Breast cancer detection in mammograms using deep learning

Abhiram Pillai[1], Amaan Nizam[2], Minita Joshee[3], Anne Pinto[4], Satishkumar Chavan[5]
Don Bosco Institute of Technology, Mumbai - 400070, India
[1]abhirampillai504pk@gmail.com, [2]amaannizam63@gmail.com, [3]minita.joshee@gmail.com,
[4]annerachelpinto@gmail.com, [5]satyachavan@yahoo.co.in

***Abstract*—Breast cancer is the most lethal cancer among women. Early stage diagnosis may reduce the mortality associated with breast cancer subjects. Diagnosis can be made with screening mammography. The main challenge of screening mammography is its high risk of false positives and false negatives. This paper presents the detection of breast cancer in mammograms using the VGG16 model of deep learning approaches. The VGG16 model is trained and tested on 322 images from the MIAS dataset. It performs better as compared to AlexNet, EfficientNet and GoogleNet models. Classification of mammograms will improve mammograms' efficient screening, which will be a support system to radiologists.**

***Keywords*: Breast cancer detection, Classification of mammograms, Digital mammography, Convolutional neural network, VGG16, Deep learning, Mammographic image analysis (MIAS) dataset.**

I. Introduction

Breast cancer disease has the second most noteworthy death rate in women [1]. According to the global cancer statics, the number of new cases in 2018 was estimated to be 18,078,957 and deaths 9,555,027 (52.85%) globally [2]. The breast cancer cases amount to 2,088,849 (11.55%) and the deaths are estimated to be 626,679 (6.56%). Sixty percentage of the deaths occur in low income developing countries like Ethiopia, noted by [3]. If the cancer is detected early, it increases the expectancy of patient's survival rate and decreases the mortality rate. Many presentations like masses, areas of symmetry and distortion, and micro-calcifications may reveal breast cancer. The most common and representative indication is masses which may not be detected due to overlapping breast tissues. Masses can be of two types, namely, undetected and misidentified. False negative cases are categorised as an undetected masses in which delayed diagnosis costs the survival of a patient. Misidentified mass adds to unwanted anxiety and pain to patients, along with the additional burden of re-screening and biopsy [4]. Many mammographic density ratings, ranging from manual classification (e.g. BI-RADS) to automatic scores, have been suggested. Radiologists classified the mammograms visually in the early years by a series of intuitive yet poorly defined breast tissue patterns. Manual classification is a low cost solution but may lead to considerable risk of misclassification. Also, mammogram interpretation is challenging and the possibility of missing abnormality for the tired radiologist or inexperienced personnel may exist. Therefore, it is expected to have an efficient, inexpensive, robust, and accurate non-invasive system or tool for breast cancer detection using mammogram. This paper presents breast cancer detection using mammograms in Cranial-Caudal (CC) and Medial-lateral oblique (MLO) views using convolutional neural network i.e. VGG16.

The paper is organized as follows: Section II discusses the earlier work in breast cancer detection. Section III explains the presented VGG16 framework for classification of mammograms. Section IV provides the experimental findings followed by the conclusions in Section V.

II. Related Work

Mammography can be used as a non-invasive method for screening purposes and supporting modality for prognosis and precise treatment. A status report of the various types of cancer is analysed for both sexes [2]. Breast cancer is the most lethal cancer in females.

There was a breakthrough in 2008 for image classification due to the development of a convolutional neural network (CNN) to classify objects in 1000 classes [5]. Singh et al. [6] presented breast cancer diagnosis efficiently in an early stage of cancer. To classify mass and non-mass regions in the breast, Petrosian et al. [7] preferred texture features. Deep learning models provided exceptional performance in the field of medical image analysis. Wang et al. [8] proposed an auto-encoder to classify breast lesions. Li et al. [9] developed CNN to classify abnormal mammograms. Detection of micro-calcification using a multi-stage system was presented in [10].

Hadush et al. [11] used faster R-CNN to detect the abnormality in mammograms for the classification of masses into benign and malignant breast cancer. Abbas [12] used multilayer deep learning architecture to classify extracted mammographic masses into benign and malignant breast cancer. CNN based classification of benign and malignant breast masses is experimented with by Arevalo et. al. [13] and Hamed et al. [4].

III. Methodology

The presented work in this paper is the detection of abnormal mammograms using the VGG16 deep learning network. The supervised learning of network is used in this work. The block schematic of the detection of abnormal mammogram is as shown in Figure 1. The dataset used for the experiments is the MIAS dataset, which consists of 322 images. The mammograms in this dataset are categorized into normal class and abnormal class. The distribution of images is 208 normal and 114 abnormal (63 benign and 51 malignant) images in the database. The scans are standardized to a size of 1024×1024 pixels [14]. Figure 2 shows sample images of cancerous mammograms in CC and MLO view from the MIAS dataset.

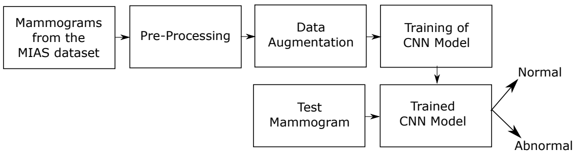

Fig. 1. The block schematic of classification approach for mammograms during breast cancer screening

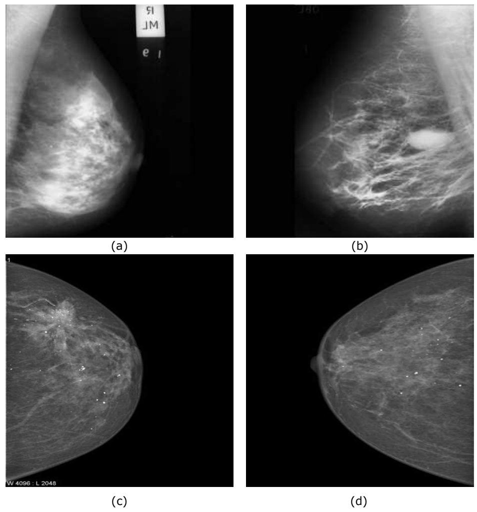

Fig. 2. Sample images of cancerous mammograms from MIAS dataset (a) and (b) MLO views (c) and (d) CC views

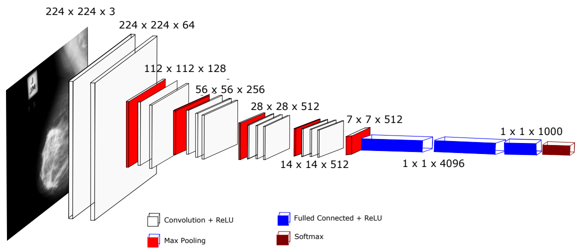

Fig. 3. Framework of VGG16 [16]

A. Pre-processing

The images from the MIAS dataset carry a lot of background noise. The presence of pectoral muscles and outer region makes it a challenging dataset for classification and segmentation. In this work, the annotations from all the images are removed, and the pectoral muscles are also cropped. If done so, it always reduces errors and increases the accuracy of classifying the mammograms. After pre-processing of data, we obtain the final cropped breast region for the classification task.

B. Data Augmentation

The CNN models trained on smaller datasets, like MIAS dataset, suffer from over-fitting problem. To mitigate the over-fitting, data augmentation is preferred [15]. Data augmentation methods like rotation, scaling, horizontal flipping, resizing of the images, shearing etc. are used in this work. Total 2600 images from 322 images of the MIAS dataset are generated using data augmentation. The percentage of mammograms used for training, validation, and testing are 70%, 15%, and 15%, respectively.

C. VGG16

VGG16 model [16] is selected for the work presented on breast cancer detection. The framework of this excellent CNN model is displayed in Figure 3.

It consists of five blocks and 16 layers of convolution for feature extraction from mammograms. Each layer is followed by ReLU and max pooling layers, supporting extraction of varied and in-depth information. Combination of these five blocks (as shown in Figure 3) results in better characterization of mammograms. This leads to improved classification accuracy. The 1×1 convolution layers [17] support the reduction of the dimensionality number of trainable parameters. VGG16 consists of 3×3 convolutions with stride 1 and max pooling layer of 2×2 filters with a stride 2. The network is extensive, and it has about 14,817,193 (approx.) parameters.

IV. Results and Discussion

We trained the dataset on the VGG16 classification model along with AlexNet [5], GoogleNet, and EfficientNet. Dropout layer, batch normalization were also used with each model to reduce over-fitting. While implementing the models, we found out that AlexNet and EfficientNet were very slow and less efficient than the other models. AlexNet, which consists of 8 convolution layers, gave an accuracy of 69.64%, while GoogleNet, which has 22 layers, provided an accuracy of 71.67%. The best results (the highest accuracy of 75.46%) were achieved using the VGG-16, which comprises of 16 layers. VGG16 performs excellent with minimum losses. EfficientNet resulted in an accuracy of 72.29%. A comparative analysis of these four models is presented in Table I. The network is trained with a learning rate of 0.001 for 250 epochs.

TABLE I
Comparison of various networks for classification of Mammograms on MIAS dataset

Name of Model	Number of Layers	Accuracy (%)	Loss	Validation Loss	Parameters (Million)
AlexNet	8	69.64	1.84	1.94	49.0
EfficientNet	17	72.29	0.49	1.53	5.3
GoogleNet	22	71.67	0.31	0.63	22.2
VGG-16	16	75.46	0.31	0.44	138.0

Even though the VGG-16 has fewer layers than some other models, it achieved the highest accuracy on the MIAS dataset. The other three models have limited accuracy compared to VGG16. However, it is still a challenge to achieve good performance with deep learning approaches to classify mammograms from the MIAS dataset.

V. Conclusion

The breast cancer detection in mammograms using VGG16 is presented in this work. The system identifies the given image as a normal or abnormal mammogram. The presented methodology includes image preprocessing, data augmentation, and predicting the outcome of new data provide to the trained model. The average classification accuracy of 75.46% is achieved for the MIAS dataset with the VGG16. It is the highest accuracy compared to AlexNet, GoogleNet, and EfficientNet. However, the number of trainable parameters are huge in the VGG16. This classification approach may help in the early diagnosis of breast cancer during the screening of mammograms. It will be helpful to radiologists for prioritizing the mammograms for abnormality during the screening programs.

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