Statistical Analysis of Law's Mask Texture Features for Cancer and Water Lung Detection

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Abstract

Lung cancer is distinguished by presenting one of the highest rates of mortality. Detecting and curing the disease in the early stages provides patients with a high chance of survival. Moreover, the presence of an excessive amount of water in lung is usually accompanied by a high mortality rate. Thus, there is an urge to develop an automatic technique for detecting and monitoring lung water. This paper reports a study conducted on the use of Laws' masks to calculate energy statistics that gives description features of a cancerous and water lung texture that can be used in turn for texture discrimination. Laws' masks method has been recognized as a very useful tool in image processing for texture analysis, however it has not been utilized in cancer or water lung characterization. The proposed algorithm proceeds in three steps: image preprocessing, lung region extraction and texture feature extraction. To reduce the feature space, statistic t-test and its p values for feature selection are proposed. DICOM CT images are used to test the proposed algorithm. Experimental results show that Laws' method has high capability to extract texture features that can discriminate between cancer and normal cases, water and normal cases as well as cancer and water cases.

Keywords: *Lung cancer, Lung water, Laws' masks, Texture analysis, Texture feature.*

1. Introduction

The use of automatic systems in the analysis of medical images has proven to be very useful to radiologists. Many image processing techniques have been developed over the past two decades to help radiologists in detection of diseases. Today several techniques are used for imaging the lung for the detection of lung diseases (lung cancer, pulmonary edema, cystic fibrosis etc.) such as Computerized Tomography (CT), Chest Radiograph (x-ray) and Magnetic Resonance Imaging (MRI scan). Nevertheless, these techniques can detect the disease only in its advanced stages, which leads to the death of a number of the patients. Hence, we need techniques to diagnose in its early stages. This will certainly enhance the speed and the quality of the diagnosis. The CT examination is non-invasive and low-radioactive thus, the applications of CT imaging for medical diagnosis become more and more important [1]. Currently, the most effective image for early detection of lung diseases is CT, which is regarded as a more reliable tool.

The objective of this study is to explore Laws' masks analysis to describe structural variations of lungs due to the incidence of cancer or presence of water on CT lung images and to check its discriminative power. Lung cancer is considered to be the main cause of death between people throughout the world. Lung cancer is a disease of abnormal cells multiplying and growing into a tumor. Cancer cells can be carried away from the lungs in blood, or lymph fluid that surrounds lung tissue. Early detection of lung cancer can increase the chance of survival among people. Furthermore, the presence of an excessive amount of water in lung is a sign of pulmonary edema which can be caused by many critical conditions, such as acute lung injury and heart failure. Pulmonary edema or lung water is the medical term for fluid filled lungs.

The organization of this paper is as follows: Section 2 discusses the previous work. Section 3 introduces methods and materials used in this work. The experimental results and discussion are explained in Section 4. Finally, section 5 concludes the paper.

2. Previews Work

Jain and Vijay in [2] proposed a method to detect the lungs caner from a MRI image, taken from a particular angle. It is found that images of lungs with suspected cancer has a big variation in intensity values while normal lung images don't show any major changes in surrounding pixels. Sharma and Jindal developed an automatic computer aided diagnosing system for early detection of lung cancer by analyzing CT images. The approach proceeds in four stages. First, the lung regions are extracted from the CT image using several image processing technique. Then, the extracted lung regions are segmented using region growing segmentation algorithm. Afterward, the obtained area for nodules are analyzed to extract a set of features to be used in the diagnostic rules. Finally, a set of diagnosis rules are generated from the extracted features [3]. In [4] Chaudhary and Singh proposed a system for finding nodules and early symptoms of cancer appearing in patients' lungs. This method is based on utilizing a modified Watershed segmentation approach to isolate a lung of an CT image, and then apply a small scanning window to check whether any pixel is part of a disease nodule. Hashemi et. al. presented a method for detecting lung nodules automatically through CT image. In the first step, Linear-Filtering technique is used for enhancement of the input image. Second, image segmentation that is based on region growing techniques is accomplished. Finally, cancer recognition are presenting by Fuzzy Inference System (FIS) for differentiating between malignant, benign and advanced lung nodules. This system uses a rule base derived from knowledge of an expert, which is basically a set of statements or facts used for decision making [5]. Sankar and Prabhakaran developed an architecture to identify the characteristics for correct image comparison as pixel proportion and mask-labeling. This architecture consists of three phases. In the first stage, image quality assessment as well as enhancement were adopted. Three techniques are used for this principle: Gabor filter (has the best results), auto enhancement algorithm, and FFT (Fast Fourier Transform) (shows the worst results for image segmentation). Second, thresholding approach and Marker-Controlled Watershed Segmentation approach are used for image segmentation. The Watershed approach has better results than thresholding. Finally, the feature extraction stage is performed. The main detected features for accurate images comparison are pixels percentage and mask-labeling with high accuracy and robust operation [6]. On the other hand, reliable tools for monitoring and detecting lung water are increasingly needed in modern intensive care and clinic therapy. Analysis of lung sounds has been used to detect water in lung [7] and [8]. Mulligan et al. in [7] developed an instrument for measuring changes in the distribution of lung fluid in the respiratory system. The system consists of a speaker that injects white Gaussian noise into the mouth and four electronic stethoscopes that record sound signals from the chest wall. Moreover, Yang et al. suggested to use the acoustic approach to detect the presence of water in lung. This approach proposes to detect lung water based on respiratory sounds collected via a stethoscope and tries to establish the feasibility of using lung sounds for detecting water in lungs. Four feature extraction methods combined with two classification methods have been investigated in this study [8].

However, there are no works reported on the use image processing techniques to detect water in lung. This study investigates the feasibility of applying Laws texture energy measures, developed by Kenneth Ivan Laws [9], to determine the texture variations on the lungs CT images due to the presence of cancer or water. Laws' masks are well established as one of the best methods for texture analysis in image processing [10] and are used in various applications, including medical image analysis. Laws' masks were used to detect defects in ceramic tiles [11], for spatial texture analysis [12], for breast cancer detection [13] and for Osteoporosis Detection [14].

In lung cancer detection an attempt was made using two types of texture analysis, Haralick's co-occurrence matrices and Laws' texture measures, to generate texture feature vectors from chest x-ray. Different neural network topologies are then used to evaluate the validity of the feature sets and are also utilized for nodule detection [15]. Our study is the first application of Laws masks to lung cancer and lung water characterization in lung CT images. The method consists of several stages; first, a lung DICOM CT image was preprocessed using histogram equalization and Weiner filter to enhance its contrast. Then, we proposed a novel segmentation framework to extract and separate both lungs. Afterward, texture feature extraction using five Laws' masks of size 5×5 is performed. Finally, the extracted features are tested and analyzed to choose the significant features. Three statistical descriptors namely mean, average of the absolute values and standard deviation will be implemented.

3. Materials and Methods

The proposed system proceeds in three phases. The original testing image slices were first processed by the pre-processing procedure to reduce the noises in images. Then, an efficient segmentation method was applied on the following image data. Subsequently, textural features are extracted from the lung images using Laws' masks descriptors. Finally, these features are investigated to select the significant ones. The following sections will describe in details these stages.

3.1 Preprocessing

Preprocessing is an important task that is used mainly to reduce the noise artifacts in the image. This step can be used for noise suppression and contrast enhancement of image quality. Image enhancement processes consist of a collection of techniques that seek to improve the visual appearance of an image or to convert the image to a form better suited for analysis by a human or machine [16]. The proposed enhancement process, which combines filters and noise reduction techniques for pre and post processing as well, is carried out using histogram equalization (HE) followed by Wiener filtering.

3.1.1 Contrast enhancement

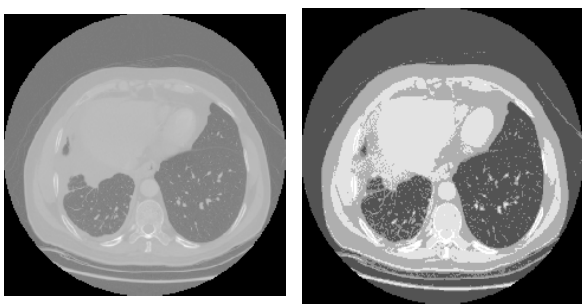
HE first calculates the occurrences of each intensity value in an image, then flattens and stretches the dynamic range of the histogram based on the probability density function [17]-[19]. Since contrast is expanded for most of the image pixels, the transformation improves the delectability of many image features. The probability density function of a pixel intensity level k is given by:

$$p(k) = \frac{n_k}{n}, \qquad \text{k} = 0, 1, 2, \ldots, \text{L} - 1 \tag{1}$$

where: n_k is the number of pixels at intensity level k, n is the total number of pixels and L is number of grey levels in image. The histogram is derived by plotting p(k) against k. A new intensity s_k of level k is defined as:

$$s_k = \sum_{j=0}^{k} \frac{n_j}{n} = \sum_{j=0}^{k} p(j) \tag{2}$$

Fig. 1 presents the improvement in the lung image contrast obtained by applying the histogram equalization. Obtained grey scale image contains noises such as white noise, salt and pepper noise etc. This can be removed by using wiener filter from the extracted lung image.



(a) (b)

Fig. 1: (a) The Lung CT image; (b) The histogram equalized image.

3.1.2 Weiner Filter

Wiener filter is designed by minimizing the mean square error between the filtered image and the original image. It can be applied to the image adaptively, tailoring itself to the local Image variance. Where the variance is large, it performs little smoothing, where the variance is small it performs more smoothing. The Wiener filter for a image in frequency domain is expressed as follows [20]

$$\text{W}(f_1, f_2) = \frac{H^*(f_1, f_2) S_x(f_1, f_2)}{\left|H(f_1, f_2)\right|^2 S_x(f_1, f_2) + S_N(f_1, f_2)} \tag{3}$$

where $Sx(f_1,f_2)$, $SN(f_1,f_2)$ are respectively power spectra of the original image and the additive noise, and $H(f_1,f_2)$ is the blurring filter. Fig. 2 demonstrates the effect of the Weiner filter on the contrast enhanced lung image.

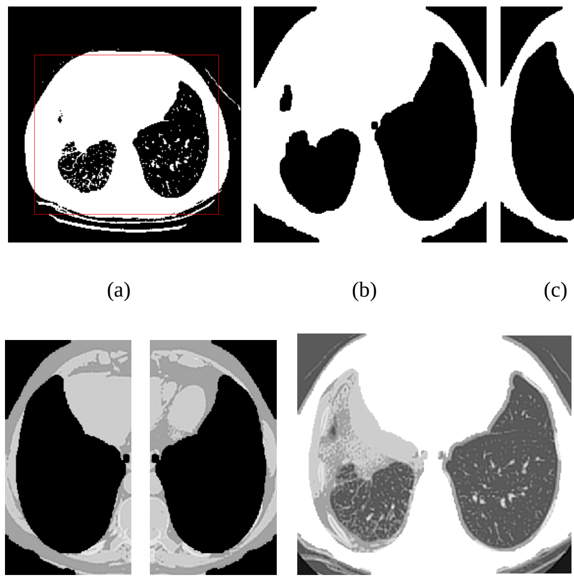
Fig. 2. The Weiner filtered output image.

3.2 Lung Region Extraction

The goal of the lung extraction step is to essentially separate the voxels corresponding to the lung cavity in the axial CT scan slices from the surrounding lung anatomy. The proposed method is based on the facts that there is a large density difference between air-filled lung tissue and surrounding tissues, as well as that the two lungs are both almost look like mirror images of themselves in a human body. Extraction of lung regions is accomplished through the following stages. In the first stage, the preprocessed CT image is converted into binary image. In this process a threshold of 128 is selected such that values greater than the threshold are mapped to white where as the values less than that are marked as black. Thus, the two lungs are marked and the area around them is cropped out. Then, the erosion morphological operation is applied in order to remove any white pixels within the two lungs. Afterward, the eroded image is divide into two equal regions, and the original lung image is also divided into two equal parts. For each eroded image region the black pixels are counted, the one with the larger black area will be considered as a lung mask. The lung mask will be mirrored in the opposite direction. Accordingly, we will have right and left lung masks. These masks will be multiplied with the corresponding original image parts, this will project the lung masks on the original two lungs images. Finally, each black pixel in the obtained images are updated by its original value otherwise the pixels are set to 255. The lung extraction process is presented in Fig. 3.

3.3 Law's Masks Texture Feature Extraction

Feature extraction is the process of obtaining higher-level information of an image such as color, shape and texture. Texture is a key component of human visual perception. The Laws method uses filter masks to extract secondary features from natural micro-structure characteristics of the image (level, edge, spot and ripple) which can then be used for segmentation or classification. Laws developed five labeled vectors which could be combined to form two dimensional convolution kernels. When convolved with a textured image these masks extract individual structural components of the image [9]. The five vectors are: L5 = [1, 4, 6, 4, 1], E5 = [-1,-2, 0, 2, 1], S5 = [-1, 0, 2, 0,-1], R5 = [1,-4, 6,-4, 1] and W5 = [-1, 2, 0,-2, 1].



(a) (b) (c)

(d) (e)

Fig. 3 Lung region extraction: (a) the thresholded image; (b) the eroded image; (c) the lung mask mirror; (d) the masks projection on the corresponding lungs images; (e) the extracted lungs.

After a series of particular convolution with selected Laws' masks, the outputs are passed to texture energy measurement (TEM) filters for the analysis of the texture property of each pixel. These consisted of a moving non-linear window operation, every pixel of the image is replaced by comparing the pixel with its local neighborhood based on three statistical descriptors (mean, absolute mean and standard deviation). These descriptors are computed as follows:

$$mean = \frac{\sum_{W} \text{neighbouring pixels}}{\text{W}} \tag{4}$$

$$absolute \quad mean = \frac{\sum_{W} \text{abs(neighbouring pixels)}}{\text{W}} \tag{5}$$

$$standard \quad deviation = \sqrt{\frac{\sum_{W} (\text{neighbouring pixels} - mean)^2}{\text{W}}} \tag{6}$$

where W is the window size. The operation will lead to the creation of three TEM images corresponding to each statistical descriptor. After the windowing operation, all the obtained images are normalized in order to be presented well as images. Min-max normalization method is utilized in this work. Subsequently, for each normalized TEM (NTEM) image we compute three statistics; absolute mean (ABSM), mean square or energy (MS) and entropy as follows:

$$ABSM = \frac{1}{\text{MN}} \sum_{x=1}^{M} \sum_{y=1}^{N} \left| I(x.y) \right| \tag{7}$$

$$MS = \frac{1}{\text{MN}} \sum_{x=1}^{M} \sum_{y=1}^{N} I^2(x.y) \tag{8}$$

$$Entropy = \frac{1}{\text{MN}} \sum_{x=1}^{M} \sum_{y=1}^{N} I(x.y)(-\ln I(x,y)) \tag{9}$$

where I(x,y) is the pixel value, and M and N are image dimensions.

The features extracted from left and right lungs NTEM images for cancer, water and normal patients are analyzed and tested in order to determine the suitable statistical analysis descriptor for the system as well as the significant features to distinguish among the different cases.

3.4 Statistical analysis

The statistical values (mean ± standard deviation) were reported for all studied cases. The analysis of the relationship between the studied parameters; in the cancerous case, the water case and the normal case is performed. Furthermore, the acquired parameters are investigated to obtain their associations with respect to both right and left lungs in all cases. A simple ranking based feature selection criterion, a statistic t-test, which measures the significance of a difference of means between two distributions, and therefore evaluates the discriminative power of each individual feature in separating two classes is implemented. The features are assumed to come from normal distributions with unknown, but equal variances. Since the correlation among features has been completely ignored in this feature ranking method, redundant features can be inevitably selected, which ultimately affects the classification results. Therefore, we use this feature ranking method to select the more discriminative feature.

4. Experimental Results

In this section we present an analysis of the various experiments conducted and results obtained. DICOM CT images of lungs are taken as test images for evaluating results. There are 10 volunteers in our study; four patients suffer from cancer, five have water in their lungs and one normal case. Twenty CT scans for each patient are considered for evaluation. The algorithm is tested in MATLAB.

We apply five 5x5 dimension Laws' masks which are $L5E5 = L5^TxE5$, $L5S5 = L5^TxS5$, $R5R5 = R5^TxR5$, $E5S5 = E5^TxS5$ and $L5L5 = L5^TxL5$, and three statistical descriptors (mean, absolute mean and standard deviation) are utilized to determine the TEM images. Afterward, the min-max normalization method is used to generate the NTEM images. Then, three amplitude features, ABSM, MS and entropy, are computed for each obtained NTEM. Since there are 15 different convolutions, altogether we obtain a total of 45 features. To reduce feature space, we apply t-test on each feature, and examine the p-value. If the p-value is less than a predefined threshold, then it is kept, otherwise, it is discarded. The significance level is chosen at $P \leq 0.01$ for the cancerous case and $P \leq 0.001$ for the water case. While to discriminate between the cancer and water cases the significance level is chosen at $P \leq 0.0001$ and $P \leq 0.0005$ for the right and left lungs, respectively. Table 1 and table 2 illustrate the significant features that can distinguish between the cancer and normal cases for both right and left lungs, respectively. While the significant features that can discriminate between the water and normal cases for both right and left lungs are presented in table 3 and table 4, respectively. Furthermore, Table 5 and table 6 show the discriminative features between the cancer and water cases in the right and left lungs, respectively.

It is worth pointing out that after t-test, 9 and 10 of 45 features are kept back for left and right lungs in the cancer case, respectively. While there are 21 and 14 significant features in the water case for the right and left lungs, respectively. On the other hand, 19 and 10 features are considered as discriminative features between the water and cancer cases. Furthermore, the mean statistical descriptor has been demonstrating lower number of significant features in all cases when compared with standard deviation and ABSM statistical descriptors.

Table 1 The significant features of the right lung in the cancer case.

Descriptor	***Feature***	***Normal***	***Cancer***	***P***
Standard deviation	ABSM - R5R5	0.097875 ± 0.004908	0.067282 ± 0.002442	1.98E-07
	MS - R5R5	0.03411 ± 0.002995	0.022989 ± 0.001097	5.98E-05
	Entropy - R5R5	4.315559 ± 0.006365	4.2142302 ± 0.01082451	1.19E-05
	ABSM - L5L5	0.202026 ± 0.005754	0.185387 ± 0.002722	0.008091
	MS - L5L5	0.08061 ± 0.00384	0.071098 ± 0.001436	0.006913
ABSM	ABSM - R5R5	0.390602 ± 0.013235	0.348298 ± 0.006806	0.006255
	MS - L5L5	0.55578 ± 0.008367	0.645141 ± 0.00797	4.5E-07
Mean	ABSM - L5L5	0.526862 ± 0.005265	0.587277 ± 0.008572	0.000772
	MS - L5L5	0.395603 ± 0.004422	0.476771 ± 0.00718	2.26E-07

Table 2 The significant features of the left lung in the cancer case.

Descriptor	***Feature***	***Normal***	***Cancer***	***P***
Standard deviation	ABSM - R5R5	0.105703 ± 0.004209	0.067806 ± 0.002117	2.35E-12
	MS - R5R5	0.038459 ± 0.002566	0.023186 ± 0.000853	1.38E-10
	Entropy - R5R5	4.322378 ± 0.005478	4.218168 ± 0.011502	2.01E-05
ABSM	MS - L5E5	0.050641 ± 0.002893	0.065057 ± 0.002126	0.001833
	ABSM - L5S5	0.300097 ± 0.00989	0.340839 ± 0.006241	0.003119
	MS - L5S5	0.086955 ± 0.004792	0.115538 ± 0.003311	0.000102
	ABSM - L5L5	1.0619 ± 0.015901	1.171484 ± 0.012465	6.36E-05
	MS - L5L5	0.553726 ± 0.007811	0.678893 ± 0.007481	1.77E-12
Mean	ABSM - L5L5	0.52155 ± 0.005809	0.599551 ± 0.011046	0.000729
	MS - L5L5	0.396378 ± 0.00571	0.484546 ± 0.00904	5.67E-06

Table 3 The significant features of the right lung in the water case.

Descriptor	***Feature***	***Normal***	***Water***	***P***
Standard deviation	ABSM - L5E5	4.576198 ± 0.006356	4.407598 ± 0.016703	1.69E-05
	MS - L5E5	0.174057 ± 0.005616	0.136687 ± 0.0043	0.000273
	Entropy - L5S5	4.574557 ± 0.006044	4.402233 ± 0.016875	1.36E-05
	ABSM - R5R5	0.097875 ± 0.004908	0.062585 ± 0.002665	1.76E-07
	MS - R5R5	0.03411 ± 0.002995	0.01999 ± 0.001187	5.75E-06
	Entropy - R5R5	4.315559 ± 0.006365	4.099389 ± 0.015826	1.6E-08
	Entropy - E5S5	4.587971 ± 0.005963	4.414258 ± 0.016683	9.49E-06
	ABSM - L5L5	0.202026 ± 0.005754	0.139298 ± 0.003538	1.12E-11
	MS - L5L5	0.08061 ± 0.00384	0.04643 ± 0.001555	1.23E-14
	Entropy - L5L5	4.534976 ± 0.006878	4.366085 ± 0.017335	3.15E-05
ABSM	ABSM - L5E5	0.169152 ± 0.006202	0.137152 ± 0.003925	0.000724
	MS - L5E5	4.554431 ± 0.006211	4.373198 ± 0.017092	6.71E-06
	ABSM - L5S5	9.117653 ± 0.012064	8.753966 ± 0.034346	6.87E-06
	MS - L5S5	0.390602 ± 0.013235	0.309444 ± 0.009236	0.000256
	MS - R5R5	13.41793 ± 0.017554	12.83505 ± 0.049361	6.8E-07
	ABSM - E5S5	0.543999 ± 0.01789	0.435295 ± 0.013506	0.000722
	Entropy - E5S5	17.99859 ± 0.022938	17.23335 ± 0.066476	1.21E-06
	MS - L5L5	0.55578 ± 0.008367	0.69594 ± 0.008429	4.14E-11
	Entropy - L5L5	22.63349 ± 0.026158	21.85383 ± 0.07832	2.14E-05
Mean	ABSM - L5L5	0.526862 ± 0.005265	0.700703 ± 0.006346	2.72E-22
	MS - L5L5	0.395603 ± 0.004422	0.567444 ± 0.008453	4.28E-15

Table 4 The significant features of the left lung in the water case.

Descriptor	*Feature*	*Normal*	*Water*	*P*
Standard deviation	Entropy - L5E5	4.57552 ± 0.005163	4.441638 ± 0.014977	0.000122
	Entropy - L5S5	4.570759 ± 0.004922	4.436167 ± 0.015206	0.00014
	ABSM - R5R5	0.105703 ± 0.004209	0.077592 ± 0.00195	3.26E-08
	MS - R5R5	0.038459 ± 0.002566	0.028445 ± 0.00093	4.76E-05
	Entropy - R5R5	4.322378 ± 0.005478	4.122464 ± 0.01485	2.39E-08
	Entropy - E5S5	4.589522 ± 0.005099	4.45556 ± 0.01514	0.000141
	Entropy - L5L5	4.537199 ± 0.005485	4.413172 ± 0.014908	0.000331
ABSM	Entropy - L5E5	4.552737 ± 0.005194	4.411022 ± 0.014988	5.12E-05
	Entropy - L5S5	9.110756 ± 0.010084	8.826526 ± 0.030429	6.2E-05
	Entropy - R5R5	13.42025 ± 0.014049	12.93455 ± 0.045132	4.94E-06
	Entropy - E5S5	18.0007 ± 0.019023	17.37233 ± 0.060612	1.02E-05
	ABSM - L5L5	1.0619 ± 0.015901	1.187949 ± 0.008942	3.05E-08
	MS - L5L5	0.553726 ± 0.007811	0.692815 ± 0.009719	5.29E-09
	Entropy - L5L5	22.62699 ± 0.022448	21.93624 ± 0.073683	5.82E-05

5. Conclusion and Future Work

In this paper, we achieved a study in developing an automatic CAD system for early detection of lung cancer and lung water by analyzing lung DICOM CT images using several steps. The approach starts by image preprocessing task to remove noise in a lung CT image using histogram equalization and Weiner filter. Then, the lung regions are segmented from the CT image using several image processing techniques. A novel segmentation framework to extract and separate both lungs is demonstrated. After the segmentation step, Law's texture features are extracted. Finally, the extracted features are analyzed using statistic t-test to select the significant features that are able to discriminate between the normal, cancer and water lung cases.

The proposed method constitutes a promising routine technique for the detection of cancer and water lungs from CT images. Therefore, we are strongly recommending the application of the 25 Law's masks in future researches for developing this system accompanied with parallel processing techniques to increase the system performance and reduce the processing time. Besides, we will suggest that future researchers need to increase the number of images included in their experiment. The small number of acquired images in this paper represents a drawback to our experiment. In future, we will extend our experiment by analyzing more statistical analysis parameters such as skewness and kurtosis to develop the texture analysis for water and cancer lung cases.

Table 5 The significant features of the right lung between the water and cancer cases.

Descriptor	*Feature*	*Cancer*	*Water*	*P*
Standard deviation	ABSM - L5E5	0.169172 ± 0.003905	0.1503 ± 0.00429691	1.31E-11
	Entropy - L5E5	4.558019 ± 0.006221	4.407598 ± 0.016703	6.1E-05
	ABSM - L5S5	0.157751 ± 0.004166	0.136687 ± 0.0043	4.76E-13
	MS - L5S5	0.049862 ± 0.002139	0.041131 ± 0.001892	4.02E-09
	Entropy - L5S5	4.552956 ± 0.006184	4.402233 ± 0.016875	6.22E-05
	Entropy - R5R5	4.214230 ± 0.01082451	4.099389 ± 0.015826	7.68E-05
	ABSM - E5S5	0.187074 ± 0.004738	0.136531 ± 0.004981	1.09E-19
	MS - E5S5	0.065083 ± 0.002647	0.041287 ± 0.002374	1.86E-05
	Entropy - E5S5	4.57464 ± 0.006298	4.414258 ± 0.016683	4.59E-05
	ABSM - L5L5	0.185387 ± 0.002722	0.139298 ± 0.003538	6.32E-32
	MS - L5L5	0.0711 ± 0.001436	0.04643 ± 0.001555	1.05E-29
	Entropy - L5L5	4.52715 ± 0.006928	4.366085 ± 0.017335	3.86E-05
ABSM	ABSM - L5E5	0.153464 ± 0.00323369	0.137152 ± 0.003925	4.53E-13
	ABSM - L5S5	0.295389 ± 0.006196	0.261901± 0.007809	1.41E-13
	M S - L5S5	0.096453 ± 0.003576	0.079257 ± 0.003259	2.39E-08
	ABSM - R5R5	0.348298 ± 0.006806	0.309444 ± 0.009236	7.04E-15
	MS - R5R5	0.112051 ± 0.003969	0.092299 ± 0.003757	9.32E-10
	ABSM - E5S5	0.515422 ± 0.010046	0.435295 ± 0.013506	1.22E-19
	MS - E5S5	0.16837 ± 0.00614	0.128496 ± 0.005631	8.77E-15

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Table 6 The significant features of the left lung between the water and cancer cases.

Descriptor	*Feature*	*Cancer*	*Water*	*P*
Standard deviation	Entropy - L5E5	4.58447 ± 0.005682	4.441638 ± 0.014977	0.000392
	Entropy - L5S5	4.57969 ± 0.005559	4.436167 ± 0.015206	0.000393
	Entropy - E5S5	4.59479 ± 0.005742	4.45556 ± 0.01514	0.000442
	Entropy - L5L5	4.56228 ± 0.006454	4.413172 ± 0.014908	0.000298
ABSM	Entropy - L5E5	4.49536 ± 0.030107	4.411022 ± 0.014988	0.002737
	Entropy - L5S5	8.99452 ± 0.060451	8.826526 ± 0.030429	0.002822
	Entropy - R5R5	13.1546 ± 0.08589	12.93455 ± 0.045132	0.003074
	Entropy - E5S5	17.6730 ± 0.115429	17.37233 ± 0.060612	0.003085
	Entropy - E5S5	22.3028 ± 0.142829	21.93624 ± 0.073683	0.003447
Mean	MS - L5S5	0.25687 ± 0.00518	0.319585 ± 0.007474	8.61E-05

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