Habou, Lung cancer screening, diagnosis, and treatment: The radiologist's perspective, Meta-Radiology, 2(1), 2024, 100066. Available From: https://doi.org/10.1016/j.metrad.2024.100066
16. Rana Khattab, Islam R. Abdelmaksoud, Samir Abdelrazek, “Automated detection of COVID-19 and pneumonia diseases using data mining and transfer learning algorithms with focal loss from chest X-ray images, Applied Soft Computing”, 162, 111806, (2024). Available From: https://doi.org/10.1016/j.asoc.2024.111806
17. Eldho KJ, Nithyanandh S, “Lung Cancer Detection and Severity Analysis with a 3D Deep Learning CNN Model Using CT-DICOM Clinical Dataset. Indian Journal of Science and Technology”,17(10), 899-910, (2024). Available From: https://doi.org/10.17485/IJST/v17i10.3085
18. Md Khairul Islam, Md Mahbubur Rahman, Md Shahin Ali, S.M. Mahim, Md Sipon Miah, “Enhancing lung abnormalities detection and classification using a Deep Convolutional Neural Network and GRU with explainable AI: A promising approach for accurate diagnosis, Machine Learning with Applications”, 14, 100492, 2666-8270, (2023). Available From: https://doi.org/10.1016/j.mlwa.2023.100492
19. Byeongju Lee, Junyeong Lee, Jin-Oh Lee, Yoohwa Hwang, Hyung-Keun Bahn, Inkyu Park, Sanghoon Jheon, Dae-Sik Lee, “Breath analysis system with convolutional neural network (CNN) for early detection of lung cancer, Sensors and Actuators B: Chemical”, 409, 135578(2024)

20. Wenyu Xing, Chao He, Jiawei Li, Wei Qin, Minglei Yang, Guannan Li, Qingli Li, Dean Ta, Gaofeng Wei, Wenfang Li, Jiangang Chen, “Automated lung ultrasound scoring for evaluation of coronavirus disease 2019 pneumonia using two-stage cascaded deep learning model, Biomedical Signal Processing and Control”, 75, 103561.(2022) Available From: https://doi.org/10.1016/j.bspc.2022.103561
21. N Venkatesan, S Pasupathy, B Gobinathan, “An efficient lung cancer detection using optimal SVM and improved weight based beetle swarm optimization, Biomedical Signal Processing and Control”, 88, Part C, 105373(2024) Available From: https://doi.org/10.1016/j.bspc.2023.105373
22. Pankaj Nanglia, Sumit Kumar, Aparna N. Mahajan, Paramjit Singh, Davinder Rathee, A hybrid algorithm for lung cancer classification using SVM and Neural Networks, ICT Express, 7(3),335-341,(2021).
23. K. Nandhini and G. Thailambal, CNN-OSBO Encoder-Decoder Architecture for Drug-Target Interaction (DTI) Prediction of Covid-19 Targets, 2022 6th International Conference on Electronics, Communication and Aerospace Technology, Coimbatore, India, pp. 1199-1206, (2022)
24. V. Sreeprada, Dr. K. Vedavathi, “Lung Cancer Detection from X-Ray Images using Hybrid Deep Learning Technique, Procedia Computer Science”, 230, 467-474 (2023)
25. Lakshmi, G., Sujatha, P. “An Efficient Approach of Heart Disease Diagnosis Using Modified Principal Component Analysis (M-PCA)”. ICCSST. Communications in Computer and Information Science, vol 1973. Springer, 2023.