Computer Aided Classification of Lung Cancer, Ground Glass Lung and Pulmonary Fibrosis Using Machine Learning and KNN Classifier

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***Abstract*—Respiratory diseases are one of the most prevalent acute and chronic ailments worldwide. According to a recent survey, there were around 545 million cases of chronic respiratory diseases worldwide. Chronic respiratory diseases such as chronic obstructive pulmonary disease (COPD), pneumoconioses, asthma, interstitial lung disease and pulmonary sarcoidosis are significant public health problems across the world. The most significant CRD (Chronic Respiratory Disease) risks have been identified including smoking, contact with indoor and outdoor pollutants, allergies, occupational exposure, poor nutrition, obesity, inactivity and other factors. Interstitial lung diseases are diagnosed on high-resolution computed tomography (HRCT) using a variety of different interstitial pattern namely such as reticular, nodular, reticulonodular, ground-glass lung, cystic, ground-glass with reticular, cystic with ground-glass. If the lung diseases are identified at an early stage life span could be increased. Computer aided diagnosis could play a crucial role in identifying lung diseases at an early stage, disease management and treatment planning. In this paper a novel method is proposed to identify and classify HRCT images of cancerous lung using ML (Machine Learning) and to identify and classify ground glass lung, pulmonary fibrosis lung and healthy lung HRCT images using LBP (Local Binary Pattern) and KNN (K-Nearest Neighbor) classifier. Experimenting the proposed method on 996 images yielded 94% accuracy.**

***Keywords*—Ground glass; healthy; KNN; LBP, lung cancer; lung diseases classification; LBP; ML and pulmonary fibrosis**

I. Introduction

Chronic respiratory disorders are among the most prevalent non-communicable diseases in the world, owing to their high prevalence. The high rate of occupational, environmental and behavioural inhalational exposures has exacerbated the problem. Chronic respiratory diseases include interstitial lung disease, pulmonary sarcoidosis and pneumoconioses such as silicosis and asbestosis [1]. Ground glass opacity (GGO), commonly referred to as ground-glass attenuation, is the term utilized to explain greater lung parenchymal attenuation on CT images that does not obscure the pulmonary vascular lines [2]. A honeycomb lung can be seen on a CT scan of the lung area. Although end-stage chronic interstitial Pneumonia can cause honeycomb like cysts, usually appears in cases of severe, progressive disease. The appearance of a honeycomb suggests that nearby bronchioles have expanded due to fibrosis or granuloma edema, causing harm to the bronchioles [3]. High-resolution computed tomography and thin-section CT are effective for viewing the lungs parenchyma. The investigation of Bronchiectasis and single pulmonary nodules has been demonstrated to benefit from HRCT. Diffuse and focal pulmonary parenchyma disease may be evaluated with HRCT [4]. The computer-aided diagnosis (CAD) system serves as a tool for the medical field by assisting doctors in providing more accurate diagnoses of illnesses with greater precision in a shorter amount of time [5].

Early diagnosis of respiratory diseases is crucial for the prognosis and to protect the quality life of the patients.

A lot of people could ignore the mild symptoms that indicate a respiratory problem, which might develop gradually. For better results and prompt action, it is essential to identify the early indicators of respiratory issues. Because of this issue with respiratory disease early detection, if an automated method is developed to recognize the changes in lung parenchyma caused by lung diseases, lung diseases can be detected early.

This research work aims at developing an automated computer aided system for classifying Lung Cancer, Ground Glass Lung and Pulmonary Fibrosis using Machine Learning and KNN Classifier.

After classifying the parenchymal changes as ground glass lung, pulmonary fibrosis lung, the data analysis carried out with clinical data would lead to the diagnosis of specific lung disease.

II. Literature Survey

Anthimopoulos et al. [6] proposed a method for assessing a convolutional neural network (CNN) for ILD pattern categorization. The architecture of the network is as follows: Three dense layers are placed after average pooling with a scaling of the final feature maps, and five convolutional layers with 2x2 kernels and LeakyReLU activations. The final thick layer has seven outputs, corresponding to the aforementioned classes: healthy, ground glass opacities (GGO), microfiber strands, consolidation, reticulation, honeycombing and a mix of GGO/reticulation. The suggested procedure has an accuracy of about 85.61%.

Lakshmi Narayanan and Jeeva [7] suggested a procedure that entails the subsequent actions: i) The user can choose which area to crop after the image has been first enhanced and the region of interest has been adjusted. ii) A morphological procedure is carried out to improve the nodules and suppress

the blood vessels. iii) Labeling is used to identify nodules. iv) The features of the nodules are extracted. v) Classifiers that operate primarily on the basis of retrieved features are implemented using neural networks. The lung nodule that is located near to the lung wall was found using the suggested method.

Shuangfeng Dai et al. [8] proposed a new lung segmentation technique and it is based on an enhanced graph cuts algorithm from the energy function. Initially, Gaussian mixture models (GMMs) are used to model the lung CT images. Then, the expectation maximization (EM) approach is used to achieve the optimum distribution parameters. We may create an enhanced regional penalty item in the graph cuts energy function using those settings. Second, taking into account the image edge data, the lung image edges are identified and extracted using the Sobel operator. This information is then utilized to enhance the graph cuts energy function's boundary penalty item. The lung is segmented using the minimum cut theory after the improved energy function of the graph cuts algorithm is finally acquired and the matching graph is made.

Yang Chunran et al. [9] suggests a method for detecting and segmenting lung nodules that makes use of the level set approach, a fully convolutional network (FCN), and other image processing tools. In order to segment the lungs, lung CT scans are first entered into the FCN. Second, the threshold method and other image processing techniques are used to detect lung nodules inside the lung area. Lastly, the level set method and threshold method based on the coordinate system transformation segment the lung nodules that have been recognized and their spiculation. The outcome of the experiment indicates that the suggested approach is capable of detecting and segmenting lung nodules.

Binila Mariyam Boban and Rajesh Kannan Megalingam [10] suggested a method using machine learning algorithms to identify and categorize lung illnesses. It has 400 CT scan images of lung diseases, such as pleural effusion, bronchitis, emphysema, cancer, and normal. Machine learning algorithms like the MLP (Perceptron), KNN (K- nearest neighbor), and SVM (Support Vector Machine) classifier are used to analyze, classify, and classify the input image. The output is segmented and the classifier's accuracy is compared after feature extraction. A CT scan image contains unnecessary information when it is fed into a classifier. Here, the Gray Level Co-occurrence Matrix (GLCM) is utilized to choose the most pertinent features (i.e., to extract characteristics). This classifier achieves 98% accuracy for MLP, 70.45% accuracy for SVM, and 99.2% accuracy for KNN.

Sunita Agarwala et al. [11] proposed the automatic segmentation of lung field from HRCT images. The technique, which is based on the active shape model, can segment the lung fields from HRCT images that contain a variety of diseased regions, including consolidation, ground glass opacity (GGO), honeycomb, and cavities. Training data of size 100 is used to construct several atlases of the lung fields, one for each lung, left and right. The active shape model that estimates lung shape fields is trained using these atlases. In order to minimize human interference, the matching step automates the seed selection process after training. For 80 HRCT slices from a publically accessible database, the segmentation outcome is assessed in terms of the Jaccard index, Dice Similarity Coefficient (DSC), and Modified Hausdorff Distance (MHD).

Nidhi S. Nadkarni and Borkar [12] developed an automated method for identifying lung cancer in CT scan images. The suggested lung cancer detection algorithm makes use of techniques like median filtering for image pre-processing, which is followed by mathematical morphological procedures for segmenting the lung region of interest. Support vector machines are used to classify CT scan pictures into normal and pathological categories based on geometrical attributes that are computed from the extracted region of interest.

Anthimopoulos et al. [13] suggested a scheme for the classification of HRCT image patches with ILD anomalies as a first step toward the quantification of the different ILD patterns in the lung, A DCT-based filter bank is used for local spectral analysis in the feature extraction process. Q-quantiles are produced to describe the distribution of local frequencies that characterize the texture of the picture after convolving the image with the filter bank. The final feature vector is then formed by adding the original image's gray-level histogram values. An RF (Random Forest) classifier is used to classify the patches that have already been described.

Bingqian Yang et al. [14] suggested a dual-branch encoder and cascaded decoder network (DECDNet) to segment honeycomb lesions,. Using separate paradigm representations for ResNet34 and Swintransformer, create a dual-branch encoder in order to extract local features and long-range dependencies, respectively. The feature fusion module will then be developed in order to further combine the various paradigm features and produce richer representation data. In order to combine the multi-stage encoder information and obtain the final segmentation result, a cascaded attention decoder is built, taking into account the issue of information loss during the decoder.

Dudhane et al. [15] demonstrated how to use the Local Binary Patterns (LBP) histogram and second-order statistics like the Grey Level Run Length Matrix (GLRLM) and Grey Level Co-occurrence Matrix (GLCM) to extract features from a (31x31) size patch. For classification, a two-layer feed-forward neural network that was trained using the Scaled Conjugate Gradient Back-propagation algorithm is employed. The outcomes are validated and juxtaposed using various classifiers, including k-NN and SVM. This investigation was conducted using an ILD case database that is accessible to the general public. ILD patches were gathered from a 2-D Region of Interest (ROI) that a professional radiologist had designated. This study takes into account five often observed ILD patterns: Normal, Emphysema, Fibrosis, Ground Glass, and Micronodule.

Joel Than Chia Ming et al. [16] suggested a method for classifying the existence of two medical features in lung diseases: Ground Glass Opacity (GGO) and Reticular Pattern (RP). Every patient's slice and lung is rated for the RP and GGO by a senior radiologist. In this investigation, five predefined level HRCT Thorax imaging slices representing the entire lung of 10 patients with disease and ten patients without

it were used. The GLCM approach is used to extract the textural information from each patient. WEKA, a machine learning tool, was used for classification. The Random Forest, K-Nearest Neighbor (KNN), Radial Basis Function Network, Random Forest, Multilayer Perceptron (MLP), and Decision Table I classifiers were the ones employed. The classifiers demonstrated that an RF classifier can produce a classifier with an overall accuracy of 0.81.

Hiram et al. [17] used SVM and a wavelet feature descriptor to classify lung nodules. Here, one and two levels of decomposition are used to compute wavelet transforms. Nineteen characteristics are computed from each wavelet sub-band. SVM is used to distinguish between CT scans that contain nodules and those that do not.

Emre EGR¸ IBOZ et al. [18] proposed a technique to recognize areas of honeycombing and ground glass patterns in High Resolution Computed Tomography (HRCT) lung images, will assist professionals in diagnosing and monitoring the IPF condition. Constructing a deep learning model from provided Computed Tomography (CT) images for the particular sick regions and developing a program module that splits the lung pair. The program module will be able to identify certain locations in newly provided CT images by using the generated model. This study tested the lung segmentation performance using the Sørensen-Dice coefficient method, yielding a mean performance of 90.7%. Additionally, testing the generated model was done using data that was not used during the CNN's training phase, yielding an average performance of 87.8% for healthy regions, 73.3% for ground-glass areas, and 69.1% for honeycombing zones.

The unique method described in this paper uses machine learning to identify and classify HRCT images of lung cancer. It also uses LBP and KNN classifier to identify and classify HRCT images of healthy lung, ground glass and pulmonary fibrosis lung.

TABLE I. COMPARISON OF ACCURACY OBTAINED BY THE PROPOSED METHOD AND OTHER METHODS

Sl.No.	*Authors*	*Accuracy in %*
1	Marios Anthimopoulos et al.[6]	85.61
2	Joel Than Chia Ming et al.[16]	81
3	Hiram et al.[17]	89.52
4	Emre EGR˘ ˙IBOZ et al.[18]	Ground glass lung : 73.3 Honeycomb lung :69.1
5	Proposed method	94

III. METHODOLOGY

In this work, the proposed method is used to identify and classify ground glass lung, pulmonary fibrosis lung and healthy lung HRCT images using LBP and KNN classifier and ML is used to detect and classify HRCT images of lung cancer.

The proposed method is shown in Fig. 1. The method includes Image acquisition, pre-processing, lung segmentation, feature extraction and classification.

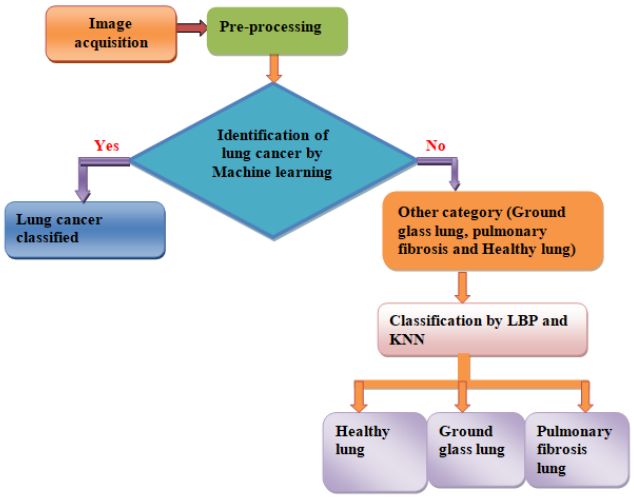

Fig. 1. Flowchart of the proposed method.

A. Dataset Collection

In this research, the first step of the proposed method involves data collection to evaluate its performance. The dataset of 996 lung HRCT images consists of 122 lung cancer images, 138 healthy lung images, 559 ground glass lung images and 177 pulmonary fibrosis lung images. Lung cancer images and healthy images were collected from Kaggle database and a set of ground glass lung HRCT images and pulmonary fibrosis HRCT images were obtained from HBS hospital, Bangalore, India.

B. Pre-processing

This stage involves pre-processing the data using the gathered lung HRCT image dataset as input. Pre-processing is important because it turns the raw data into a format that is both effective and valuable.The pre-processing stage involves filtering and enhancement. The acquired PNG image is converted into a gray scale image from RGB image and also is resized to 512x512. For DICOM dataset normalization is applied.

1) Median filter: Noise present in the image is eliminated by applying the median filter. The image's crispness is preserved while noise is eliminated by the median filter. As suggested by the name, the neighborhood pixels' median value is substituted for each pixel. This filter uses a 3 x 3 window [19].

2) Histogram equalization: The following stage involves employing histogram equalization to improve the filtered images. The process of improving an image's quality is called image enhancement. Improving the contrast of medical images is essential for improved comprehension and analysis. Histogram equalization is the standard procedure for this process. Using this procedure, a small change to the image pixel intensity is made. The intensity of each pixel is mapped in accordance with its rank among the nearby pixels [19].

C. Segmentation

Region of interest is selected from the pre-processed image. Here Unet architecture [20] is used for segmentation. There are two ways to segment biomedical images using the U-Net architecture. An encoder, also known as a contraction, is the first path. The encoder uses a small feature map to record context. The encoder is a stock of convolution layers such as Vgg-16 and max-pooling. A uniform expanding path, which is the second path and is also referred to as a decoder, makes up the other half of the design. Transposed convolution was used in the second step to achieve the exact localization. There are numerous contraction blocks in the encoder section. The encoder adheres to ConvNet's traditional architecture. The network employs a 2×2 max-pooling operation with stride 2 for contraction and a repeating implementation of two 3×3 convolutions (ReLU). As the number of features decreases by half, the number of feature channels doubles. The wide path includes two 2×2 convolutions (also known as "up-convolutions"), which reduce the number of feature channels in a feature map, concatenation with the matching feature map from the skip connection, and two 3×3 convolutions before ReLU. The component feature vector is mapped using a 1×1 convolution at the last layer. The network consists of 23 convolutional layers in total.

1) Lung tumor extraction: The pre-processed image is first tested for lung cancer. Lung cancer is identified using machine learning method by suitably annotating the image. If cancer is present it is identified and classified as lung cancer image, if not the image could belong to healthy lung, pulmonary fibrosis lung or ground glass lung category. Fig. 2 shows the lung cancer classification by machine learning method. The acquired pre-processed image is annotated and the lung tumor is segmented using U-net architecture. By labeling the tumor area in the image, machine learning is used to identify tumors. A dataset is created where the cancer images are annotated. To train the model, the U-net architecture receives the dataset and masks. This model uses a threshold value(tumor area) to test and classify lung cancer images.

2) Lung cancer classification: The area of segmented tumor images is found. Based on the area size tumor classification is done. The threshold of 1500 pixels (area size) is fixed based on training data. If the image under test is cancer, the segmented area would have number of pixels more than 1500; if not, the segmented area would have number of pixels less than 1500. Thus, the incoming image is currently categorized as either lung cancer or another type of condition (ground glass, pulmonary fibrosis lung, or healthy lung).

3) Lung lobes segmentation: If the incoming image falls into the other image category, it might be any image from the other group, which includes images of ground glass lung, pulmonary fibrosis lung and healthy individuals. The next step is to categorize these images which are shown in Fig. 3. Lung segmentation is now done by annotating the whole lung portion on training image. Masks and datasets are now transferred to the U-net architecture to get the lung segmented.

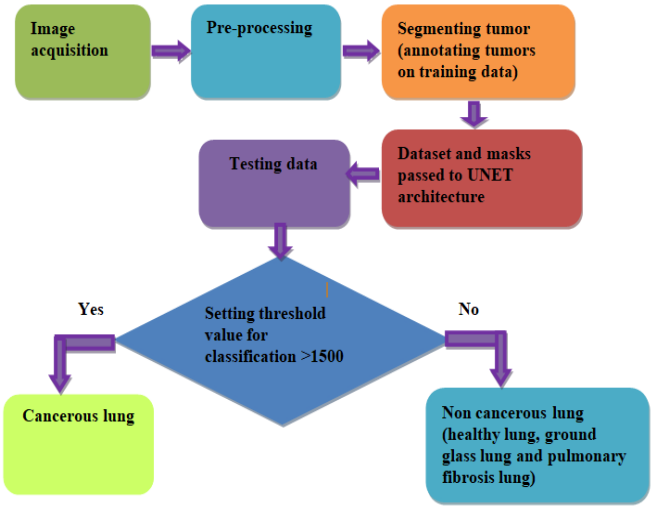

Fig. 2. Classification of lung cancer using ML.

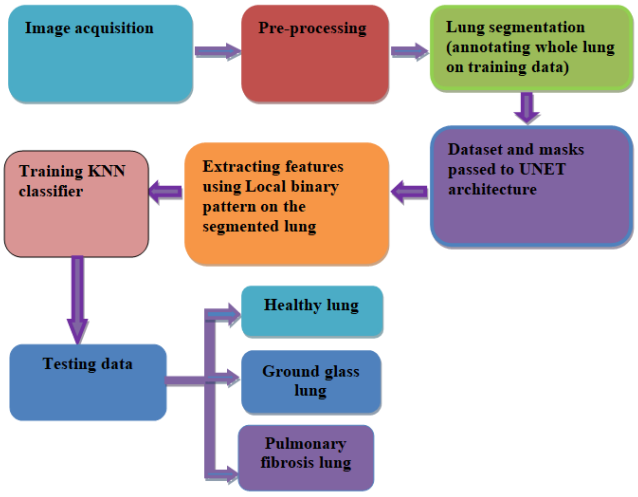

Fig. 3. Classification of ground glass lung, pulmonary fibrosis lung and healthy lung using LBP features and KNN classifier.

D. Feature Extraction

Following the segmentation procedure, the local binary pattern is used to extract the features from healthy lung, ground glass lung and pulmonary fibrosis lung images.

1) Local binary pattern: Ojala et al. [21] first introduced the LBP as a gray-scale invariant measure to describe local structure in a neighborhood of three by three pixels. Eight bit codes were provided based on the neighborhood pixels surrounding the central pixel when it was first designed for 3x3 neighborhoods. The decimal representation of the resulting LBP, given a pixel at (pc, qc), is given by Eq. (1).

$$\mathrm{LBP}(\mathrm{pc}, \mathrm{qc}) = \sum_{r=0}^{7} \mathrm{i}\,(\mathrm{an} - \mathrm{ac})2^{r} \qquad (1)$$

Where r represents 8-neighbours of the central pixel, a_c and a_n are gray-level values of the central pixel and the surrounding pixels, and the function i(x) is defined is shown in Eq. (2) .

$$i(x) = \begin{cases} 1 & if\ x \geq 0 \\ 0 & if\ x < 0 \end{cases} \quad (2)$$

Since LBP can only operate on grayscale images, the input image must first be converted to grayscale. A 3x3 neighborhood is chosen around the current pixel in this grayscale image, and the LBP value is calculated. Update the value of a specific pixel once its LBP value has been determined. Evaluate the values of the central and surrounding pixels. You can take in pixels in either a clockwise or counterclockwise manner by starting with any neighboring pixel value, but you have to utilize the same order for every pixel.

There are eight nearby pixels, and eight comparisons are made for each pixel. Set to 1 if the current pixel value is greater than or equal to the value of the neighboring pixel; otherwise, set to 0[22]. Fig. 4 shows 3x3 matrix LBP calculation.

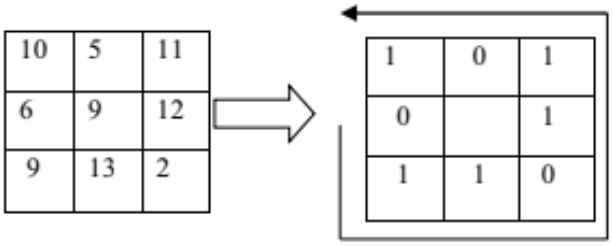

Fig. 4. 3x3 Matrix LBP calculation.

The binary number that is acquired from Fig. 4 and translated to decimal.

1 0 1 1 0 1 1 0

2^7 + 0 + 2^5 + 2^4 + 0 + 2^2 + 2^1 + 0

128+0+32+16+0+4+2+0=182

10	5	11
6	182	12
9	13	2

E. KNN Classification

1) KNN classifier: The similarity function is used by the algorithm for K-Nearest Neighbors (KNN) to estimate values for the new data points. This suggests that a score will also be assigned to the current data points based on how well they match the training points. The stages listed below assist in comprehending how it functions:

a) Phase 1: A data set is necessary for any method. Therefore, load the training and test data during the KNN's initial stage.

b) Phase 2: The K value, or the nearest points of information, will be chosen first. The difference between each training row and the test data is then computed. Euclidean distance is the distance metric used to sort the distance, which is computed in ascending order based on distance values. Phase 3: Next, select the top k rows from the list of categories. The actual class is the most prevalent.

2) Image classification: The extracted LBP histogram features of segmented sections of ground glass lung, pulmonary fibrosis lung and healthy lung are used to train KNN classifier. A trained model is put to the test images in order to identify and classify the healthy lung, pulmonary fibrosis lung and ground glass lung images.

IV. RESULTS

A set of images consisting of lung cancer, healthy lung images, ground glass lung images and pulmonary fibrosis images is shown in Fig. 5, Fig. 6, Fig. 7 and Fig. 8 respectively. Extraction of lung tumor is depicted in Fig. 9. Block diagram showing classification process of ground glass lung, pulmonary fibrosis lung and healthy lung images is illustrated in Fig. 10. Lung cancer classification based on number of pixels in the segmented area using sample images are tabulated in Table II. Table III shows lung cancer classification accuracy. Table IV displays the classification accuracy using the LBP and KNN classifier for the images of the ground glass lung, pulmonary fibrosis lung and healthy lung. Table I shows the comparison of accuracy obtained by the proposed method and other methods.

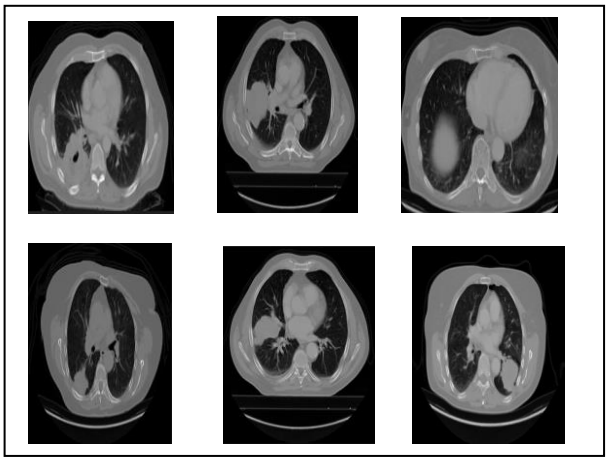

Fig. 5. A set of lung cancer images.

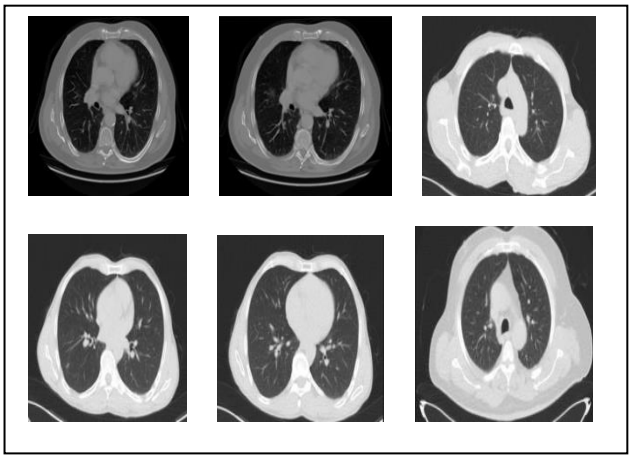

Fig. 6. A set of healthy lung images.

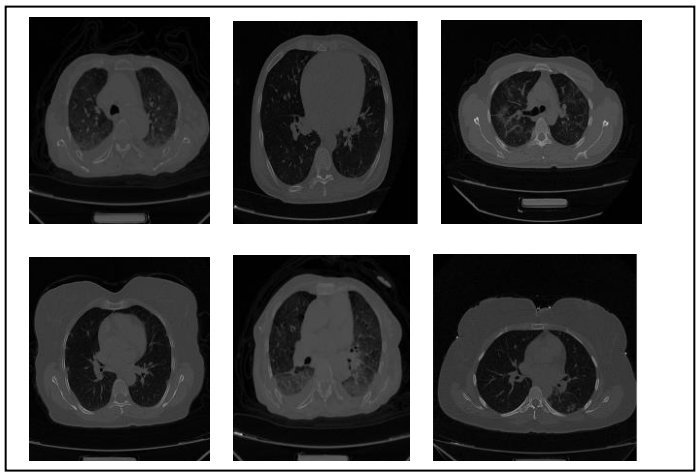

Fig. 7. A set of ground glass lung images.

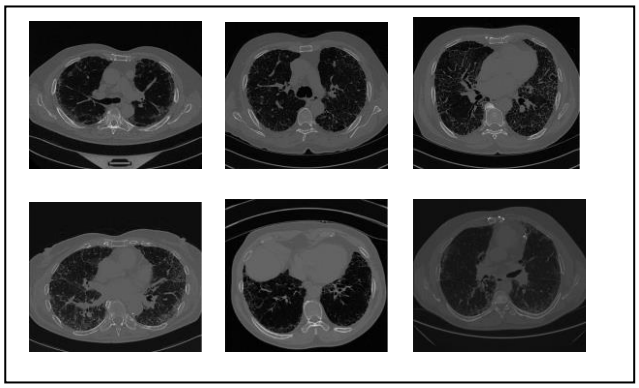

Fig. 8. A set of Pulmonary fibrosis images.

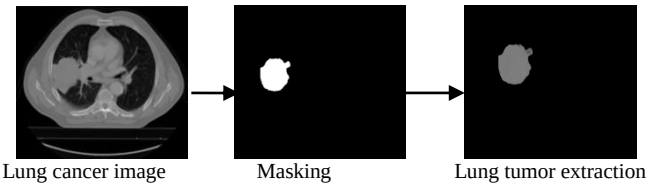

Fig. 9. Lung tumor extraction.

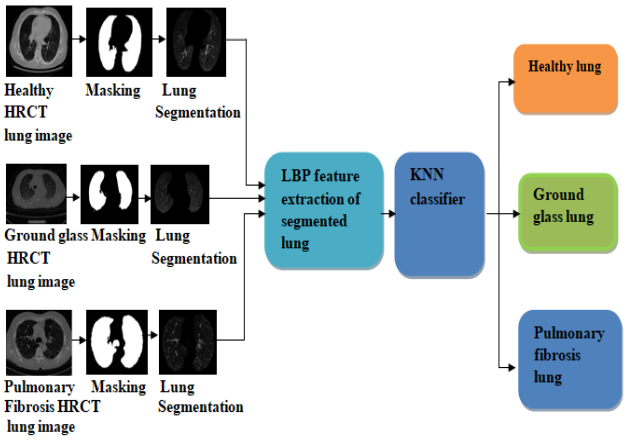

Fig. 10. Block diagram showing classification process of ground glass lung, pulmonary fibrosis and healthy lung images.

TABLE II. LUNG CANCER CLASSIFICATION BASED ON NUMBER OF PIXELS IN THE SEGMENTED AREA USING SAMPLE IMAGES

Image Category	Number of Pixels in segmented area	Class
Healthy1	708	Non Cancerous
Healthy2	402	Non Cancerous
Healthy3	5	Non Cancerous
Cancer1	6378	Cancer
Cancer 2	5161	Cancer
Cancer 3	13066	Cancer
Ground glass1	0	Non Cancerous
Ground glass 2	0	Non Cancerous
Ground glass 3	108	Non Cancerous
Pulmonary fibrosis 1	0	Non Cancerous
Pulmonary fibrosis 2	197	Non Cancerous
Pulmonary fibrosis 3	0	Non Cancerous

TABLE III. CLASSIFICATION ACCURACY – LUNG CANCER

Number of images trained	No. of images tested	% Accuracy
42	80	92.20

TABLE IV. CLASSIFICATION ACCURACY USING LBP AND KNN CLASSIFIER – HEALTHY LUNG,GROUND GLASS LUNG AND PULMONARY FIBROSIS LUNG IMAGES

Number of images trained	Number of images tested	% Accuracy
699	175	94.85

V. DISCUSSION

The anatomical changes in the lung parenchyma brought on by lung diseases including lung cancer, pulmonary fibrosis, ground glass lung and healthy lung are identified using the proposed method. A set of total 996 lung CT images, in which 138 healthy lung images,122 lung cancer images,559 ground glass lung images and 177 Pulmonary fibrosis lung images is taken for experimentation. The proposed method is shown in Fig. 1. The obtained images go through a pre-processing step that involves enhancement and filtration. Tumor identification is done using machine learning by annotating the tumor area in the image as shown in Fig. 2. Training dataset consists of 42 lung cancer images and testing dataset includes 80 lung cancer images. The tumor identification is done by machine Learning. A dataset is formed in which the cancer images are annotated. The dataset and masks are passed onto U-net architecture to train the model. A group of images are tested using this model. If the image under testing is a cancerous one, segmented area would have pixels more than 1500 if not segmented area would have lesser than 1500 in number the threshold (1500 pixels) is fixed based on training data. So at this stage, the incoming image is classified as cancerous or other category (ground glass, Pulmonary fibrosis or healthy), results are tabulated in Table II. Table III shows the accuracy of proposed system obtained is 92.20%. If the incoming images fall under the category “other image”, it could be anyone of the other group consisting of healthy lung, pulmonary fibrosis lung and ground glass lung images. The following stage is to classify these images shown in Fig. 3. Lung segmentation is now done on annotating the whole lung on training data. Now dataset and

masks are passed onto U-net architecture. LBP features are extracted from the segmented lung portions of ground glass lung, pulmonary fibrosis lung or healthy lung and KNN classifier is trained using LBP pattern of ground glass lung, Pulmonary fibrosis and healthy lung. Trained model is tested on 112 images of ground glass lung, 37 pulmonary fibrosis lung images and 26 healthy lung images and obtained an accuracy of 94.85% as shown in Table IV. The overall accuracy of the proposed system found to be 94%.

VI. Conclusion and Future Work

The proposed method developed a computer aided diagnosis and classification system for classifying lung cancer, healthy, ground glass lung and pulmonary fibrosis images. The dataset consisted of 996 images in total. Training dataset consists of 42 lung cancer, 112 healthy lung, 447 ground glass lung and 140 pulmonary fibrosis lung images; testing dataset includes 80 lung cancer, 26 healthy lung, 112 ground glass lung and 37 pulmonary fibrosis images. Lung cancer diagnosis and classification is done by using machine learning algorithm. Healthy, ground glass and pulmonary fibrosis classification is done using LBP and KNN classifier. LBP histogram features are found to be useful in effective classification of healthy, ground glass and pulmonary fibrosis images. The obtained accuracy of the proposed system is 94%.The accuracy of computer aided diagnosis model may be increased by increasing number of training images obtained from hospitals. Computer aided diagnosis of lung diseases identification and classification would identify the diseases at an early stage thereby increasing the life span and quality life of the patients.

Based on the research outcome an automated system can be developed in future to identify lung diseases at an early stage. After identifying the parenchymal pattern a data analysis can be carried out with patient's clinical data to diagnose the specific lung disease. For parenchymal pattern identification reticular lung images and emphysema can also be included in the future work; the future work can be carried out on a larger dataset.

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