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A Novel Enhanced Pre-Activation Residual CNN Approach for Lung Nodule Detection Using LIDC Dataset

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***Abstract* - Early detection of lung nodules from computed tomography images is important for supporting timely lung cancer diagnosis. The research work represents a novel Pre-activation residual convolutional neural network with long short-term memory for lung nodule detection using LIDC dataset respectively. The proposed approach combines pre-activation residual learning with convolutional feature extraction to improve information propagation and preserve important image characteristics across deeper network layers. An LSTM component is incorporated to learn dependencies among the extracted feature representations and provide additional contextual information for classification. The framework includes image pre-processing, normalization, augmentation, feature extraction, sequential feature learning, and nodule classification consistently. The proposed approach is designed to capture both detailed local characteristics and higher-level contextual patterns associated with pulmonary nodules respectively. The performance of the classification and prediction accuracy were measured the area under receiver operating characteristic curve. The proposed method aims to provide a reliable and efficient computer-aided approach for automated lung nodule detection and to improve the consistency of computed tomography image analysis respectively.**

Keywords: Lung nodule detection, pre-activation residual CNN, LSTM, deep learning, computed tomography, LIDC dataset, lung cancer, medical image analysis, computer-aided detection.

I. INTRODUCTION

Lung nodule detection from computed tomography images is an important step in computer-aided lung cancer assessment. The appearance of nodules can vary in size, shape, texture, and intensity, making their identification difficult, particularly when small nodules have similar characteristics to surrounding lung tissues. The LIDC provides a widely used annotated CT database for developing and evaluating automated lung nodule detection methods. Initial computer-aided approaches relied on image processing and conventional machine-learning techniques for segmentation, feature extraction, and classification [7] [11]. These methods demonstrated the usefulness of texture and morphological information, but their performance can depend on the quality of manually designed features. Radiomics-based methods have also combined handcrafted features with classifiers such as support vector machines and random forests for LIDC nodule classification [6]. The development of convolutional neural networks has enabled automatic learning of discriminative features from CT images. Three-dimensional CNN architectures have been investigated to preserve volumetric information during nodule detection, with hybrid two-stage networks showing strong detection capability on LIDC [13]. Other deep-learning systems have demonstrated the potential of automated CAD for reducing missed nodules during CT interpretation [5]. Hybrid CNN-LSTM models have further introduced sequential feature learning for pulmonary nodule classification and have reported promising results on LIDC [1]. Recent work has also demonstrated the growing clinical application of AI-assisted pulmonary nodule diagnosis respectively [15]. However, existing approaches do not adequately address **deep feature propagation together with contextual learning** within a unified architecture. Therefore, the study proposes a **novel enhanced Pre-Activation residual CNN Approach for lung nodule detection using the LIDC dataset**, designed to improve feature propagation through pre-activation residual learning and strengthen feature representation for reliable nodule detection.

II. LITERATURE REVIEW

The research work explored machine learning and deep learning techniques for automated lung nodule detection and classification from computed tomography images. Traditional machine-learning approaches have used segmentation, handcrafted features, support vector machines, random forests, and artificial neural networks to identify pulmonary nodules [7] [11]. These methods demonstrated the usefulness of machine learning for computer-aided diagnosis respectively and their performance depends strongly on the quality of segmentation and manually extracted features. Radiomics-based approaches have further improved nodule

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characterization by combining quantitative image features with artificial intelligence classifiers [6]. Such methods provide useful diagnostic information but may have limitations in automatically learning complex spatial representations from CT images. Deep convolutional neural networks have subsequently become widely used because they can learn discriminative image features directly from CT data. A two-stage three-dimensional CNN was developed for pulmonary nodule detection, demonstrating the effectiveness of volumetric feature learning [13]. Similarly, deep-learning-based lung nodule classification using computed tomography images has shown improved performance compared with conventional machine-learning approaches [14]. Other studies have introduced artificial-intelligence-based segmentation and classification frameworks to improve the identification of nodules from CT scans [4], [5]. These developments indicate that CNN-based architectures can effectively learn complex nodule characteristics from medical images.

Residual learning has also been investigated to overcome the difficulties associated with training deeper networks. Residual architectures improve information propagation through shortcut connections and have demonstrated strong performance for lung nodule analysis. More advanced approaches have incorporated attention mechanisms to emphasize important nodule regions [12]. Finally the hybrid form of CNN-LSTM architectures have been proposed to combine spatial feature extraction with sequential feature learning, with promising results on the LIDC-IDRI dataset respectively.[1] The studies were investigated optimized deep-learning and artificial-intelligence frameworks for pulmonary nodule diagnosis prominently [3] [15]. Moreover the approaches have achieved promising results, **limited work has specifically investigated the combination of pre-activation residual learning with CNN-based feature extraction and LSTM-based contextual learning for lung nodule detection using the LIDC dataset**. Pre-activation residual blocks can improve gradient propagation and feature learning in deeper networks, while LSTM can capture relationships among extracted feature representations. Therefore, the study proposes **a novel enhanced pre-activation residual CNN approach for lung nodule detection using LIDC dataset**, aiming to combine effective residual feature propagation with enhanced representation learning for improved and reliable pulmonary nodule detection.

III. PROBLEM STATEMENT

Nodule detection: Small and low-contrast nodules are difficult to distinguish from normal lung tissue in CT images.

Feature extraction: Conventional machine-learning methods depend on manually selected features and may miss important nodule characteristics.

Deep-network training: CNN depth can lead to weak gradient flow and loss of useful feature information.

Contextual information: CNN mainly learn spatial features but have limited ability to model relationships between extracted feature representations.

Model integration: An effective framework combining pre-activation residual learning, enhanced CNN feature extraction, and LSTM-based contextual learning is needed for reliable lung nodule detection using the LIDC dataset.

IV. PROPOSED FRAMEWORK

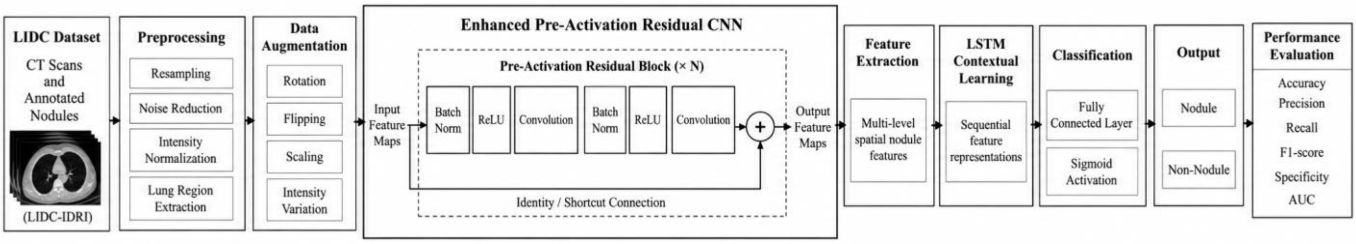

Figure 1: Proposed Lung Nodule Detection using Enhanced pre-activation residual CNN with LSTM on the LIDC dataset

Figure 1 represents the proposed framework with LIDC CT image pre-processing and augmentation. The enhanced pre-activation residual CNN extracts discriminative features, with LSTM contextual relationships among the extracted representations respectively.

Steps involved in this approach

Pseudo code of the proposed Enhanced Pre-Activation Residual CNN with LSTM for automated lung nodule detection.

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Input : $\mathcal{D} = \{(X_i, y_i)\}_{i=1}^{N},\ y_i \in \{0,1\}$

Output : $\hat{y}_i \in \{0,1\}$

for each $(X_i, y_i) \in \mathcal{D}$ **do**

$X_i' = \text{Resize}(\text{Norm}(\text{Lung}(X_i)))$

$\tilde{X}_i = A(X_i')$

$F_0 = \text{Conv}_{3\times3}(\tilde{X}_i)$

for $l = 1, 2, \dots, L$ **do**

$Z_l = \text{BN}(F_{l-1})$

$A_l = \text{ReLU}(Z_l)$

$C_l^{(1)} = \text{Conv}_{3\times3}(A_l)$

$Z_l^{(2)} = \text{BN}(C_l^{(1)})$

$A_l^{(2)} = \text{ReLU}(Z_l^{(2)})$

$C_l^{(2)} = \text{Conv}_{3\times3}(A_l^{(2)})$

$F_l = C_l^{(2)} + S(F_{l-1})\ ,\quad S(F_{l-1}) = \begin{cases} F_{l-1}, & \text{if dimensions match} \\ W_s * F_{l-1}, & \text{otherwise} \end{cases}$

end for

$F = F_L$

$F \in \mathbb{R}^{H\times W\times C} \rightarrow Q = \{q_1, q_2, \dots, q_T\}$

for $t = 1, 2, \dots, T$ **do**

$i_t = \sigma(W_i q_t + U_i h_{t-1} + b_i)$

$f_t = \sigma(W_f q_t + U_f h_{t-1} + b_f)$

$\tilde{c}_t = \tanh(W_c q_t + U_c h_{t-1} + b_c)$

$c_t = f_t \odot c_{t-1} + i_t \odot \tilde{c}_t$

$o_t = \sigma(W_o q_t + U_o h_{t-1} + b_o)$

$h_t = o_t \odot \tanh(c_t)$

end for

$H = h_T$

$z = W_c H + b_c$

$p_i = \sigma(z) = \frac{1}{1+e^{-z}}$

$\hat{y}_i = \begin{cases} 1, & p_i \geq 0.5 \\ 0, & p_i < 0.5 \end{cases}$

$\mathcal{L} = -\frac{1}{N}\sum_{i=1}^{N}\left[y_i \log(p_i) + (1-y_i)\log(1-p_i)\right]$

$\theta^* = \arg\min_{\theta} \mathcal{L}(\theta)$

Evaluate using standard parameters

return $\hat{y}_i$

V. RESULTS AND DISCUSSIONS

Table 1: Accuracy for the Enhanced Pre-activation Residual CNN in LIDC DATASET images

No. of Images	Accuracy (%)
100	98.61
200	98.33
300	98.81
400	98.91
500	97.82

The above table represents the Accuracy achieved by the enhanced Pre-activation Residual CNN for different numbers of input images respectively.

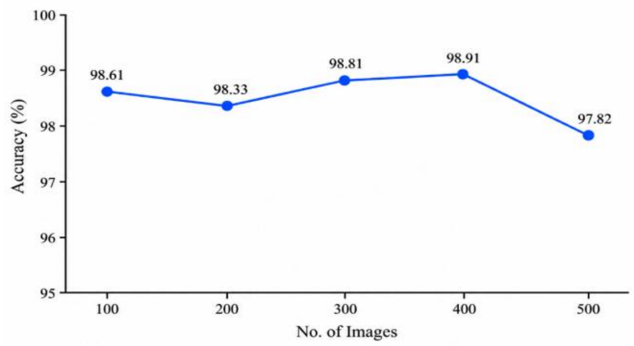

Figure 2: Accuracy for Enhanced Pre-activation Residual CNN in LIDC DATASET

The above graph illustrates the Accuracy trend of the proposed model across the selected image counts. The increasing trend indicates consistent improvement in nodule classification performance with more input images respectively.

Table 2: Precision for the Enhanced Pre-activation Residual CNN in LIDC DATASET

No. of Images	Precision (%)
100	88.11
200	84.23
300	83.78
400	84.45
500	84.88

The above table represents the Precision achieved by the Enhanced Pre-activation Residual CNN in LIDC DATASET for different numbers of input images respectively.

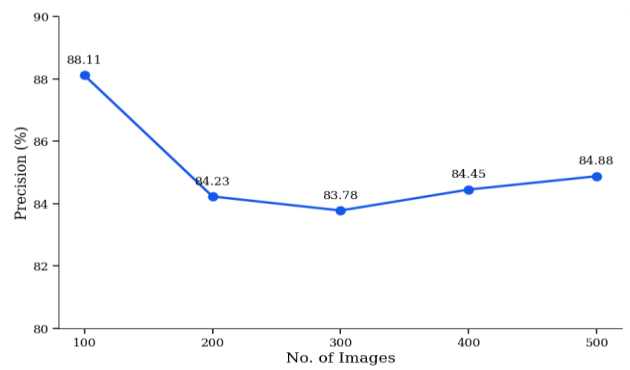

Figure 3: Precision for Enhanced Pre-activation Residual CNN in LIDC DATASET

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The above graph illustrates the precision trend of EPRCNN across different numbers of input images respectively.

Table 3: Recall for the Enhanced Pre-activation Residual CNN in LIDC DATASET

No. of Images	Recall (%)
100	98.19
200	98.36
300	98.50
400	98.80
500	98.97

The above table represents the Recall achieved by the Enhanced Pre-activation Residual CNN in LIDC DATASET for different numbers of input images respectively.

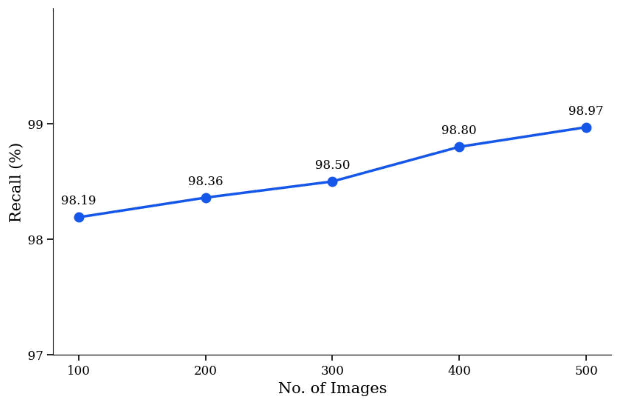

Figure 4: Recall for Enhanced Pre-activation Residual CNN in LIDC DATASET

The above graph illustrates the Recall trend of EPRCNN across different numbers of input images respectively.

Table 4: F-Measure for the Enhanced Pre-activation Residual CNN in LIDC DATASET

No. of Images	F-Measure (%)
100	93.01
200	93.26
300	93.46
400	92.89
500	92.95

The above table represents the F-Measure achieved by the Enhanced Pre-activation Residual CNN in LIDC DATASET for different numbers of input images respectively.

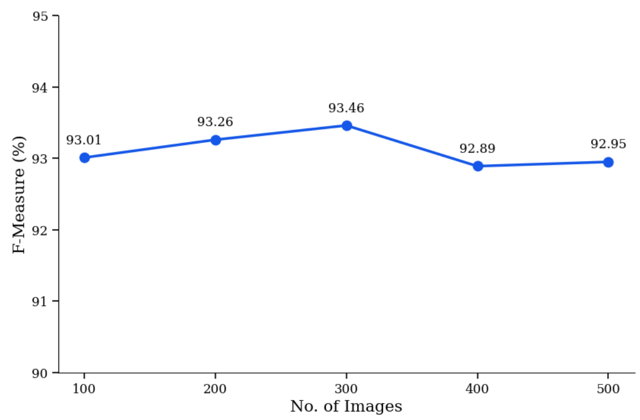

Figure 5: F-Measure for Enhanced Pre-activation Residual CNN in LIDC DATASET

The above graph illustrates the F-Measure trend of EPRCNN across different numbers of input images respectively.

The proposed Enhanced Pre-activation Residual CNN with LSTM was evaluated using different numbers of images from the LIDC dataset. The experimental results demonstrate that the model provides consistently strong performance across the selected image sets. Accuracy remained high, indicating reliable classification of nodule and non-nodule cases. Precision showed some variation with the number of images, while recall exhibited a steady improvement as the dataset size increased. The high recall demonstrates the model's ability to identify pulmonary nodules effectively and reduce missed detections. The F-measure also remained stable, indicating a good balance between precision and recall. The improved feature propagation provided by pre-activation residual learning contributes to effective extraction of discriminative image features. In addition, the LSTM component helps capture contextual relationships among the extracted feature representations. The results the stability and effectiveness of the proposed approach. Hence, the proposed model demonstrates its suitability for automated lung nodule

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detection using CT images from the LIDC dataset respectively.

VI. CONCLUSION

The proposed model represented a novel Enhanced Pre-Activation Residual CNN with LSTM for automated lung nodule detection using the LIDC dataset. The framework combines residual feature propagation with contextual learning to improve the representation of pulmonary nodule characteristics. The experimental results demonstrated stable performance across different numbers of input images, with strong accuracy, recall, precision, and F-measure. The integration of LSTM further supports learning relationships among extracted feature representations. Hence, the proposed approach provides a reliable framework for automated lung nodule detection from CT images and demonstrates its potential for computer-aided lung cancer analysis respectively.

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