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A Survey of Convolutional Neural Networks For Mammograms

[1]Likitha P, [2]Dr. B G Prasad,

[1]Student, [2]Professor,

[1, 2] Department of Computer Science & Engineering,

[1, 2] B. M. S. College of Engineering, Bengaluru, India

Abstract: The study of Mammograms is important as it allows an inside look into the breast health of women. It serves to be a preventive screening method for Breast Cancer. A Radiologist is able to detect variations in breast tissue such as calcifications, masses, and also comment on the density of the breast. These findings aid in the early detection and diagnosis of breast diseases. Studying a mammogram however is a tedious and time-consuming task that additionally requires a certain amount of experience. Automating detection and classification of masses, identifying regions of interest, and determination of breast density all aid a Radiologist to effectively and quickly report the findings in a Mammogram. This paper gives an overview of the current work that has been directed to accomplish this objective utilising Deep Learning techniques.

***Index Terms* - Mammogram processing, Deep Learning, Convolutional Neural Networks, Mammography.**

I. INTRODUCTION

Breast cancer is the most generally occurring cancer and also the second leading cause for death due to a disease in women. The preventive screening modality for breast cancer and other related breast ailments is mammography. Mammography is the method of using X-rays to investigate the breast tissue after compressing it so as to make the thickness uniform. The resulting X-ray image is called a mammogram. Radiologists and experts are able to identify abnormal regions such as microcalcifications and masses, as well as determine breast density. The quality and expectancy of life greatly improves upon early detection.

This manual effort of studying mammograms by Radiologists may be supplemented by deep learning models which perform exceedingly well on images. There is a need to automate this process so as to make it quicker, more reliable, and less dependent on specialists. Convolutional neural networks (CNNs) have beat the best in class techniques in visual identification tasks and can be employed for classification and detection tasks [1]. This advancement is due to the expansion in computational capabilities and the accessibility of larger datasets than those a few years prior. The improvements made in CNNs for processing of image data can be leveraged to successfully detect lesions and classify mammograms.

This paper details the diverse types of CNNs that can be used to understand and derive information from Mammograms. It presents the different preprocessing and augmentation techniques that are available for mammograms followed by the networks that are successfully being utilized for the various applications. The remainder of this paper presents the applications and challenges using CNNs for mammograms. The last section holds the conclusion of the review.

II. LITERATURE SURVEY

2.1 Data Preprocessing

Mammogram images need to be pre-processed before training CNNs with them. Separating out the background pixels from the foreground pixels while retaining information in images is seen as an imperative part of pre-processing [2].

2.1.1 Main Preprocessing Steps

The main pre-processing steps for mammogram images are noise removal, contrast enhancement, and breast segmentation. Noise reduction and contrast enhancement is most commonly achieved using the following filters - median filter, adaptive mean filter, or Contrast Limited Adaptive Histogram Equalization (CLAHE) [3]. The process of breast segmentation includes the removal of artifacts, labels, background area, and pectoral muscles as these hinder the detection of masses or calcifications by models [4].

2.1.2 Image Resizing, Cropping, and Down-Sampling

Two main issues while working with mammogram images are - limited training data, and large file sizes causing high computational costs. To overcome these hurdles, most studies use segmented Regions of Interest, or ROIs, which can be obtained via an or an automatic detection system or via manual segmentation using ground truth data. With the lesion centered in the image, the ROIs are cropped and re-scaled to m×m pixels. If the resolution for ROI images is too small, there may not be enough detail to improve classification results [2].

Apart from using ROIs, there have been two strategies that use the full mammogram image for training CNNs. The first employs the down-sampling technique, where the high-resolution mammogram images are down-sampled to a resolution of around 250×250. This strategy, however, fails to find small mass regions or small calcification clusters due to the inevitable loss of information [5]. The second strategy employs an image-level model with a feature extractor. A CNN classifier is trained on segmented patches of the images, which then acts as the feature extractor in this model. The patches are segmented from the input images, such that there is minimal overlap and that each patch is contained within the image. An aggregation across these patches and the CC and MLO views of the mammogram images is used for the final classification [5].

2.2 Data Augmentation

Data augmentation is a technique used to boost performance of deep learning models by reducing overfitting and increasing generalization. Overfitting is a phenomenon which occurs when a model learns the details from training data too well, without learning to generalize well enough. This causes stifled performance when the model is presented with unseen data during testing.

2.2.1 Creation of New Samples

The common cause for overfitting is insufficient data for training the model, especially compared to the number of model parameters that need to be learned from the training data. The data augmentation process helps overcome this issue by artificially creating new sample images using the existing dataset. Common techniques for augmenting mammography images include horizontal flipping, 90°, 180° and 270° rotations, random scaling, and jittering. These techniques do not alter the pathology of lesions, and generate relevant training samples on mammogram images because masses may exist in various sizes and orientations. Data augmentation has been a common process, seen in many studies [2, 6, 7].

2.2.2 Balancing Datasets

The nature of medical data is such that there is a gross mismatch in the number of abnormal to the number of normal cases. This mismatch may introduce a generalisation bias in the CNN model and negatively affect the performance of the model. It may lead to a higher rate of false negatives where the minority class is often misclassified. The papers [4, 9] have noted that the performance of the system is severely impacted by the imbalance in the dataset. Thus, it is recommended to employ a balanced dataset which has a nearly equal share of normal and abnormal cases [9].

Resampling techniques are used to balance the datasets. These techniques involve either increasing the number of instances of the minority class or decreasing the number of instances of the majority class until both classes are equally populated. Random under-sampling involves random removal of normal cases whereas random over-sampling involves random duplication of abnormal cases. In general, one of the two resampling approaches is used based on the problem, available data, and performance. In the case that resampling is not performed as in the case of [7], accuracy alone is not an effective metric to measure the performance. Some alternative metrics such as F1 score, precision, recall, sensitivity, and specificity are used.

2.3 Feature Extraction

CNNs are a popular model used to obtain a mapping from an image to an output. Since CNNs are able to extract features from the images, they do not require any additional information to predict an output, However, augmenting CNNs with features that are relevant to the problem at hand may improve the performance of the model [10], especially when the dataset is of a limited size. The additional characteristics also aid in reducing the number of false positives and false negatives of the system [11]. For mammograms, texture and shape features have been shown to improve the classification performance [12]. Some guidelines for selection of extraction of features given in [13] are independence, reliability, discrimination, and optimality.

2.4 Convolutional Neural Networks

Convolutional neural networks or CNNs are deep learning models that learn through a series of convolutional, pooling and fully connected layers (in order) to classify or predict an output. The convolutional layer uses a kernel of defined size to go over the pixels of input images to extract high level features from the inputs. The pooling layer takes as input the large feature map from the convolutional layer, and uses down-sampling to output a smaller version of the map while retaining the most important information from the input. The fully connected layer is principally the same as a traditional multi-layer perceptron neural network. A loss function connected to the fully connected layer's output helps the model predict either a single class or a probability of classes corresponding to an input image [14].

The ImageNet is an extensive database with 14 million images that was put together for use in research. There is an associated ImageNet Large Scale Visual Recognition Challenge (ILSVRC) which rates the performance of various networks and ranks them accordingly. A number of networks that have done well in the challenge have also been successful for mammograms, some examples being LeNet, Alex-Net, ZF-Net, VGG-Net, ResNet, Faster RCNN, and Mask RCNN [15, 17, 20, 21, 23, 27, 31].

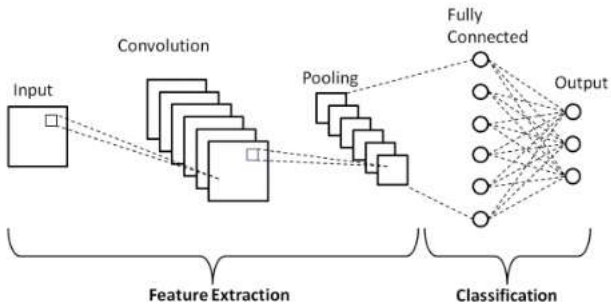

Fig. 1. Convolutional Neural Network Architecture [14]

2.4.1 LeNet

The LeNet by LeCun et al 1998 [15] accepts an input of size 32x32 and processes it in a seven-level convolutional network. The architecture contains a couple of convolutional and mean value pooling layers. This is followed by a flattening convolutional layer, two penultimate fully connected layers and an ultimate SoftMax layer. The LeNet has been successfully used by authors in [16] for early detection of breast cancer.

2.4.2 Alex-Net

The Alex-Net by Alex K et al 2012 [17] won the ImageNet challenge. It accepts an input of size 256x256 and consists of three fully connected and five convolutional layers. The network employs ReLU nonlinearity activation and overlapping pooling layers. The model reduces overfitting by employing data augmentation and dropout techniques. Some more enhancement techniques relevant to mammograms have been identified in [18]. The network has been used to identify dense breasts in [19].

2.4.3 ZF-Net

The ZF-Net by Zeiler et al 2013 [20] tuned the hyperparameters of the Alex-Net without altering the architecture and elements of the earlier network. This network won the ILSVRC in 2013 and with a halved error rate compared to Alex-Net. Some key differences in the ZF-Net are smaller sized filters to mitigate loss of pixels and an increased number of filters in further layers.

2.4.4 VGG-Net

The VGG-Net or Visual Geometry Group Network by Simonyan et al 2014 [21] was a runner-up of the ILSVRC 2014. The network uses even smaller filters compared to ZF-Net and is widely used for feature extraction from images. The weights of the VGG-Net are freely accessible and it has been utilized in a number of different applications as a standard feature extractor. The network has been used to identify mammogram regions of interest for further classification in [22].

2.4.5 ResNet

The ResNet or Residual Network by Kaiming He et al 2015 [23] increases the number of layers in the network to reduce the error and it won the ILSVRC 2015. The network employs skip connections and batch normalisation as a solution to the vanishing gradient problem of deep networks. The network has been effectively used for breast cancer classification in [24, 25].

2.4.6 Fast RCNN

The Fast RCNNs by Girshick et al 2015 [26] are a Region based network that reduces the processing time by obtaining all the regions of interest at once. Fast RCNNs give quicker results as they execute the CNN just once per input and share the information across all regions using selective search. Faster RCNNs by S. Ren et al 2017 [27] however use a region proposal network. These are used for a number of applications ranging from breast detection to breast cancer classification and even detection of calcifications in [28, 29, 30].

2.4.7 Mask RCNN

Mask RCNN by Gkioxari et al 2017 [31], established on Faster RCNN, identifies objects and their classes from input images. Instead of working with bounding boxes, this network identifies the pixels of each object. The authors in [32] have employed the network to be used for breast lesion detection and classification.

III. Applications

3.1 Breast Cancer Detection and Classification

Mammograms are classified in a number of different ways based on the application. Some possible classifications are a simple two class (benign and malignant, normal and abnormal) [6], three class (normal, benign, and malignant) [11], and five class BIRADS score based [33].

3.2 Breast Density Determination

Radiologists realize thick breast tissue makes malignancy screening increasingly troublesome and it expands the risk of breast cancer. Breast density can be classified roughly into four categories: Fatty, Scattered fibroglandular density, Heterogeneously dense, and Extremely dense [33]. The authors in [34] automated breast density classification with CNNs.

3.3 Breast Mass Localization

Unexpected areas of the breast are identified as they are likely to be masses, calcifications, or other similar regions of interest. The detection and localization of such areas in mammograms help in aiding the radiologist by reducing their workload. This has been achieved in [35] by using YOLO-based deep networks.

3.4 Mammogram Enhancement and Indexing

The image quality of mammograms determines the amount of information that can be inferred from it. Authors in [36] apply CNNs to low resolution and noisy mammograms in order to obtain higher resolution clearer mammograms. Searching mammograms based on content is a difficult task that can take advantage of CNNs being able to learn features. This has been implemented in [37] for 24 different classes of images.

IV. CHALLENGES

Mammogram datasets are often of a limited size and this negatively affects the performance of deep learning models. This is in spite of data augmentation and transfer learning techniques that allay this by a large degree. The datasets are also often not well annotated with descriptors for abnormalities.

Scaling issues in resizing large mammograms to a standard size of around 224x224 for use in deep learning networks. This may reduce the size of the region of interest by such a large factor that they may reduce the accuracy of the model. Processing full size mammograms however increases the memory and an overload of features.

Medical datasets are typically imbalanced and this may increase the rate of false negatives of the model. Random resampling techniques aim to reduce this but the effectiveness of the techniques depends on the application. Deep learning models are also prone to higher numbers of false positives which may cause unnecessary discomfort and mistrust in patients.

Finding the balance between accuracy and computation costs. Some networks perform better than others but also require intensive processing time and memory. The trade-off between the two depends on the application at hand.

V. CONCLUSION

This review methodically analyzes the latest methodologies of CNNs in mammograms, and exhibits the advances in deep learning strategies that give promising outcomes which can help radiologists. It serves as a means for the comparison of mammography methods and may be used as a premise in their current and future endeavors. Following the research in the numerous techniques that exist for mammogram processing, it is seen that the appropriate strategies are the ones that follow the unsupervised learning model, mulling over the type of datasets available. Deep learning models have showcased the tremendous applications that are feasible on mammograms. Datasets accessible in large quantities are rarely well annotated and subsequently unsupervised deep learning models provide better performance. In any case, one can't rely upon any single model for mammogram processing as the datasets, applications, and required performance metrics all vary. The training of various models is dependent on not only the size of the dataset or the size of mammograms, but also on the hardware and software available to the researchers. Thus, it is not fitting to recommend one model as the best for execution as every one of them have their own strengths and weaknesses. Additionally, this is a growing and evolving field and there is a need to investigate, explore, and inspect the best yet reasonable technique for the usage.

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