Medical Image Recognition and Classification for Lung Cancer Disease Diagnosis using Deep Learning

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Abstract

The automated recognition of lung cancer in Computed Tomography (CT) images requires effective variability reduction in the images with maintaining important pulmonary features. In this research proposes a preprocessing, segmentation, and CNN-based model for the classification of lung CT images in three classes. The pipeline applies Gaussian filter for noise reduction, normalization and contrast enhancement of the image inputs and subsequently, thresholding segmentation for isolating the lungs. The segmented CT images are then fed into the convolutional extraction of features, rectified linear unit (ReLU), max pooling and fully connected feature transformation layers. The output of the model comes from the Softmax classification layer which discriminates between normal, benign and malignant classes. Evaluation of the model performance is assessed through class-specific measures of accuracy, precision, recall and F1 score, supported with confusion matrix and technical comparisons. The reported evaluation demonstrates consistent classification performance across all three diagnostic classes, confirming the feasibility of using the entire preprocessing, segmentation, and CNN-based classification process for analyzing lung CT images.

Keywords: Lung CT Image Classification, Threshold-Based Lung Segmentation, Contrast-Enhanced CT Preprocessing, CNN Feature Learning, Softmax Multiclass Discrimination, Pulmonary Abnormality Recognition.

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1. Introduction

Lung cancer diagnosis heavily depends on imaging, where CT scan providing a comprehensive structural image for detecting lung lesions and nodules. Difference in size, shape, texture, and intensity of the lesions makes interpretation of CT image difficult especially in a scenario where many images have to be analyzed. These challenges have motivated computer-assisted methods of analysis and classification of lung images. The latest development in deep learning, in the form of Convolutional Neural Network (CNN), has proved its ability to learn discriminative spatial and texture representation directly from the images without relying much on handcrafted features.

The reliability of DL-based medical image classification is significantly affected by the quality of representation provided as input. Noise, variations in intensity, contrast, and non-relevant parts of the anatomy may affect feature extraction and classification. Thus, the proposed framework uses Gaussian filtering for noise removal, normalization and enhancement of contrast for image standardization, and finally thresholding-based segmentation of lungs to confine further analysis to the relevant part of the anatomy. Finally, the images are classified into normal, benign, and malignant using a CNN.

This research proposes an automated lung disease classification system that incorporates the following processes: CT image pre-processing, segmentation of lung regions, convolutional neural network for feature extraction, and multi-class classification using the Softmax function. The proposed system forms a common workflow where image enhancement and lung region segmentation come before feature extraction and classification. Contributions of this research include:

- Development of an automated image analysis system for categorization of lung diseases as normal, benign, and malignant.
- Integration of image pre-processing methods such as Gaussian filter, normalization and contrast enhancement for improving CT-image quality.
- Application of lung segmentation to extract the important areas and minimize the effect of unnecessary background data.

- Implementation of CNN for feature extraction and classification of spatial and textural features of CT images.
- Multi-class classification performance evaluation through accuracy, precision, recall, and F1 score.

2. Related Works

Chen et al. [1] researched image classification based on high resolution through RmRMR Bag of Visual Words, which proves the significance of feature selection techniques. Shafiq et al. [2] discussed the use of deep residual learning and explained how the use of residual architectures can prove beneficial for feature extraction from images. Wang et al. [3] compared conventional machine learning and deep learning and stressed the benefits of using CNNs for automatic feature learning. Cheng et al. [4] proposed an enhanced SSD model for image-based object detection, which shows the potential of deep-learning models. Singh et al. [5] used deep learning on chest CT images to diagnose COVID-19Liu et al. [6] have researched on the application of Object-Oriented CNN to image classification problems, and Lu et al. [7] have studied multi-scale feature fusion using semantic segmentation. The researchers Zhang et al. [8] have used an enhanced version of U-Net framework for image segmentation problem, while Adegun et al. [9] have researched on Vision Transformers for automated image classification. Abdelmonem et al. [10] have proved once again the effectiveness of customized CNN based architectures for image classification. A comparative review of all these existing methods is shown in Table 1.

Collectively, these researches demonstrate the importance of Deep Feature Learning, CNN-based classification, and segmentation for automated image analysis [1]– [10]. Nevertheless, these methods focus primarily on remote sensing, security, general image classification, or specific diseases, paying little attention to developing a CT-based approach for the classification of normal, benign, and malignant lung conditions. The above-described shortcomings have been considered as the rationale behind the development of the proposed CT image analysis system based on CT pre-processing, lung region segmentation, and CNN-based classification.

Table 1. Consolidated review of existing image classification and deep-learning approaches

Ref	**Technical Category**	**Representative Techniques**	**Major Contribution**	**Limitation for Lung CT Diagnosis**
[1],[3]	Feature Selection and Visual Representation	RmRMR–BoVW, SVM, KNN, CNN	Demonstrated the importance of discriminative feature selection and automated feature learning for image classification	Conventional feature representation is not optimized for complex CT-based pulmonary patterns
[2], [6], [10]	Deep CNN and Residual Learning	ResNet, object-oriented CNN, custom deep CNN	Improved hierarchical feature extraction and classification through deeper and customized CNN architectures	Primarily validated on general or remote-sensing imagery rather than lung CT diagnosis
[4]	Deep Object Detection	Improved SSD	Enhanced feature-map representation and detection efficiency for challenging visual data	Focuses on object detection rather than medical disease classification
[5]	CT-Based Medical Image Analysis	CNN, chest CT, edge-cloud computing	Demonstrated the applicability of deep learning for automated CT-image disease analysis	Focused on COVID-19 and does not perform normal–benign–malignant lung classification

[7], [8]	Segmentation-Based Deep Learning	Multi-scale feature fusion, U-Net	Demonstrated the importance of semantic segmentation and multi-scale spatial representations for isolating relevant regions	Applications are outside medical imaging and do not address pulmonary-region segmentation
[9]	Transformer-Based Image Classification	Vision Transformer	Demonstrated advanced representation learning using transformer-based architectures	Computationally demanding and developed for remote-sensing image classification

3. Proposed Methodology

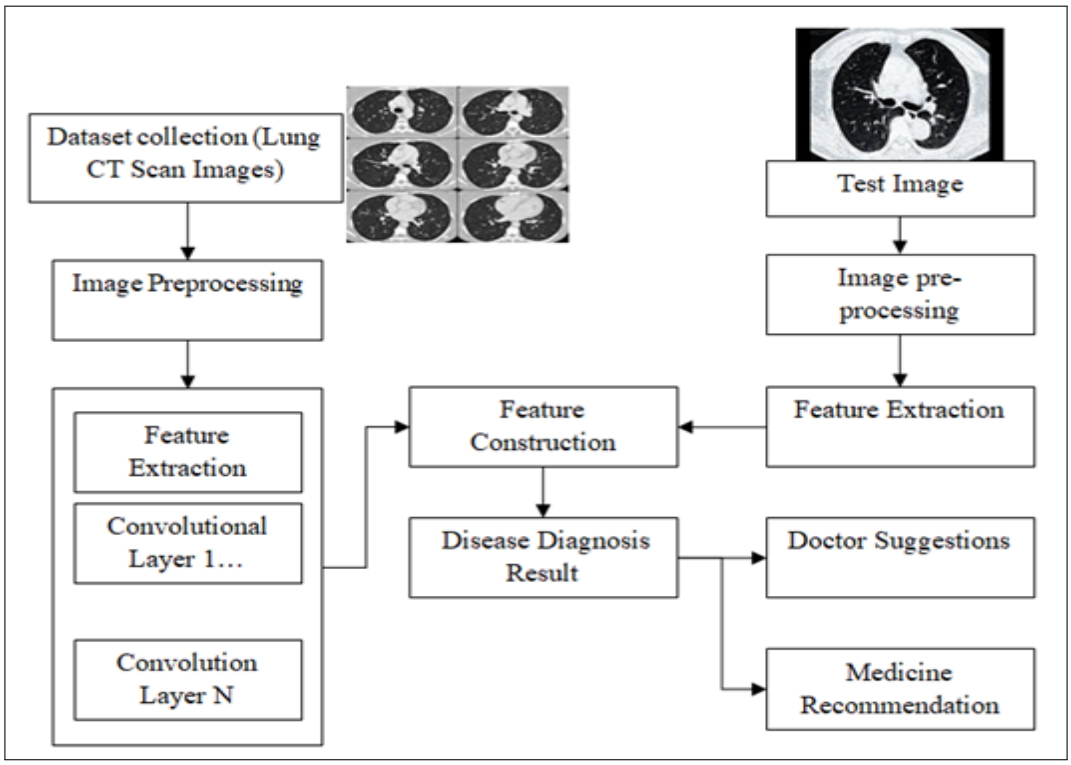


Figure 1. Overall methodology flow of the proposed lung CT image classification system.

The proposed framework implements automated three-way classification of CT lung images using a sequential pipeline that involves dataset preparation, image preprocessing, lung

segmentation, feature extraction through CNN, and Softmax classification. The input CT images are subjected to Gaussian filtering, intensity normalization, and contrast enhancement of applying segmentation based on thresholds to extract the lung region. The extracted lung regions are further fed into convolutional layers, ReLU activation function, max pooling layers, and fully connected layers to learn features hierarchically. Softmax classification finally classifies the image to the normal, benign, or malignant. The processing pipeline is shown in Figure 1.

3.1 Dataset Description

The Lung Condition Classification system is based on IQ-OTH/NCCD Lung Cancer Dataset [11], which is a CT image dataset having three different diagnostic categories: Normal, Benign, and Malignant.

Table 2. Description of the IQ-OTH/NCCD Lung Cancer Dataset

Parameter	**Description**
Dataset	IQ-OTH/NCCD Lung Cancer Dataset [11]
Imaging modality	Computed Tomography (CT)
Total CT slices	1,190
Total cases	110
Diagnostic classes	Normal, Benign, Malignant
Normal cases	55
Benign cases	15
Malignant cases	40
Original image format	DICOM
CT scanner	Siemens SOMATOM
Annotation	Oncologists and radiologists
Data source	Iraq-Oncology Teaching Hospital and National Center for Cancer Diseases

As summarized in Table 2, the dataset provides three diagnostic categories included in the dataset that relate directly to the target classes of the CNN classification algorithm. The images are first sorted by their labels before being processed further for preprocessing and segmentation. Since multiple CT slices are associated with individual cases, it is considered in the process of arranging the dataset.

3.2 Image Preprocessing

The CT images obtained from the dataset are subjected to preprocessing before to lung region segmentation and feature extraction through CNNs. The purpose of preprocessing is to eliminate noise in the images, normalize intensity and improve visibility of the relevant pulmonary features in the images. The steps in the preprocessing process include Gaussian filtering, intensity normalization and contrast enhancement, as illustrated in Figure 1.

3.2.1 Gaussian Filtering

Initially, the Gaussian filter technique is used to reduce the noise that exists in the form of high frequencies within the CT images. This technique smoothens the image on a spatial level wherein pixels closer to the kernel center are assigned more weight. The process of filtering is described as:

$$I_g = I * G_\sigma \tag{1}$$

where I represents the input CT image, G_σ denotes the Gaussian kernel with standard deviation σ, and I_g represents the resulting filtered image. This process decreases the intensity fluctuation but preserves the necessary information needed to analyze the lungs.

3.2.2 Intensity Normalization

Intensity normalization is performed after noise reduction to have a constant intensity range within the set of CT images. Normalized image is represented by min-max normalization as follows:

$$I_n = \frac{I_g - I_{\min}}{I_{\max} - I_{\min}} \tag{2}$$

where I_g is the Gaussian-filtered image, while $I_{\min}$ and $I_{\max}$ represent its minimum and

maximum intensity values, respectively. Normalization decreases variability in the intensity of images and creates a common representation for further processing.

3.2.3 Contrast Enhancement

The normalized images are further subjected to contrast enhancement to improve the visibility of pulmonary structures and potential abnormal regions. Histogram-based contrast enhancement redistributes intensity values across the available range, allowing relevant structures to become more distinguishable from their surrounding regions. The enhanced images are then passed through the lung segmentation process.

3.3 Lung Region Segmentation

Following image preprocessing, lung-region segmentation is applied where the lung region is separated from any background that does not pertain to the pulmonary region. This is an essential step since by limiting the image to the region of the lungs alone, the ensuing CNN can concentrate only on the parts of the image pertaining to the classification of lung conditions.

Binary segmentation mask is generated based on preprocessed CT scan by applying intensity threshold. The mask can be expressed as:

$$Mx,y = \begin{cases} 1, & I_n x,y \geq T \\ 0, & I_n x,y < T \end{cases} \tag{3}$$

where $I_n x,y$ represents the normalized CT image and T denotes the selected threshold. The pixels that satisfying the threshold criteria will be retained in the segmentation mask, and all other pixels will be suppressed. The mask will be used on the preprocessed image, and the resulting image will be:

$$I_s x,y = I_n x,y \times Mx,y \tag{4}$$

where $I_s x,y$ represents the segmented lung image. This operation reduces the impact of the non-lung regions and gives a specific representation for the CNN-based feature extraction.

3.4 CNN-Based Feature Extraction

The segmented CT scan images are fed to a Convolutional Neural Network (CNN) for automated feature extraction and learning. This CNN learns the necessary features from the lung-specific CT scan images without the requirement of manual feature design. The learning of features takes place through a process of convolution, ReLU activation function, max-pooling, and fully connected layers.

3.4.1 Convolution Operation

The convolution layer uses learnable filters on the segmented CT scan image to recognize certain patterns and structures. The convolution operation is represented as:

$$F_k = I_s * W_k \; b_k \tag{5}$$

where I_s represents the segmented lung image, W_k denotes the k^{th} learnable filter, b_k is the corresponding bias, and F_k represents the generated feature map. Various filters learn different patterns from the input, which allows the network to form progressively more informed representations.

3.4.2 ReLU Activation

These extracted feature maps are passed to the Rectified Linear Unit (ReLU) activation function. The ReLU activation function helps introduce non-linearity in the model and enables the CNN to learn complex feature interactions:

$$Rx = max0, x \tag{6}$$

This process helps to retain feature activations while suppressing negative activations, supporting effective hierarchical feature learning.

3.4.3 Max Pooling

Max-pooling is performed after the convolutional and activation layers to minimize the spatial dimensions of the feature maps but maintain their prominent activations. This minimizes the representation size and preserves the prominent features extracted from the CT images.

Through successive convolution, ReLU activation function, and pooling process, the CNN model converts the segmented CT images into high-level features. Such features contain information that is related to lung pathologies and then transferred to the fully connected layers for feature fusion.

3.4.4 Fully Connected Feature Representation

The final output feature maps are transformed into a condensed form using the fully connected layer. This encoding layer helps in combining all the learned features of the different parts of an image and generate the needed feature representation for the final classification process. The generated feature representation is finally fed to the Softmax classifier to classify between the different classes of the tumor.

3.5 Softmax-Based Multi-Class Classification

The learned feature representation generated by the fully connected layers is passed on to the final classification layer. As the system differentiates between normal, benign, and malignant lung disease conditions, the Softmax classifier is employed to generate class probability scores of the outputs of the CNN. It gives probability scores for the three classes, enabling the selection of the class with the highest probability score. The base paper mentions that the Softmax classifier acts as the classification method for the multi-class problem.

The Softmax probability for the k^{th} class is calculated as:

$$P_k = \frac{e^{z_k}}{\sum_{j=1}^{3} e^{z_j}} \tag{7}$$

where z_k represents the output, score generated for class k, and the denominator represents the combined scores of the three classes. The resulting probabilities satisfy:

$$P_{\text{Normal}} \; P_{\text{Benign}} \; P_{\text{Malignant}} = 1 \tag{8}$$

The class with the greatest probability is chosen as the output class. Thus, the CNN outputs one of the following three classes:

- **Normal** - No malignant or benign condition is predicted.

- **Benign** - The image is classified as representing a benign lung condition.
- **Malignant** - The image is classified as representing a malignant lung condition.

The Softmax layer thus maps the high-level feature representation of the CNN to a meaningful three-class output.

4. Results and Discussion

4.1 Classification Performance

The classification results obtained from the proposed framework have been provided in Table 3. The analysis will be performed considering individual diagnostic categories to determine whether the model behaves consistently while classifying normal, benign, and malignant CT images.

Table 3. Performance evaluation of the proposed CNN-based system

Class	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Normal	96.8	95.9	96.5	96.2
Benign	95.4	94.8	95.1	94.9
Malignant	97.2	96.7	97.0	96.8
Overall	96.5	95.8	96.2	96.0

These results demonstrate the consistent classification performance across the three different classes. The normal class demonstrates good precision and recall performance, which denotes a good ability to classify normal CT scans. The benign class is associated with comparatively lower results, which suggests more complicated classification. The malignant class performs the best among all the other classes, with excellent precision, recall, and F1 score results. Thus, the results demonstrate that the proposed method provides consistent three-class classification performance.

4.2 Confusion Matrix Analysis

The prediction performance of each class further analyzed through the confusion matrix in Figure 2. This is a matrix that represents the relationship between the real diagnosis and its predicted counterpart. Diagonal values depict correctly classified observations while off-diagonal values depict errors in the classification of different diagnosis categories.

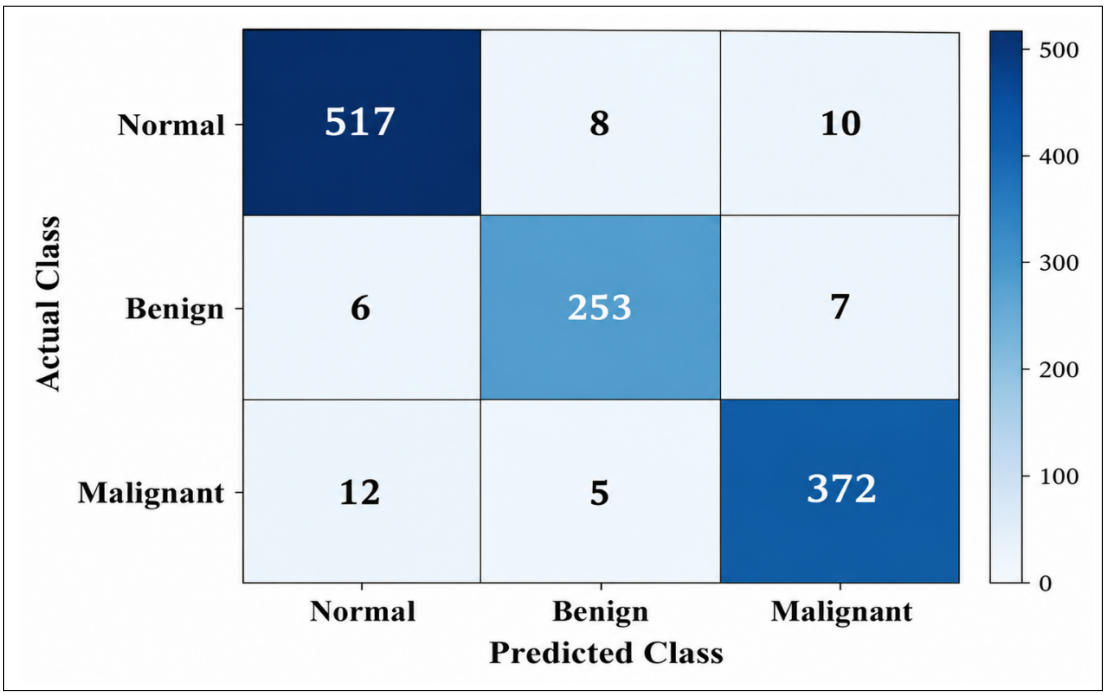


Figure 2. Confusion matrix for lung CT image classification.

The confusion matrix shows that most of the samples concentrated along the principal diagonal, demonstrating that most of the time the model predicts the CT images belonging to their respective classes. The low value on the off-diagonal indicates less confusion among classes. The benign category demonstrates more interaction with other categories in comparison to its evaluation values in Table 3, which are comparatively low. On the other hand, the malignant category exhibits strong interaction along the diagonal axis, supporting the high recall of the class-wise classification.

5. Conclusion and Future Work

The proposed research introduces a framework for lung CT images classification based on deep learning. This framework incorporates the application of Gaussian filtering, intensity normalization, contrast enhancement, and threshold-based lung region segmentation to form a

focused representation of CT images for CNN-based feature extraction. The learned features are converted to multi-class classifications by the means of fully connected layers followed by the Softmax function. The class-specific experiments show that this approach exhibits consistent classification behavior for the selected classes. Future research can investigate advanced lung segmentation approaches, light and deep CNN models, multi-scale feature extraction, data augmentation techniques, and explainable AI methods to enhance representation quality and interpretability. Validation through larger independent datasets and patient-level testing could provide additional insights into the robustness and generalizability of the proposed framework.

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