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Enhanced Lung Cancer Detection Using Combined Edge–Threshold Segmentation And Fine-Tuned CNN Model

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Abstract
The use of computer tomography (CT) imaging has become commonplace since it provides cross-sectional images of internal structures in the diagnosis of lung disease. It is more sensitive than traditional radiography, but even a single CT-use still subjects one to the risk of misdiagnosis, because artefacts and low contrast can hide nodules in their early stages. In the recent literature, it is emphasized that automated tools are required to complement the images and isolate the lung area and categorize nodules as benign or malignant. The use of otsu and adaptive thresholding has stayed in use to isolate the foreground and the background but thresholding in most cases does not work well with small lesions or when the background is not uniform. DenseNet and ResNet machine learning models are capable of producing good classification, but they need fine-grained segmentation and significant datasets. As a result, there exists a gap in techniques combining edge-based and threshold-based segmentation with a hybrid classifier. The proposed work presents a combination of a computer-aided diagnostic pipeline of lung cancer. The first stage is pre-processing where noise is removed, morphology, and adaptive histogram equalization are performed and then a merged segmentation is performed where an edge detector is used to highlight the nodule boundaries and an adaptive threshold is used to segregate lung tissue. Features are extracted using various Convolutional Neural Network (CNN) architectures and classified through a fine-tuned CNN-based classification framework with optimized hyper-parameter settings. The proposed hybrid model incorporates hyper-parameter optimization techniques including learning rate tuning, batch size optimization, dropout regularization, Adam optimizer configuration, and epoch selection to enhance classification performance and model generalization. The hybrid method was tested using a benchmark dataset, where the accuracy and F1-score achieved 99.24%, outperforming individual CNN models. The improvements were made due to the joint segmentation approach and the use of fine-tuned CNN architecture for final classification. The results suggest that the use of edge and threshold information together with a fine-tuned CNN model would significantly enhance early lung cancer detection.

Keywords: Deep Learning Classification, Edge–Threshold Segmentation Fusion, Multi-Architecture Feature Fusion, Nodule Boundary Enhancement, Lung Cancer Detection, CT Imaging.

1. Introduction

Lung cancer is one such malignancy that is one of the deadliest globally with millions of deaths per year. Early diagnosis enhances the likelihood of effective treatment so much, but a considerable number of patients are diagnosed at the intermediate or advanced stage. In lieu of the screening technique which is required to be the chest radiography, the computed tomography (CT) imaging has become the procedure of choice due to its resolution of high-resolution cross-sectional images that can detect minute abnormalities [1]. CT scanning is more sensitive than the old X-rays and it allows early nodules to be detected. Nevertheless, the CT data is usually noisy and patient and machine variability. CT Scans are time consuming and open to subjectivity during the interpretation process. These difficulties lead to studies on automated computer-aided diagnosis (CAD) systems with the ability to identify and categorize lung nodules with high precision [2].

1.1 Background and present situation.

The main purposes of a CAD system are to improve CT images, segment the lung area correctly, extract discriminating features and predicate the nodules as benign and malignant. Image enhancement Image enhancement normally entails noise reduction, contrast enhancement and artefact elimination. Histogram equalization has been reported to minimize noise and artefacts in CT images and enhance further analysis [3]. Segmentation tries to separate the lung parenchyma and candidate nodules of the surrounding tissues. The thresholding methods including the Otsu method estimate an ideal threshold of intensity based on the maximization of the between-class variance. The Otsu thresholding is easy and can be done in a matter of seconds but has some problems when the intensity difference across the lung is high. Adaptive thresholding helps solve some of these problems by calculating a local threshold per region, but also requires parameter fine-tuning [4].

Edge-based segmentation focuses on edges by identifying the difference in the intensity. Recent efforts have shown that incorporating multi-scale information gives improved segmentation of pulmonary nodules when using edge information. These methods ensure that boundary cues are an important part of the process for defining irregularly shaped and/or low-contrast nodules. But, purely edge-based techniques can be noise sensitive and can give fragmented contours when applied all by themselves [5].

Classification is also an important element. Deep learning models such as DenseNet, ResNet and AlexNet can automatically learn hierarchical features from images without any prior information [6][7]. Learning of the optimal hyper-parameter settings is also getting special attention since it has a significant impact on improving the classification performance, the learning capability of the features and the overall efficiency of the deep learning models. In the field of medical image classification, the fine-tuned CNN architectures have been shown to achieve high accuracy in the recent studies. Optimized deep learning frameworks can thus provide a better feature representation and classification performance with satisfactory computational efficiency, as is indicated by the aforementioned findings.

1.2 Research gap

Nonetheless, there are still weaknesses in the combination of segmentation and classification processes. Most of the current techniques are concentrated on either thresholding or edge detection by itself, and this may result in missing a complete segmentation. Edge based techniques can over-segment areas of noise and thresholding can fail to detect low contrast lesions. In addition, there are deep models where segmentation and classification are distinct processes, resulting in irregular pipelines. It is also deprived of mechanisms in the combination of various CNN structures to extract features and employ an effective classifier to minimize the computation requirement. The lack of datasets and assessment procedures similarity between studies also prevents making a direct comparison. Thus, the consolidated pre-processing and combination segmentation and hybrid classification framework are required.

1.3 Objectives

This research paper seeks to fill these gaps in two ways:

- Design a hybrid segmentation method that combines edge detection and adaptive thresholding to obtain precise lung regions and nodule candidates. The algorithm must be able to improve boundary data and cope with intensity variations without creating jagged edges.
- Create a combined classification model that integrates features extracted from multiple CNN architectures (DenseNet, ResNet, and AlexNet) and performs lung nodule classification using an optimized CNN-based classification framework.
- Evaluate the proposed model using benchmark lung cancer datasets and performance metrics such as Accuracy, Precision, Recall, and F1-Score.

1.4 Significance of the study

Early detection of lung cancer is essential for improving survival rates, although existing diagnostic techniques continue to yield false positives and false negatives. The proposed segmentation should provide a more complete description of nodules, particularly compared to individual methods, by combining edge and threshold information. The use of deep features and an enhanced CNN-based classification model is anticipated to augment classification accuracy and efficiency. A CAD system based on the proposed approach can support radiologists by providing consistent results and potentially reducing unnecessary follow-up procedures.

2. Analysis of existing work

The CT imaging of Lung cancer detection has been giving much attention to the ever-increasing need of early and precise diagnosis. The recent trends in the field of medical image analysis have been dedicated to enhancement of performance of detection by means of sophisticated segmentation and classification. Conventional methods used simple methods of image processing, but the inability to deal with noise, tumor shape variability and low contrast have stimulated more advanced methods. In this regard, edge-based and threshold-based is a popular methodology of segmentation that allows isolating lung regions and nodules. The techniques form the basis of deriving significant details of the CT images.

As machine learning improved, CNNs are progressively used for automated feature extraction and classification. DenseNet, ResNet, and AlexNet architectures have shown good capabilities in identifying complicated patterns in medical images. Also, deep learning-based classification frameworks have been proposed as useful solutions for enhancing classification accuracy. The literature in this field shows a transition from single-method models toward integrated frameworks that combine preprocessing, segmentation, and classification methodologies. This section provides an overview of recent works in CT-based lung cancer detection, segmentation approaches, thresholding techniques, CNN-based methods, and hybrid learning models.

2.1 CT-based Methods of Lung Cancer Detection

The use of CT in imaging has become one of the standard modalities in the early diagnosis of lung cancer in terms of its capacity to give clear cross-sectional images of the structures of the lung. In the recent past, studies have been done on enhancement of detection precision by combining deep learning and optimization algorithms to help radiologists detect malignant nodules at the earliest stage. The aim of these approaches is to minimize diagnostic errors and enhance the performance in classification of various conditions of the lungs.

A number of researches have been conducted on the use of deep learning-based CT image classification. Ensemble-based learning method was shown to have a higher detection accuracy because it used a combination of several classifiers and feature representation optimization using CT scans [11]. Likewise, to augment model generalization and model robustness, data augmentation methods like random pixel swapping, transformation techniques, and so on have been applied, particularly to limited datasets [12]. Hybrid artificial intelligence systems that involve several feature extraction methods have also performed better in that they extract both local and global features in the CT images [13]. Deep learning models that can optimize yield an improvement in classification anyway that the parameters are optimized by bio-inspired algorithms, resulting in an improved convergence and prediction accuracy [14]. Moreover, convolutional neural networks trained using modern searching strategies have shown a high level of detection and fewer cases of false positives in lung cancer diagnosis [15].

All these research indicate that the diagnosis of lung cancer by CT has markedly progressed with the implementation of deep learning algorithms. Nevertheless, there are still the difficulties of variability of the image quality, noise, and complexity of a calculation. Despite all these limitations, the hybrid up of improved learning patterns and optimization modalities have shown promising results in the improvement of diagnostic accuracy. Overall, detection systems based on CT provide a good starting point for creating more accurate and automated lung cancer diagnosis systems.

2.2 Edge-based Segmentation Techniques.

In the identification of lung cancer, segmentation is important because it separates certain areas of the CT, such as the lung nodules and the lung tissues. Segmentation methods based on edges are based on the observation of boundaries and structural transitions in an image and allow one to draw precise boundaries of the lungs. The described methods work especially well when it comes to emphasizing irregular tumor borders that are significant in diagnosis.

Recent studies have suggested using hybrid segmentation techniques whereby edge detection is used alongside other techniques in order to enhance performance. It has been applied as a threshold-gradient combination technique to improve the accuracy of the segmentation using the boundary detection and region-based technique [16]. It has been established that multiscale segmentation models with edge-enhancement and attention have better detection of small nodules by maintaining finer structural information [17]. It has also introduced transformer-based architectures with boundary enhancement modules, which aim at enhancing segmentation accuracy by taking into consideration both the global and local contextual information [18]. Moreover, edge-enhanced versions of U-Net have also been created to enhance the precision of features extraction and segmentation especially in complex CT images [20]. The wavelet-based deep learning structures also reduce the boundaries and noise even more by modeling multi-resolution feature.

These studies demonstrate the significance of edge information in enhancing better segmentation. The edge-based methods are useful in detailing the structure and they are therefore useful in identifying abnormal tumor shapes. Nevertheless, they are vulnerable to noise and might have to undergo more pre-processing before they stabilize their results. All in all, edge-based segmentation methods add to the enhancement of the quality of the lung region extraction and are an important step in the detection pipeline.

2.3 Thresholding (Otsu, Adaptive) Techniques.

One of the most popular image segmentation algorithms applicable in medical image analysis is thresholding, which is simple and can be computed with a lot of efficiency. It divides the foreground and background areas depending on the intensity value of pixels, which is applicable in isolating the lung tissues in CT imaging. Other sophisticated thresholding techniques like Otsu and adaptive thresholding have been widely used to enhance better segmentation.

Some of the studies have been directed towards the improvement of threshold-based segmentation with the help of hybrid techniques. It has been suggested that a threshold-gradient combination method can enhance the segmentation by combining intensity-based and structural features [21]. Multi-threshold segmentation methods have been designed to represent the significant intensity ranges in CT scans and this has resulted in the more effective segregation of lung nodules [22]. Enhanced deep learning architecture using threshold-based pre-processing has been demonstrated to exhibit better feature extraction through feature separation using relevant regions prior to classification [23]. There are also optimization-based thresholding algorithms based on evolutionary algorithms that are used to automatically compute optimal threshold values, which have been shown to enhance segmentation accuracy [24]. Fuzzy entropy-based thresholding methods have also been used to deal with uncertainty in medical images, which give stronger segmentation outcomes [25].

Such methods show that thresholding is still an effective pre-processing method in the detection of lung cancer. Simple thresholding techniques are both computationally efficient and more advanced adaptive and multi-threshold techniques are more accurate in demanding imaging conditions. Nonetheless, thresholding algorithms might have a problem with low contrast images and need to be combined with other algorithms to perform better. Threshold-based segmentation is a crucial procedure for enhancing image quality and facilitating subsequent classification processes.

2.4 Deep Learning Models in Medical Imaging.

CNNs have significantly transformed medical image analysis by autonomously extracting and classifying information. DenseNet, ResNet and AlexNet models have also been extensively employed in the detection of lung cancer as they are capable of learning hierarchical features based on the CT images.

The recent findings have proven usefulness of CNN-based models when it comes to medical imaging. Models trained on AlexNet using metaheuristic algorithms have demonstrated better classification performance with the improvement of the feature learning ability [26]. DenseNet networks, which are densely connected, have been adopted to enhance better feature sharing and gradient flow with superior performance in lung cancer classification [27]. Blended frameworks of deep feature optimization comprising CNNs with sophisticated strategies in learning have also been suggested to augment classification accuracy and curb overfitting [28]. Pre-trained DenseNet models have been employed as transfer learning techniques, and demonstrated to achieve higher accuracy due to learning knowledge from large amounts of data [29]. Also, comparative analyses of various CNN models have revealed that a combination of various models can result in greater classification accuracy and robustness [30].

These results signify that CNN models are critical towards detecting lung cancer as they have high accuracy and are effective in extractions of features. Nevertheless, there are issues like overfitting, high computational needs and reliance on big data. Despite these drawbacks, CNN-based systems have been the backbone of the modern medical image analysis systems.

2.5 Hybrid Models

Advanced classification models are hybrid machine learning models, which is a combination of machine learning or deep learning models and advanced classification models, to improve the classification performance. CNN has been utilized in the identification of lung cancer by several Authors with excellent feature extraction and automated classification. The objective of this hybrid combination is to achieve improved classification accuracy while at the same time keeping the computational complexity low.

There are a couple of studies that have explored the use of hybrid methods for detection of lung cancer. In order to effectively combine deep feature extraction with efficient classification, the attention-based U-Net was integrated with deep classification frameworks, which also showed enhanced performance [31]. The use of deep feature optimization frameworks has also been presented to improve the classification accuracy and feature representation [32]. In the comparisons, it was found that hybrid models using deep features obtained through CNN models can also obtain competitive classification results [33]. Hybrid frameworks using the optimized classification methods with deep learning techniques have been shown to provide greater interpretability and better classification performance [34]. Moreover, more sophisticated CNN models embedded in hybrid models have achieved higher performances for medical image classification tasks [35] [37].

literature reviewed reveals the substantial progress achieved in detecting lung cancer with the application of deep learning and image processing techniques. Edge detection segmentation algorithms have good results in the identification of the structural boundaries, while thresholding segmentation algorithms have good results for separating lung regions by intensity level. There were some CNN models that have shown good performance in feature extraction and classification accuracy, including DenseNet and ResNet. Furthermore, hybrid models based on different deep learning techniques have demonstrated high effectiveness, with the integration of deep feature learning and improved classification techniques resulting in better diagnostic performance.

In spite of these progresses, there are various limitations. Most of the research has concentrated on either segmentation or classification as a stand-alone process and there is little combination of both processes into a common framework. Edge based techniques are mostly susceptible to noise whereas thresholding techniques have difficulty in detecting low contrast, and intensity variations in CT images. The CNN-based models, despite their accuracy also demand huge datasets and computational resources and this could restrict their practical use. Hybrid models have demonstrated good results but their structure is not usually well-tuned to the combination of several pre-processing methods.

These constraints are indicative that an organized methodology that includes edge based segmentation and threshold based segmentation, and an appropriate hybrid classification system is necessary. This gap is filled in the current work whereby a hybrid pre-processing framework and a hybrid model are developed to enhance the accuracy of lung cancer detection without compromising on the level of computational efficiency.

3. Methodology

The section describes in detail the proposed pipeline. The proposed pipeline of lung nodule classification is divided into seven stages and is applied to CT images from the IQ-OTH/NCCD database. The raw DICOM scans are subjected to HU windowing normalization, median filtering to reduce noise, and adaptive histogram equalization to increase contrast in the pre-processing stage. The outputs of adaptive threshold segmentation and edge-based segmentation are combined by morphological refinement processes of dilation and erosion to obtain a combined segmentation mask and then accurately extracting the lung region from the image. Feature extraction is then carried out in parallel with three pre-trained CNN architectures, DenseNet, ResNet and AlexNet, to extract dense, residual and shallow convolutional features from the images, respectively, and then concatenated in a single multi-feature vector. This vector is then subjected to Principal Component Analysis (PCA) that helps to remove dimensions while retaining maximum variance. The compressed feature representation is then fed into a fine-tuned CNN classifier optimized by systematic hyperparameter tuning of learning rate, batch size, dropout, Adam optimizer hyper-parameters and epoch selection. Finally, the classifier outputs a binary prediction — benign or malignant — and model performance is assessed using accuracy, precision, recall, and F1-score.

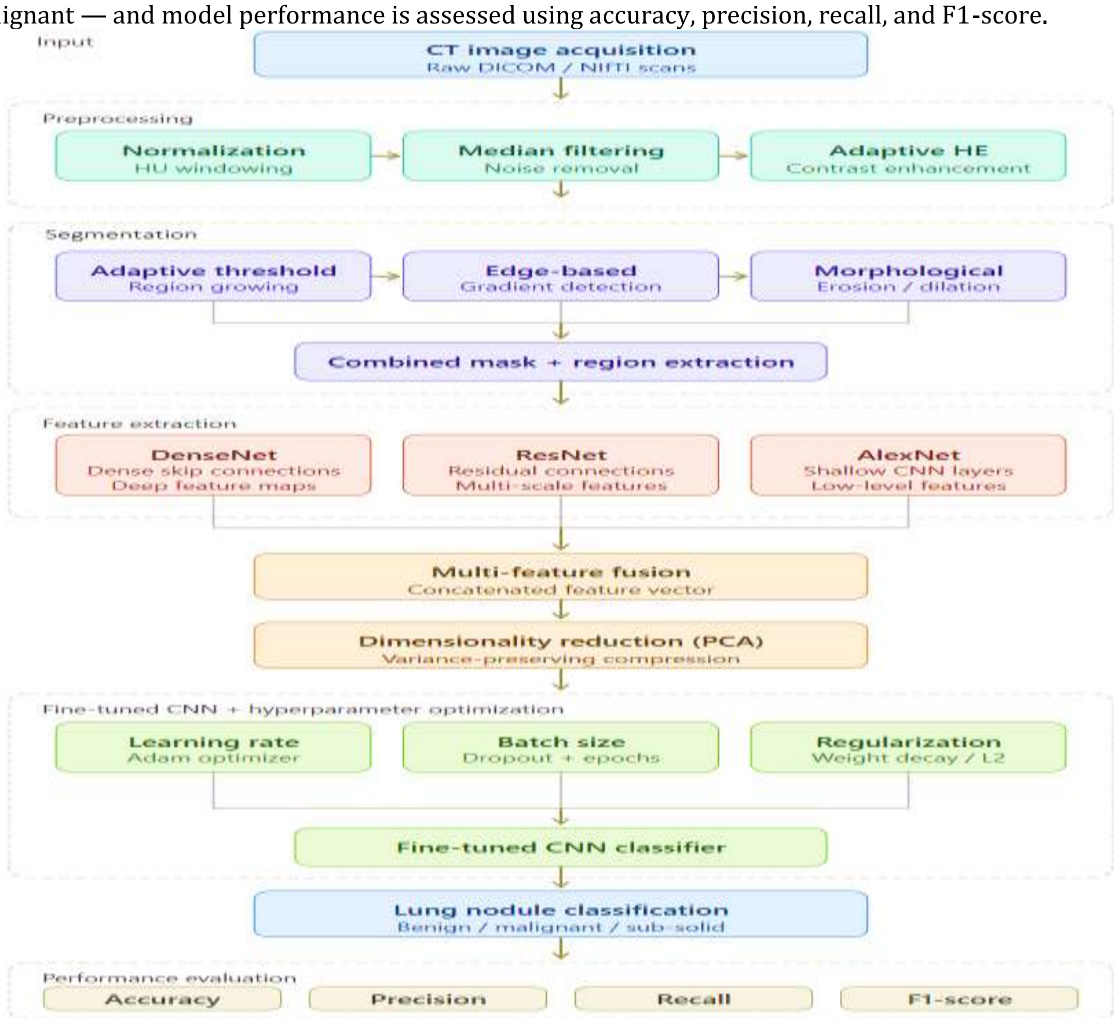

Figure 1. Proposed System Architecture of Lung Cancer Classification

3.1 Data preparation
CT images from a publically accessible dataset, “The IQ-OTH/NCCD lung cancer dataset,” were utilized [36]. All images were scaled to a uniform resolution and normalized. Data augmentation techniques, including rotation, flipping, and scaling, enhanced training diversity, as illustrated in Figure 2. The dataset was divided into a training set and a testing set.

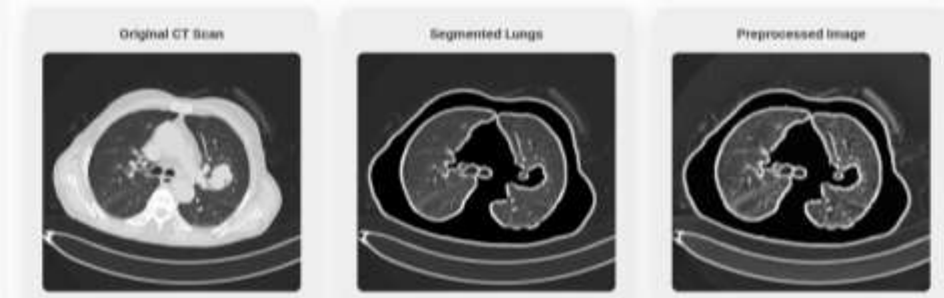

Figure 2. Image pre-processing steps

3.2 Preprocessing and combined segmentation
- Noise reduction and contrast enhancement: Median filtering reduces impulse noise while preserving edges. “Contrast limited adaptive histogram equalization” (CLAHE) improves local contrast.
- Adaptive thresholding: For a given image I, let f_1 denote the filtered image. The threshold T is computed for each local window by averaging the intensities and subtracting a bias value. Binary segmentation assigns pixels to the foreground if $f_1(x, y) \geq T(x, y)$.
- Edge detection: The gradient magnitude at each pixel (x, y) is computed as in eq.1:

$$g(x,y) = \sqrt{((\partial f_1/\partial x)^2 + (\partial f_1/\partial y)^2)} \quad (1)$$

Where $\partial f_1/\partial x$ and $\partial f_1/\partial y$ are Sobel gradients. A high threshold τ_1 identifies strong edges, and non-maximum suppression yields thin edge maps. To emphasise fine details, the gradient map is multiplied elementwise with the thresholded image.

4. Proposed model
The suggested method presents a hybrid framework for lung cancer diagnosis that amalgamates segmentation techniques with a fine-tuned CNN classification model. The methodology encompasses pre-processing, segmentation, feature fusion, and classification steps within a mathematically delineated pipeline.

Input Representation and Normalization is shown as in eq.

Input Representation and Normalization is expressed as let the input CT image be denoted as $I(x,y)$, where each pixel intensity lies within a grayscale range. The normalized image X_i is obtained as in eq.2:

$$X_i = \frac{I(x,y) - \mu}{\sigma} \quad (2)$$

Where, μ represents the mean intensity and σ represents the standard deviation. This normalization stabilizes intensity variations across CT images.

Median filtering for noise reduction is computed as noise in CT images is reduced using a median filter. For each pixel is represented as in eq.3:

$$f_1(x,y) = median\,\{X_i(p,q) \mid (p,q) \in N(x,y)\} \quad (3)$$

Where, $N(x,y)$ represents the local neighborhood window. This preserves edges while removing impulse noise.

Adaptive threshold segmentation $T(x,y)$ is computed locally computed as eq.4:

$$T(x,y) = (1 / |W|) \sum_{i=1}^{n} f_1(x_i, y_i) - C \quad (4)$$

Where, W is the local window and C is a constant bias. The thresholded image $S_1(x,y)$ as in eq. 5 & 6:

$$S_1(x,y) = 1, if\ f_1(x,y) \geq T(x,y) \quad (5)$$

$$S_1(x,y) = 0, otherwise \quad (6)$$

This step separates lung tissue from the background.

Edge-based segmentation the gradient magnitude is computed to extract boundary information as in eq.7:

$$g(x,y) = \sqrt{((\partial f_1/\partial x)^2 + (\partial f_1/\partial y)^2)} \quad (7)$$

Using a threshold τ in eq. 8 & 9:

$S_2(x,y) = 1, if\ g(x,y) \geq \tau$ (8)
$S_2(x,y) = 0, otherwise$ (9)

This captures structural boundaries of nodules.

Morphological Refinement used to remove small holes and connect regions using eq.10:

$S_3 = (S_1 \oplus B) \ominus B$ (10)

where $\oplus$ denotes dilation and $\ominus$ denotes erosion, and B is the structuring element. This improves segmentation continuity.

Combined segmentation mask use to find final segmentation mask $M(x, y)$ is obtained by combining threshold and edge outputs depicted in eq.11:

$M(x,y) = S_1(x,y) \vee (S_2(x,y) \wedge S_3(x,y))$ (11)

This ensures that both intensity-based and boundary-based features are preserved.

CNN-based feature extraction used for segmenting region. Let the segmented region be passed through multiple CNN models. The extracted feature vectors are represented as eq.12, 13 & 14:

$F_1 = DenseNet(X_i)$ (12)
$F_2 = ResNet(X_i)$ (13)
$F_3 = AlexNet(X_i)$ (14)

The fused feature vector is represented in eq.15:

$F = [F_1 ; F_2 ; F_3]$ (15)

This concatenation captures multi-level features.

Principal Component Analysis (PCA) is applied for dimensionality reduction:

$Z_i = W^T F$ (16)

Where, W is the projection matrix. This reduces redundancy and computational cost.

For a test sample Z_i, the Euclidean distance is computed as eq.17:

$d(Z_i, Z_j) = \sqrt{(\sum_k (Z_{ik} - Z_{jk})^2)}$ (17)

The predicted class is obtained using majority voting as in eq.18:

$y_i = \arg\max(c) \sum_j \delta(y_j = c)$ (18)

Where, δ is the indicator function.

The proposed approach combines adaptive thresholding and edge detection to obtain proper segmentation, which is succeeded by multi feature fusion and Fine-tune CNN classification. The integration of intensity-boundary information enhances segmentation quality, while hybrid feature learning enhances classification performance.

Hyperparameter setup

The selection of hyper-parameters is crucial in influencing the classification efficacy of deep learning models utilized on medical imaging datasets, such as the IQ-OTH/NCCD Lung Cancer Dataset. In this study, the main approach used for hyperparameter optimization is called Random Search, in which combinations are sampled from the search space according to a random sampling process with the help of a given distribution. It is empirically more efficient than grid search, and can find near-optimal configurations with significantly less training iterations, as CNN training for CT image data can be very expensive.

Random Search was utilized for essential hyper-parameters such as learning rate, batch size, dropout rate, L2 regularization coefficient, and the number of training epochs. Each sampled configuration underwent evaluation using five-fold cross-validation to guarantee dependable generalization across data subsets, with early stopping implemented at a patience of 10 epochs to avert overfitting. The best parameters for training the fine-tuned CNN classifier on the IQ-OTH/NCCD dataset were determined to be a learning rate of 0.001, a batch size of 32, a dropout rate of 0.4, and an L2 regularization coefficient of 0.0001. Table 1 shows the hyper parameter setup used for fine-tuning the CNN model.

Table 1. Hyperparameter Tuning for CNN-based Lung Nodule Classification

Hyperparameter	Values Explored	Selected Value	Justification
Learning Rate	0.1, 0.01, 0.001, 0.0001	0.001	Balanced convergence speed and stability with Adam optimizer
Batch Size	8, 16, 32, 64	32	Optimal trade-off between memory efficiency and gradient estimation
Dropout Rate	0.2, 0.3, 0.4, 0.5	0.4	Reduced overfitting while retaining sufficient feature representation
Optimizer	SGD, RMSprop, Adam	Adam	Adaptive learning rates yielded faster convergence on CT image features
Epochs	20, 50, 75, 100	100	Model reached stable validation loss without significant overfitting

Activation Function	ReLU, Sigmoid, Tanh	ReLU	Mitigated vanishing gradient and improved training speed in deep layers
Weight Initialization	Random, Xavier, He Normal	He Normal	Well-suited for ReLU-activated deep CNN architectures
Pooling Strategy	Max pooling, Average pooling	Max pooling	Better preserved dominant spatial features from lung CT slices
L2 Regularization (λ)	0.001, 0.0001, 0.00001	0.0001	Penalized large weights effectively without underfitting
Input Image Size	128×128, 224×224, 256×256	224×224	Standard input resolution compatible with DenseNet, ResNet, and AlexNet

5. Grad-CAM heatmap

Grad-CAM ("Gradient-weighted Class Activation Mapping") is a visualization technique that highlights the most significant regions of an image contributing to a model's prediction, as illustrated in figure 3. It operates by calculating gradients off the last convolutional and applying them to feature maps in the form of importance weights. The resulting heatmap indicates the discriminative regions with warmer colors like red meaning more influence and cooler colors like blue meaning less influence. In medical imaging, it assists in tracking of important areas such as lung nodules or abnormal tissues that influence the classification decision. It improves the interpretability of the model since it displays the location at which the model is concentrating and especially important in validating the model predictions in clinical tasks.

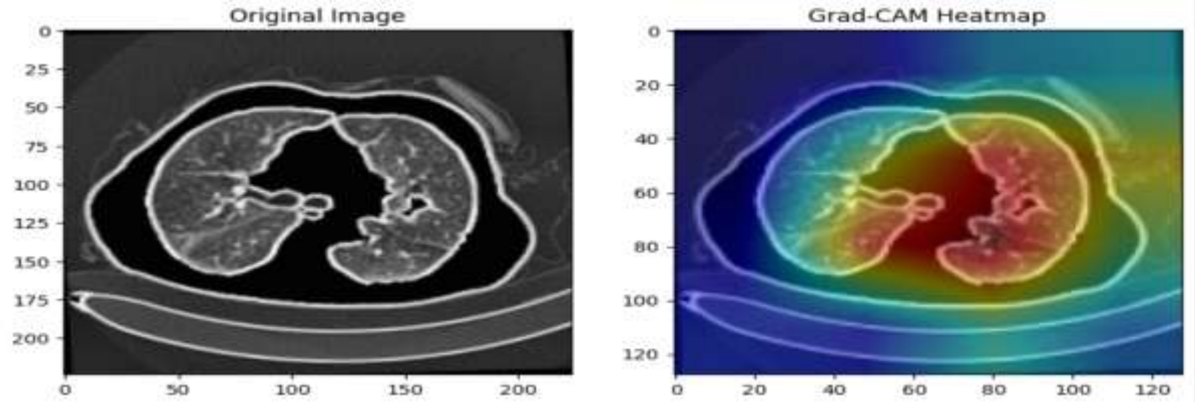

Figure 3. Grad-CAM Heatmap

6. Results and Discussion

6.1 Proposed model confusion matrix

The confusion matrix illustrates the classification performance of the Proposed Fine-tune CNN model across three categories: benign, malignant, and normal instances, as depicted in figure-4. The majority of predictions are on the diagonal, which means that the classifications are correct. The model classified 287 benign cases properly with a single misclassification but all the 1347 malignant cases were properly identified with no mistake. In the same manner, the prediction of all the normal cases (998) was accurate, and it has been perfectly classified. There are no large off-diagonal values which means that there is very little confusion among classes. In general, the model is highly accurate, has high class separation, and effective in identifying conditions of the lungs.

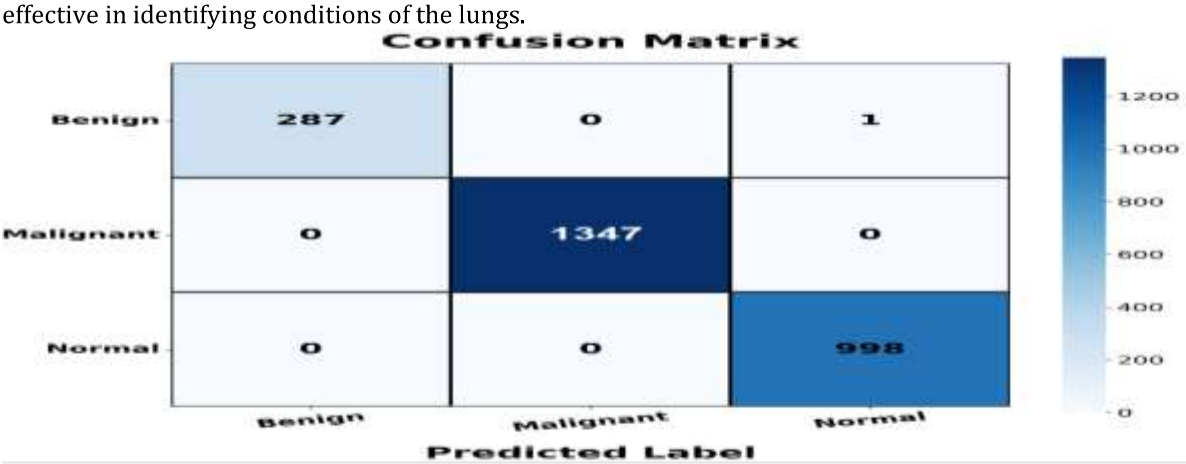

Figure 4. Proposed model Confusion matrix (Fine-Tune CNN)

6.2 Comparative Analysis of Models

The suggested system was evaluated using the test set, comprising 20% of the data. The integrated FineTune CNN model utilizing Edge and Threshold techniques achieved an accuracy of 99.24%, precision of 99.24%, recall of 99.24%, and an F1-score of 99.24%. In comparison, an average DenseNet classifier reached an accuracy of 97.62%, a ResNet classifier reached 97.77% and an AlexNet classifier reached a 77.21% when Hybrid Per-processing applied. The enhancement of the hybrid model proves that edge and threshold information are to be combined in segmentation to extract more complete regions as shown in table 2 and 3. The recall and high precision indicate that the model can successfully reduce false positives and false negatives. The comparison of the respective graphs is illustrated in Figure 5.

Table 2. Evaluation Comparison of Threshold, Edge and Hybrid Pre-processing Technique

Pre-processing Type	Model	Accuracy	Precision	Recall	F1 Score
Threshold Pre-processing	DenseNet	98.21	98.28	98.21	98.21
	ResNet	97.94	97.94	97.94	97.94
	AlexNet	77.21	82.53	77.21	75.44
	FineTune CNN	98.49	98.73	98.49	98.49
Edge Pre-processing	DenseNet	96.42	96.53	96.42	96.42
	ResNet	98.04	98.14	98.04	98.04
	AlexNet	75.13	74.39	75.31	74.13
	FineTune CNN	98.28	98.28	98.38	98.28
Edge + Threshold Pre-processing	DenseNet	97.62	97.58	97.76	97.62
	ResNet	97.77	97.77	97.77	97.77
	AlexNet	77.21	82.53	77.21	75.44
	FineTune CNN	99.24	99.24	99.24	99.24

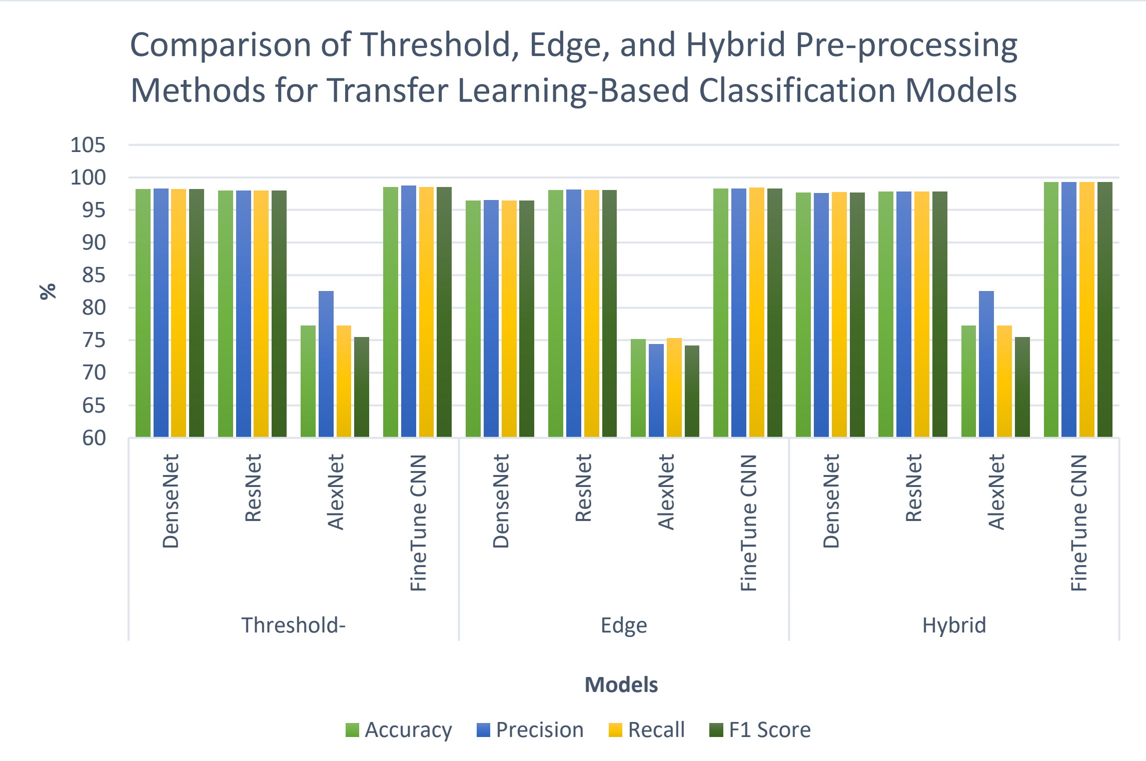

Figure 5. Comparison of Threshold, Edge, and Hybrid Pre-processing Methods for Transfer Learning-Based Classification Models

6.3 SOTA Analysis

The suggested framework was assessed in comparison to cutting-edge techniques using the IQ-OTH/NCCD Lung Cancer Dataset. Existing approaches including CNN with Ebola Optimization [14], AlexNet with Modified Bowerbird Optimization [26], pre-trained CNNs [30], an optimized CNN architecture [35], and a hybrid AI framework [13] reported accuracies ranging from 96.45% to 98.60%. The proposed methodology, which integrates edge-based and adaptive threshold preprocessing with multi-backbone feature extraction (DenseNet, ResNet, AlexNet), PCA-based dimensionality reduction, and a Random Search-optimized fine-tuned CNN classifier, attains an exceptional accuracy, precision, recall, and F1-score of 99.24% across all evaluation metrics, surpassing all comparative methods and exhibiting resilient, unbiased classification performance on the IQ-OTH/NCCD dataset.

Table 3. Comparison with State-of-the-Art Methods on IQ-OTH/NCCD Lung Cancer Dataset

Authors	Method	Accuracy (%)	F1-Score (%)
Mohamed et al. [14] (2023)	CNN + Ebola Optimization Search Algorithm	97.80	97.00
Xu et al. [26] (2022)	AlexNet + Modified Bowerbird Optimization	96.45	95.95
Rawashdeh et al. [30] (2025)	Pre-trained CNNs (VGG, ResNet, DenseNet)	98.10	97.80
Kamala and Mohan [13] (2026)	Hybrid AI Framework + CT Classification	98.60	98.30
Pathan et al. [35] (2024)	Optimized CNN Architecture	97.50	97.10
Ours	Edge + Threshold Pre-processing + Fine-Tuned CNN (DenseNet + ResNet + AlexNet)	99.24	99.24

7. Conclusion, Limitations and future scope

In this work the authors introduced a computer-aided diagnostic pipeline for lung cancer detection from computed tomography images consisting of an adaptive thresholding method followed by an edge detection method and subsequently a fine-tuned CNN-based classification framework. The segmentation strategy was combined to perform enhanced boundary information and precise localization of lung nodule, which can miss the regions by thresholding only. Multiple CNN models such as DenseNet, ResNet and AlexNet were then integrated into the proposed framework for feature extraction, and a fine-tuned CNN model with optimal hyper-parameter settings was used to classify the last classification. The results showed that hyper-parameter optimization, such as tuning the learning rate, optimizing the batch size, dropout regularization, Adam optimizer configuration, and choosing the optimal number of epochs, had a significant impact on improving the classification results and the generalization of the model. The proposed hybrid method was tested on the benchmark dataset and the result showed that the accuracy and F1-score obtained by the proposed hybrid method is 99.24%, which outperforms the individual CNN models and existing hybrid methods. The enhancements are mostly credited to edge-based and threshold-based segmentation along with the optimized fine-tuned CNN architecture. The results showed that deep learning and the use of edge and threshold information are combined to detect lung cancer in the early stage and enhance the diagnostic reliability to a large extent. Although these benefits exist, there are some limitations to this study. The number of data is relatively small and may not be representative of the data obtained in a real clinical setting. Moreover, the segmentation is based on threshold and edge parameter values which could be changed to adapt the segmentation to other datasets and imaging conditions. The fine-tuned CNN framework enhanced performance, however, with larger datasets and deeper architectures, computational complexity and training times could potentially increase.

Future studies may investigate the framework on larger and more diverse clinical datasets and improve the segmentation process to 3D CT images to perform more detailed analysis. Furthermore, transformer-based architectures and vision transformer approaches could be considered to achieve better performance for the detection task while still being computationally efficient, as they have shown the ability to capture long-range dependencies.

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