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Implementing a Local Binary Fitting Median Filter for noise reduction in lung image datasets and subsequent classification

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Abstract:- The classification of medical data is the most difficult problem to solve among all research problems since it has more commercial significance in the context of health analytics. Data are labelled by classification, which enables efficient and productive performance in worthwhile analysis. According to research, the effectiveness of the categorization may be negatively impacted by the quality of the characteristic. This research work initiate a proposed method named modified Local Binary Fitting Median Filter with Artificial Neural Network (LBFMF/ANN) for identifying appropriate feature subsets related to detect the person weather he/she is affected by Lung disease. Local Binary Fitting Median Filter algorithm is derived based on deterministic and mathematical properties of the Local Binary Fitting median filter and Artificial Neural Network, a deep learning method makes an efficient classification of the prediction of Lungs disease in patient. The suggested research study examines the effects of feature selection as effectiveness is essential when a user shares a sample lung disease feature for the selection of pertinent features from a databank, and vice versa. Qualitative assessment of proposed the Local Binary Fitting Median Filter with Artificial Neural Network classification mechanism has been made with classification Accuracy 87.30%, Sensitivity 87.50%, Specificity 87.50% and better precision than the existing method respectively. A statistical examination of accuracy ratings and performance duration shows that the suggested systems outperform conventional methods.

Keywords: Lungs Disease dataset, Local Binary Fitting Median Filter with Artificial Neural Network, confusion matrix, classifier, segmentation.

I.INTRODUCTION

The data mining reveals the enormous amount of datasets that result from the unabated rise in the number of people with lung diseases worldwide. The data analytics used extract hidden patterns and hidden values in images have been revealed. The recent rapid growth of websites has increased the amount of available information, which makes pattern prediction more difficult. The term "big data," which refers to the excessive data extraction, collecting, and analysis from websites, particularly for the medical industry, has been popular due to the excessive volume of data flow and the various kinds of data, including text, image, audio, and video (Kalimuthu Sivanantham et al., 2021). So real world of data analytics, the expansion of volume, diversity, and velocity has created

significant hurdles. The fast expansion of patient data from diverse medical conditions has increased the amount of data that is kept and sent between devices. In machine learning, the large datasets are generally well characterised under the uncertain increase of data on global lung disorders. The complexity of the traditional datasets' data creation, data access, data analysis, and storage can be attributed to their size (Sivanantham Kalimuthu et al., 2022) Many machine learning approaches for diagnosis the disease Lung, stroke, cancer and diabetics with poor accuracy. The classification of various Lung diseases using a large database enables quick, accurate diagnosis in the medical area as well as the provision of the appropriate treatment.

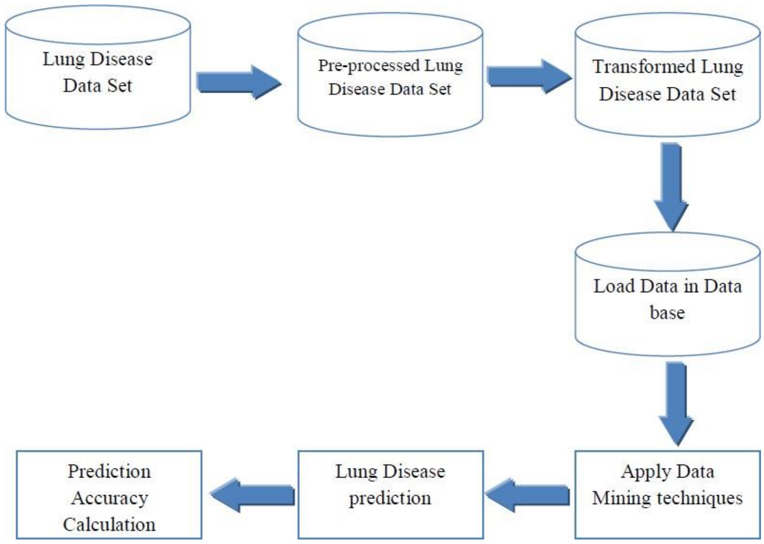

Figure 1 Lung disease Prediction Systems

A significant research area in medical practise is required to develop an effective and efficient classifier for the prediction of lung diseases. The discovery of interesting fields from the medical dataset is reserved for different issues. These challenges are referred to as classification problems (Ekız Simge and Pakize Erdoğmuş., 2017). The general block diagram for the lung disease prediction system is shown in Figure

1. The concerns associated to lung diseases that are addressed to the control over the classification performance are the same for the division of the human test set's poses and views, as well as the probe and training datasets.

Pre-processing approach becomes essential during the modification of the image acquisition process. Many Pre-processing algorithms concentrate on recovering noises. It is also essential to recover the low-frequencies for high noise levels. Lung can be separated from the background by searching the object boundary or by utilizing the characteristics of objects like color, texture, shape, brightness and size (Hadavi Nooshin et al., 2014). Image texture is a set of features that is computed to quantify the perceived texture of the image. Image texture provides data about the spatial arrangement of intensity or color in an image or selected region of an image. Brightness is used to brighten the complete image from the shadows to the highlights equally. Image pre-processing is an approach to enhance the data in the images prior to computational processing. Reprocessing and enhancement phase in medical image processing regenerates the input lung image into a standard format with enhanced image

contrast, sharpened edges, reduced noise through background removal, image filtering and elimination of film artifacts (Punithavathy K et al., 2015). In the development of automated lung detection system, the lung detection depends on the quality of the image. The medical images are usually complex and noisy in nature. Noise not only reduces the image quality but also cause the feature extraction, analysis algorithm to be unreliable. Hence, an image Pre- processing method is required to preserve the image quality. The objectives proposed Pre- processing techniques of images involves,

- Removal of low-frequency background noise
- Normalization of individual particle image intensity
- Removal of reflections
- Masking certain portions of images

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Therefore, this paper to investigate the different kinds of filters such as Gaussian, Weiner, and Median filter in addition to the use of proposed Local Binary Fitting Median Filter to achieve the best for reaching the desired target output by pre-processing the lung X-ray images for lung disease classification accurately. Through this pre-processing, the different results were attained by using different techniques and shown and compared to each other to explore the best technique for performing pre- processing.
The reminder of this research is organized as. Section2, Lung diseases prediction and its related work, Section 3 discussed to Local Binary Fitting Median Filter with artificial neural

network algorithm, section 4 presents proposed system and existing systems experimental results comparison. Finally, section 5 provides the concluding remarks and future scope of the work.

Neighbour) approach is used last. The suggested approach faces nitpicking difficulties in the electrical properties such as permittivity and conductivity of the human body prediction. By obtaining this data, the Gabor transform's

II. LITERATURE REVIEW

The classical methods existing machine learning approach in the functional level of Lung diseases dataset classification, feature extraction and the influence of the classifier on anomaly prediction are briefly discussed here.

Ahmed Saadaldeen Rashid Ahmed et al. (2019) have proposed that affine frameworks and the determination of Euclidean distance improve the classification performance of algorithms. The effectiveness of the traditional sparse models is improved by using the nearest neighbours that correspond to the target pixels for prediction. The differentiation performance was improved by the integration of neighbours by the pixels during the creation of the novel set. For the categorization of the UCI lung dataset to change in appearance or temporarily store information, certain surface architectures and temporary associations are necessary.

Elaiwat S. Mohammed Bennamoun and Farid Boussaid (2016) hypothesised that by simultaneously encoding the multiple feature types, the Constructive Divergence (CD) approach is expanded. The alignment problem has not been explored in earlier publications. When compared to several machine learning approaches by (Bayrak Ebru Aydndag et al. 2014), the UCI Wisconsin Lung Diseases dataset performs effectively in patch-based visualisations due to its robustness against misalignment. Medical image processing is greatly influenced by CAD (Computer Aided Diagnosis), which offers precise therapy and quick diagnosis tools. The structural divergence and substantial appearance alterations have made diagnosing brain tumours difficult down to the last detail (Bustos Aurelia et al., 2020).

Bhowal Pratik et al., (2016) have suggested two- tier classification established on the Lung diseases dataset in adaptive segmented approaches. Pre-processing of the segmental pictures has been carried out using the clustering method adaptive pillar k-means. The feature vector is estimated using the DWT (Discrete Wavelet Transform). To achieve classification accuracy, the K-NN (K-Nearest allocation. To improve classification performance and K-NN improvement in pattern recognition, appliances are disadvantage in this system suggested by Khairandish, M.O et al., (2021).

For heart MRI images, high level features are learned through the combination of ensemble learning with an unsupervised DBN, the SVM, Neural Network, and tree approaches introduced by Dargan Shaveta et al., (2020), and Latif Jahanzaib et al., (2020). An effective classification performance was achieved through the choice of either any MRI or a specific CT image set, as well as the effective creation of discriminant features. Dimensionality, difficulty in detecting the tumour or impacted areas from diverse data, and robustness against noise abnormalities all provide significant obstacles from the standard methods, which are highlighted in the review. In this work, a novel technique is presented to lessen the drawbacks of the current approaches. The majority of data mining involves unlabeled data. In these situations, accurate categorization and feature extraction play crucial roles that researchers often overlook. For the classification of medical datasets, diverse rather than homogeneous lung disease data must be taken into account. Instead of placing a high priority on data categorization, researchers are concentrating on increasing classification accuracy using appropriate noise removal approaches.

III. SYSTEM DESIGN

Dataset: The data represent a small subset of cancer imaging repository images. They are made out of the central portion of each X-REY image where valid age, modality, and contrast tags were detectable. 475 series from 69 distinct patients are produced as a result. For 24 photos, we use a randon selection. The dataset is made to enable the testing of several approaches for analysing the patterns in X-REY image data connected with employing contrast and patient age. The basic concept is to identify the statistical patterns, features, and image textures that strongly correlate with these traits and, if possible, to build straightforward tools for automatically classifying these images when they have been incorrectly categorised using the image in the data set in the database that is set as the reference image for detecting lung diseases. The following sections detail explanation for lung diseases classification system implementation.

3.1 Local Binary Fitting Median Filter

Local Binary Fitting Median Filter algorithm is derived based on deterministic and mathematical properties of the median filter. The suggested proposed median filter first detects impulses in the pixels of a specific length. The window size is then determined based on the width of the impulses, and the pixels are then subjected to a median filter operation. Mathematical measurements of both positive and negative impulses are taken into account and removed at the same time. The median filter is one of the most well-known order-statistic filters because of how well it performs for particular types of noise, such as "Gaussian," "random," and "salt and pepper" noise.

Here two statistics measurement are used in median filter,

1. Window length
2. Number of impulse signal Process:
    1. Select the maximum window length (example L=5X5)
    2. Get the pixels from the window (how many impulses present in that particular window.) If the number of impulses is less than or equal to 4, 3 x 3 window is enough to remove impulses because output of the window is the median value.
3. Find the maximum (max) and minimum (min) value of the window
4. If Xn = max or Xn = min: then Xn is the corrupted pixel Go to step 5 Else Xn is the uncorrupted pixel; assign the value of Xn as output value.
5. If n<=4 Take square shaped 3X3 window Else if n<=8 Take square shaped 5X5 window Else if n>8 and n.

The pre-processed noise removed dataset process the following segmentation algorithm.

3.2 K-means segmentation

Segmentation is an important step in medical image analysis and classification for radiological evaluation or computer aided diagnosis. Image segmentation refers to the process of partitioning an image into distinct regions by grouping together neighbourhood pixels based on the some predefined similarity criterion (Dinçer Esra and Nevcihan Duru., 2016).
The K-means algorithm is the superior algorithm to solve the clustering problem. The k-Means algorithm runs multiple times to make a group of a cluster (Senthil Kumar et al., 2019). The algorithm works in following steps:

• The clusters are non-hierarchical and do not overlap.
• There are always K clusters.
• There is always at least one item in each cluster.
• Since proximity does not always require the clusters' "centre," every member of a cluster is closer to its cluster than any other cluster.
3.2.1 K-means algorithm process
• The dataset is divided into K clusters, and the data points are given to each cluster at random. This produces clusters with nearly the same number of data points.
• Each data point: Figure out how far each cluster is from each data point.
• Leave the data point at its current location if it is closest to its own cluster. The closest cluster should be used if the data point is not closest to its own cluster.
• To achieve a complete pass, repeat the previous step.

There is no data point that moves from one cluster to another after considering all the data points. The clustering process comes to an end at this point since the clusters are stable. The final clusters that are formed can differ significantly in terms of cohesiveness and distances between and within clusters depending on the initial division that is used. The figure 2 explains the flow chart process for lung nodule segmentation algorithm. Segmented result extracts the features for following feature extraction techniques.

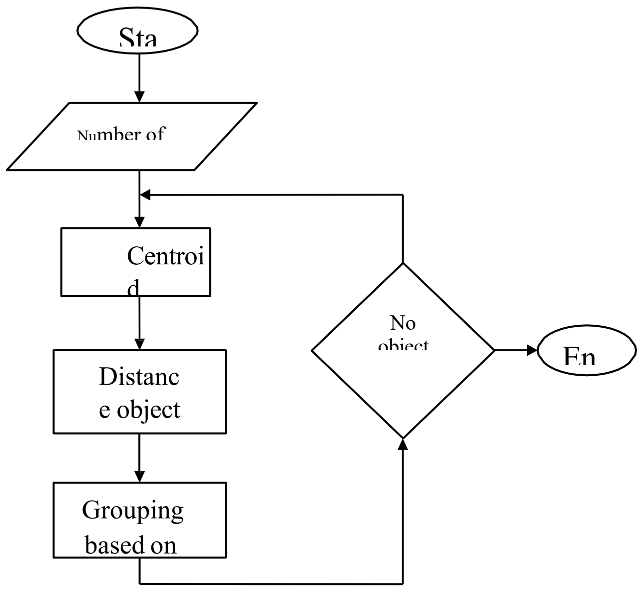

Figure 2 K-means algorithm segmentation flow

Different approaches are used to extract the image's various aspects, such as binarization and Gray Level Co-Occurrence Matrix (GLCM), both of which are based on facts about lung anatomy and information from lung X-REY imaging (Zotin Aleksandr et al., 2019). To find and isolate different desired areas or forms (features) of the image, the features are extracted. The GLCM is a summary of the frequency with which certain combinations of pixel brightness values (grey level) appear in an image. Here, the grey co-matrix function in MATLAB is used to create the matrix from the image (Ramalho Geraldo Luis Bezerra, et al., 2014). The following features are extracted using this method

1. Mean
2. Standard_Deviation
3. Variance
4. Skewness
5. Uniform
6. Entropy
7. Contrast
8. Energy

The final extracted features classified using following machine learning techniques. The proposed system classification using artificial neural network. The neural network classifier uses extracted information to determine

whether the input sample represents a lung that is diseased or not. A neural network is a group of connected neurons that transmits patterns of electrical signals. A group of learning neurons known as an artificial neural network (ANN) is based on biological neural networks seen in the human brain (Khobragade Shubhangi, et al., 2016). A neural network typically comprises of 100 billion neurons, each of which is connected to up to 10,000 other neurons. Artificial neural networks are typically shown as systems of interconnected "neurons" that communicate with one another. In order to make neural nets that can learn and adapt to inputs, connections have numerical weights that can be changed based on experience. The benefit of ANNs is that they can frequently tackle issues that are too complicated for traditional methodologies to handle or for which algorithmic solutions are difficult to come by (Ding Shifei et al., 2013). For the above general model of artificial neural network, the net output can be calculated as follows:

$Y = X1\,W1 + X2\,.\,W2 + \cdots \ldots \ldots .\,.\,Xm\,Wm$ (3.1)
$Net\ input\ Yin = \sum Xi.\,Wi.\,Mi.$ (3.2)
The output can be calculated by applying the activation function over the net input.

$Y = f(Yin)$ (3.3)
Output = function (net input calculated)
There are two layers: one for input variables and one for output. The layers consist of: neural network. A few layer connections' weights are changed throughout the training phase. These properties can be taught to ANN models using sample data, and this knowledge can be applied to predict or categorise data in a

• Input Layer - The raw information supplied

dataset. The following section described to the network is indicated by the input units in the input layer.
• Hidden Layer - This layer consists of hidden units that are determined by the behaviour of the input unit and weighted neurons that link the input to the hidden units.
• Output Layer: This layer is based on the weighted neuron and hidden unit specificity.
The following Steps to implementation for classification:

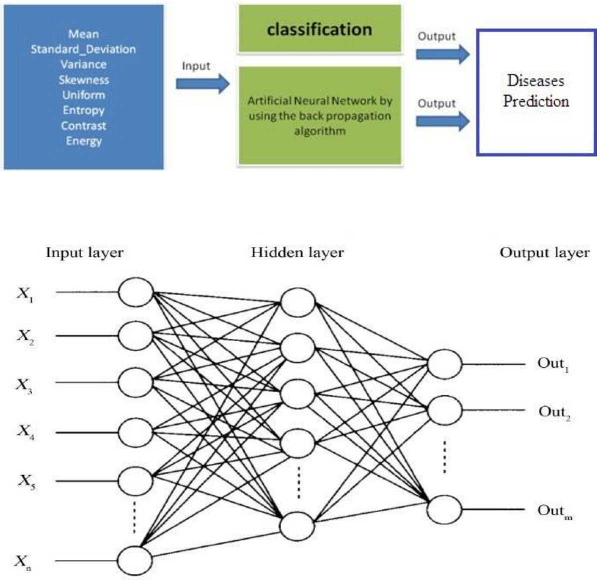

Figure 3 Neural Network

The above diagram 3 explains the BPNN classification for lung diseases prediction. Neurons and weighted direct connections, which link one layer of neurons with another layer of neurons, are the two main building blocks of a obtained results.

IV. Result and discussion

This section discussed to the existing system performance result with the accuracy of 74.137%, sensitivity of 75.50%, Specificity of 79.41% with some of the drawback for this prediction. This proposed system with the new method of diseases perdition will be more efficient when compare to existing system. Also have the better result with this process of prediction.

The case we have some of the trained image with it having a data set as a reference for the new patient data comparing with the existing data sets to give a better result for the medical field as with this method for the patient lungs diseases prediction process. As the total no of features are present in this system is among almost 13 features are there with it. Thus the set of data will be stored as a predefines images and data to this system to make a better result for the medical patient with the new technology. The compare with the pre processed data with the new patient data will give the result of matching output for this system. The system will have the trained image for this process to give a better accurate for the result with the more prediction of the diseases. will have a 24 image as a reference image for the process of compare the image and it will store some of the mathematical derivation for the accurate result prediction method with it, also this system will have a feature of around 8 with it the 8 feature and 24 images are used to mix with the 192 samples to get the better accuracy for this system. The process of the tested data will be stored for the reference for the patient detection with the accurate system design process flow with the data set. The tested data will be more accurate with the process of the lungs data to predict the diseases for the patient data with the calculation for the data set with the use of the system and the accurate method for the better result.

The input of the system will be the patient lungs data will contain some of the mathematical calculation for the accuracy, sensitivity and Specificity for the calculation process prediction with the data to be

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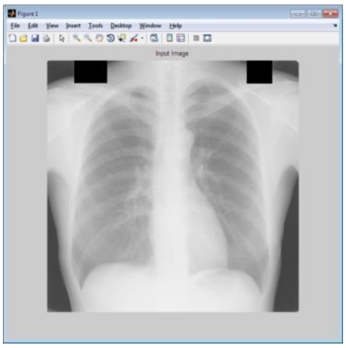
compare with the pre defined data set with the newly calculated derivation result compared based on the numerical method

with the confirm clear vision in figure 4. After the process of adding the data to the image with it and the calculation there is some of the noise are there in the image with the error. After the remove of the noise in the image the values are used to keep a better calculated value for the result method with the current data set are used to check with the sets with the confirm clear vision shows in figure 5. The final of the proposed system is the segmentation of the result data set with it flow of the data and the number with the answer for the system with the lungs prediction method with the confirm clear vision shows figure 6.



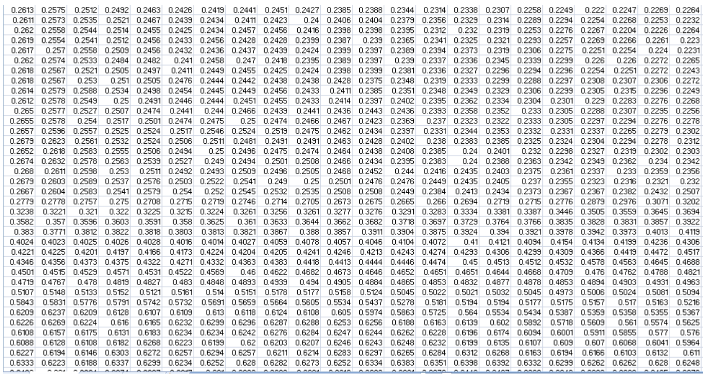


Figure 4 Input images

0	0.047619	0.047619	0.047619	0.047619	0.047619	0.047619	0.047619	0.047619	0.047619	0.031746	0.031746	0.031746	0.031746	0.031746
0.047619	0.063492	0.047619	0.047619	0.047619	0.047619	0.047619	0.047619	0.047619	0.047619	0.047619	0.031746	0.031746	0.031746	0.031746
0.063492	0.063492	0.063492	0.047619	0.047619	0.047619	0.047619	0.047619	0.047619	0.047619	0.047619	0.031746	0.031746	0.031746	0.031746
0.047619	0.063492	0.063492	0.047619	0.047619	0.047619	0.047619	0.047619	0.047619	0.047619	0.047619	0.031746	0.031746	0.031746	0.031746
0.063492	0.063492	0.063492	0.047619	0.047619	0.047619	0.047619	0.047619	0.047619	0.047619	0.047619	0.047619	0.031746	0.031746	0.031746
0.047619	0.063492	0.063492	0.047619	0.047619	0.047619	0.047619	0.047619	0.047619	0.047619	0.047619	0.031746	0.031746	0.031746	0.031746
0.063492	0.063492	0.063492	0.047619	0.047619	0.047619	0.047619	0.047619	0.047619	0.047619	0.047619	0.047619	0.031746	0.031746	0.031746
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0.047619	0.063492	0.063492	0.047619	0.047619	0.047619	0.047619	0.047619	0.047619	0.047619	0.047619	0.047619	0.047619	0.047619	0.047619
0.063492	0.063492	0.063492	0.047619	0.047619	0.047619	0.047619	0.047619	0.047619	0.047619	0.047619	0.047619	0.047619	0.047619	0.047619
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0.047619	0.063492	0.063492	0.063492	0.047619	0.047619	0.047619	0.047619	0.047619	0.047619	0.047619	0.047619	0.047619	0.047619	0.047619
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0.063492	0.063492	0.063492	0.063492	0.079365	0.079365	0.063492	0.063492	0.079365	0.079365	0.079365	0.079365	0.079365	0.079365	0.079365
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0.063492	0.079365	0.095238	0.095238	0.095238	0.095238	0.095238	0.095238	0.095238	0.095238	0.095238	0.095238	0.095238	0.095238	0.095238
0.063492	0.095238	0.111111	0.095238	0.095238	0.111111	0.111111	0.111111	0.111111	0.111111	0.111111	0.111111	0.111111	0.111111	0.111111

Figure 5 noise removed image

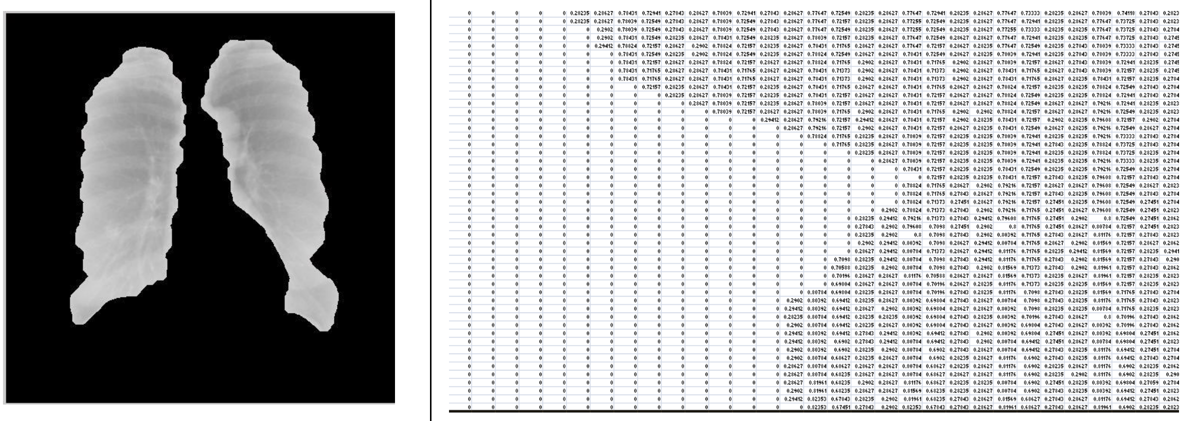

Figure 6 Segmentation Image

No.	AVG Gray Level	Energy	Entropy	std deviation	variance	skewness	mean	contrast
1	49.54	0.84	4.2	57.2	0.25	1.83	0.648	0.48
2	43.55	0.55	2.2	52.8	0.12	1.66	0.559	0.46
3	43.29	0.64	1.2	56	0.14	1.46	0.636	0.46
4	32.66	0.43	3.5	57.5	0.26	1.63	0.646	0.4
5	26.9	0.45	3.9	57.7	0.16	1.55	0.63	0.44
6	64.53	0.43	4.2	56.4	0.14	1.52	0.6	0.43
7	94.55	0.27	5.2	57.8	0.21	1.73	0.582	0.42
8	81.76	0.3	4.6	57.4	0.22	1.83	0.615	0.42
9	114	0.49	4.6	56.5	0.15	2.41	0.621	0.48
10	54.89	0.31	5.1	56.2	0.17	1.81	0.622	0.45

Table 1 features are extracted using this method

The confusion matrix is the process of matrix that consists of the row and column with it having the result for the machine learning techniques (Banerjee Nikita and Subhalaxmi Das., 2020) for the refer table 1.
True positives (TP): These are cases in which we predicted yes (they have the disease), and they do have the disease.
True negatives (TN): We predicted no, and they don't have the disease.
False positives (FP): We predicted yes, but they don't actually have the disease. (Also known as a "Type I error.")
False negatives (FN): We predicted no, but they actually do have the disease. (Also known as a "Type II error.").
The formula for the calculation of the accuracy is the addition of true positive and true negative (tp+tn) divided with respectively addition of true positive, true negative, false positive, false negative (tp+tn+fp+fn).

$tp + tn$ (4.1)

$tp + tn + fp + fn$ (4.2)

$Accuracy = equ1/equ2$ -------- (4.3)

$Accuracy = (tp + tn)/(tp + tn + fp + fn)$ --(4.4)

$Sensitivity: (true\ positives /$
$all\ actual\ positives) = (TP / TP + FN)$ (4.5)

$Specificity: (true\ positives /$

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$predicted\ positives) = TP\ /\ TP + FP.$ –(4.6)

Table 3 confusion matrixes Result binary Median+ann
TN= 16 FP=7
FN=9 TP=27

In table 3 confusion matrix value for the image to detect the lungs diseases with the values Median+ann are calculated. The Following calculation for Median+ann to calculate obtained accuracy. (Accuracy = ((16+27)/(16+27+9+7)) = 74.137 %). The
accuracy of the method is 74.137% out of 100 with the lower accuracy value in the method. So, the error rate occurs in the accuracy value is 25.863%. (Sensitivity = 27/(9+27)= 75.50 %)
The Sensitivity of the method is 75.50 % out of
100 with the lower Sensitivity value in the method. So, the error rate occurs in the Sensitivity value is 24.50%. Specificity: (27/27+7)=79.41% The Specificity of the method is 79.41% out of 100 with the lower Specificity value in the method. So, the error rate occurs in the Specificity value is 20.59%.
Table 4 confusion matrixes Result Gaussian+Ann

TN= 24 FP=5
FN=06 TP=19

In table 4 confusion matrix value for the image to detect the lungs diseases with the values Gaussian+Ann are calculated. The following calculation for Gaussian+Ann to calculate

obtained accuracy. The accuracy of the method is 79.629% out of 100 with the lower accuracy value in the method. So, the error rate occurs in the accuracy value is 20.371%. Accuracy = ((24+19)/(24+5+6+19))=79.629%. The
Sensitivity (Sensitivity = 19 + (19+6)=76.00%) of the method is 76.00% out of 100 with the lower Sensitivity value in the method. So, the error rate occurs in the Sensitivity value is 24.00%. The Specificity of the method is 79.166% out of 100 with the lower Specificity value in the method. So, the error rate occurs in the Specificity value is 20.834% (Specificity: 19/ (19+5) =79.166%).
Table 5 confusion matrixes Result Weiner + ANN
TN= 56 FP=12
FN=9 TP=39

In table 5 confusion matrix value for the image to detect the lungs diseases with the values Weiner + ANN are calculated. The Following calculation for Gaussian+Ann to calculate obtained accuracy. The accuracy of the method is 83.333% out of 100 with the lower accuracy value in the method. So, the error rate occurs in the accuracy value is 16.667% (Accuracy = ((56+39)/ (56+12+9+39))=83.333%). The
Sensitivity of the method is 81.25% out of 100 with the lower Sensitivity value in the method. So, the error rate occurs in the Sensitivity value is 18.75% (Sensitivity: 39/ (39+9)=81.25%). The Specificity of the method is 76.470% out of
100 with the lower Specificity value in the method. So, the error rate occurs in the Specificity value is 23.530% (Specificity: 39/(39+12)=76.470%).

Table 5 confusion matrixes Result
LBFMF/ANN
TN=27 FP=4
FN=4 TP=28

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In table 5 confusion matrix value for the image to detect the lungs diseases with the values LBFMF/ANN are calculated. The Following calculation for LBFMF/ANN to calculate obtained accuracy. The accuracy of the method is 87.50% out of 100 with the lower accuracy value in the method. So, the error rate occurs in the accuracy value is 12.70% (Accuracy = ((27+28)/(27+28+4+4))=87.30%). The Sensitivity of the method is 87.50% out of 100 with the lower Sensitivity value in the method. So, the error rate occurs in the Sensitivity value is 12.50%. (Sensitivity = (28/(28+4)) = 87.50%). The Specificity of the method is 87.50% out of 100 with the lower Specificity value in the method. So, the error rate occurs in the Specificity value is 12.50%. (Specificity: 28/(28+4) = 87.50%).

When, compare to any other existing method the values get from the local binary fitting median filter process the result value get from this method is very accuracy when compare to the existing method filters. The figure 7, 8 ,9 shows the value of the accuracy result is 87.5%, Sensitivity: 87.50%,and Specificity: 87.50%. So, we prefer this method for the better result than the existing method using the proposed method.

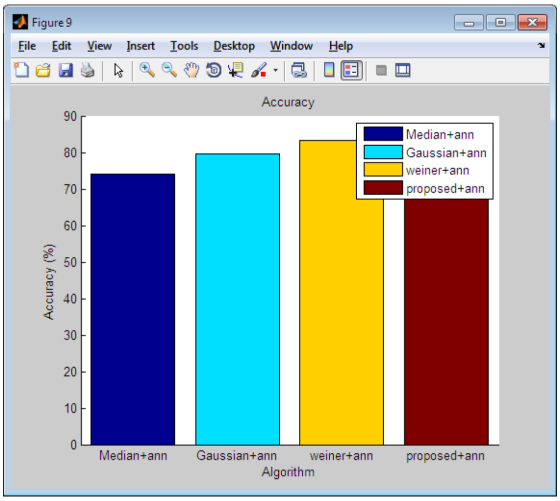

Figure 7 Accuracy comparison

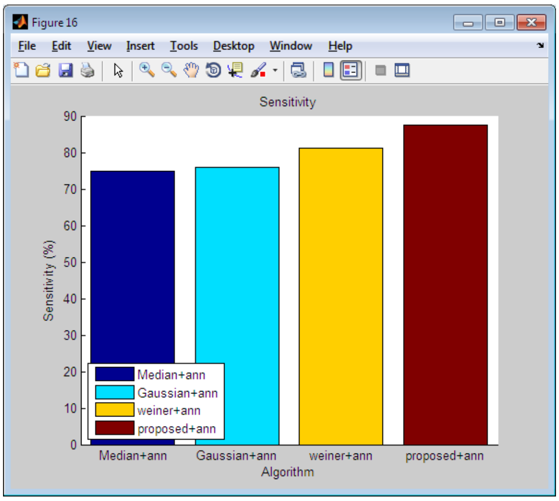

Figure 8 sensitivity comparison

From several results of the classification trials for lung diseases that have been carried out, it can be concluded that this system has an accuracy value of 87.5%. The segmentation results from the correlation of k-means clustering get quite good results and are able to segment the right and left parts of the resultant lung image, so that the classification results from feature extraction can distinguish X-ray images of lung image diseases prediction.

V. Conclusion

Lung diseases are a major cause of death that warrants the need for an early detection the world over. A forecasting system of Lung disease assisted by computers will help pulmonologists diagnose these diseases successfully. By means of eliminating these qualities that are now redundant, their performance in classification is enhanced with a huge reduction in the cost of classification. LBFMF is a population that has its basis on the approach to optimization duly inspired by the searching behavior of certain animals and their group living theory. In this work, a LBFMF-ANN has been rightly proposed by the modification of equations of solution search for properly assimilate datas of its globalbest (gbest). The LBFMF-ANN algorithm, tends to take merits of various information in the global best for the purpose of guiding and searching of various new candidate solutions for further improving exploitation. Their results have proved that this LBFMF-ANN has a higher accuracy of classification by about Accuracy 87.30%, Sensitivity 87.50%, Specificity 87.50% and better precision than the existing method respectively.

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