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Mammograms Classification Based on Convolutional Neural Network

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Abstract:
This study presents computer aided diagnosis (CAD) of breast cancer. Using Convolutional Neural Network (CNN) algorithm, designation of CAD for classification of mammogram images into normal and breast cancer classes was done. From Digital Dataset for screening Mammography (DDSM); a system evaluated with 268 mammograms gave an accuracy, precision,sensitivity and specificity of 92%, 85.8%, 100% and 83.7% respectively.Through these results, robustness of the system to assist radiologists during breast cancer diagnosis can be described.
Key words: *Augmentation; mammogram; convolutional neural network, breast cancer; Computer Aided Diagnosis (CAD).*

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I. Introduction

Breast cancer is one of the most common diseases that cause death to several women in the world[1], [2]. About 2.1 million (15%) women are reported annually to suffer from breast cancer and 30% of the affected die due to the illness[3].The rate of breast cancer has been growing linearly reaching up to 19% in 2018[3].

Breast cancer usually takes time to develop and symptoms are shown very late [2]. The role of the early diagnostic techniques becomes imperative for saving lives. As there are no effective ways to cure later stages, many lives can be saved if detection is done at early stage.

Methods like digital mammography and Clinical Breast Examination (CBE) for early detection have been proposed in classifying the mammograms images manually[3]. Nevertheless it is still an open research area due to the intrinsic challenges in attaining better accuracy, efficiency, robustness, and precision when using these methods[4].

Computer-aided diagnosis (CAD) systems have been success-fully used to support human decision-making in radiological image analysis[5]

Due to improved result (accuracy, precision) obtained from the system, the proposed study presents CAD system to assist radiologist in detecting the state of breast from mammograms automatically. By using Convolutional Neural Network algorithm (VGG16), the comparison of two schemes of mammogram classification (Normal and abnormal) was done.

II. Materials and Methods

Dataset

The dataset for training and evaluating the approach was obtained from DDSMdataset [6]. Twotypes of cases were identified: normal and abnormal mammograms. DDSM contains 4362 mammograms, 2187 being normal and 2175-abnormal. These were later divided into training, validation and testing during CAD designing by using python programming language.

CAD System

Preprocessing, Feature extraction, and Classification were the steps involved in CAD system designing (Fig.1).

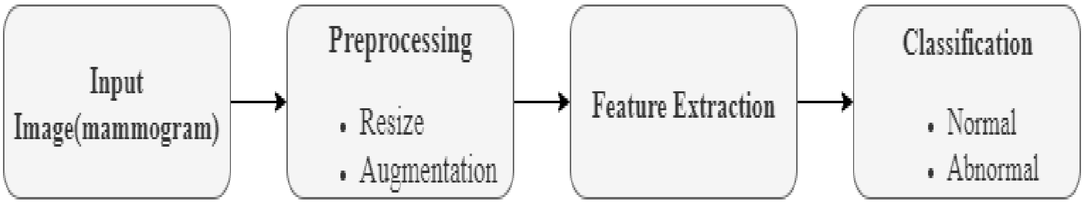


Fig.1: The block diagram CAD system

Preprocessing

This process involved mammograms gray scale images resize and augmentation. Images were resized to $224x224$ in a way that, the model handled data precisely.

Thepixel values of an image,$I(x, y)$ between 0 and 255 were normalized to [0, 1], this is due to the fact that, CNN prefer to work on small intensity value.

$$P(x, y) = I(x, y)/255 \qquad (1)$$

Where by,

$I(x, y)$isInput image and

$P(x, y)$isnormalized image intensity

Augmentation was used during training to increase dataset for the model to learn and avoid over fitting.

Image augmentation techniquesused include: rotation, width and height shift, zoom, shear and horizontal flip (Fig.2). The images were rotated by 40^0, and the application of all techniques resulted into randomly change during training examples to reduce model dependence on certain properties.This leads intoimprovementof the ability of the model for generalization[7], [8].

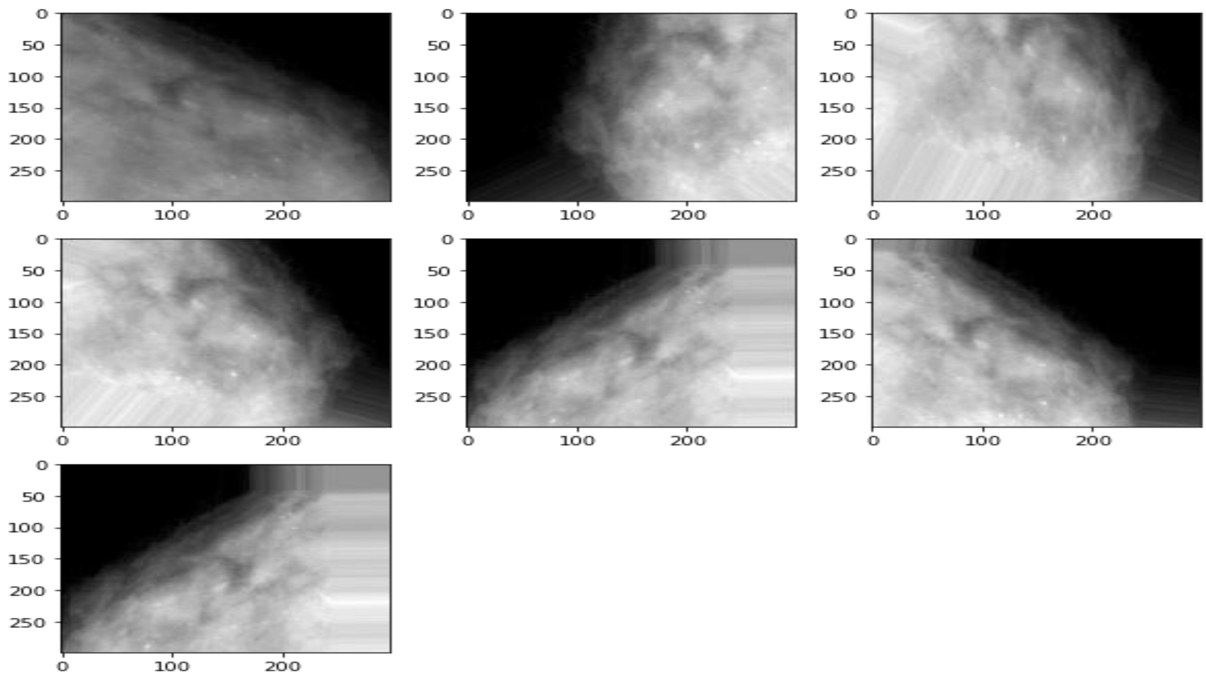


Fig.2: Mammogram images and their randomly augmentation

Feature extraction

Convolutional Neural Network was used for feature extraction. Image features in different convolutional (conv1-13) and Max pooling (Max Pool1-5) layers were involved during theprocess (Fig.3).

Convolutional layer

The image intensity at stage of convolutional layers convolved with 3x3 filters to produce a feature map (Fig. 4) which distinguishes each class during training of the model. This makes the model to learn and identify unique features for every class[8].

The convolutional output size was kept the same as input image. This was done by applying zero padding techniques[8].The size of input image (HxW), convolutional filter/kernel size (hxw) and number of channels (C) convolved to produce feature mapsize. The convolutional output size was calculated by using equation 2 and 3.

$H_0 = H - h + 1$ (2)
$W_0 = W - w + 1$ (3)
Where
H_0 is convolutional output height
W_0 is convolutional output width
W is input image width
H is height of the input image
h is convolutional filter height
w is convolutional filter width
The numbers of channels (64,128,256,512, 512) for every block (1, 2, 3, 4 and 5) were presented respectively as shown in fig. 3.
The convolutional/feature map function was obtained by applying sum of dot product of normalized image intensity and filter window ($f(x, y)$)
$[p \circledast f](x, y) = \sum_{x_0} \sum_{y_0} p(x_0, y_0) \,.\, f(x - x_0, y - y_0)$ (4)
Where:
$[p \circledast f](x, y)$ Is the feature map output

Maximum pooling layer
MaximumPooling (max pool)was used to reduce spatial resolution gradually by down sampling of convolved images to give maximum pixel value for every window slide[1], [8]. Thisenables the model to reduce computation amount by fixing window of 2x2 that slides over all regions of convolved image pixels. The strides(s) were fixedby two steps for every max pooling layer as shown in Fig.3.
The Max pool output size ($H_0 \times W_0 \times C$) was obtained from equation 5 and 6.
$H_0 = \frac{H-2}{S} + 1$ (5)
$W_0 = \frac{W-2}{S} + 1$ (6)

Classification
The pre-trained VGG16 adopted from ImageNet challenge architecture, top layers were excluded and the intended neurons size such as dense1-256 neurons, dense2-128 neurons and last fullyconnected layer were set to binary class (normal and cancer) shown in Fig.3

Rectified linear unit (ReLU) and Dropout
Rectified linear unit (ReLU) was applied to dense1 and2 for easy way of train neural network. 20% dropout was applied on dense layer 2 to avoid over fitting. However, dropout had no any contribution on the forward pass and back propagation (Fig.3)[8], [9]
Letting $f(x_i)$ beReLU activation function and x_i be i-element vectors of dense1 and2 in which the ReLU function that are less than zero were set to zero.
The function is defined by:
$f(x_i) = \max(0, x_i)$ (7)

Sigmoid function
Sigmoid function was applied for output layer to give probabilistic prediction of classes. The output layer is binary (Fig.3) which was generated from normal and cancer classes.
The sigmoid function, $\sigma\big(f(x_i)\big)$ is defined as
$\sigma\big(f(x_i)\big) = \frac{1}{1-e^{-f(x_i)}}$ (8)

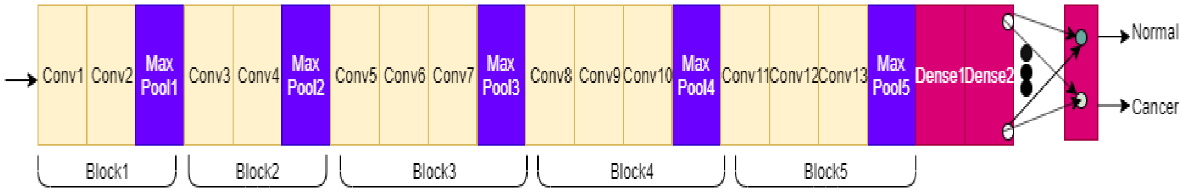


Fig.3: VGG16 sytem for CAD designing

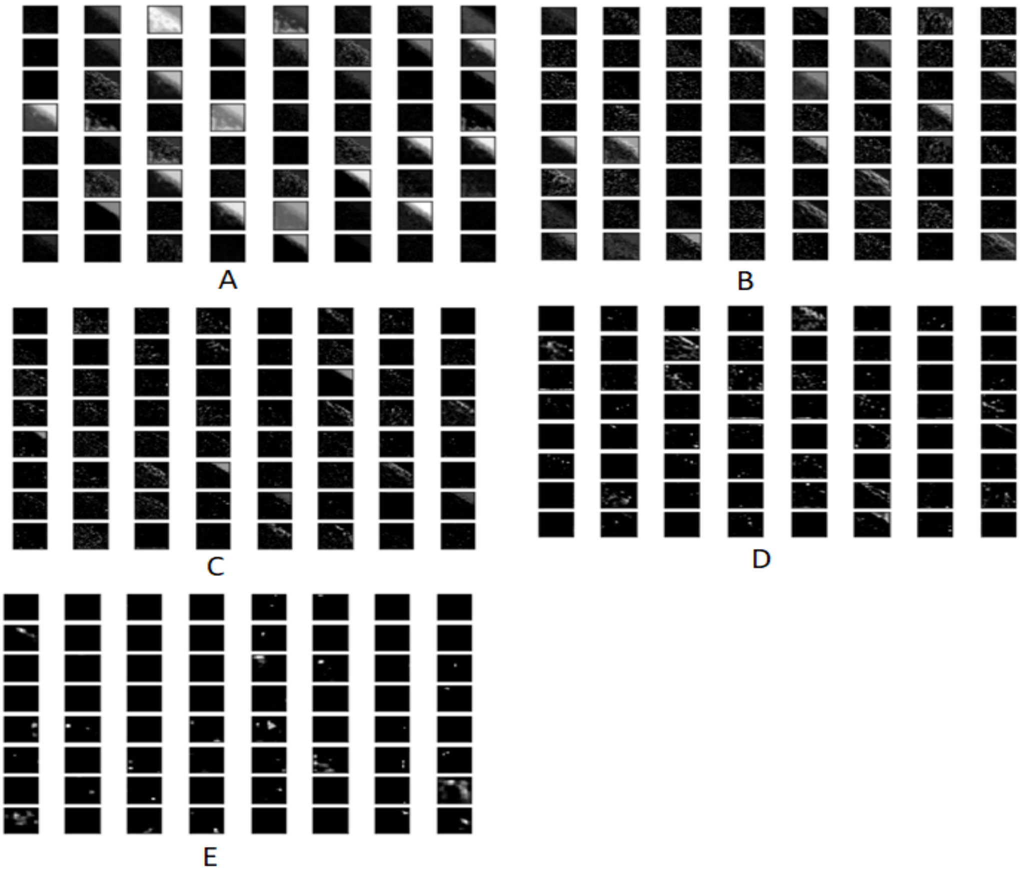
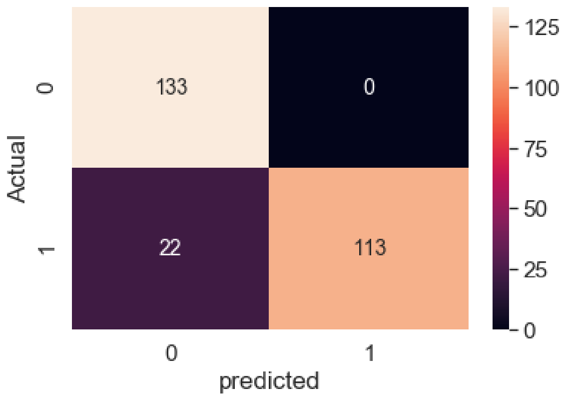


Fig.4: Feature maps visualizations from CAD (fig.3). (A) Conv2, (B) Conv4, (C) Conv7, (D) Conv10, (E) Conv13 for 64 channels

III. Result

The confusion matrix result obtained by running python codes in evaluating the 268 DDSM images, 135 and 133 were foundto be normal and abnormal respectively (Table 1).

Table no1: Confusion Matrix of System Test Data (0 For Abnormal and 1 for Normal Class)



FromTable 1, thestatistical analysis of accuracy, precision, sensitivity, specificity and F1 score for testing mammogram images were determined and by using equations 9, 10, 11, 12[10], [11], results were obtained and presented in Table 2.

Table no2:Accuracy, Precision, Sensitivity, Specificity and F1 Score for the Tested Mammogram Images

Accuracy	Precision	Sensitivity	Specificity	F1 score
		(%)		
92	85.8	100	83.7	92.3

$Accuracy = \frac{TP+TN}{TP+TN+FP+FN}$(9)
$Precision = \frac{TP}{TP+FP}$(10)
$Sensitivity(TPR) = \frac{TP}{TP+FN}$(11)
$Specificity(FPR) = \frac{TN}{TN+FP}$(12)
$F1\ score = \frac{2\times sensitivity\ \times precision}{sensitivity\ +precision}$(13)
Where:TN:True negative, TP: True positive,FN: False negative and FP: False positive
TN and TP represent the number of correctly classified samples, while FN and FP represent number of misclassified samples

The performance measures of the optimally tuned fully connected layers (top layers) of vgg16 convolutional neural network classifier in comparison with the other classifiers method are presented in Table 3

Table no3: Comparative Analysis

	Accuracy	Sensitivity	Specificity
		%	
AlexNet-SVM[11]	87.2	86.2	87.7
SONN[12]	89.873	90.984	86.111
SVM-MLP[13]	87	95	75
K-NN[14]	89	90.74	86.96
CNN[15]	85	-----	-----
Proposed method	92	100	83.7

IV. Discussion

The proposed algorithm for mammographic breast cancer detection achieves better results (of 92% accuracy) as compared to what was reported by Soriano et al[15] , Dheeba et al[12], Ragab et al [11], Srivastava et al [13] and Karahaliou et al [14]. The work of Singh et al[16] achieves higher results, though different approaches with higher order textural features which are computationally very expensive were employed.

Sensitivity or true positive rate (TPR) is the measure of total images predicted correctly positive (cancer) to a total images predicted correct positive and images predicted false negative(FN)[17].It describes the way CADClassifies cancerous mammogram images correctly [11]. This is to say that, the higher the sensitivity the higher the rate of cancerous mammogram detected correctly.

In the present study, sensitivity of 100% was achieved.This describes that, all cancerous mammograms used during testing of CAD were classified correctly.

Specificity or false positive rate (FPR) is the measure of total images predicted correctly negative (normal) to total images predicted correctly negative and images predicted false positive (FP)[11]. This describes how the CAD classifies non-cancerous mammogram images correctly.The higher the specificity, the higher the rate of non-cancerous mammogram detected correctly[11].

In this study 83.7%Specificity of all normal mammograms wasclassifiedcorrectlyby the CAD, 16.3% classified as cancer mammograms this is due to micro calcification detected from those images.

Summarizing the results in Table no3for actual experimentation of mammograms, the classification accuracy of tuned fully connected layers of vgg16 is higher than that of the other well-known classifier models. This is because of the fact that the vgg16 incorporates convolutional layer for unique feature maps and tuned fully connected layers. This superior performance makes tuned fully connected layers (top layers) of vgg16 appropriate for powerfully detecting of abnormalities in mammograms.

V. Conclusion

The goal of this work was to detect breast cancer based on CAD mammogram images. The proposed CAD gave the accuracy sensitivity and specificity of 92%, 100%, 83.7% respectively when tested with 268 images from DDSM dataset. 8% of tested images miss classified by the proposed algorithm.

False positive and negative rateneed to be reduced in future studies leading into the increase of sensitivity and specificity; hence improve robustnessto assist radiologists during breast cancer detection from mammography.

References

[1]. V. Kumar *et al.*, "Breast tumor segmentation and shape classification in mammograms using generative adversarial and convolutional neural network R," *Expert Syst. Appl.*, vol. 139, p. 112855, 2020.

[2]. J. E. Bower, B. E. Meyerowitz, K. A. Desmond, C. A. Bernaards, J. H. Rowland, and P. A. Ganz, "Perceptions of positive meaning and vulnerability following breast cancer: Predictors and outcomes among long-term breast cancer survivors," *Ann. Behav. Med.*, vol. 29, no. 3, pp. 236–245, 2005.

[3]. "https://www.who.int/cancer/prevention/diagnosis-screening/breast-cancer/en/," *retrieved on Dec 28*. 2019.

[4]. R.Gadgil,A;Sauvaget,C;Roy,N;Muwonge,R;Kantharia,S;Chakrabarty,A;Sankaranarayanan, "cancer early detection programs based on awareness and clinical breast examination..interim results from an ubarn community in Mumbai,India," *The breast*, vol. vol.31, p. pp.85-89, 2017.

[5]. M. M. Jadoon, Q. Zhang, I. U. Haq, S. Butt, and A. Jadoon, "Three-Class Mammogram Classification Based on Descriptive CNN Features," *Biomed Res. Int.*, vol. 2017, 2017.

[6]. "https://www.kaggle.com/skooch/ddsm-mammography," *retrieved on Oct 22*. 2019.

[7]. A. Rakhlin, A. Shvets, V. Iglovikov, and A. A. Kalinin, "Deep Convolutional Neural Networks for Breast Cancer Histology Image Analysis."

[8]. O. I. S. C. Manning, *Deep Learning with Python*. .

[9]. P. Hansson, "Fracture Analysis of Adhesive Joints Using The Finite Element Method," *Lund Inst. Technol.*, vol. 60, no. February, pp. 84–90, 2002.

[10]. R. Singh, V. P; Srivastava, S; Srivastava, "Effective mammogram classification based on center symmetric-LBP features in wavelet domain using random forests," *Technol. Heal. Care*, vol. 25, no. 4, pp. 709–727, 2017.

[11]. D. A. Ragab, M. Sharkas, S. Marshall, and J. Ren, "Breast cancer detection using deep convolutional neural networks and support vector machines," pp. 1–23, 2019.

[12]. S. Dheeba, J; Tamil , Selvi, "A swarm optimized neural network system for classification of micro calcification in mammograms," *J Med Syst*, vol. 36, no. 5, pp. 3051–61, 2012.

[13]. R. Srivastava, S; Sharma, N; Singh, SK; Srivastava, "Quantitative analysis of a general framework of a CAD tool for breastcancer detection from mammograms," *J. Med. Imaging Heal. Informatics*, vol. 4, no. 5, pp. 654–74, 2014.

[14]. L. Karahaliou, A; Boniatis, I; Sakellaropoulos, P; Skiadopoulos, S; Panayiotakis, G; Costaridou, "Can texture of tissue sur-rounding microcalcifications in mammography be used for breast cancer diagnosis?," *Nucl. Instruments Methods Phys. Res. Sect. A Accel. Spectrometers, Detect. Assoc. Equip.*, vol. 580, no. 2, pp. 1071–4, 2007.

[15]. M. Soriano, D; Aguilar, C; Ramirez-Morales, I; Tusa, E; Rivas, W; Pinta, "Mammogram classification schemes by using convolutional neural networks," *Int. Conf. Technol. Trends*, pp. 71–85, 2017.

[16]. R. Singh, V, P; Srivastava, S; Srivastava, "Effective mammogram classification based on center symmetric-LBP features in wavelet domain using random forests," *Technol. Heal. Care*, vol. 25, no. 4, pp. 709–727, 2017.

[17]. M. H. Yap, G. Pons, J. Mart, R. Zwiggelaar, A. K. Davison, and R. Mart, "Using Convolutional Neural Networks," vol. 22, no. 4, pp. 1218–1226, 2018.

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