A Web Based MATLAB Solution for Classifying Micro-Calcification on Mammograms

Karuna Sharma, Saurabh Mukherjee

***Abstract**: In the aeon of deep learning, CNN outperform significant part in medical image analysis. CADx("Computer Aided Detection and Diagnosis ") for Mammography utilizes significant features to detect and diagnose breast malignancy. Now a day CNNs based CADx are worth popular due to automatic relevant features extraction. CNNs can be trained from ground up for medical images but due to finite number of medical images transfer learning and data augmentations are used for training. And also performance of CADx can be decreased due to some factors like appearance of noise, artifacts, low contrast in both CC and MLO views of Mammogram and pectoral muscles which appears in MLO view of Mammogram. Mammograms can contain different types of abnormality like Micro-Calcification, Masses, Architectural distortion in case of breast cancer. In this work we developed a Web Based MATLAB Solution for the classification of Micro-Calcification malignancy either benign or malignant. This web based solution performs different steps to remove artifact, to enhance contrast, to segment pectoral muscle and to extract breast profile. At the final step proposed system classify mammograms either into benign or malignant. It has been examined on mammographic images containing both views from CBIS-DDSM database.*

***Keywords:** Computer Aided Detection and Diagnosis, Image enhancement, Segmentation, Deep learning, Convolutional Neural Network, Transfer Learning, Data Augmentation, Breast tumor classification, Micro-Calcification.*

I. INTRODUCTION

The breast carcinoma utmost continual ill health spotted amongst women,in both emerging and established countries death. As stated by "World Health Organization" (WHO) and "National Carcinoma Institute" **[1]** in 2004 breast carcinoma reported as 13% of total demises in the globe**[2]** and one among eight women face breast carcinoma in some phase throughout her life time in the "United States" (US). The radiologist use mammogram "Computer Aided Detection and Diagnosis "(CADx) system extensively as aninvestigative and assessment tool for breast carcinoma detection at primary phase. It is extremely trustworthy technique for primary identification of carcinoma, decreasing life-threatening rates up to 25%.

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* Correspondence Author
Karuna Sharma*, Assistant Professor in the department of Computer Science, Banasthali Vidyapith, Rajasthan, India.
Saurabh Mukherjee, Professor in the department of Computer Science, Banasthali Vidyapith, Rajasthan, India.

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But the performance of CADx can be degraded due to some factors like appearance of impulse and speckle noise, artifacts and low contrast both in CC and MLO views and pectoral muscles appears in Mammogram's MLO view.

For this reason, noise elimination, artifacts and pectoral muscles, Mammogram Image enhancement and breast profile extraction are significant preprocessing stages in CADx system to analyze the breast carcinoma.**[9]** **P**roposed an algorithm to remove artefacts and pectoral muscle by using a region description, split and merge method to extract pectoral muscle. In **[7]** authors studied the several filters as mean, median and wiener filter by applying various window size using DDSM ("Digital Database for Screening Mammography") database, evaluated with PSNR ("Peak Signal to Noise Ratio'). **[8]**Proposed an approach to remove pectoral muscles by using ROR ("Robust Outlying Ratio") method and to remove Gaussian and impulse noise by using DCT ("Discrete Cosine Transform") filter ROR-NLM.**[3]** Performed histogram equalization,**[4]** uses histogram equalization with Grey Relational Analysis for enhancement of mammogram.**[6]** uses Homomorphic Filtering (MH-FIL) method to Modify the Histogram Based Contrast Enhancement method. CLAHE enhances smaller regions in mammograms better [**5**]. **[10]**Proposed CLAHE ("Contrast Limited Adaptive Histogram Equalization") based Mammogram image enhancement, mathematical morphology and multiscale laplacian Gaussian pyramid transform.**[11]**Proposed Otsu threshold and multiple regression analysis based pectoral muscle segmentation. Shape-based mask with morphological operators is employed to the mammographic image by**[12]** and fitting function with cubic polynomial for segmentation pectoral muscle region.**[13]**In this paper clustering technique based on K-Means to eliminate pectoral muscle morphology based operations and "seeded region growing"(SRG) techniques to remove noise and artifacts are proposed.**[14]** used iterative "cliff detection" to detect pectoral muscles region. The pectoral muscle detection with morphology based operations and the "random sample consensus" method named as "RANSAC" is proposed in**[15]**.Region of pectoral Muscle is segmented by using geometry shapes and CLAHE for Mammogram Image enhancement is proposed in **[16].**In **[17]**histogram based 8-neighborhood connected component labelling to remove pectoral muscle is proposed.**[18]** Proposed Binary thresholding based pectoral Muscle segmentation. In **[19]** a hybrid approach to delineate the pectoral region border by applying Hough transform and to segment pectoral muscle active contour is proposed.

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In **[20]** threshold with active contour model for breast boundary extraction and canny edge detection for pectoral muscle removal is used.

The radiologist use mammogram "Computer Aided Detection and Diagnosis "(CADx) system extensively as an investigative and assessment tool for breast carcinoma detection at primary phase. All the conventional methods for breast cancer CaDx estimates malignancy probability based on investigated clinically identified tumor features like desnsity and shape of tumor. **[21][22]**On other hand approaches learnshidden features directly from the whole images contains more information than clinically investigated featuresby using"convolutional neural networks" (CNNs).**[23][24]** The recent success of "convolutional neural networks" (CNNs) in computer vision tasks has resulted in an influx of publications and implementations applying CNNs to mammography. A recent publication by **[25]** showed that deep learning improves the performance of clinical radiologist while taking a decision in breast cancer diagnosis. In **[26]** proposedDeep Leaning algorithm based on CNN for diagnosed breast cancer using Wisconsin Breast Cancer database. In **[27]** authors developed a decision support system "Man and Machine Mammography Oracle" (MAMMO) which consist two parts a "multi-view "convolutional neural network" (CNN) and "multi-task learning" (MTL). In **[28]** author proposed two phase Segmentation of Microcalcification in Mammograms using CNN consisting detection and segmentaion phases. In **[29]** author proposed a multi-input CNN based on patch size 28x28 which uses symmetry knowledge for mass detection to improve breast cancer detection . In **[30]** author provides a review based on study of different types of uses of CNNs ("Convolutional Neural Network") in diagnosing breast cancer using mammograms. In **[31]** author proposed a comparative study between a pretrained fine tuned network and network trained from scratch. In [**32**] proposed breast mass segmentation using a conditional Residual deep network U-Net by merging the benfilts of "residual" learning and graphical probability modelling of U-Net. In **[33]** author proposed breast cancer detection with CNN extracted features by using tranfer learning with alexnet pretrained netwotk and svm classifier. In **[34]** author provided a literature survey to show potential of deep convolutional networks for various tasks as lesion detction, localization, segmentation ,risk assement, classification in breast cancer diagnosis using mammog. In **[35]**author used transfer learning with GoogleNet, VGGNet and RESNet for identification and discrimination of breast tumor in mammograms.In **[36]** author used transfer learning with GoogleNet, AlexNet for identification and discrimination of breast mass tumor in mammograms. In **[37]** author used transfer learning with AlexNet for identification and discrimination of breast tumor in mammograms and compared results of SVM classifer with CNN extracted features and shows that tarnsfer learning provide better results than other one.In **[38]** author proposed a CAD to detect and discriminate breast tumor into in cancerous and non-canceroususing Faster R-CNN using INBreast database.

In this proposed application, we investigated the transfer learning to classify Microcalcification in mammogram images.Transfer learning is the improved learning of new featuresby transfering the knowledge from features which have already been fine learned and validated**[39].** There are many publicly available models based on "Convolutional Neural Networks" for recognition of objects and fine tuning with these models have been implemented successfully in disease diagnosis and analysis of medical images**[40].**

II. RESEARCH GAPS

After going through literature review, we found the following research gaps:

A. There is little research work available for segmenting mammographic images including both CC and MLO views using a single system.
B. There is only little research work available for integration of artifact removal, noise suppression, pectoral muscle segmentation, breast boundary extraction and mammogram image enhancement.
C. Few research work available for classification of micro-calcification in mammogram images using CNN.
D. Only few little research work available for automatic feature extraction with pre-trained CNNs with different parameters using Transfer Learning.

III. RESEARCH OBJECTIVES

A. To develop a comprehensive algorithm for completely automated segmentation of Mammogram on CC and MLO views.
B. To develop a framework to classify Micro- Calcification from Mammogram into benign and Malignant Using Transfer Learning.
C. To Create a Web Based Matlab Solution for the implementation of automated segmentation and Classification of Micro-Calcification on Mammogram with CC and MLO views.
D. To compare performance of pre-trained CNNs Alex Net and Google Net with different parameters on same data using Transfer Learning.

IV. RESEARCH METHODOLOGY

A.Research Methodology for proposed Web Based MATLAB Solution for classification of Micro-Calcification on Mammograms.

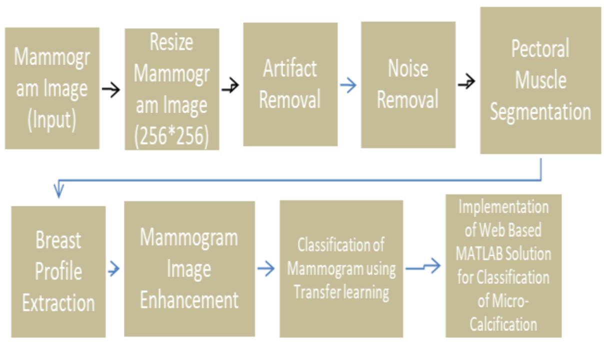

Fig.1. Sequence of Methods used in this research

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V. EXISTING SYSTEM

The conventional CAD were proposed with certain features on Mammograms and traditional classification approaches like linear and non- linear classifier were used for classification task like SVM, Clustering, K-Means Algorithms and others. Some of them were perform pectoral muscle segmentation and some of them were using whole mammogram images for breast cancer classification. There are little few CAD are available in market but they are also based on traditional approaches. In spite of traditional CAD, YOLO a deep learning Based CAD was also developed but it used whole mammogram image for classification and it can detect and classify only the masses malignancy.

VI. PROPOSED SYSTEM

The system has developed with MATLAB2018b. Following tools and techniques have been used to developed the Web Based Matlab Solution.

1. Datasets

- The secondary data is used for this study "Curated Breast Imaging Subset" of DDSM ("CBIS-DDSM"). The DDSM consist of 2,620 mammograms and we used Mammographic images containing only Micro-calcification abnormality along with verified pathology information of benign, malignant and normal cases.
- To provide authentication to enter into the system, user information is stored in database. SQLite Studio 3.2.1 database application with Matlab2018b is used. Structure of database is given in Fig. 2
-

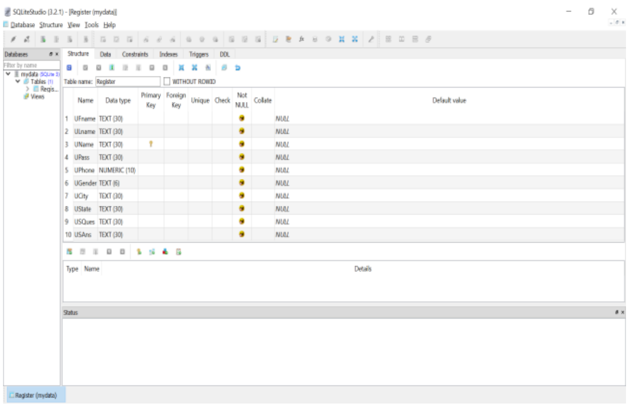

Fig.2. Structure of database used in this solution.

2. Data Augmentation and PreProcessing

Mammograms are low contrast images, so we have preprocessed the mammograms using CLAHE method to enhance the contrast for better and more feature extraction. Training a CNN with large number of input images performs better by resulting in higher accuracy. However, medical image datasets are relatively small due to limited number of patients. Therefore, data augmentation method is used to augment the number of the input images by engendering newer images from the ground truth input images

3. Transfer Learning

Transfer Learning is a method of machine learning to retrain a pretrained network to llearn new features to classify new images. Fine-tune with transfer learning is fast and easy than training with random initialized weights from scratch a network. We have used Both AlexNet and GoogleNet for transfer learning.

a) Transfer Learning with AlexNet

AlexNet architecture is 25 layer architecture containing eight weighted layers consisting five convolutional and three fully_connected layers, AlexNet is trained on ImageNet dataset to classify objects into 1000 categories. This network have image input size of 227 X 227.To fine Tuned AlexNete with new images ,we have modified the architecture of Alexnet, we have replaced fullly convoltional layer with different Weights and Bias factors.

Table 1: AlexNet architecture with all 25 layers used for transfer learning.

Layer Number	Layer Name	Activations for Layers	Features learned at layers	
			Weights	Bias
1	Input Image	227×227×3	-	
2	"Convolution_layer_1	55×55×96	11×11×3×96	1×1×96
3	ReLU_1	55×55×96	-	-
4	Cross Channel Normalization_1	55×55×96	-	-
5	Max Pooling_layer_1	27×27×96	-	-
6	Convolution_layer_2	27×27×256	5×5×48×256	1×1×256
7	ReLU_2	27×27×256	-	-
8	Cross Channel Normalization	27×27×256	-	-
9	Max Pooling_layer_2	13×13×256	-	-
10	Convolution_lyaer_3	13×13×384	3×3×256×384	1×1×384
11	ReLU_3	13×13×384	-	-
12	Convolution_layer_4	13×13×384	3×3×192×384	1×1×384
13	ReLU_4	13×13×384	-	-
14	Convolution_layer_5	13×13×256	3×3×192×256	1×1×256
15	ReLU_5	13×13×256	-	-
16	Max Pooling layer_3	6×6×256	-	-
17	Fully Connected_layer_1	1×1×4096	4096×9216	4096×1
18	ReLU_6	1×1×4096	-	-
19	Dropout_layer_1	1×1×4096	-	
20	Fully Connected_layer_2	1×1×4096	4096×4096	4096×1
21	ReLU_7	1×1×4096	-	-
22	Dropout_layer_2	1×1×4096	-	-
23	Fully Connected_layer_3	1×1×2	2×4096	2×1
24	Softmax	1×1×2	-	-
25	Classification Output	-	-	-

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b)Transfer Learning with GoogleNet

GoogleNet architecture is a 22 layers deep CNN which consist of 9 inception modules stacked linearly without including pooling layers and 27 layers deep CNN including Pooling layers .This is trained on imageNet dataset and classifies among 1000 categories of objects. This network have image input size of 224 X224. To fine Tuned Google Net with new images, we have modified the architecture of Google Net, we have replaced fully convolutional layer with different Learning Rate Factors for Weights and Learning Rate Factors for Bias.

Table 2: Google Net architecture: All convolutional layers and inception modules have a depth of two.

Layer Number	Type	Activations	Features Learned At Layers	
			Weights	Bias
1	Image Input	224×224×3	-	
2	Convolution_1	112×112×64	7×7×3×64	1×1×64
3	ReLU_1	112×112×64	-	
4	Max Pool_1	56×56×64	-	
5	Cross Channel Normalization_1	56×56×64	-	
6	Convolution_2	56×56×64	1×1×64×64	1×1×64
7	ReLU_2	56×56×64	-	
8	Convolution_3	56×56×192	3×3×64×192	1×1×192
9	ReLU_3	56×56×192	-	
10	Cross Channel Normalization_2	56×56×192	-	
11	Max Pool_2	28×28×192	-	
12	Depth concatenation_1	28×28×256	Inception_3A	
13	Depth concatenation_2	28×28×480	Inception_3B	
14	Max Pool_3	14x14x480		
15	Depth concatenation_3	14×14×512	Inception_4A	
16	Depth concatenation_4	14×14×512	Inception_4B	
17	Depth concatenation_5	14×14×512	Inception_4C	
18	Depth concatenation_6	14×14×528	Inception_4D	
19	Depth concatenation_7	14×14×832	Inception_4E	
20	Max Pool_4	7x7x832		
21	Depth concatenation_8	7×7×832	Inception_5A	
22	Depth concatenation_9	7×7×1024	Inception_5B	
23	Average Pool_1	1×1×1024		
24	Dropout_1	1×1×1024	-	
25	Fully Connected_1	1×1×2	2×1024	2×1
26	Softmax	1×1×2	-	
27	Classification Output	-	-	

VII. WORKING SOLUTION

The Application consist of the following modules:

A. **Sign In** module to enter into the system by entering user name and password for registered users.

B. **Sign Up** module to register the users to enter into the system.

C. **About Us** module to provide information about developers.

D. **Contact Us** module to provide contact information for the support in case of application access problem.

E. **Breast Cancer Guide** Module to provide general information about breast cancer.

F. **Forgot Password** module to provide facility to change password in case of forgotten password.

G. **Web Based Matlab solution for Microcalcification Classification** module is used to process the mammogram according to the CADx steps .This module provide the basic functionality for:

- To load the mammogram
- To remove the artifacts
- To check for Views of Mammogram as CC or MLO
- To remove pectoral muscles in case of MLO view
- To extract breast profile after removing the pectoral muscle
- To select model for classification from 4 best models given in this work.
- To classify the mammogram consisting micro-calcification abnormality either benign or malignant.

VIII. RESULT AND DISCUSSION

The Mammographic image data consisting 1360 Microcalcification patterns including benign and malignant is trained with fine tuned pretrained AlexNet and GoolgeNet networks. We have splited dataset into 70% for training and 30% of testing images to train the network for classification. We investigated that training of same data with same paremeters on both AlexNet and googlenet networks. The results with accuracy values are given in table 3.

Table.3 show the result of Fine Tuned AlexNet and GooleNet with ifferent parameters using transfer learning

Validation Patience	Learn Rate Factor for weights	Learn Rate Factor for Bias	L2 Factor for Weights	Validation Accuracy AlexNet	Validation Accuracy GoogleNet
15	1	2	1	91.01	85.9

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15	10	20	1	87.13	85.35
15	15	20	1	86.46	96
15	15	30	1	86.24	96.34
10	20	30	1	86.9	96.67
30	20	30	1	82.91	95.01
30	20	30	10	90.57	94.89
30	20	30	5	92.79	95.45

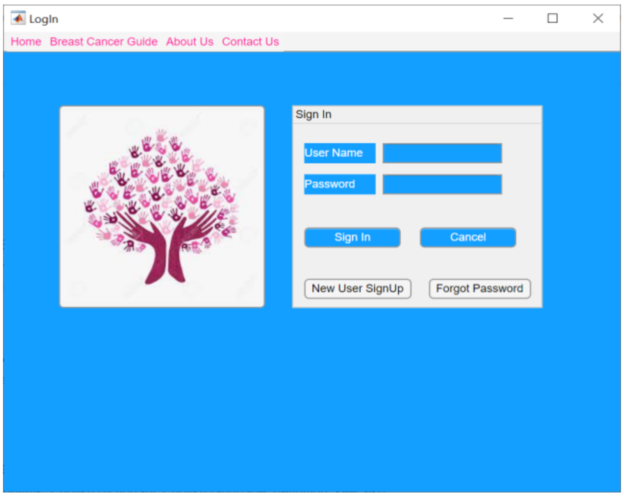

Fig.3. Sign In Module

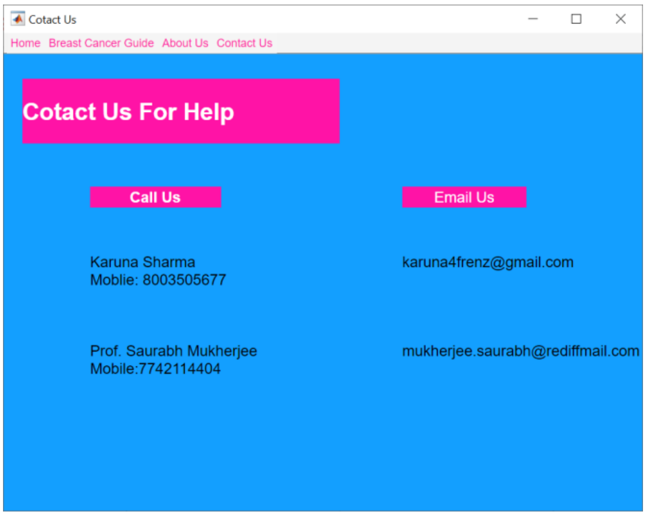

Fig.4. Contact Us Module

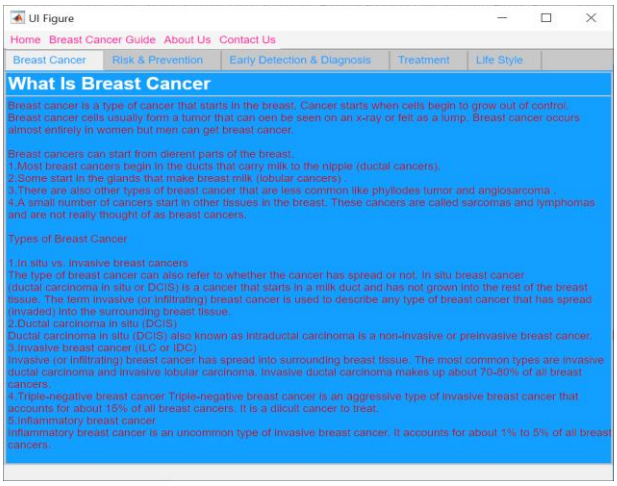

Fig.5. Breast Cancer Guide Module

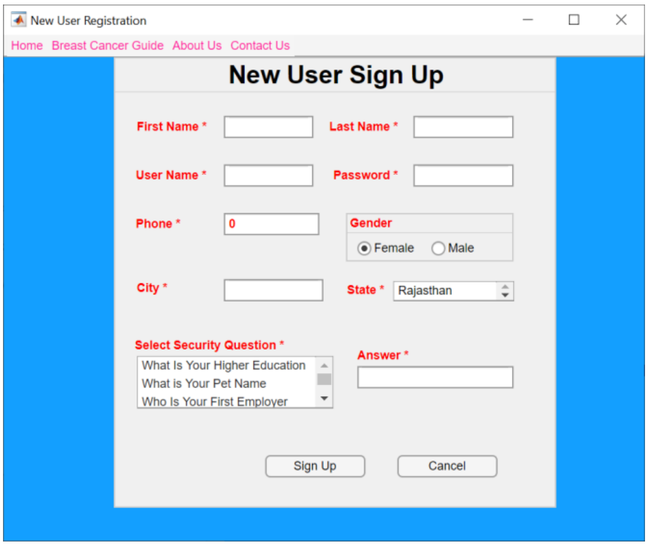

Fig.6. Sign Up Module

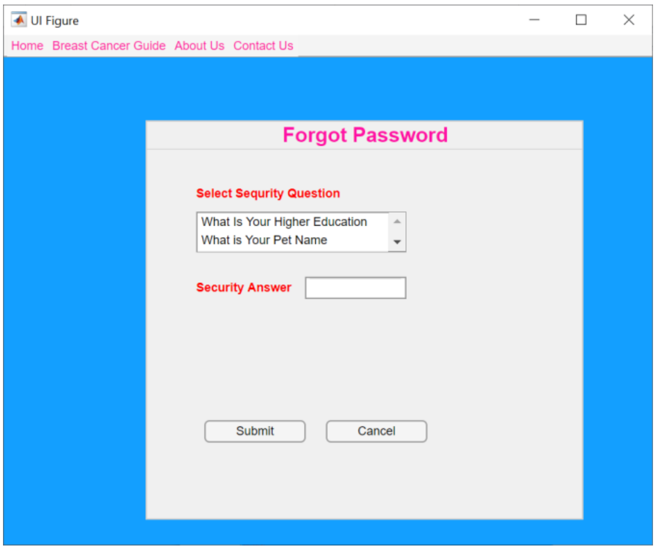

Fig.7. Forgot Password Module

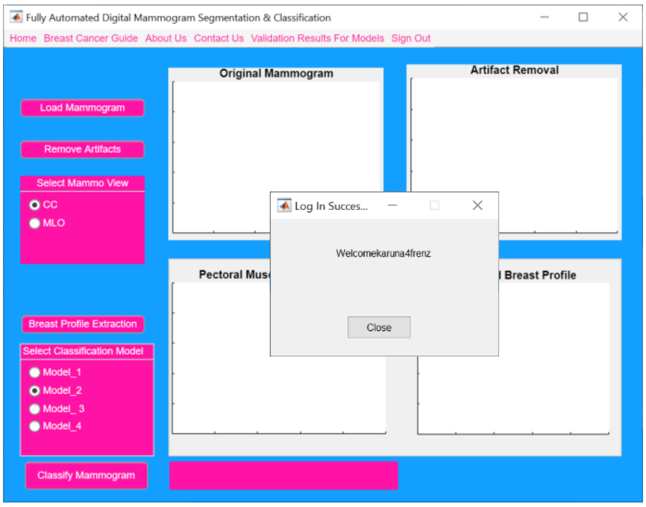

Fig.8. Module for segmentation of breast and classification of Micro-Calcification

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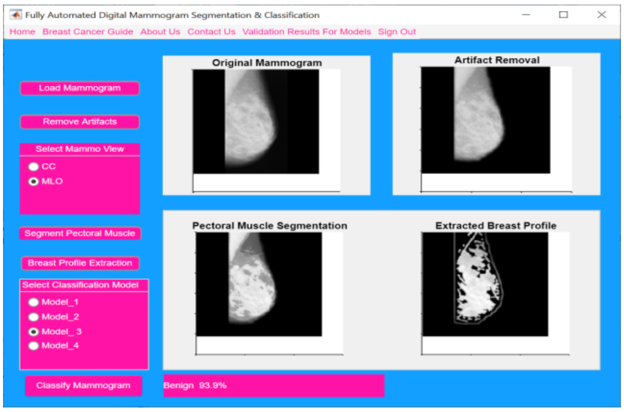

Fig.9. Module for segmentation of breast and classification of Micro-Calcification

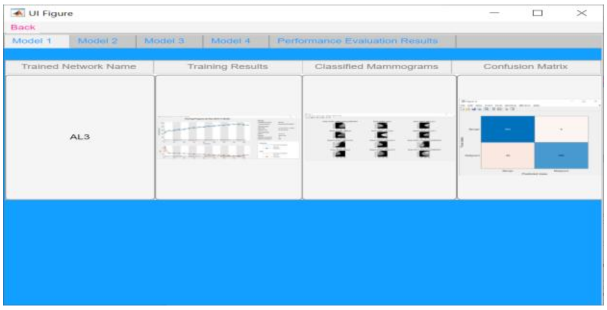

Fig.10. Module for displaying the models used in this application

X.PERFORMANCE EVALUATION FOR CLASSIFIER MODELS

Table 4 :Performance Evaluation of Fine Tuned AlexNet and googleNet Network.

Network Name	True Negative	False Negative	True Positive	False Positive	Accuracy
Alnet_1	491	68	329	13	91.01
Alnet_2	487	99	298	17	87.13
Alnet_3	407	25	372	97	86.46
Alnet_4	417	37	360	87	86.24
Alnet_5	478	92	305	26	86.9
Alnet_6	385	35	362	119	82.91
Alnet_7	466	47	350	38	90.57
Alnet_8	490	51	346	14	92.79
Glnet_1	390	13	384	114	85.9
Glnet_2	421	49	348	83	85.35
Glnet_3	496	28	369	8	96
Glnet_4	487	16	381	17	96.34
Glnet_5	491	17	380	13	96.67
Glnet_6	501	42	355	3	95.01
Glnet_7	461	3	394	43	94.89
Glnet_8	484	21	376	20	95.45

Table 5 :Performance Evaluation of Fine Tuned AlexNet and googleNet Network.

Network Name	Recall/Sensitivity	Precision	Specificity	F-Measure
Alnet_1	97.42	87.84	82.87	92.38
Alnet_2	96.63	83.11	75.06	89.36
Alnet_3	80.75	94.21	93.7	86.96
Alnet_4	82.74	91.85	90.68	87.06
Alnet_5	94.84	83.86	76.83	89.01
Alnet_6	76.39	91.67	91.18	83.34
Alnet_7	92.46	90.84	88.16	91.64
Alnet_8	97.22	90.57	87.15	93.78
Glnet_1	77.38	96.77	96.73	86
Glnet_2	83.53	89.57	87.66	86.44
Glnet_3	98.41	94.66	92.95	96.5
Glnet_4	96.63	96.82	95.97	96.72
Glnet_5	97.42	96.65	95.72	97.03
Glnet_6	99.4	92.27	89.42	95.7
Glnet_7	91.47	99.35	99.24	95.25
Glnet_8	96.03	95.84	94.71	95.93

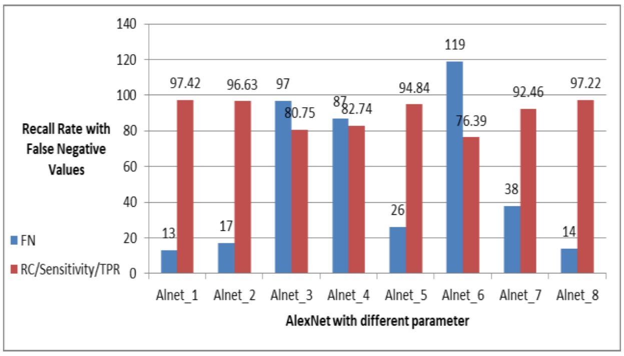

Fig.11. Trained Models with Recall rates and False Negative Rates.

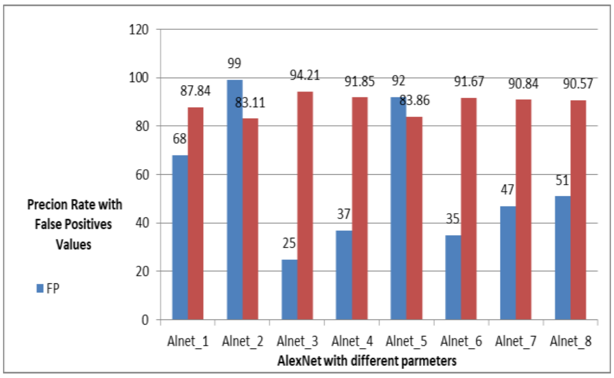

Fig.12. Trained Models with Precision rates and False Positive Rates.

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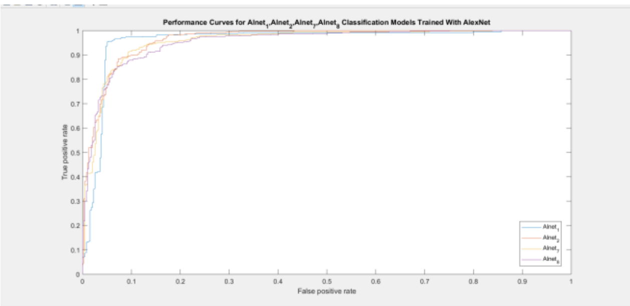

Fig.13. Performance Curve among four best fine-tuned Alex Net Models.

Table 6 :Area Under Curve in selected best four Alex Net fine-tuned Models.

Network Name	AUC	Model Selection Rank
Alnet_2	96.46	1
Alnet_1	95.98	2
Alnet_7	95.76	3
Alnet_8	95.44	4

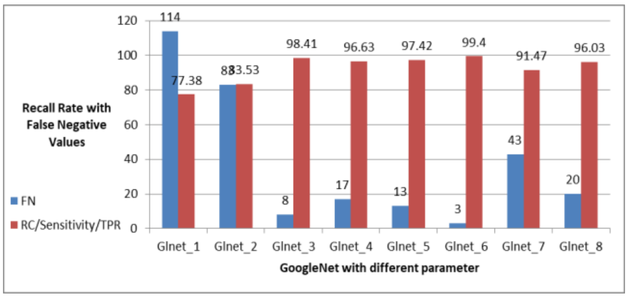

Fig.14. Trained Models with Recall rates and False Negative Rates.

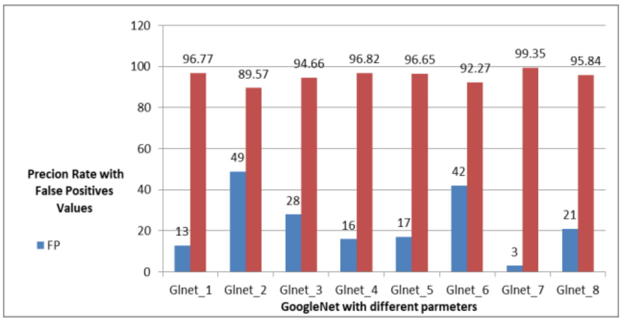

Fig.15. Trained Models with Precision rates and False Positive Rates.

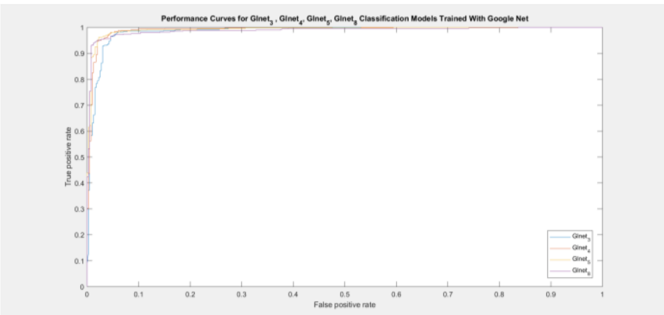

Fig.16. Performance Curve among four best fine-tuned Google Net Models.

Table 7 :Area Under Curve in selected best four googleNet fine-tuned Models.

Network Name	AUC	Model Selection Rank
Glnet_5	99.18	1
Glnet_4	99.06	2
Glnet_8	98.80	3
Glnet_3	98.51	4

XI. CONCLUSION

This Web based application must be utilized by the medical experts who are well trained and tested with the basic knowledge. The medical experts utilize their necessary skill in decision making while looking at the mammogram. It will be beneficial to provide an aid as a second look while investigating mammograms. Because the web based application is provided with all operations that can provide enough support to radiologist to take a decision about breast cancer. The system can be enhanced by expanding the scope of breast malignancy by using other types of tumor representations. The future works for this system includes mainly using the volume of mammogram data containing different type of breast malignancy and also by increasing the scope of application as it can identify the stage of breast cancer after detecting the tumor as malignant.

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AUTHORS PROFILE

Karuna Sharma, Karuna Sharma is working as an Assistant Professor in the department of Computer Science, Banasthali Vidyapith, Rajasthan. She is having 12 years of teaching experience, Currently, she is pursuing PhD under the guidance of Prof. Saurabh Mukherjee. Her research area is Medical Image processing, Machine Learning and Deep learning.

Saurabh Mukherjee, Prof. Saurabh Mukherjee is working as a Professor in the department of Computer Science, Banasthali Vidyapith, Rajasthan. He is having 20 years of teaching and research experience in Medical Image Processing, Machine Learning, Deep learning, Data science to name a few. He has guided 12 PhD students under his credit. Currently, 06 students are pursuing PhD under him.

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