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SUPERVISED LEARNING AT CHEST RADIOGRAPHY USING ARTIFICIAL NEURAL NETWORK

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Abstract

chest radiograph is a low-cost medical screening technique widely used to screen interstitial lung diseases. Since the images produced are 2D, it requires a highly experienced and qualified radiologist to review and detect the disease correctly. Also, X-Rays are more prone to noise and therefore it is arduous to see the findings with the naked eye. Lack of qualified radiologists paves way for CAD techniques to interpret the X-Rays. The approach presented in this paper employs a range of image processing techniques along with supervised learning at CXRs, to screen the diseases and classify them into normal and abnormal. K-means clustering is used to split the lung region and markers alike as mean, variance, entropy, kurtosis, and skewness are using the local data patterning statistics to derive. The features are validated using t-test and significant features are used to train the classifier. ANN is utlized for classification as it produced better classification results with 85% accuracy, 80% specificity and 90% sensitivity.

Keywords: Canny Edge Detector, Structured Edge Detection (SED), Watershed Algorithm, K-means clustering, Local Binary Pattern (LBP), Artificial Neural Network (ANN)

1. INTRODUCTION

Medical Imaging plays a fundamental role in modern healthcare. It aids physicians in precisely identifying the disease in different areas of the body, thereby enabling accurate diagnosis. The commonly used medical imaging modalities persist X-rays, MRI, CT scan, PET and many more [1]. All these medical imaging modalities persist widely used to locate fractures, tumors and other medical conditions. The most used and commonly employed diagnostic imaging technique is X-ray imaging. Even though CT scans and MRI produce detailed, high-quality images of the body, they are highly sophisticated and more expensive than X-ray imaging and not always available at small or rural hospitals [2-3]. Therefore, X-rays are usually recommended to patients for initial diagnosis. The chest X-ray, also referred to as Chest Radiograph, CXR or Chest The most often used diagnostic X-ray is a roentgenogram [4].

Examination. Depending on the densities, each organ within the chest cavities consumes various amounts of ionizing radiation generating varied shadowing on the image [5-6]. The standard presentation of chest X-ray images is in black and white, wherein variations in brightness and darkness serve to define the diverse structures. For example, the bones of the chest wall absorb more radiation and hence appear whiter on the film, whereas lung tissue, which is primarily air, enables most of the radiation to flow through. As a result, the film appears darker. The heart and aorta will be white, but less so than the bones, which are denser [7-8].

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This technique captures images of the heart, lungs, airways, blood vessels, as well as the spinal and chest bones and thus helps in diagnosing interstitial lung diseases. Reviewing the Chest X-rays heavily depends on the experience of radiologists as the CXR images have no spatial information and the overlap of different body parts may sometimeshide diseased tissues [9]. Also, when the lesions are inlow contrast or overlap with large pulmonary vessels, the images become more difficult to read. Further, each chest X-ray takes a trained radiologist several minutes to review and write thereport. The lack of qualified radiologists to reviewthese X-rays is a major challenge. This instigates the need for Computer Aided Diagnosis.

The proposed method aims to address the above problems. The setup is formulated to take the CXRs as the input, process it and then classify into normal and abnormal CXRs [10].

The processing involves morphological operations, segmentation, feature extraction, classification, validating the classifier and finally testing it using testing samples i.e., the input CXRs.

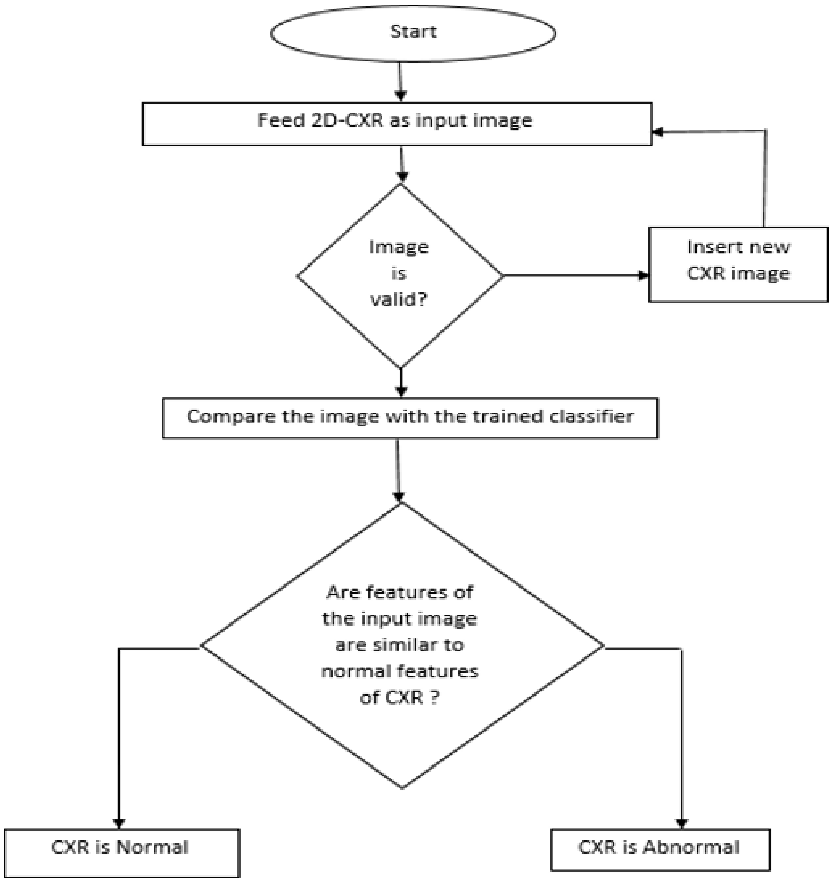

Figure 1: Flowchart for overall process

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2. METHODOLOGY

A. Outline

This work aims to develop a practical and useful method for automatically classifying CXRs into normal and abnormal. As shown in Fig. 1, the pre-processing was performed where an input CXR‟s was first normalized and resized to 256 x 256. Further the image was converted to gray scaleimage in the Gradient of luminance [0, 1]. Next, for imagesegmentation, various algorithms were applied, and finally K-means clustering was selected. Aftersegmentation, empirical aspects like mean, variance, entropy, kurtosis, and skewness were derived using the local binary pattern approach (LBP). The reliability of the features was tested using T- Testing and then the required features wereextracted to train the classifier into normal and abnormal CXRs. Finally, testing CXRs were used to determine the result accuracy.

B. Segmentation

Segmentation is used to identify the region of interest where specific attributes are sought. In our case, the lung region is of relevance. Initially various conventional edge detectors were used to demarcate the lung region. some of them include Prewitt, Robert, Sobel, and Canny. These edge detectors were heavy.

Affected by the noise. Even though the clever edge detector produced better edges, which are thresholding technique was an intensive process.

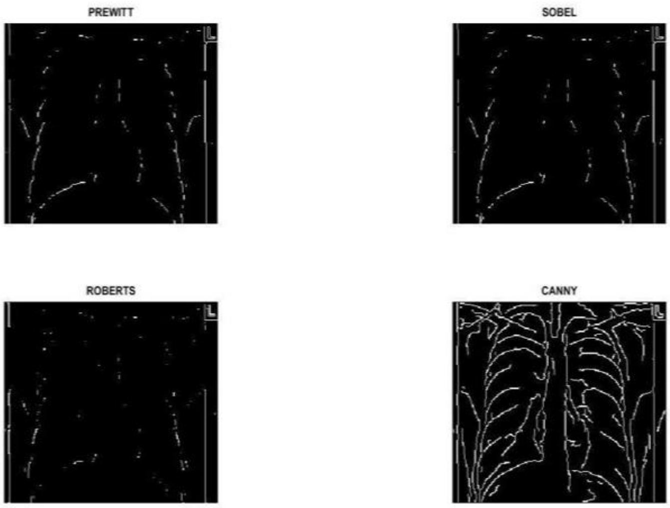

Figure 2: Outputs of various edge detectors

I. Structured Edge Detection (SED)

The goal of this methodology is to create a viable and usable way for autonomously splitting the pulmonary fields in CT scans. An input CXR was first normalized into the intensity range [0,1] and decomposed as the input of SED to the base and detail layers by a guided filter. The SED model was trained to recognize lung field borders, resulting in a border map. The ribcage and spinal center line were retrieved from the boundary map and the input CXR. Further, these

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segments were utilized to divide the CXR into right and left thorax sections and to clear the border map for additional analysis. Following that, the candidate lung regions and outlines were created using the MWT and UCM transforms (MWT -UCM). The contours with the pinnacle of confidence were then chosen as the right and left lung outlines

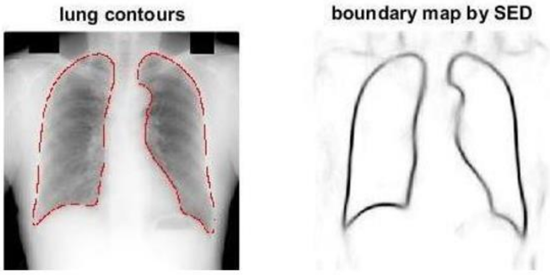

Figure 3: Output of SED

II. Watershed

In the image processing, the transformation used was watershed transformation. It is always definedon a grayscale image. In general, the word watershed is wielded to define a region which helpsin assisting in draining water into a river, usually rainwater. In this transformation, it considers the brightness of each point as its height and thensearches the lines that go along the top of theedges. This transformation treats the image like a topographic map. The approach is usually used inthe image processing for segmentation, when two regions of interest are in close vicinity to each other i.e., whentheir edges touch. The seeds that indicate the presence of objects or background at specific image locations are extracted by this technique, and then the marker locations are set within the topological surface to be regional minima. Further our methodology incorporates the watershed algorithm. In the realm of image processing, nothing is more challenging than the separation of touching objects, where the watershed transform is often applied to such problems. External associated with the background and Internal associated with the objects of interest are the two types of approaches of Marker-controlled watershed approach. The watershed transforms, an image segmentationtechnique can “mark” or identify background locations and foreground objects, to find “watershed ridge lines” and “catchment basins” bytreating it functioning as a surface in an image where dark pixels are low and light pixels are high.

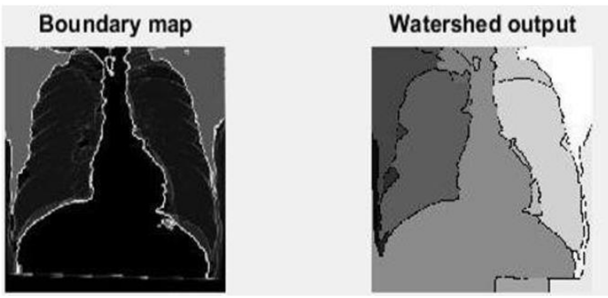

Figure 4: Output of watershed algorithm

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III. K-means clustering

In cases where data is unlabeled and lacks defined groups or categories, K-means clustering is employed as an unsupervised learning approach. The primary goal of this algorithm is to find groups in the data, with the variable K determining the number of clusters. Consequently, the algorithm leverages the provided features to achieve this outcome, this algorithm works the task is to assign each data point to one of K predefined groups. Based on similarity in features data points are clustered. The output of the K-means clustering algorithm includes the following results:

1. The K cluster centroids, which can be made use of for identifying new data.
2. The training data is labeled (each data point in a single cluster is assigned a label).

Clustering permits locating and evaluating naturally generated categories as opposed to designating types before examining the data. Each cluster centroid comprises a collection of feature values that define the resulting subgroups. Weights can be used to evaluate qualitatively what type of group each cluster represents when a center is examined.

IV. Algorithm

The result of the K-means algorithm is obtained through iterative refinement. The algorithm requires two inputs: the number of clusters K and the dataset, which consists of feature collections for each data point. Initially, the K centroids are initialized using either random generation or random selection from the dataset. The algorithm undergoes an iteration that alternates between two steps:

1) Data assignment step

Each centroid corresponds to a specific cluster. During this step, each data point is assigned to the centroid that is closest in terms of squared Euclidean distance. To put it formally, if ci represents the centroids in the set C, then each data point x is assigned to a cluster based on its nearest centroid.

$$\underset{c_i \in c}{\arg\min}\, dist(c_i, x)^2$$

Si signifies the data point set assignments for each centroid of the ith cluster, while dist.(•) denotes the standard (L2) Euclidean distance.

2) Update centroid

The re-computation of centroids occurs in this step, where the mean of all data points is computed and then assigned to the centroid cluster they belong to.

$$c_i = \frac{1}{|S_i|}\sum_{x_i \in S_i} x_i$$

Until a specific stopping condition is met, which could be either no data points changing clusters, minimizing the sum of distances, or reaching a predetermined maximum number of iterations, the algorithm will iterate between steps one and two. It is worth noting that the obtained result could be a local optimum, which may not be the optimal solution. Enhancing

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the outcome can be achieved by evaluating the algorithm through multiple runs with randomized starting centroids.

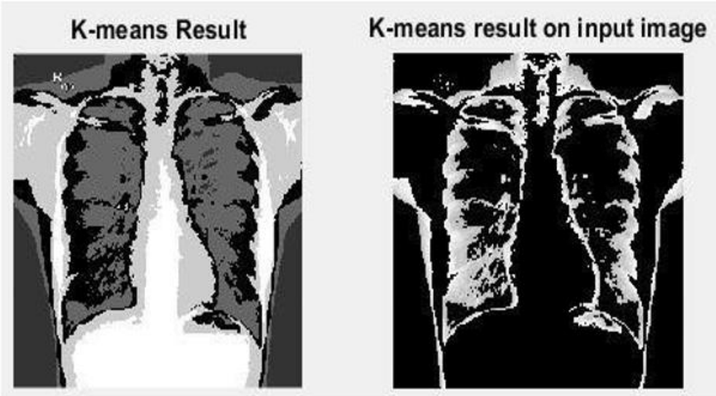

Figure 5: K-Means output

C. Feature extraction algorithm

Feature extraction is a very important step. By keeping as much information as possible from large data sets, the features are extracted. In the field of computer vision and image processing, a feature iscondensed form of the required relevant information which is pertinent for solving certain tasks. Features are the condensed form of the required data which will help further for distinguishing classes. These features will be relevant for solving the computational task relevant for solving application. Features can be statistical, visual, texture, color, or geometrical features.

1) Local Binary Pattern Algorithm

The local binary pattern (LBP) was originally created for the purpose of texture description. Its invariance to monotonic grey-scale transformations plays a vital role in texture analysis, enabling real-time image processing due to its computational simplicity. Utilizing the Local Binary Patterns (LBP) technique, an electronic digital image is partitioned into several small regions. From these regions, relevant features are extracted, enabling an explanation of the image's texture and model. The regions are analyzed to extract binary patterns that characterize the adjacent pixels. These region-based features are combined to form a consolidated feature histogram, providing a representative depiction of the image. The comparison of images involves measuring the similarity (distance) between their histograms. Research studies have shown that the LBP method yields favorable outcomes in terms of both speed and discrimination performance. Based on how the texture and model of images are described, it appears that the technique is highly robust.

The LBP algorithm has its roots in 2D textureanalysis. The fundamental concept involves capturing the local structure within an image by comparing each pixel with its surrounding neighborhood. By considering a pixel as the center and applying a threshold to its neighboring pixels, the information can be summarized. By comparing the intensity of the center pixel with

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its neighboring pixels, a binary notation of 1 is assigned if the intensity is greater or equal, and 0 if it is not. This process generates a binary number for each pixel. Considering the 8 surrounding pixels, there are a total of 2^8 combinations possible, referred to as local binary patterns.

Each image can be considered as a composition ofmicro-patterns which can be effectively detected by the LBP operator. To consider the shape information, the images are divided into „m‟ non- overlapping regions R_0, R_1… R_m. The extracted feature histogram describes the local texture of theimages.

The LBP factor vector is created as follows:

- Divide the examined window into cells.
- Every pixel within a cell undergoes a comparison process with its eight adjacent pixels, progressing along the circular path either clockwise or counterclockwise.
- Where the center pixel is greater than the neighbor's value writes, '0' otherwise 1‟.As a result, an 8-digit binary representation is obtained.
- Calculate the frequency distribution of each number in the cell and create a histogram. Normalize the resulting histogram.
- Combine the histograms of all cells together to create the feature vector for the window. The features extracted from the LBP histogram were mean, variance, entropy, kurtosis, and skewness.

2) T- Testing

The T-Test is used to check whether the extracted statistical features are reliable enough to train the classifier. It measures the difference between the groups and compares it to the difference within the groups. It gives an inferentialstatistic i.e., the value obtained from T-Testing will help to generalize to the whole populationbeyond the sample. It tells whether the difference is reliable or just by chance.

In line with the null hypothesis, this test postulates that there is no significant statistical difference between the two values acquired. When the T value is low, the null hypothesis is accepted, and it is rejected when the T value is high. Each T value.

has a P value. P value is the probability that the pattern of data in the sample could be produced byrandom data. According to the two -tailed test p= 0.05, which means that 5% accept the null hypothesis and 95% rejects it.

T value is calculated as shown:

$$T = \frac{\bar{x}_1 - \bar{x}_2}{\sqrt{\frac{s_1^2}{N_1} + \frac{s_2^2}{N_2}}}$$

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Using the above formula, the values obtained for various extracted features are Here is a breakdown of the items:

Table 1: Values obtained by T-Testing

Sl. No.	Features	T-Testing Values
1.	Mean	5.53528e-07
2.	Variance	0.461504388
3.	Entropy	3.33216e-15
4.	Skewness	0.220415548
5.	Kurtosis	0.102644875

Generally, values less than 0.05 are accepted and greater than that are rejected. Hence, it showed that only mean and entropy satisfied this condition, andthe rest features did not. Therefore, for furtherclassification only mean and entropy was taken.

D. Classification

To conclude the process, it is necessary to sort the images into two classes: normal and abnormal. To perform classification, two sequential steps are followed. The first step entails training, wherein a classifier is created to characterize a predetermined set of data classes. In the second step, the classifier model developed in the previous stage is applied to classify test data and evaluate the accuracy of the classification. Among the various classification algorithms, such as Decision tree, K nearest neighbor, Bayesian classifier, and Artificial Neural Network, we decided to employ Artificial Neural Network (ANN) for classification owing to its efficiency and simplicity in implementation.

1) Artificial Neural Networks (ANN):

An Artificial Neural Network (ANN) is comprised of interconnected nodes that facilitate the flow of information. Every connection within the network is assigned a weight. The architecture includes an input layer, one or more hidden layers, and an output layer. Neural network learning occurs through the adaptation of connection weights. The performance of the network can be improved by updating the weights iteratively.

ANN is of 2 types i.e., feed-forward network and recurrent network. The fundamental distinction between a feed forward neural network and a recurrent neural network lies in the absence of cyclic connections in the former and their presence in the latter. The learning rules, architecture, and transfer function employed by a neural network have a direct impact on its behavior. Neurons within the network respond to stimuli by activating based on the weighted sum of their inputs. By applying a transfer function to the activation signal, the neuron generates a singular output. This transfer function introduces non-linear characteristics to the network. Throughout the training period, the interconnection weights are adjusted and fine-tuned until the network achieves the specified level of accuracy. This approach provides several advantages, including parallelism, reduced vulnerability to noise, and effective learning capability.

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2) Algorithm for learning of ANN

Beginning the classification procedure, the dataset is initially segregated into the training sample and the test sample. The training sample facilitates network learning, while the testing sample measures the classifier's accuracy. Various approaches, including the hold-out method, cross-validation, and random sampling, can be employed to divide a data set. Outlined here are the step-by-step learning processes of a neural network.

- The network's configuration includes a specific number of nodes assigned to the input, output, and hidden layers.
- An algorithm is used for the learning process.
- The neural network's capability to adjust its network structure and learn through weight alterations renders it highly applicable in Artificial Intelligence.

Algorithm:

Input: Dataset D, Adaptation rate Network.

Output: A trained neural network.

Step1: Receive the provided input.

Step2: Multiply the inputs by random weights. Prior to inputting them into the network, multiply each input by a randomly generated weight ranging from -1 to +1 to account for their significance.

Step3: Sum all the weighted input.

Step4: Produce the outcome. The network generates its output by passing the sum through the activation function.

3. RESULTS AND DISCUSSIONS

The designed system worked well for frontal chestX-ray images where imaging conditions were thoroughly controlled. A data set containing 50 normal and 50 abnormal diagnosed images was obtained from Fr. Mullers Medical College. The images were pre-processed, and various segmentation techniques were applied to segment the lung region. Some of the techniques used include conventional edge detectors such as Sobel,Prewitt, Robert and Canny, SED, WatershedTransform and K-means clustering. It was observed that K-means clustering gave the best results. To feature extraction, LBP was used. The features extracted were mean, variance, entropy, kurtosis, and skewness of theLBP histogram. The t-test was performed on the features for 2 class classification.

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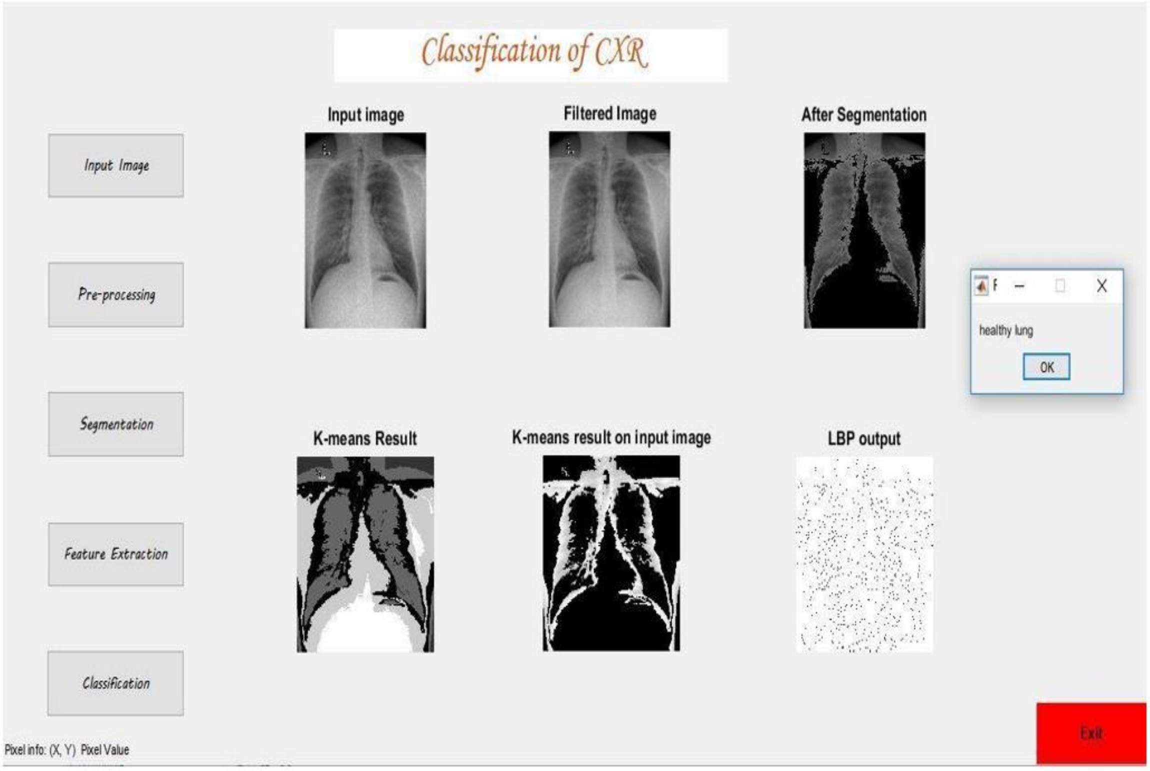

Figure 6: GUI output for Normal CXR

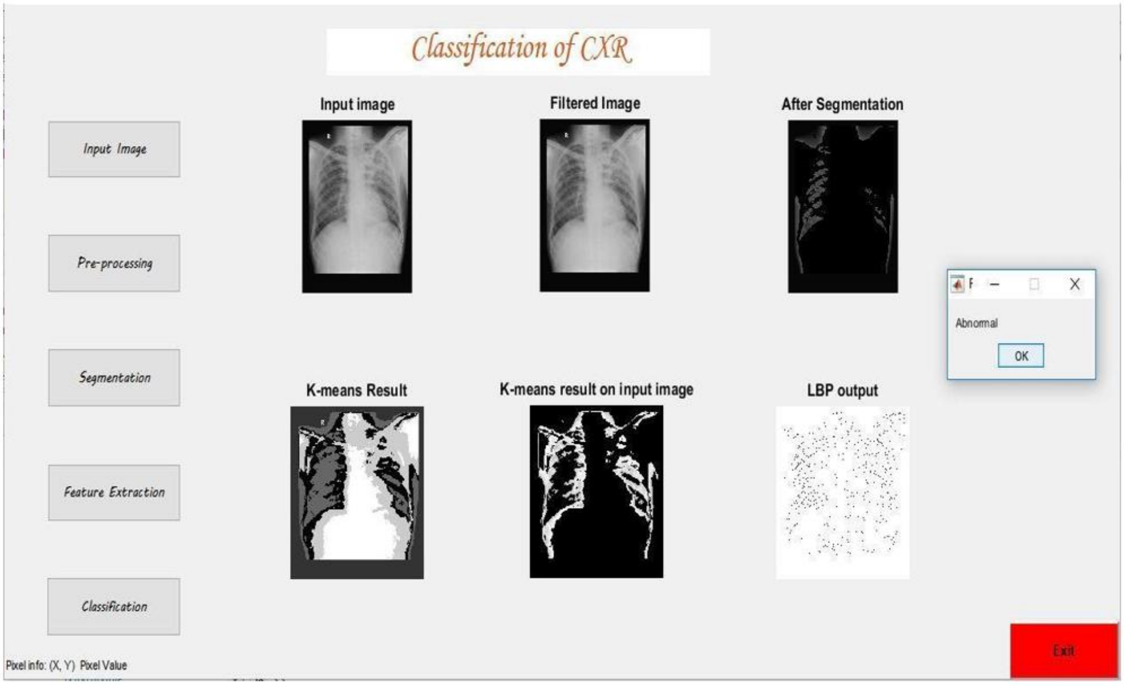

Figure 7: GUI output for Abnormal CXR

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It was observed that only mean and entropy were the significant features. Training was performed using 2 different classifiers i.e., ANN classifier andSVM (Support Vector Machine) classifier. SVMs are a set of related supervised learning methods used for classification. Both the classifiers were trained using 40 normal and 40 abnormal images. Testing was performed using 20 images (10 normal and 10 abnormal CXRs). It was observed that ANN classifier outperformed the SVM classifier with 85% accuracy.

Table 2: Comparison of classifier models

Method	Accuracy	Specificity	Sensitivity
ANN	85%	80%	90%
SVM	80%	90%	70%

4. CONCLUSION AND FUTURE SCOPE

In this work, we proposed a method to classify CXRs which is based on deep learning using ANN. The features were obtained using k-mean clustering and LBP. We have designed an ANN network which classifies CXR images into normaland abnormal with good accuracy. A future scope in the project will be to classify images into different abnormalities such as pleural effusion,nodules, cavities and various other interstitial lungdiseases for which a larger dataset is required. Useof manually designed features can be reduced by using CNN for classification as it detects the most discriminative features automatically according to the target objective.

It might be frightening for our community to replace Radiologists with a system, but we arenot there yet. Overall, this techniquewill mainly help doctors by taking the minimum time required for the patient's consultancy. Using this technique, it is perfectly fine and legal for the non-radiologist physician (called clinician) to checkthese X-rays and give an immediate feedback and intervention to the patient if needed urgently because clinicians tend to be more focused on the principle disease of the patient and hence to make a very selective analysis of the Chest X-ray based on their experience.

We can also improve our system by making use ofCNN (Convolutional Neural Network) for the classification of normal and abnormal samples of CXRs, since it has a great level of control over performance that can be achieved by making effective use of theoretical and mathematical insights and it does not require the tedious manualspatial annotation. Further, an android app can be developed to provide ease of use for the doctors as well as for the patients. However, the accuracy of the system must be improved to classify the CXRs correctly and efficiently.

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