

Detection & Classification of Lung Cancer at an Early Stage by Applying Feature Extraction-Optimization and Neural Network on Hybrid Structure

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Abstract: As of now the detection and classification of lung cancer disease is one of the most tedious tasks in the field of medical area. In the diversified sector of medical industry usage of technology plays a very important role. Detection and diagnosis of the lung cancer at an early stage with more accuracy is the most challenging task. So, in this research article 400 set of images has been used for this experiment. Best feature extraction technique and best feature optimization technique has been analyzed on the basis of parameter minimum execution time with minimum error rate. Then finest selection of features leads to an optimal classification. In this context, one of the best classification algorithm the support vector machine has been proposed in this hybrid model for the binary classification. Further Feed forward back propagation neural network has been implemented with SVM. This proposed hybrid model reduces the complexity of the system on the basis of minimum execution time that is 1.94 sec. with minimum error rate 29.25. Further better classification accuracy 99.6507% has been achieved by using this unique hybrid model.

Keywords: Hybrid Structure, Lung Cancer Detection, Feature Extraction, SIFT, SURF, PCA and Feature optimization.

I. INTRODUCTION

Lung cancer is one of the most dangerous diseases that is common today. In India alone, lung cancer causes more than 10,000 deaths per year [1]. The mortality rate is increasing by 10-12% every year. This deadly disease has attracted much attention in the medical industry, and many attempts have already been made to automate the detection process to reduce mortality [1-3]. Identifying lung cancer requires two steps if the research industry is trying to automate the detection process. The first stage is called the training phase, and the second stage is called the classification stage. Phase architecture is easy to understand by looking at the doctor's procedure.

An experienced doctor goes through five to six years of training, and then applies his knowledge to treat people. The learning phase requires effective functions and, therefore, the function extraction algorithm plays a vital role when it comes to system training. This paper describes the methods used to extract the features. The algorithm for extracting attributes is followed by an optimization algorithm, since each evaluated attribute does not fall into the corresponding category of attributes. The optimized set of functions is passed to the learning algorithm, which creates a controlled learning architecture [2,3-4]. The architecture of supervised learning is used for a disease classification mechanism. The learning algorithm is also divided into two categories, namely, controlled and uncontrolled learning. Inadequate training leads to a process in which a machine can think independently, which is 100% impracticable, and, therefore, even in modern frame architectures, controlled training is used. The entire classification process is presented using a flowchart as follows.

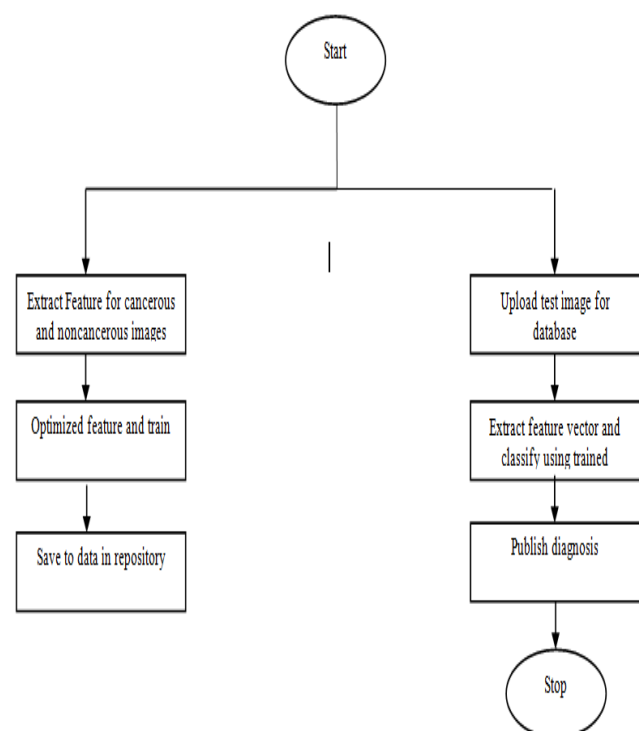


Fig.1. Hybrid Architecture Diagram for Lung Cancer Classification

Revised Manuscript Received on December 30, 2019.

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The algorithmic architecture of the classification process is as follows:

Algorithm1 Classification Process (Train Samples [Cancerous, Non-Cancerous], Test Set)

- a. For each Cancerous/ Non-Cancerous Image
- b. Extract Feature Vector
- c. Optimize Feature Vector
- d. Store to db
- e. End for
- f. Train Optimized Feature Vector
- g. Upload Test Sample
- h. Extract Feature Vector and Optimize
- i. Use trained db for classification
- j. Classify and diagnose

In this context, many researchers and scientist produce a lot of effort to classify the lung cancer diseases at an early stage. S. H. Hawkins et.al (2014) proposed an automated CAD system which performed on the CRs and CT scans images. In this CAD system SFS method has been used for feature selection and putting this SFS algorithm for the features of cluster which is based on the collective classifier traits supports better features that are good for clustering

[4]. The classification performance of this hybrid CAD obtained was 75.2.

Similarly, D. D., Westaway et.al (2013) were used Radiomic approach to choose the 3-D features from the lung cancer images for giving prognostic information. As we know classifiers are created to forecast the survival time. In this experiment CT scan images has been used and these images were collected from Moffitt Cancer Center, Tampa [5]. The image traits from CT scans may signify phenotypes which are proficient of permitting more good forecasts which can be created by human analysis. By using the decision tree the prediction of survival and accuracy of this was observed 77.5%. In another experiment that was performed by Abidi Kureshi, N.et.al (2016) in which an automatic pathological diagnosis method has been proposed which is known as Neural ensemble based detection(NED). In this proposed method preprocessing, feature extraction, classification and diagnosis were used. In this experiment

data has been taken from the X ray chest films by Bayi hospital. This proposed method used to use to recognize lungs cancer cell of needle biopsies, identification rate is high and provides less number of false negative identification which improves the accuracy automatically that helps the people to save the life [6].

This paper mainly focusses on the early detection and accurate classification of the lung cancer. In this research article first Region of interest(ROI) has to be find out by using different feature extraction techniques via. SIFT, SURF and PCA. As shown in the fig.2 ROI has to be detected and marked after that preprocessing of the image has to be implemented in which scaling of the image has to done and key points has to extracted. The performance of these feature extraction technique has to be depends on the minimum execution time with minimum error rate. Now, this hybrid model gone through the second phase in which extracted feature has to be optimizes via. Genetic algorithm, Particle Swarm Optimization and Ant Bee Colony. It is clearly shown by the fig.2 in which Mean square error has been calculated. The third phase of this hybrid model training and classification has to be performed on 1000 images in which 25%images used for training and 75%images used for classification. In this research article training and classification has been done by Feed forward back propagation neural followed by SVM. So, this hybrid models consists of three phase:

- a) Selection of Feature extraction algorithm
- b) Selection of the Optimization algorithm
- c) Training and Classification

II. SELECTION OF FEATURE EXTRACTION ALGORITHM

Three different feature extraction algorithms have been implemented as discussed in Section 1 and Section 2.

SIFT return key points of any image, which is relevant in the ROI (Region of Interest). The ROI is the section, which is the most relevant part of any image toward the required operation [7-8].

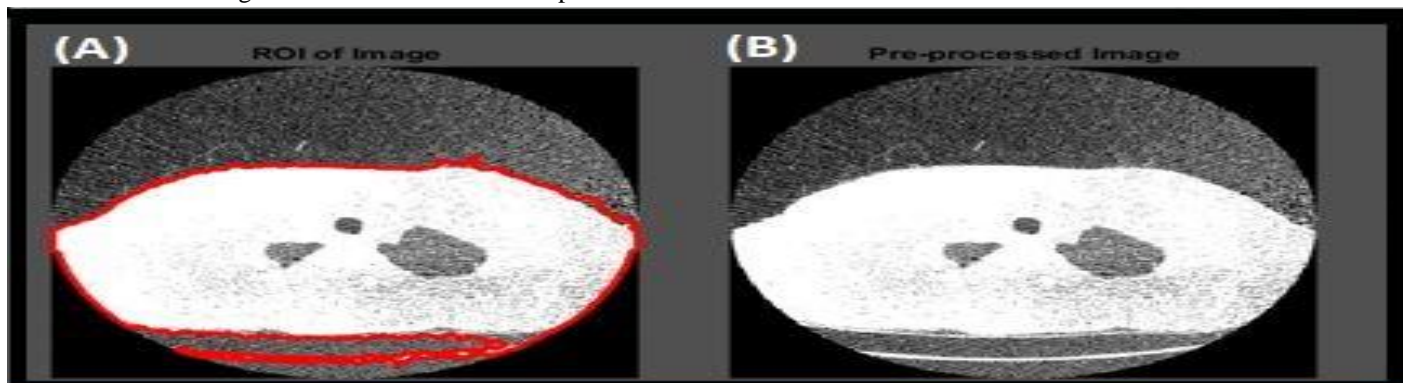


Fig.2 ROI analyses of the lung cancer images for classification (a) ROI region for feature extraction (b) Pre-processed image of lung cancer

Figure 3(a), 3(b) and 3(c) represents the ROI selection and finalized image after morphological process [9-10]. Any feature extraction algorithm does not RGB format image directly for the feature extraction. In addition to that, specific region selection prevents the feature extraction

Table – I: Different feature set of different algorithms

Image	PCA->Principle Eigen Vector)	SIFT-> Key Points	SURF -> Key Points
Image 1(255 * 393)	256 *1	252*252	224*62

algorithm from any kind of irrelevant time laps. The extracted region is passed to feature extraction algorithm turn by turn. The following table illustrates the architecture of extracted key points / Eigen values.

Image 2 (196*250)	256 *1	253*252	164*52
Image 3 (181*277)	256 *1	252*252	163*26
Image 4 (195*200)	256 *1	253*252	180*45

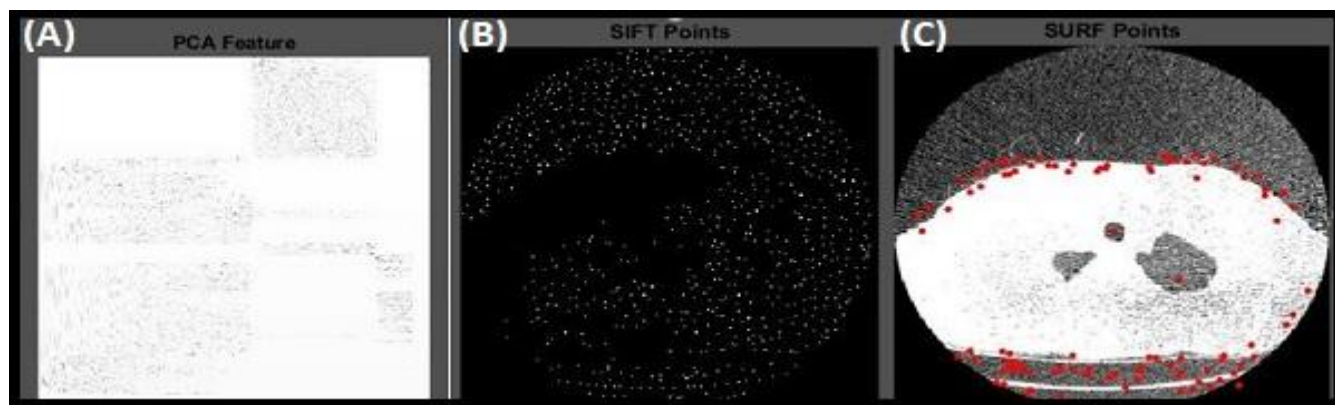


Fig.3. Feature extraction of the different feature extraction technique (a) PCA Eigen Components (b) SIFT Key (c) SURF Key Point

Figure 3. represents different feature set samples of different feature extraction algorithm. Although, as discussed in previous sections, each feature extraction has its own significance and architecture. Based on the parameters SURF is considered the best feature extraction algorithm as it consumed least time and produced least error rate [11-12]. Also in Figure (3), it is clearly visible that the most relevant points are extracted by SURF. Out of the extracted key points by SURF, only few are the most relevant key points for

Cancer Identification and optimization algorithms have judged.

III. SELECTION OF OPTIMIZATION ALGORITHM

The selection of the most suitable optimization technique has been done based on the execution time and mean square error. The entire process is summed up in one architecture whose algorithm design is given as follows

Table – II: Optimized feature set

SURF SELECTION	GA	PSO	ABC
224*65	36*8	36*9	11*15
164*53	25*3	35*2	12*16

163*27	24*6	39*4	13*11
180*47	26*7	41*3	14*15

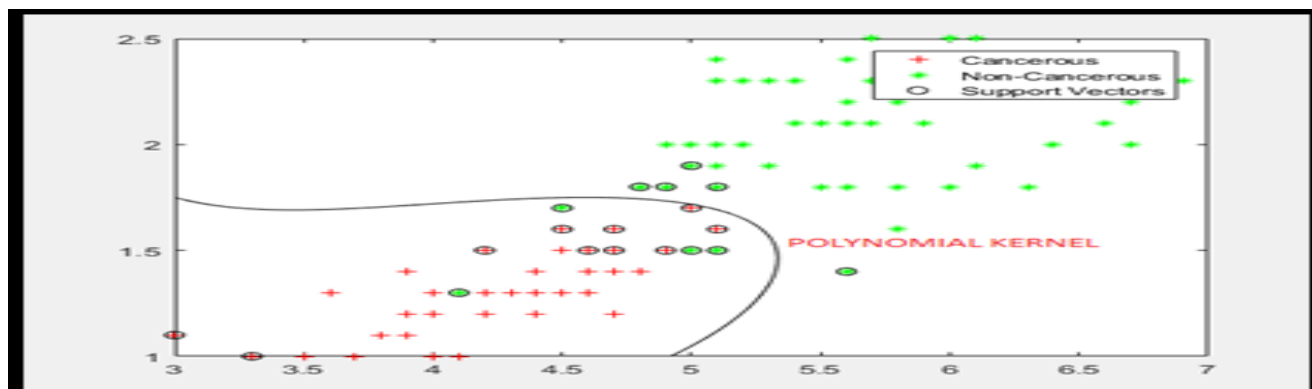


Fig. 4. SVM Training

Algorithm 2. Select_Suitable(Image_Set)
Function
Find_Best_Suitable_Feature_Selction_Algo(Image_Set)

1. Foreach img in Image_set // for every image in Image_Set

2. ROI= Identify_ROI(img); // Evaluating the ROI
3. F1=Feature_Sift(ROI); // Evaluating SIFT Key points
4. F2=Feature_Surf(ROI); // Evaluating Surf Key Points
5. F3=Feature_Pca(ROI); // Evaluating Principle Eigen Vector
6. End For
7. [Time of execution, Error]
=Evaluate_Time_Error(F1,F2,F3);
8. Find minimum_time,Error Rate select feature extraction algorithm
9. End function

Table – I: Utilized fitness functions

GA	$\begin{matrix} 1 & \text{if } fs > ft \\ 0 & \text{otherwise} \end{matrix}$
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IV. TRAINING AND CLASSIFICATION

In this section the training and classification of the data set is to be done by using the SVM and FFBPNN. As SVM is a binary classifier and hence it can categorize only two categories at a time. Some researchers have utilized SVM as multiclass classifier in medical industry but they would be too complex in the required frame [13-15]. But in this hybrid architecture to get the desired results whether the image is cancerous or non- cancerous with more accuracy SVM with FFBPNN are sufficient. enough. The extracted and optimized feature set is passed to SVM for the training first. SVM does not pick each.

feature for training. The selection of the feature set depends completely on the type of Kernel used in the training. The proposed architecture has used Polynomial Kernel due to various regions.

- a) Polynomial Kernel covers a lot of area as compared to any of the kernel function of SVM.
- b) Unlikely liner kernel is quite flexible and results into simulations that are more accurate.

The trainset for SVM is formed in the following manner.

Algorithm Train_SVM(N1, Opt_set1, N2, Opt_set2)

Where N1= Total number of cancerous images

Opt1= Optimized Feature vector for N1

ABC	$\begin{matrix} 1 & \text{if } fs \text{ sum}(ft.^2); \\ 0 & \text{otherwise} \end{matrix}$
PSO	$\begin{matrix} 1 & \text{if } fs * v > ft * v \\ 0 & \text{otherwise} \end{matrix}$

where fs is current feature vector and ft is the threshold of selection.

Algorithm3.Select_Suitable_Optimization(Selected Feature_Set)

Function Select_Best_Optimization(Feature_Set)

1. Foreach f in feature_set
2. O1=GA_Fit(f);
3. O2=ABC_Fit(f);
4. O3=PSO_Fit(f);
5. End for
6. Min_time=Min(O1T, O2T,O3T);
7. Select Optimization Algorithm with minimum time
8. End Function

N1= Total number of cancerous images

Opt1= Optimized Feature vector for N1

1. gcount=1; Train_set=[]; //group count
2. Foreach fvec in Opt1.Row
3. Train_set(gcount,:)= Opt1_set1.Row.Value
4. Group(gcount)=1;
5. Gcount=gcount+1;
6. End for
7. Foreach fvec1 in Opt_set2.Row
8. Train_set(gcount,:)=Opt_set.Row.Value
9. Group(gcount)=2
10. End for

The train set is initialized as empty and group set is accordingly set. The train set will contain both the values of the cancerous and the non- cancerous feature set. This data is passed to SVM training with polynomial kernel and the following graphical representations are attained [16-17] As described in the section earlier, SVM only takes those feature vectors, which is supported by the support vectors. The support vectors are marked as rounded object in Figure 5. In the similar fashion, the classification procedure takes place [18-19]. The classification procedure takes the test image as input, extracts its feature vector, optimizes it and finally passes it to trained architecture as described in the flow diagram in Section

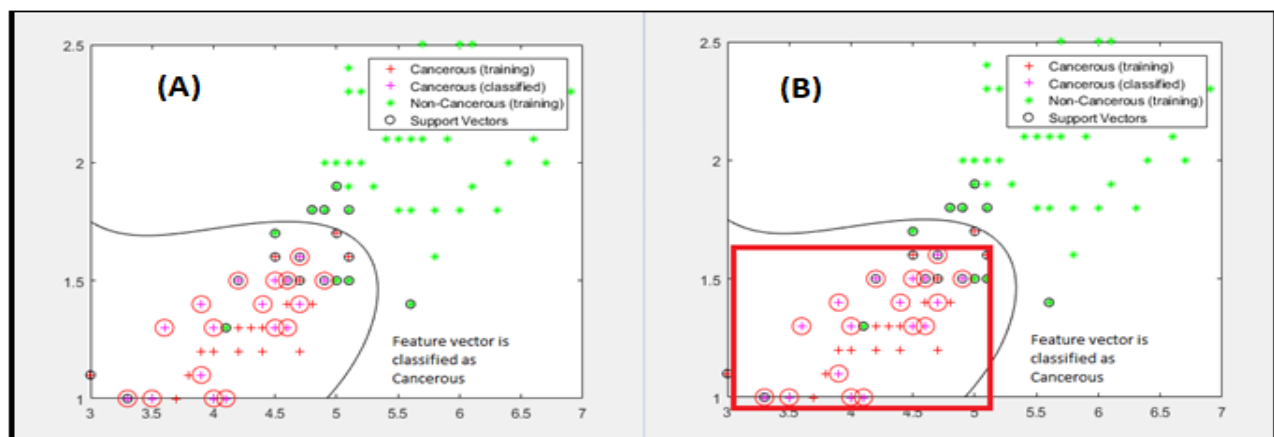


Fig.5. Classified and Classified Region after SVM training

As the SVM use only that data which are close to the kernel. However, the count of extracted feature will be high so here SVM reduce the complexity of data size [20-21]. Concurrently only the selected features passed to the Feed forward back propagation neural network. Moreover, FFBPNN reduce the size of raw data by using the property

of FFBPNN. So in this hybrid model in the first module train the data set by using SVM and in the second module trains the FFBPNN with selected Kernel [22-23]. The fig.6 shows the how the neural network implemented on the reduced and filtered size of data set with different numbered of neuron count.

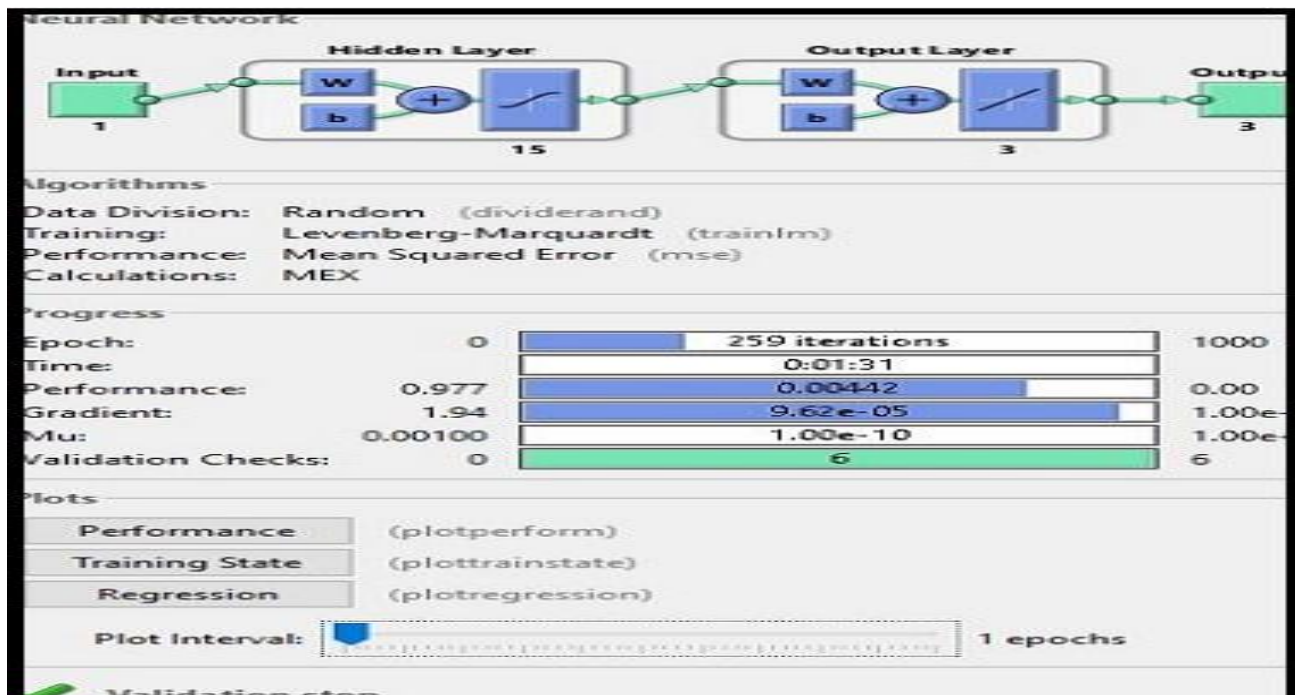


Fig. 6. Neural Network with Neuron Count

In this section FFBPNN calculate the weight of extracted feature set. Here the mean square error is the parameter which act as a cross validator in propagating back to FFNN, whereas gradient act as a cross validator in propagating back to FFBPNN [25-27]. It is clearly shown by the fig.7. The

best propagating value is to be stored in the repository of this hybrid structure. However, value of regression R propagating the impact of one data to another data means there is very minute mismatch between trained and testing data [28-30].

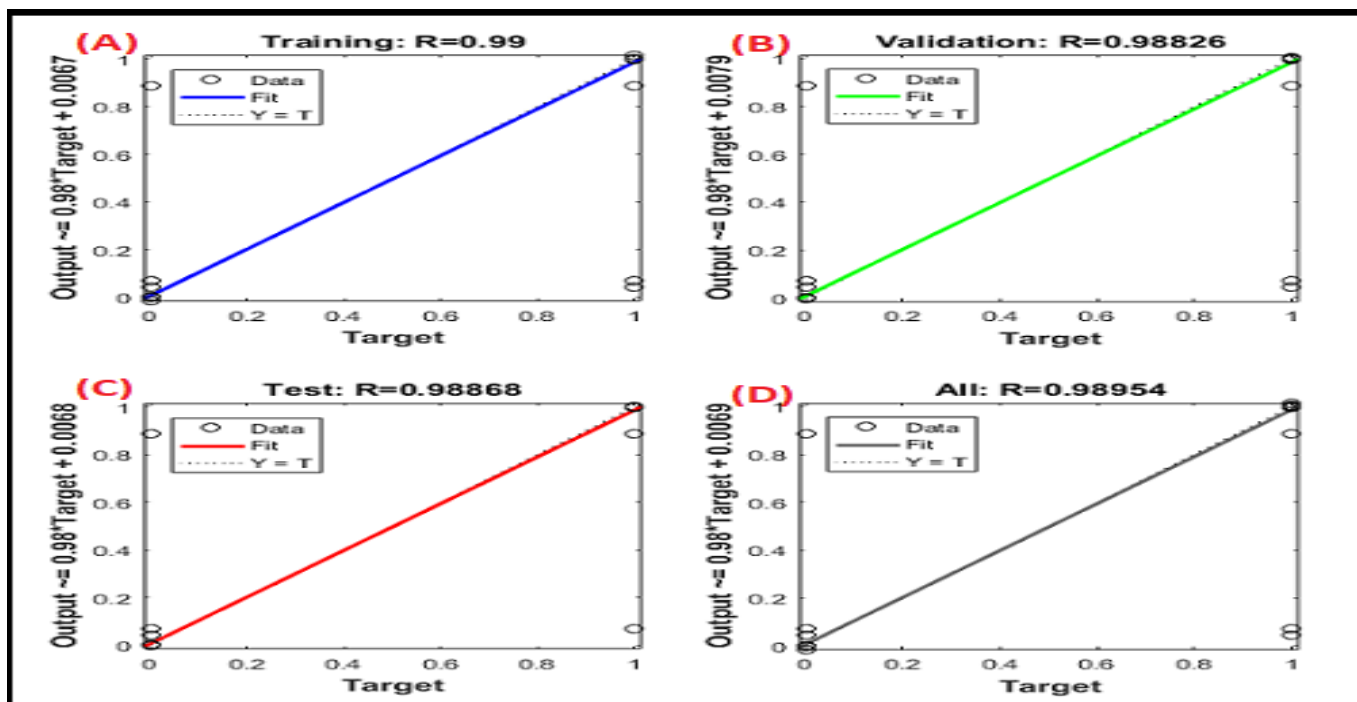


Fig.7.R shows the relation between Training and Test Data (a) R=.99 (b).98 (C) R=.98 (d) R=.98954

V. RESULT AND DISCUSSION:

In the proposed work, initially three feature extraction algorithm (SURF, SIFT, PCA) and three feature optimization algorithms (GA, ABC and PSO) have been implemented. A comparative analysis of feature extraction algorithms and feature optimization

algorithm on the basis of time and error rate has been calculated as shown in the table 5. In this section, the results obtained after simulating the code in MATLAB that has been discussed in detail The simulation is carried out in MATLAB software. The simulation environment in which the work has been done is shown in below table.

Table – IV: Simulation Environment

Language Utilized	MATLAB
Version	2016 (a)
Tool Boxes	Image Processing Toolbox , Data Acquisition Tool box
RAM	Minimum 4 GB
Processor	I3 and above
Image Set Source	Research Lab , Chandigarh

error rate after the successful implementation of Feature extraction algorithms.

This section compares the feature extraction techniques and evaluated the parameters in the form of parameter time and

Table – V:Performance parameters of feature extraction algorithm

Algorithm	Time (sec)	Error rate
SURF	1.94	29.25

SIFT	5.71	30.38
PCA	14.49	31.62

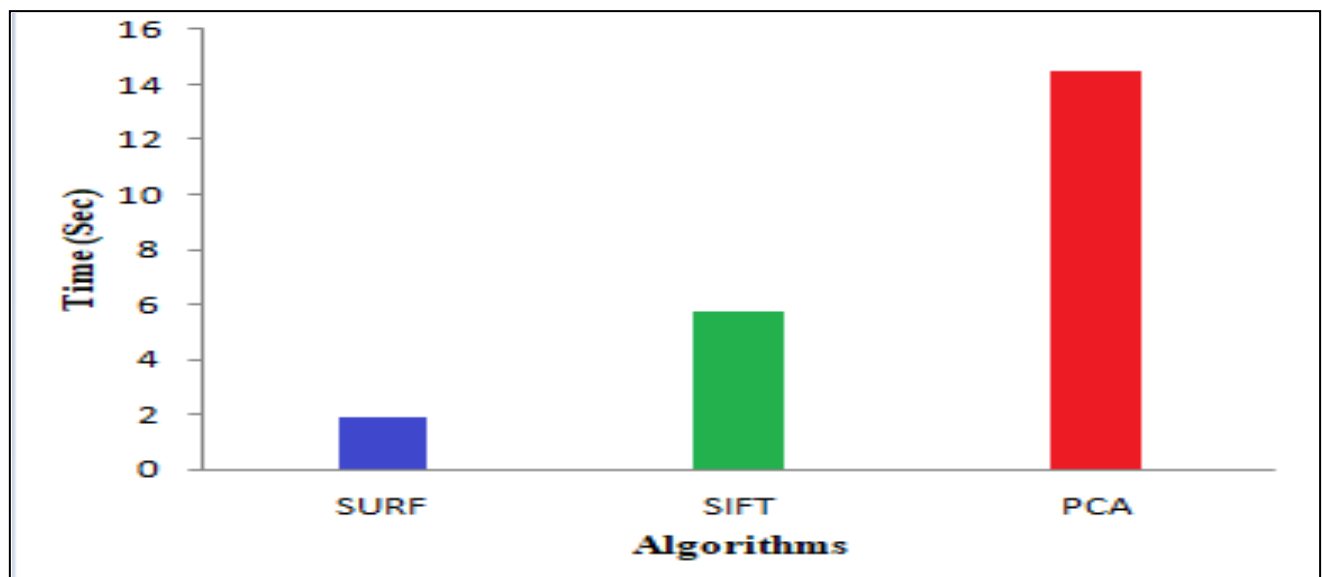


Fig.8. Time verses feature extraction algorithm

Figure8 represents the graphical architecture of the values presented in Table 6. Surf feature extraction technique has the least consumption time in order to extract the features whereas the PCA is on the higher side. SIFT manages to lie in between SURF and PCA.

Another evaluation has been made on the basis of the error rate generated in the feature extraction procedure. Table 6 represents the Error rate corresponding to the time consumed

Table – VI: Performance parameters of feature extraction algorithm for five samples

Number of Iterations	Time			Error rate		
	SURF	SIFT	PCA	SURF	SIFT	PCA
1	1.94	5.71	14.4	29.25	30.38	31.62

2	2.04	4.57	13.25	30.47	30.24	30.25
3	1.65	4.97	16.54	28.54	29.36	32.56
4	2.52	6.57	17.85	29.65	31.25	32.79
5	1.12	7.85	13.97	29.87	32.25	29.86

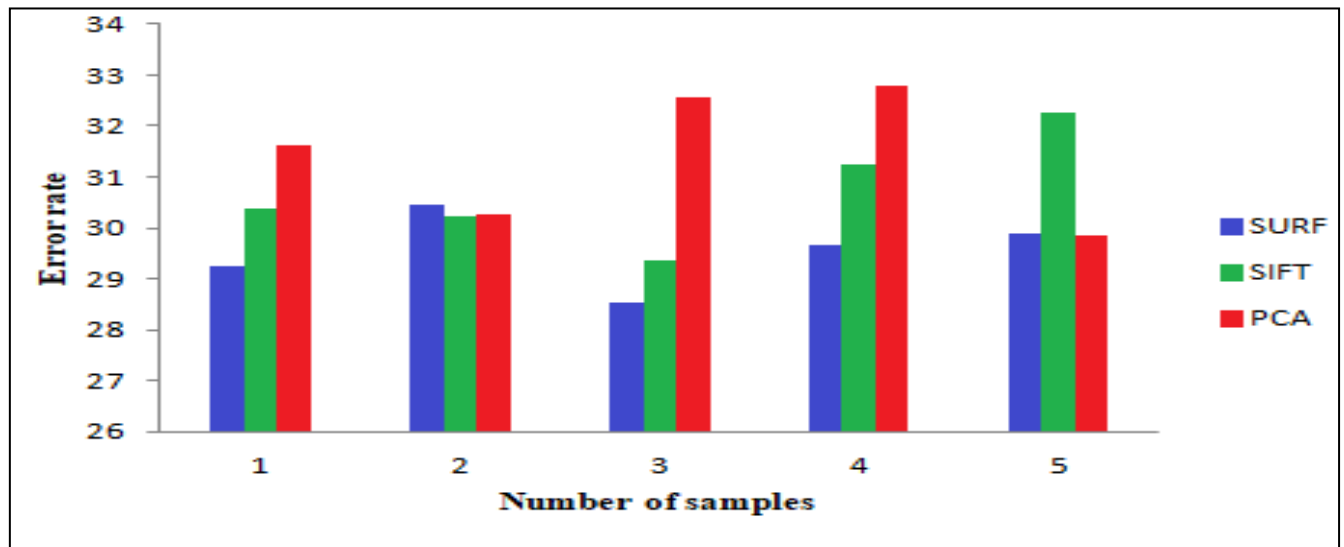


Fig.9. Error rate verses feature extraction algorithm for five samples

Figure 9 represents the graphical structure of the values drawn in table 6. Even for this parameters, the SURF seems to perform well as compared to SIFT and PCA. The maximum error generated by SURF is 30.47 units whereas SIFT generates a maximum error of 32.25 units. The PCA on the other hand stands tallest prone to error and generates a maximum value of 32.79. Similarly, the mean square error has been calculating for three optimization algorithm GA=24.59, PSO=84.20 and ABC=28.10. So the GA has the least mean square error. Finally, the performance of this proposed hybrid architecture can be evaluated in the terms of parameter Recall(R), Precision(P), F-measure(F) and Accuracy.

$$A. \text{ Recall}(R) = \frac{(\text{Total true classified Samples})}{\text{Total Supplied Samples}}$$

$$B. \text{ F-measure}(F) = 2 \frac{P \times R}{P + R}$$

C. Accuracy: It is the accuracy of supplied samples

The presented work focuses on the enhancement of true positive rate and accuracy. A GUI has been prepared in the Matlab that is shown by the figure10

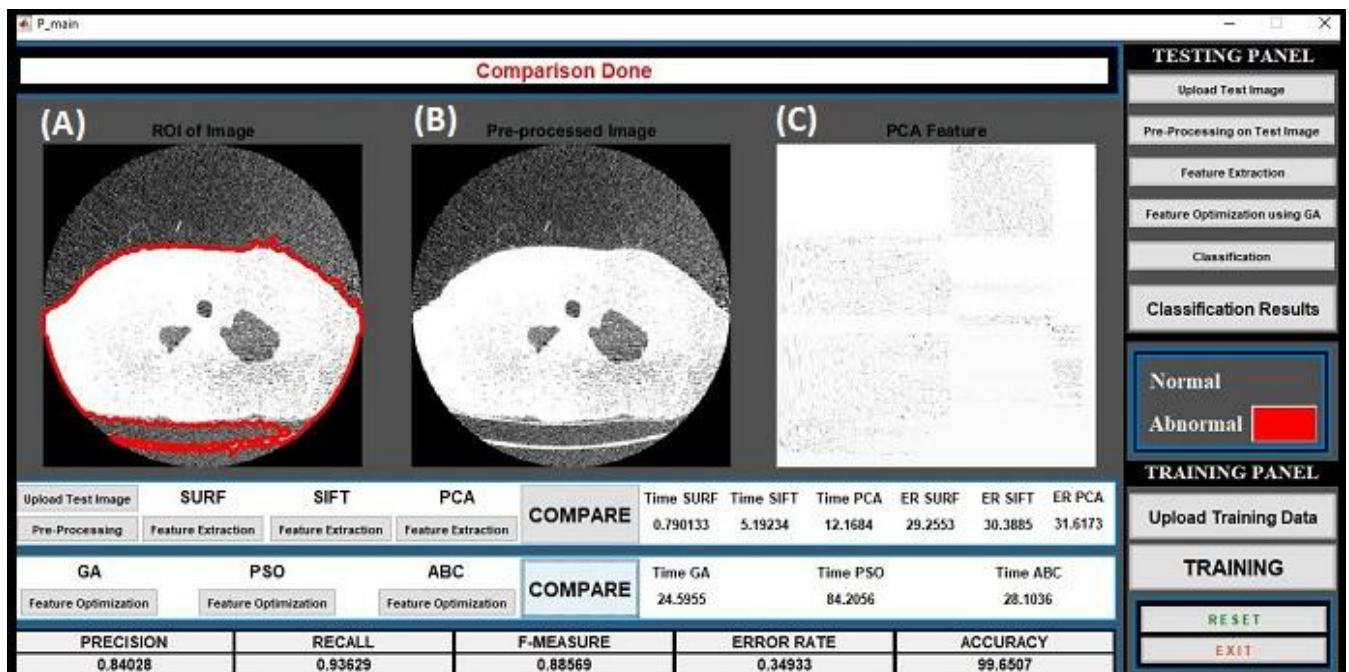


Fig.10. GOI of Hybrid model represent the pictorial view (a) ROI of the image (b) Pre-processed image (c) Valid and key points of PCA

The value of precision for this hybrid model .84028, value of recall .93629 value of f-measure .88569 and accuracy 99.6507 has to be obtained. So this hybrid model achieves high value of accuracy with minimum execution time and

minimum error rate which means provides best classification of lung cancer at an early stage.

VI. CONCLUSION

This work determines the possibility of detection the lung cancer at an early stage by employing the feature extraction technique, feature optimization technique and classification by using classifier and neural network on this hybrid structure. The Proposed hybrid model which provides the comparative analyses of feature vector and feature optimization algorithms. The best selected feature passed through the different optimization algorithm. So the best feature extraction technique Surf and best optimization algorithms GA analysed on the basis of parameter like minimum tic-toc time and mean square error. More over both these techniques have been implemented on this hybrid model. The optimized feature vector is trained & classified by SVM and FFBPNN. Some significant finding of this hybrid structure are as:

- The work evaluated the best feature extraction technique Surf with minimum tic-toc time 1.94 sec and minimum mean square error 29.25 among the techniques SIFT and PCA and it is clearly shown by the figure no.8.
- The proposed hybrid structure determines the best optimization algorithms GA which has minimum error rate 24.59 among the technique PSO and ABC.
- The main objective of this paper to enhance the true positive rates which automatically increase the accuracy of the system. By applying the best feature extraction, optimization, SVM classifier and neural network FFBPNN the hybrid structure achieved the better accuracy of 99.6507%. The classification accuracy proves that the features were optimized correctly. It means lot of life can be saved if the detection and diagnosis of the lung cancer should be done at proper stage.

The current research work has opened many gates for the future research fellows. Different types of Lung Cancers or different stages of Lung cancers can be analysed through same architecture. It will also be interesting to see that how Deep Neural Network acts in this scenario.

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