Classification of Micro-Calcification in Breast from Mammographic Images using Transfer Learning

Karuna Sharma, Saurabh Mukherjee

Abstract: Early detection of cancer is most important for long term survival of patient. Now a days CADx are widely used for early identification of breast cancer automatically. CAD uses significant features to identify and categorize cancer. CADx based on Convolutional Neural Network are becoming popular now a days due to extracting relevant features automatically. CNNs can be trained from scratch for medical images due to various input sizes and tumor structures. But due to limited amount of medical images available for training ,we have used transfer learning approach.We developed a deep learning framework based on CNN to discriminate the breast tumor either benign or malignant using transfer learning. We used digital mammographic images containing both views from CBIS-DDSM database. We have achived training(100%) and validation accuracy greater than 90% with minimum training and validation loss. We have also compared the reaults with transfer learning using pretrained network alexnet and googlenet on same dataset.

Keywords : Deep learning, Convolutional Neural Network, Tranfer Learning, Data Augmentation, Breast tumor classification,Micro-Calcification.

I. INTRODUCTION

Current statistics states that breast carrcinoma is the utmost commonly diagnosed carcinoma among women. Early detection is more crucial in order to enhance the good treatment chances to reduce overall mortality rates.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 an investigative and assessment tool for breast carcinoma detection at primary phase. It is extremely trustworthy method for primary detection of breast cancer. All the conventional methods for breast cancer CaDx estimates malignancy probability based on investigated clinically identified tumor features like desnsity and shape of tumor. **[3][4]** On other hand approaches learns hidden features directly from the whole images contains more information than clinically investigated features by using "convolutional neural networks" (CNNs). **[5][6]** 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 **[7]** showed that deep learning improves the performance of clinical radiologist while taking a decision in breast cancer diagnosis. In **[8]** proposed Deep Leaning algorithm based on CNN for diagnosed breast cancer using Wisconsin Breast Cancer database. In **[9]** 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 **[10]** author proposed two phase Segmentation of Microcalcification in Mammograms using CNN consisting detection and segmentaion phases. In **[11]** author proposed a multi-input CNN based on patch size 28x28 which uses symmetry knowledge for mass detection to improve breast cancer detection . In **[12]** author provides a review based on study of different types of uses of CNNs ("Convolutional Neural Network") in diagnosing breast cancer using mammograms. In **[13]** author proposed a comparative study between a pretrained fine tuned network and network trained from scratch. In **[14]** 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 **[15]** author proposed breast cancer detection with CNN extracted features by using tranfer learning with alexnet pretrained netwotk and svm classifier. In **[16]** 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 **[17]** author used transfer learning with GoogleNet, VGGNet and RESNet for identification and discrimination of breast tumor in mammograms. In **[18]** author used transfer learning with GoogleNet, AlexNet for identification and discrimination of breast mass tumor in mammograms. In **[19]** 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 **[20]** author proposed a CAD to detect and discriminate breast tumor into in cancerous and non-cancerous using Faster R-CNN using INBreast database.

In this study, we investigated the transfer learning to classify Micro-calcification in mammogram images. Transfer learning is the improved learning of new features by transfer the knowledge from features which have already been fine learned and validated **[21].**

Revised Manuscript Received on January 28, 2020.

Karuna Sharma, Assistant Professor, Department of Computer Science, Banasthali Vidyapith, Rajasthan, India.

Saurabh Mukherjee, Professor, Department of Computer Science, Banasthali Vidyapith, Rajasthan, India.

There are many publicly available models based on CNN architectures which have been well feature trained for recognition of objects and fine tuning with these models have been implemented successfully in disease diagnosis and analysis of medical images **[22].**

II. METHODOLOGY

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.

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 increase the number of the input images by generating newer images from the original input images. Rotation, Flipping,Scaling, Resizing, Color PreProcessing and noise perturbation methods can be used for data augmentation **[23]**.

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 **[25]** contains eight weighted layers consisting five convolutional as well as three fully connected layers, AlexNet is tained 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 WeightLearnRateFactors and BiasLearnRateFactors .

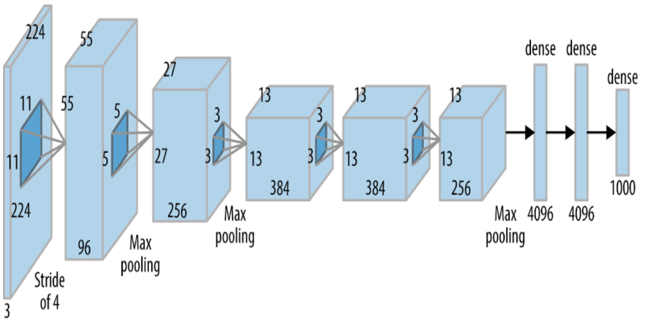


Fig. 1: AlexNet architectur all eight weighted layers including layres five convolutional ,three fully connected.

b) Transfer Learning with GoogleNet

GoogleNet architecture **[24]** 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 googleNet with new images, we have modified the architecture of googleNet, we have replaced fully convolutional layer with different WeightLearnRate and BiasLearnRate Factors.

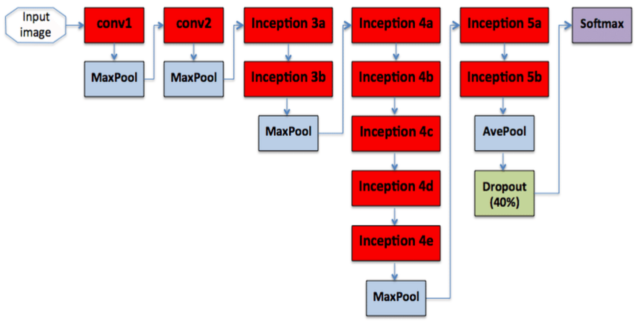


Fig. 2: GoogleNet architecture: All convolutional layers and inception modules have a depth of two.

III. EXPERIMENTAL RESULTS 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, AlexNet gives better results as well as takes less time as it contains less number of layers also. The results with sensitivity and specificity values are given in table 1 and table 2.

Table.1 show the result of Fine Tuned AlexNet with different parameters using transfer learning

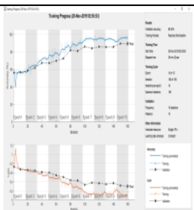
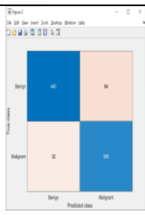
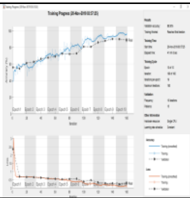
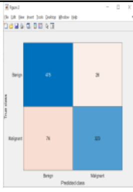
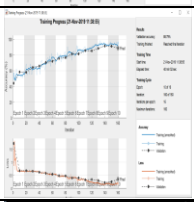
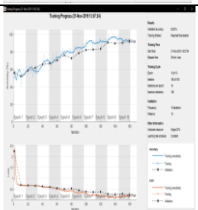
Trained Network Name	Validation Patience	Weight Learn Ratae Factor	Bias Learn Rate Factor	Weight L2 Factor	Validation Accuracy
Al1	15	1	2	1	0.8935
Al2	15	10	20	1	0.889

Al3	15	15	20	1	0.9478
Al4	15	15	30	1	0.9223
Al5	10	20	30	1	0.8568
Al6	5	20	30	1	0.8901
Al7	30	20	30	1	0.8935
Al8	30	20	30	10	0.8879
Al9	30	20	30	5	0.9012
Al10	40	20	30	1	0.9034

Table. 2 show the result of Fine Tuned googleNet with different parameters using transfer learning

Trained Network Name	Validation Patience	Weight Learn Rate Factor	Bias Learn Rate Factor	Weight L2 Factor	Validation Accuracy
Gl1	15	1	2	1	0.8179
Gl2	15	10	20	1	0.8513
Gl3	15	15	20	1	0.7814
Gl4	15	15	30	1	0.8579
Gl5	10	20	30	1	0.8246
Gl6	5	20	30	1	0.8679
Gl7	30	20	30	1	0.8368
Gl8	30	20	30	10	0.8113
Gl9	30	20	30	5	0.8568
Gl10	40	20	30	1	0.8657

Table 3: Results of Fine Tuned AlexNet Network with different parameters

Results of Fine Tuned AlexNet Network with different parameters			
Trained Networ Name	**Training Result**	**Classified Mammograms**	**Confusion Matrix**
AL1			
AL2			
AL3			
AL4			

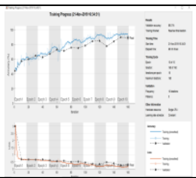
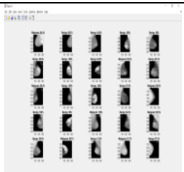
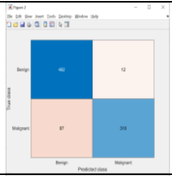
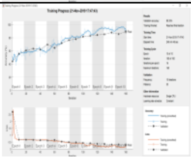
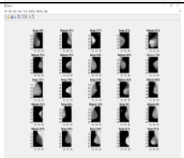
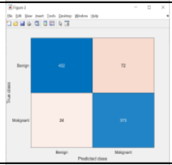
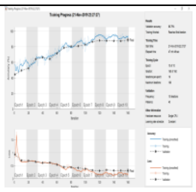
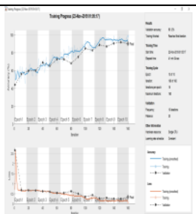
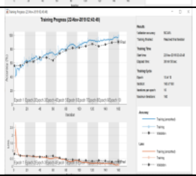
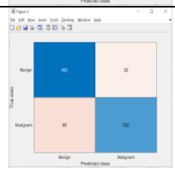
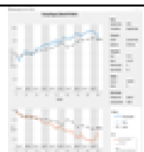
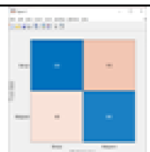
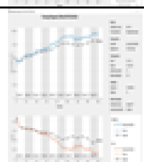
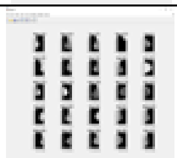
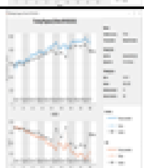
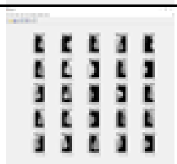
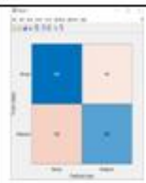
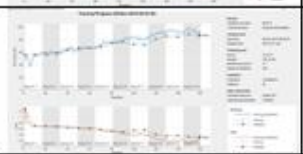
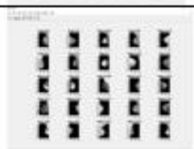
AL5			
AL6			
AL7			
AL8			
AL9			
AL10			

Table 4: Results Fine Tuned googleNet Network with different parameters

Results of Fine Tuned GoogleNet Network with different parameters			
Trained Network Name	**Training Result**	**Classified Mammograms**	**Confusion Matrix**
Gl1			
Gl2			
Gl3			

GI4			
GI5			
GI6			
GI7			
GI8			
GI9			
GI10			

IV. PERFORMANCE EVALUATION OF FINE-TUNED NETWORKS WITH DIFFERENT PARAMETERS

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

Network Name	True Negative	False Negative	True Positive	False Positive	Accuracy
AL1	440	32	365	64	0.8935
AL2	478	74	323	26	0.8890
AL3	500	43	354	4	0.9478
AL4	474	40	357	30	0.9223
AL5	473	98	299	31	0.8568
AL6	492	87	310	12	0.8901
AL7	432	24	373	72	0.8935

AL8	446	43	354	58	0.8879
AL9	484	69	328	20	0.9012
AL10	482	65	332	22	0.9034
GL1	389	49	348	115	0.8179
GL2	423	53	344	81	0.8513
GL3	492	185	212	12	0.7814
GL4	444	68	329	60	0.8579
GL5	427	81	316	77	0.8246
GL6	409	24	373	95	0.8679
GL7	460	103	294	44	0.8368
GL8	444	110	287	60	0.8113
GL9	460	85	312	44	0.8568
GL10	444	61	336	60	0.8657

Table 6 :Performance Evaluation of Fine Tuned AlexNet and googleNet Network.

Network Name	Recall/ Sensitivity/ True Positive Rate	Precision/ Positive Predicted Value	Specificity/ True Negative Rate Selectivity	F-Measure
AL1	0.9194	0.8508	0.8730	0.8838
AL2	0.8136	0.9255	0.9484	0.8660
AL3	0.8917	0.9888	0.9921	0.9378
AL4	0.8992	0.9225	0.9405	0.9107
AL5	0.7532	0.9060	0.9385	0.8226
AL6	0.7809	0.9627	0.9762	0.8623
AL7	0.9395	0.8382	0.8571	0.8860
AL8	0.8917	0.8592	0.8849	0.8752
AL9	0.8262	0.9425	0.9603	0.8805
AL10	0.8362	0.9379	0.9564	0.8842
GL1	0.8766	0.7516	0.7718	0.8093
GL2	0.8665	0.8094	0.8393	0.8370
GL3	0.5340	0.9464	0.9762	0.6828
GL4	0.8287	0.8458	0.8809	0.8372
GL5	0.7959	0.8041	0.8472	0.8
GL6	0.9396	0.7970	0.8115	0.8624
GL7	0.7406	0.8698	0.9127	0.8
GL8	0.7229	0.8271	0.8809	0.7715
GL9	0.7859	0.8764	0.9127	0.8287
GL10	0.8464	0.8485	0.8809	0.8474

V. CONCLUSION

The target of this research work is to classify mammograms containing micro-calcification abnormality into benign and malignant lesions using transfer learning to enhance performance of prediction. Transfer learning enhances the capacity of conventional method it also removes the obstruction of inadequate data samples for training deeper networks. Similarly, we have used the augmentation of data approach to increase the volume of data to enhance the efficiency of CNNs. Finally, the performance of the both pre-trained fine-tuned CNN architectures is also compared with different parameters. It has been perceived that the fine-tuned AlextNet gives better outcomes for classification accuracy and other measures than googleNet. In this paper we have used the whole mammogram images for feature extraction but in future, both manually-crafted lesion attributes together with pre-trained fine-tuned CNN attributes can be used to further enhance the accuracy of classification.

REFERENCES

1. Ferlay, J, Soerjomataram, I, Dikshit, R, Eser, S, Mathers, C, Rebelo, M, Parkin, D.M, Forman, D and Bray, F, 2015, "Carcinoma incidence and mortality worldwide: sources, methods and major patterns in GLOBOCAN 2012", International journal of carcinoma, vol. 136, no.5, pp.E359-E386.
2. Dhillon, PK 2009," _ Breast carcinoma fact sheet", Mortality , vol. 11, no. 5, pp. 10-8.
3. M. L. Giger, J. Boone, and H. Chan, "History and status of CAD and quantitative image analysis," Med. Phys. 35(12), 5799–5820 (2008).
4. M. L. Giger, N. Karssemeijer, and J. A. Schnabel, "Breast image analysis for risk assessment, detection, diagnosis, and treatment of cancer," Annu. Rev. Biomed. Eng. 15, 327–357 (2013).
5. S.-C. B. Lo et al., "Artificial convolution neural network for medical image pattern recognition," Neural Networks 8(7), 1201–1214 (1995).[P2_3]
6. A. R. Jamieson, K. Drukker, and M. L. Giger, "Breast image feature learning with adaptive deconvolutional networks," Proc. SPIE 8315, 831506 (2012).
7. N. K. I. S. R. M. M. Alejandro Rodriguez-Ruiz, JanJurre Mordang, "Can radiologists improve their breast cancer detection in mammography when using a deep learning based computer system as decision support?" Proc.SPIE, vol. 10718, pp. 10718 – 10718 – 10, 2018
8. Khuriwal, N., & Mishra, N. (2018, October). "Breast Cancer Diagnosis Using Deep Learning Algorithm". In 2018 International Conference on Advances in Computing, Communication Control and Networking (ICACCCN) (pp. 98-103). IEEE.
9. Kyono, T., Gilbert, FJ, & van der Schaar, M. (2018). "MAMMO: A Deep Learning Solution for Facilitating Radiologist-Machine Collaboration in Breast Cancer Diagnosis". arXiv preprint arXiv: 1811.02661
10. Valvano, G., Santini, G., Martini, N., Ripoli, A., Iacconi, C., Chiappino, D., & Della Latta, D. (2019). "Convolutional Neural Networks for the segmentation of microcalcification in Mammography Imaging". Journal of healthcare engineering , 2019 .
11. Hagos, YB, Mérida, AG, & Teuwen, J. (2018). "Improving breast cancer detection using symmetry information with deep learning. In Image Analysis for Moving Organ, Breast, and Thoracic Images" (pp. 90–97). Springer, Cham.
12. Zou, L., Yu, S., Meng, T., Zhang, Z., Liang, X., & Xie, Y. (2019). "A Technical Review of Convolutional Neural Network-Based Mammographic Breast Cancer Diagnosis. Computational and mathematical methods in medicine", 2019 .
13. Tsochatzidis, L., Costaridou, L., & Pratikakis, I. (2019). "Deep Learning for Breast Cancer Diagnosis from Mammograms — A Comparative Study". Journal of Imaging , 5 (3), 37.
14. Li, H., Chen, D., Nailon, W. H., Davies, M. E., & Laurenson, D. (2018). "Improved breast mass segmentation in mammograms with conditional residual u-net. In Image Analysis for Moving Organ, Breast, and Thoracic Images" (pp. 81-89). Springer, Cham.
15. Ragab, DA, Sharkas, M., Marshall, S., & Ren, J. (2019). "Breast cancer detection using deep convolutional neural networks and support vector machines". PeerJ , 7 , e6201.
16. Abdelhafiz, D., Yang, C., Ammar, R., & Nabavi, S. (2019)." Deep convolutional neural networks for mammography: advances, challenges and applications". BMC Bioinformatics , 20 (11), 281.
17. Khan, S., Islam, N., Jan, Z., Din, IU, & Rodrigues, JJC (2019). "A novel deep learning based framework for the detection and classification of breast cancer using transfer learning". Pattern Recognition Letters , 125 , 1-6.
18. Jiang, F., Liu, H., Yu, S., & Xie, Y. (2017, January)." Breast mass lesion classification in mammograms by transfer learning". In Proceedings of the 5th international conference on bioinformatics and computational biology (pp. 59–62). ACM.
19. Huynh, BQ, Li, H., & Giger, ML (2016)."Digital mammographic tumor classification using transfer learning from deep convolutional neural networks". Journal of Medical Imaging , 3 (3), 034501.
20. Ribli, D., Horváth, A., Unger, Z., Pollner, P., & Csabai, I. (2018)."Detecting and classifying lesions in mammograms with deep learning". Scientific reports , 8 (1), 4165.
21. Krizhevsky A, Sutskever I, Hinton G E." Imagenet classification with deep convolutional neural networks[CNN]".Advances in neural information processing systems. 2012: 1097-1105.
22. C. Szegedy, W. Liu, Y. Jia, P. Sermanet, S. Reed, D. Anguelov, D. Erhan, V. Vanhoucke, and A. Rabinovich, "Going deeper with convolutions," IEEE CVPR, 1-9 (2015).
23. A. Krizhevsky, I. Sutskever, G. E. Hinton," Imagenet classification with deep convolutional neural networks", in: Advances in neural information processing systems, 1097–1105, 2012.
24. Szegedy, C., Liu, W., Jia, Y., Sermanet, P., Reed, S., Anguelov, D., Erhan, D., Vanhoucke, V., and Rabinovich, A. (2015)." Going deeper with convolutions". In Computer Vision and Pattern Recognition (CVPR'15), the IEEE Conference on.
25. Krizhevsky, A., Sutskever, I., and Hinton, G. E. (2012). "Imagenet classification with deep convolutional neural networks". In Advances in neural information processing systems, pages 1097–1105.

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.

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.