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Towards Breast Cancer Diagnosis Using Multiple Mammography Views

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Abstract. This study introduces a novel computer aided diagnosis system to diagnose breast cancer using two mammography views as input i.e. MLO and CC. The pipeline consists of a convolutional autoencoder that is trained to extract features from different mammograms' views, and one-dimensional convolutional neural network to classify the input embeddings into two classes i.e. benign or malignant. We compare the one-dimensional convolutional neural network classification results with a support vector machine trained on the same latent embeddings. We conclude that the combination of autoencoders and one-dimensional convolutional neural networks yields the best classification accuracy on the test set of the INbreast dataset.

Keywords. Breast Cancer, Mammography, Deep Learning, Convolutional Neural Neutworks

1. Introduction

According to [13], breast cancer is the most common type of cancer in women in the world. Breast screening, or in other terms mammography, can be used as a method to diagnose this type of disease. Since determining the correct type of breast abnormality is a difficult task for an experienced radiologist, researchers have developed computer-aided diagnosis (CADx) systems to early diagnose this disease.

This study proposes a machine learning algorithm to classify mammography images. The CADx system is composed of two parts i.e. the autoencoder and the one-dimensional convolutional neural network (1D CNN). We train an autoencoder to extract features from two mammography views i.e. MLO and CC. The result of the encoder is fed into a 1D CNN to perform the binary classification task. We use a support vector machine (SVM) as a baseline model to classify the input embeddings, and we compare its result with our proposed network.

2. Related Work

Li et al. [9] proposes a handcrafted feature extraction and classification pipeline. The descriptors are extracted using local binary patterns and, then, combined with multi-fractal texture features. The resulting descriptors are selected using two methods i.e. autoencoders and principal component analysis. The reduced features are fed into a support vector machine to perform the classification task. Kulkarni et al. [8] introduced a deep dilated fully convolutional network (DDFCN). The proposed network consists of an encoder, a decoder, a feature module, and a dilation module. Kulkarni et al. [6] introduced a deep learning model to localize and classify tumors from mammography images. The proposed model employs a UNet model to generate the mask and draw the bounding box around the mass. In a second step, the UNet model is used to generate a feature map that is fed into fully connected network for classification purpose. Swetha et al. [16] proposed a machine learning framework to classify and segment mammography images. First, the input image is fed to an edge detector and Gabor transforms. To perform the binary classification a lightweight CNN model is employed with only four convolutional blocks. If the image is abnormal, the result is fed into a segmentation network to localize the tumor.

Liu et al. [10] proposed TrEnD segmentation model that consists of two parallel branchs i.e. a shallow high resolution branch acts on the full resolution of the input image which role is to learn high resolution features, and the deeper low-resolution branch is applied on small patches of the input image to engage on local details and gains multi-scale features. Kulkarni et al. [7] introduced a UNet variant to segment and classify mammography images. The proposed sequeezUNet model consists of an encoder, decoder, and a bottleneck and unlike standard UNet model, squeezeUNet introduces a squeeze block in the encoding phase. After segmenting the mass, the result is fed to a SqueezeUNet model for classification purpose. This study concluded that the use of SqueezeUNet model yield better performance than the use of standard UNet models.

3. Terms Definition

3.1. Convolutional Autoencoders

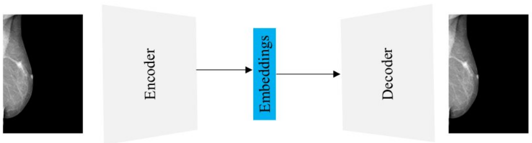


Figure 1: The architecture of a convolutional autoencoder

Convolutional Autoencoders (CA) [2] are convolutional neural networks that are composed of two blocks i.e. the encoder and the decoder, as shown in Figure 1. The aim of a CA is to reconstruct the input image while trying to minimize the loss between the generated and the input images. The mean squared error (MSE) [4] is the loss function that is generally used in autoencoders and it is expressed using the formula below;

$$mse(a, p) = \frac{1}{n} \sum_{i=0}^{n} (p_i - a_i)^2 \tag{1}$$

In this study, we propose a CA with five encoding blocks and five decoding blocks. The encoding block is made of a convolutional layer, a batch normalization [3] layer, and a Leaky Rectified Linear Unit Layer (ReLU) [1]. We adopt a similar architecture in the decoding blocks except that we use de-convolutional layers instead, as shown in Figure 2.

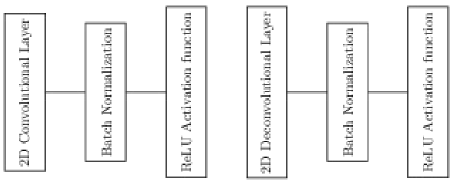


Figure 2 : The architecture of the encoder and the decoder blocks

3.2. One-dimensional Convolutional Neural Networks

Convolutional neural networks [14] are inspired by the human visual cortex, and they consist of convolutional layers, batch normalization layers, and pooling layers. The 1D convolutional layer uses kernel filters to extract features from a sequence, and it is generally used to process audio data, time series, and embeddings. In our case, we use this kind of neural networks to extract features from the embeddings generated by convolutional autoencoders.

We propose a lightweight 1D CNN to extract features from input embeddings, then we feed the result into a fully connected network, as shown in Figure 3.

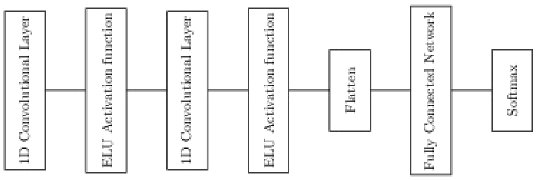
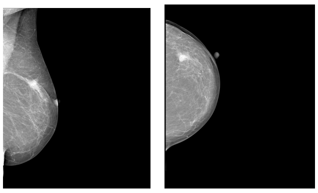


Figure 3 : The architecture of the proposed one-dimensional convolutional neural network

4. Dataset

This study considers using the INbreast mammography dataset [11] which consists of 115 cases and a total of 410 mammograms. The dataset contains medilateral oblique (MLO) and Craniocaudal (CC) mammography views for each study. Each mammogram is labeled according to the Bi-RADS [15] standards and, in this study, we set a threshold in order to keep only the benign and malignant cases. The images have 2560 X 3328 size and they are saved in DICOM [12] format.



(a) (b)

Figure 4 : (a) is an MLO mammography view, and (b) is a CC mammography view

5. Methodology

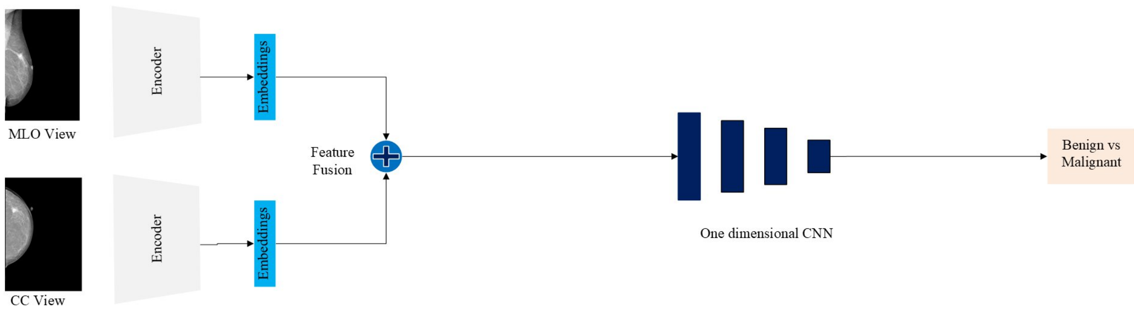


Figure 5 : The dual input model architecture

As a preprocessing step the input images are converted into tensors and normalized. The CA takes as input a grayscale mammography images with one input channels and generate latent embeddings that are concatenated with the second view embeddings and fed into a 1D CNN which predicts the type of abnormality present in both mammogram views, as shown in Figure 5.

The autoencoder is trained during 1000 epochs with an MSE loss function, an Adam optimizer, and a 1e-4 learning rate. The 1D CNN is trained during 100 epochs using a cross entropy loss function and the same optimizer as the autoencoder. The total number of features extracted by the encoder is 1024 and the 1D CNN takes as input 2048 features which represents the combination of both embeddings of the encoders.
As a baseline model, we propose using the same autoencoder to extract features and a support vector machine (SVM) [5] with a radial basis function to classify the embeddings into their appropriate class.

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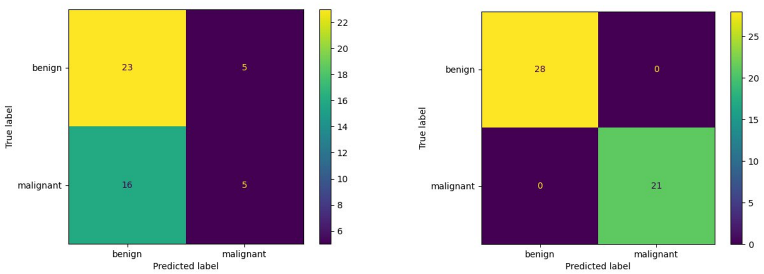
6. Results and Findings

The proposed deep learning model yields the best classification accuracy while scoring 100% on the test set of the INbreast dataset. Table 1 shows the recorded metrics using our proposed model and the baseline.

Method	Accuracy	Precision	Recall
CA-CNN	100%	100%	100%
CA-SVM	57%	53%	54%

Table 1 : The recorded metrics of the baseline and the proposed model on the INbreast's test set

Figure 6 shows the confusion matrices of the two models mentioned in the previous table. The false positive rate of the model that uses 1D CNN is 0 as well as the false negative rate. This means that the proposed model has managed to classify all the test set correctly.



(a) (b)

Figure 6 : (a) is the confusion matrix of the baseline model and (b) is the confusion matrix of our proposed model

7. Conclusion :

This study proposed a deep learning model to classify input mammography images while taking as an input MLO and CC views. The combination of CA and 1D CNN yield the best classification accuracy and outperformed the baseline model that uses an SVM to classify input embeddings. In further studies, we propose exploring other feature extraction techniques such as pre-trained CNNs.

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