



Design of an image retrieval system using Artificial neural networks for the identification and classification of lung diseases

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Abstract

The rapid advancement of medical imaging technologies has propelled the development of automated systems for the identification and classification of lung diseases. This study presents the design and implementation of an innovative image retrieval system utilizing artificial neural networks (ANNs) to enhance the accuracy and efficiency of diagnosing lung diseases. The proposed system focuses on addressing the challenges associated with the accurate recognition and classification of lung diseases from medical images, such as X-rays and CT scans. Leveraging the capabilities of ANNs, specifically convolution neural networks (CNNs), the system aims to capture intricate patterns and features within images that are often imperceptible to human observers. This enables the system to learn discriminative representations of normal lung anatomy and various disease manifestations. The design of the system involves multiple stages. Initially, a robust dataset of annotated lung images is curated, encompassing a diverse range of lung diseases and their corresponding healthy states. Subsequently, a pre-processing pipeline is implemented to standardize the images, ensuring consistent quality and facilitating feature extraction. The CNN architecture is then meticulously constructed, with attention to layer configurations, activation functions, and optimization algorithms to facilitate effective learning and classification. The system also incorporates image retrieval techniques, enabling the efficient searching and retrieval of relevant medical images from the database based on query inputs. This retrieval functionality assists medical practitioners in accessing similar cases for comparative analysis and reference, ultimately supporting accurate diagnosis and treatment planning. To evaluate the system's performance, comprehensive experiments are conducted using benchmark data sets, and performance metrics such as accuracy, precision, recall, and F1-score are measured. The experimental results demonstrate the system's capability to distinguish between various lung diseases and healthy states with a high degree of accuracy and reliability. The proposed system exhibits substantial potential in revolutionizing lung disease diagnosis by assisting medical professionals in making informed decisions and improving patient outcomes.

Keywords: Image retrieval, lung diseases, artificial neural networks, convolution neural networks, medical imaging, diagnosis, classification, deep learning, automated system

1. Introduction

The field of medical imaging has witnessed remarkable progress over recent years, ushering in a new era of diagnostic accuracy and efficiency. Within this landscape, the identification and classification of lung diseases have emerged as crucial tasks that demand innovative solutions. In response to this, the present study introduces a cutting-edge image retrieval system underpinned by artificial neural networks (ANNs), particularly focusing on convolution neural networks (CNNs), to revolutionize the diagnosis and understanding of lung diseases as Figure 1 [1-5].

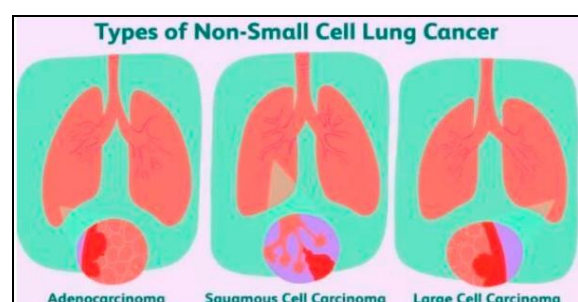


Fig 1: Different types of non-small-cell lung cancer [5].

Lung diseases present a significant global health challenge, contributing to substantial morbidity and mortality rates. Traditional diagnostic methods often rely on the expertise of radiologists to interpret medical images such as X-rays and

CT scans. CNNs, a subset of ANNs, excel in capturing intricate patterns and features within images, enabling them to identify subtle anomalies indicative of various lung diseases as Figure 2 [6-11].

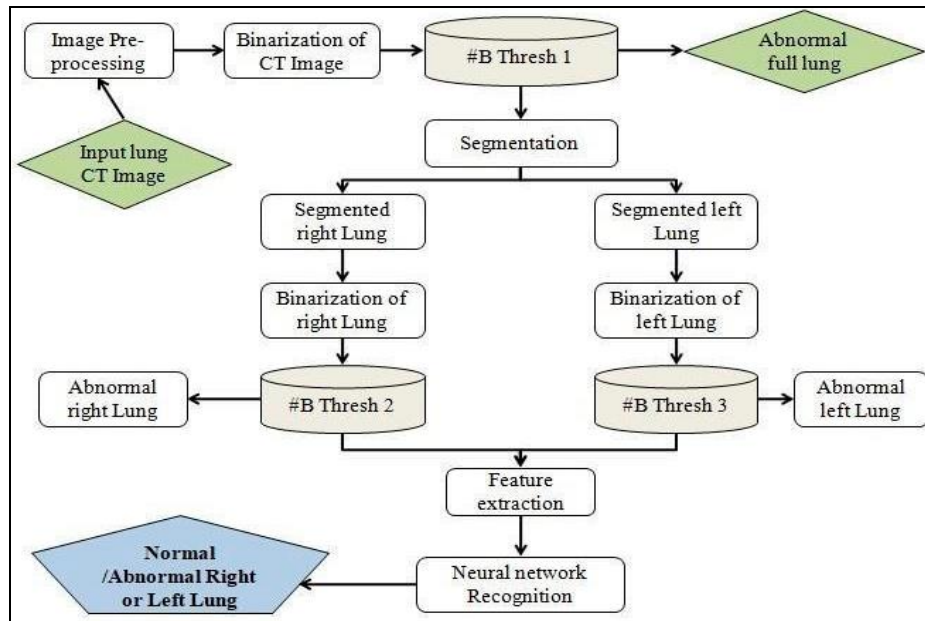


Fig 2: Architecture of detection of lung disease [10].

The cornerstone of the proposed system lies in its ability to learn complex representations from labeled data sets containing a diverse array of lung images. The collected data are meticulously pre-processed to ensure consistency and quality, facilitating subsequent feature extraction. By leveraging the hierarchical structure of CNNs, the system effectively learns and discriminates between normal lung anatomy and various disease manifestations. Additionally, the incorporation of image retrieval techniques enhances the system's utility by allowing medical practitioners to swiftly access relevant images for comparative analysis and reference [12-16].

1.1 Motivation

The motivation behind this study stems from the pressing need to advance the field of lung disease diagnosis and classification using state-of-the-art technology. Traditional methods reliant on human expertise for interpreting medical images are often time-consuming and subject to human error. As a result, misdiagnosis and delayed treatment can have serious consequences for patients suffering from lung diseases. The advent of artificial neural networks (ANNs) and deep learning has shown remarkable potential in various domains, including image analysis. Convolutional neural networks (CNNs), a subset of ANNs, have exhibited exceptional proficiency in recognizing intricate patterns and features within images. Leveraging these advancements, the proposed image retrieval system aims to significantly improve the accuracy, efficiency, and speed of diagnosing lung diseases.

2. Related Work

The related work section explores existing research and developments in the fields of medical image analysis, lung disease diagnosis, and the application of artificial neural

networks (ANNs). The goal is to establish the context for the current study and highlight the gaps and opportunities for further research. Key themes in related work include the following:

Medical image analysis using ANNs: Numerous studies have demonstrated the efficacy of ANNs, particularly CNNs, in medical image analysis. Researchers have successfully employed CNNs for tasks such as tumor detection, organ segmentation, and disease classification. These studies highlight the potential of deep learning techniques to extract meaningful features from medical images [23-26].

Automated lung disease diagnosis: The literature reveals a growing interest in automated methods for diagnosing lung diseases. Researchers have applied machine learning and ANNs to analyze lung images for conditions like pneumonia, tuberculosis, and lung cancer. These studies emphasize the need for accurate and efficient diagnostic tools to alleviate the burden on health care professionals [27-29].

CNNs for medical image classification: Prior research shows the effectiveness of CNN architectures in classifying medical images. Studies have employed transfer learning, data augmentation, and specialized architectures to enhance CNN performance in diagnosing various diseases. This body of work provides insights into optimizing CNNs for specific medical tasks [30-33].

Image retrieval in medical imaging: Studies on image retrieval systems within medical imaging focus on improving access to relevant images for healthcare practitioners. These systems assist in diagnosis and treatment planning by retrieving similar cases from databases. Researchers have investigated content-based image retrieval methods and semantic indexing to enhance retrieval accuracy.

Integration of clinical expertise: Related work also emphasizes the importance of incorporating clinical expertise into automated diagnostic systems. Collaborative efforts between medical professionals and computer scientists are essential for developing tools that align with real-world clinical practices and support health care decision making.

Challenges and future directions: The existing literature acknowledges challenges such as the interpretability of deep learning models, generalization to diverse patient populations, and regulatory approval for clinical use. These challenges offer opportunities for future research, including model explain ability techniques, large-scale validation studies, and compliance with medical standards.

The related work demonstrates a growing interest in leveraging ANNs, particularly CNNs, to automate the diagnosis of lung diseases through medical image analysis. The studies underscore the potential of deep learning techniques to enhance diagnostic accuracy and efficiency. However, the need for robust datasets, the integration of expert knowledge, and addressing challenges in model deployment remain critical areas for further exploration. The current study contributes by designing an innovative image retrieval system that leverages ANNs for accurate lung disease identification and classification while

addressing these challenges [37, 38].

3. Materials and Methods

In its later stages, lung cancer has a rather slow rate of recovery. If accurate early detection could be achieved, lung cancer survival rates might be greatly increased. Finding lung cancer early is essential for human health. Early lung cancer detection is an exciting area of study for experts in lung cancer diagnosis. The proposed method, which comprises two steps, seeks to detect lung cancer at an early stage. Image capture, binarization, pre-processing, thresholding, division, feature extraction, and brain organization identification are only a few of the innovation sin corporate din to the suggested method. There covered properties are used to build the framework of the brain, which is subsequently scanned for signs of malign an ncyorb benignity. The proposed technique has a precision of 94%, and the provided frame work generates pass able outcomes.

3.1 Detailed study of the process has been described in the following section of the chapter. The schematic diagram illustrates the whole process of classification through flow chart in figure

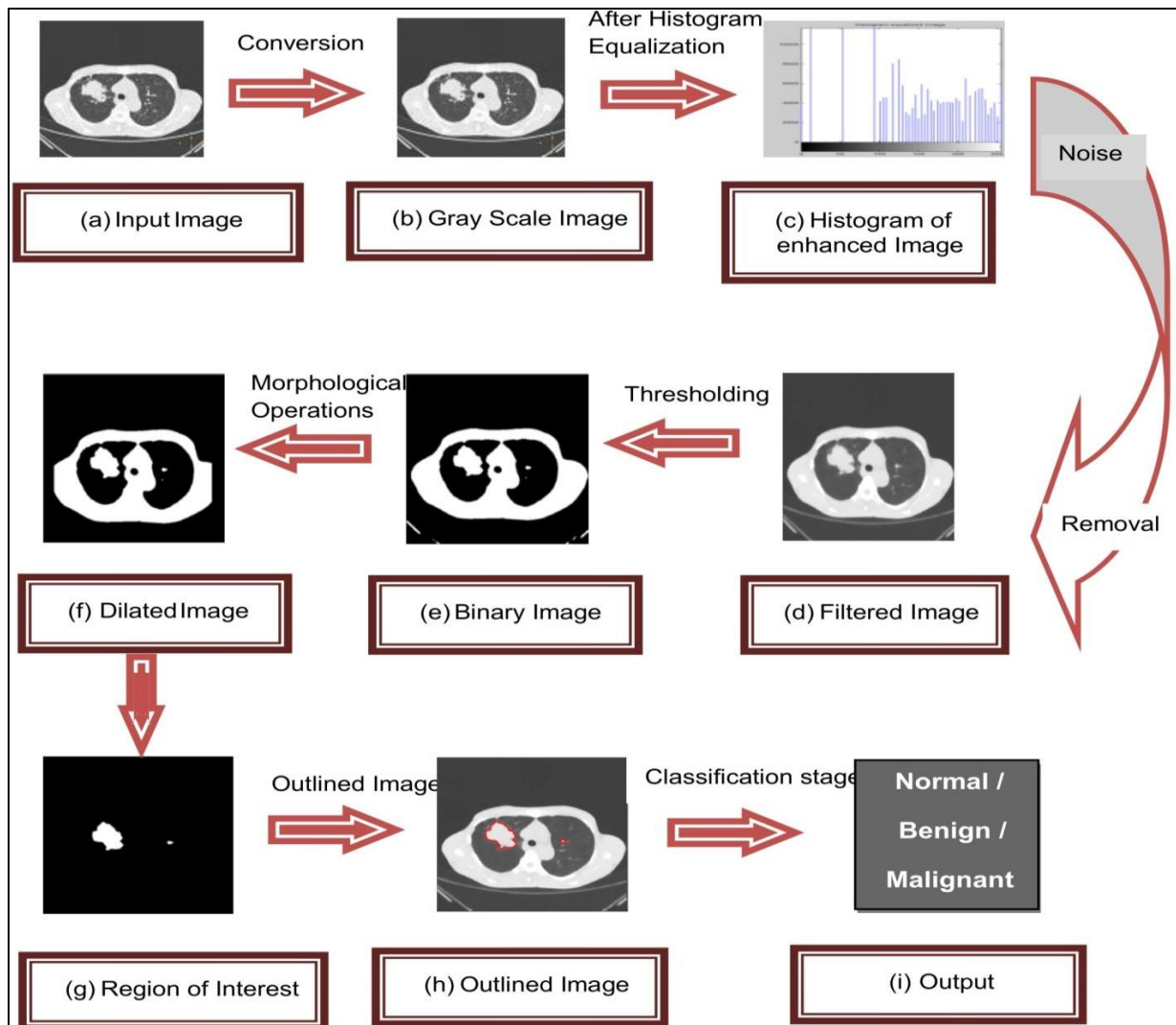


Fig 3: Flow Chart Symbolizes the Proposed System

4. Results and Discussion

4.1 Training and testing: The neural network is then organized using the extracted attributes. The proposed frame work aims to establish which lung is impacted, the left or right. In any case, the only values used to produce affirmative examples (cancerous left lung) are 0 and 1. Only one offers positive examples (malignant right lung), where as the others all dosing negative way. The framework designs the organization using 20 CT scans of the lungs;

ensuring that the system correctly diagnoses lung cancer. The frame works categorize the malignant CT scan images after processing and identify the afflicted lung. As indicated in Figure 3 the frame work has been assessed for both positive and negative outcomes and is deemed to be acceptable. Two criteria are used to determine whether the suggested frame work is effective: neural networks and the Binarization Methods Technique. It provides nearly 100% of the ideal results for this framework.





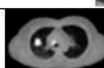
Types of Images	No. of frames	Correct detection rate	Error rate (%)
	30	96.67	3.33
	30	93.33	6.67
	30	100.00	0.00
	30	93.33	6.67
	30	100.00	0.00
Total	150	96.67	3.33

Fig 4: Testing results on different types of images.

Histogram A computation, known as equalization, uses two-dimensional pixel exhibits to address digital images. Each pixel reflects the brightness or shade of the image at any given instant. A picture with a balanced distribution of intelligence levels across the entire range of grandeurs produced using his to gram equalization. As demonstrated in Figure 4, the pre-processing method removes noise and obscuration from CT images and yields an unmistakable result.

4.2 Data acquisition



Fig 5: Original CT image

In medical image processing, image acquisition is the foremost step. CT images are acquired for input due to low noise, better clarity and distortion. The original CT image which has low contrast is shown in figure 5. This image has been used as input image for the proposed algorithm.



Fig 6: Original CT image

4.3 Conversion to Gray Scale image

Conversion of the original image to gray scale image is the initial step to reduce the processing time and produce a faster algorithm. It not only eliminates the information related to saturation and hue but also helps in retaining the luminance. Figure 6 shows the gray scale image converted from the original image.







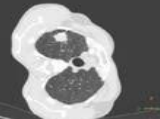

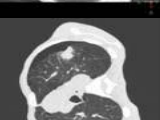

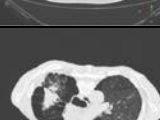
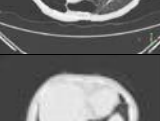
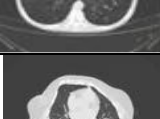
Fig 7: Gray Scale conversion of Original CT image

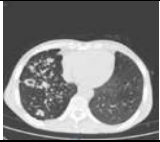



4.4 Image enhancement

Often the quality of the acquired image is not satisfactory due to factors such as blur, unnatural colors, noise, and artifacts. It is necessary to remove that irrelevant information using image enhancement which makes the image more useful for further processing. The goal of image

enhancement is to process the image to remove the unwanted information [Hemalatha Vetal, 2014] due to which the relevant in formation of the image does not appear clearly. This includes improvement in image brightness with the modification in the image histogram.

Table 1: PSNR and MSE values of Median, Average and Wiener filter

Case	CT image	Median Filter		Average Filter		Wiener Filter	
		PSNR	MSE	PSNR	MSE	PSNR	MSE
1		41.27	4.89	39.09	8.08	48.73	0.88
2		41.15	5.03	38.72	8.79	48.03	1.03
3		42.87	3.38	40.79	5.46	48.62	0.90
4		41.26	4.90	39.02	8.21	48.15	1.00
5		41.64	4.49	39.87	6.76	50.15	0.63
6		40.71	5.57	38.38	9.53	49.07	0.81
7		40.62	5.69	38.35	9.58	49.00	0.82
8		43.41	2.99	40.79	5.46	48.88	0.85
9		41.10	5.09	38.75	8.60	47.72	1.11
10		42.90	3.36	40.68	5.60	49.44	0.75
11		43.89	2.67	41.24	4.03	50.49	0.59
12		41.47	4.68	39.79	6.89	49.23	0.78

13		36.55	14.52	36.89	13.41	49.35	0.76
14		43.37	3.02	39.67	7.07	49.47	1.17
15		41.17	5.00	38.81	8.63	49.13	0.80
16		41.16	5.02	39.16	7.95	48.40	0.95

The results show that wiener filter offers the best outcomes with higher PSNR and lower MSE measures. On the basis of the evaluation of his to gram and performance of PSNR and MSE, wiener filters has been applied in proposed algorithm. It has been done using noise removal wiener filter which removes the Gaussian noise from the image shown in figure 7.

4.5 Feature extraction

Important features could be used to discriminate between benign and malignant in both the cancer. Geometric features

are based on compactness, perimeter (number of pixels around ROI boundary), area (a set of pixels inside ROI), shape etc. Shape is very important feature in the classification of tumor as benign or malignant. Feature extraction has been performed on segmented lung region obtained from above step (figure 7) that distinguishes one region of interest from another shown in figure.8. The aim of extracting features from the image is to minimize original dataset by evaluating certain characteristics that differentiate one region of interest from other [Bhuvanewari Cetal, 2014].



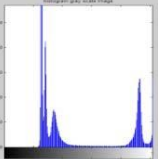
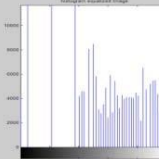
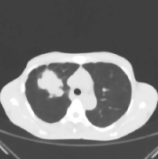
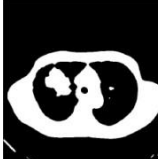


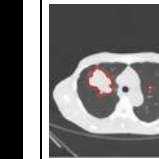

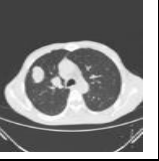
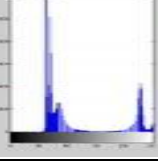
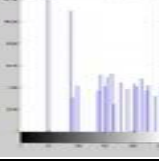
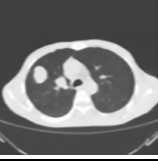


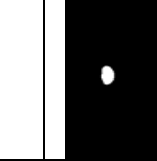
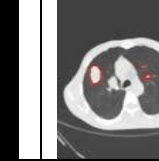


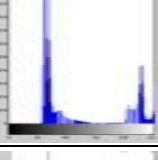

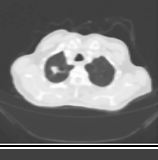



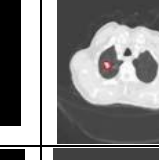


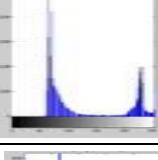

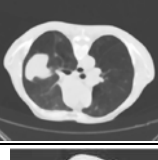






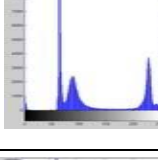
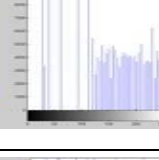



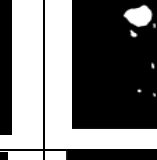



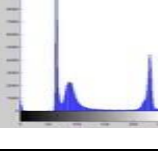
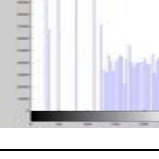
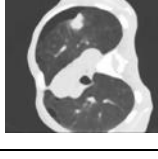



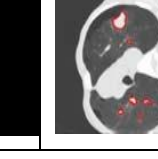


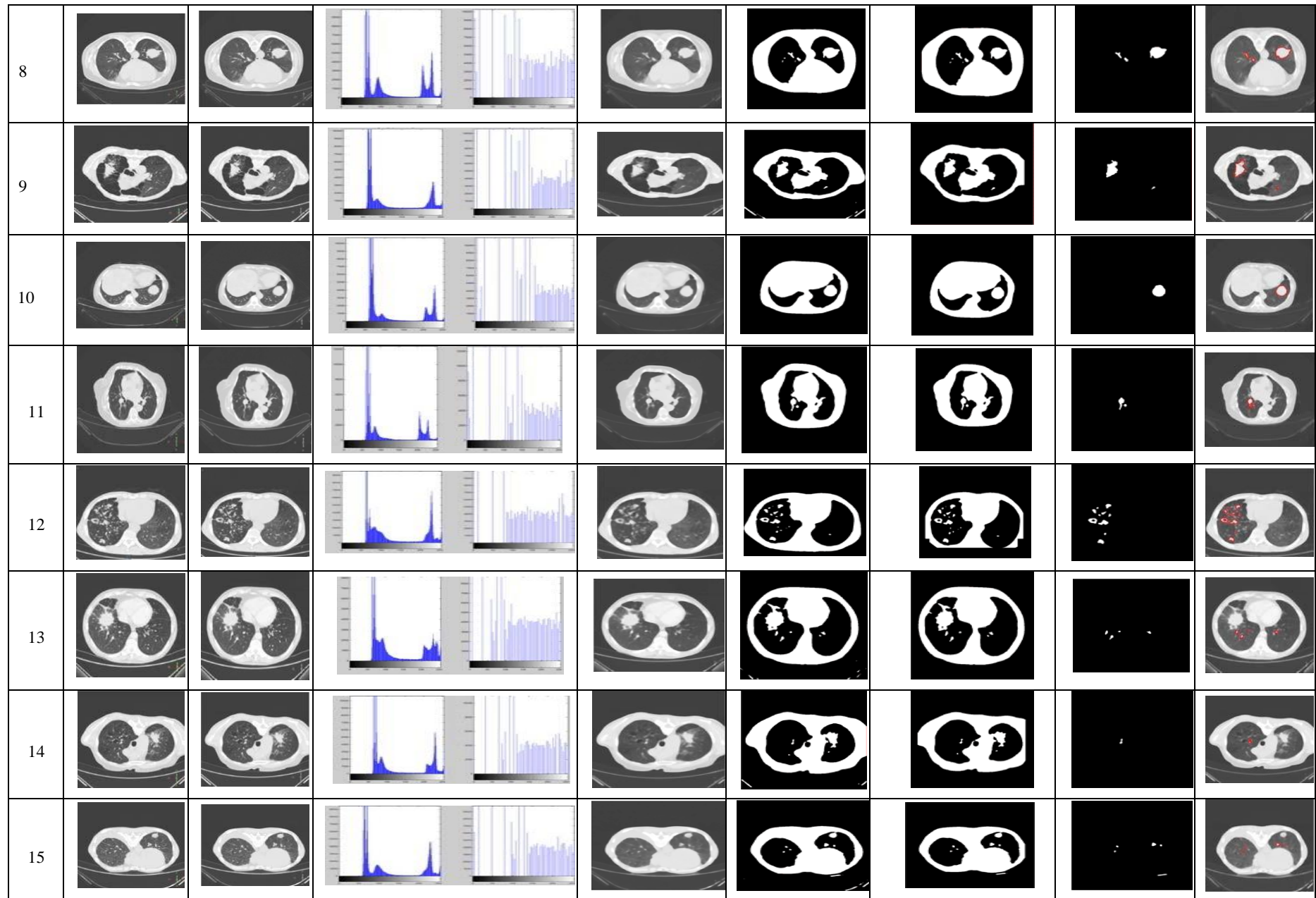
Fig 8: Region of Interest

Table 2: Accuracy measurement of FNN and RBF models with different features

Data Set	Classification	10 Features	15 Features	20 Features	25 Features
		RBF	RBF	RBF	RBF
30	Correct	90.0	90.0	90.0	90.0
	Incorrect	10.0	10.0	10.0	10.0
50	Correct	95.9	95.9	95.9	93.9
	Incorrect	4.1	4.1	4.1	6.1
70	Correct	98.6	98.6	98.6	97.1
	Incorrect	1.4	4.1	4.1	2.9
90	Correct	98.9	98.9	98.9	96.7
	Incorrect	1.1	1.1	1.1	3.3
110	Correct	99.1	99.1	94.5	92.7
	Incorrect	0.9	0.9	5.5	7.3
130	Correct	99.2	99.2	98.5	96.9
	Incorrect	0.8	0.8	1.5	3.1
150	Correct	99.3	99.3	95.3	94.0
	Incorrect	0.7	0.7	4.7	6.0
170	Correct	99.3	99.3	95.9	94.7
	Incorrect	0.7	0.7	4.7	5.3

Table 3: Region of interest (ROI) obtained after preprocessing

Case	Original image	Gray scale image	Histogram of		Filtered Image	Thresholding	Morphological Operation	Feature Extraction	Outlined image
			Original image	Gray Scale image					
1									
2									
3									
4									
6									
7									



The table 4 shows 16 cases of different views studied throughout the research. The table provides steps of how to obtained ROI. ROI is highlighted with colored boundary in

outlined image. Extracted features help in determining and classifying the suspected region of the lung [Lingayat NS *et al.* 2013].

Table 4: Comparison of FNN and RBF on lung data set for classification

Image Dataset	FNN		RBF	
	Correct Classification (%)	Incorrect Classification (%)	Correct Classification (%)	Incorrect Classification (%)
30	86.7	13.3	90.0	10.0
50	86.0	14.0	98.0	02.0
70	90.0	10.0	97.1	02.9
90	91.1	08.9	97.8	02.2
110	88.2	08.0	96.4	03.6
130	89.2	10.8	98.5	01.5
150	88.0	12.0	98.7	01.3
170	89.4	10.6	98.8	01.2

The outcomes obtained from FNN and RBF neural networks are shown in table 4. The percentage of correct classification of RBF is better than percentage of correct classification of FNN. RBF diminishes incorrect classifications.

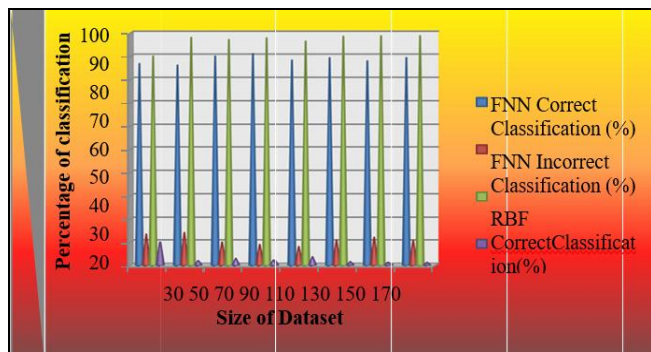


Fig 9: Graphical representation of classification obtained through FNN and RBF

The graph illustrates in figure 9. study of correct and incorrect classifications on lung cancer datasets of different sizes. The percentage of correct classification has shown improvement with the increased size of the dataset, RBF getting increased performance in all measurement criteria as shown in table 5.

Table 5: Comparison of performance of FNN and RBF on lung data set

Image dataset	ANN (%)	RB (%)
30	0.0551	0.0310
50	0.0645	0.0100
70	0.0983	0.0270
90	0.0615	0.0109
110	0.0412	0.0088
130	0.0387	0.0075
150	0.0120	0.0128
170	0.0969	0.0113

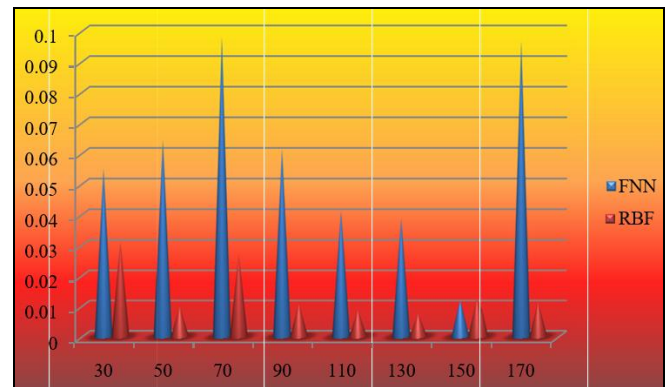


Fig 10: Graphical representation of performance shown by FNN

The farthest left and up the line is the fewer false positive need to be accepted in order to get a high True Positive Rate (TPR). The best classifiers will have a line going from the bottom left corner, to the top right corner, to the top left corner or close to that. It has been observed that from figure 10. (b) ROC of RBF has been shown in the form of line going from the bottom left corner, to the top left corner, to the top right corner. To evaluate the performance of the system, sensitivity, specificity, and accuracy is measured. The outcomes are shown in table 6 and represented graphically.

Table 6: Sensitivity, specificity, and accuracy of proposed system using RBF

Image dataset	Sensitivity	Specificity	Accuracy
30	100	80.0	90.0
50	100	96.2	98.0
70	97.4	96.9	97.8
90	100	95.2	96.4
110	100	94.2	98.5
130	100	97.1	96.7
150	98.6	97.5	98.7
170	100	97.8	98.8



Fig 11: Graphical representations of sensitivity, specificity, and accuracy of proposed system using RBF

The proposed system set up a CAD system to detect the lung carcinoma in its early phase, introducing feature extraction procedure. When the outcomes of the proposed system are compared to various existing system, it gives better performance More.

5. Conclusions

In conclusion, this study has presented a comprehensive approach to addressing the challenges associated with noise reduction in image processing, particularly within the context of the construction domain. The utilization of the two-dimensional median filter, *medfilt2*, has demonstrated its efficacy in enhancing image quality while preserving essential edge details, a crucial consideration in fields like medical imaging and construction analysis. This study's findings underscore the superiority of the median filter over convolution-based techniques when the objective is to minimize image disturbance while safeguarding edge integrity. The nonlinear nature of the median filter ensures that extreme noise values are effectively suppressed, resulting in clearer and more reliable images. This property is of paramount importance in applications where accurate interpretation and subsequent analysis are imperative. By applying the median filter within the construction process, this study contributes to the optimization of image quality, setting the stage for improved analysis and decision making. The noise reduction technique employed here prepares images for further investigation, enhancing the accuracy of subsequent measurements and assessments. As a whole, this research sheds light on the significance of noise reduction techniques in image processing and underscores the value of the median filter in scenarios where maintaining edge fidelity is essential. The findings of this study have direct implications for various fields, from medical imaging to construction analysis, where image quality directly impacts the accuracy and reliability of outcomes. In future research, exploring the integration of advanced noise reduction techniques and evaluating their performance across diverse datasets could further enrich our understanding of image enhancement. Additionally, investigating the combination of noise reduction methods with other image processing techniques holds promise for achieving even more robust results.

6. References

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