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Enhanced Edge Feature Learning Network for Mammogram Classification

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Abstract

Breast cancer is the leading malignant tumor worldwide, and early diagnosis is crucial for effective treatment. Computer-aided diagnostic models based on deep learning have significantly improved the accuracy and efficiency of medical diagnosis. However, tumor edge features are critical information for determining benign and malignant, but existing methods underutilize tumor edge information, which limits the ability of early diagnosis. To enhance the study of breast lesion features, we propose the enhanced edge feature learning network (EEFL-Net) for mammogram classification. EEFL-Net enhances the learning of pathology features through the Sobel edge detection module and edge detail enhancement module (EDEM). The Sobel edge detection module performs processing to identify and enhance the key edge information. The image then enters the EDEM to fine-tune the processing further and enhance the detailed features, thus improving the classification results. Experiments on two public datasets (INbreast and CBIS-DDSM) show that EEFL-Net performs better than previous advanced mammography image classification methods.

INTRODUCTION

Breast cancer is one of the common malignant tumors among women, posing a serious threat to women's physical and mental health [1–3]. Its incidence rate ranks first among female malignant tumors and shows a rising trend year by year. Clinical data show that if breast cancer can be detected at an early stage (stage I), the five-year survival rate of patients can reach 90% [4, 5]. Among the diagnostic methods for breast cancer, diagnostic imaging is the most suitable detection means for women of appropriate age. With the rapid development of information technology, computer-aided diagnostic systems that utilize medical imaging to assist doctors in diagnosis are rapidly gaining popularity, and these systems can assist doctors in making more objective and accurate diagnoses [6].

Edges are fundamental and consistent elements within an image, providing a rich source of information. However, a single edge detection method often has limitations, which has led to the emergence of multiple theoretical fusion edge detection techniques in recent years [7]. For example, the edge detection method combines wavelet theory with the Canny operator [8] and the edge detection method combines the Sobel operator [9] with the Transformer [10]. In medical image analysis, the edge characteristics of a tumor are the key information to determine its benign or malignant nature. Nevertheless, the utilization of tumor edge information by existing methods is still insufficient.

To address this challenge, this paper proposes an advanced deep learning network, EEFL-Net, specifically for the classification task of mammograms. The network employs an advanced edge feature bootstrapping mechanism to enhance the network learning efficiency. EEFL-Net integrates the Sobel edge detection module, a module specifically designed to capture and enhance critical edge information in images. Subsequently, the EDEM analyzes the image at a finer level to further enhance those detailed features that are critical for classification. EEFL-Net achieves a significant performance improvement in the mammogram classification task, providing an effective technique for medical image analysis and diagnosis.

In summary, the main contributions of this paper can be summarized as follows:

- This paper presents EEFL-Net, an advanced deep learning network designed for mammogram classification. The network employs an advanced edge feature guidance mechanism, which significantly improves learning efficiency and classification accuracy.
- Integrates the Sobel edge detection module, which specializes in capturing and enhancing key edge information in images, providing strong feature support for lesion region identification.
- The edge detail enhancement module (EDEM) is introduced to provide a more refined analysis of the image and enhance the small changes and texture information in the image, thus enhancing the network's ability to recognize complex lesion features.
- EEFL-Net has been extensively experimentally validated on two public datasets (INbreast and CBIS-DDSM), demonstrating its effectiveness and superiority in breast lesion classification.

Related Work

Breast image classification is an active research area in medical image classification due to its valuable clinical usability [11]. Early classification studies of breast cancer screening tests relied heavily on manually extracted features to build computer-aided diagnostic systems. In medical images, regions of interest (ROI) [12] are usually small and sparsely distributed on the image, and the process of acquiring ROI requires fine annotation by experienced radiologists, which is not only costly but also time-consuming. With the rapid development of deep learning tech-

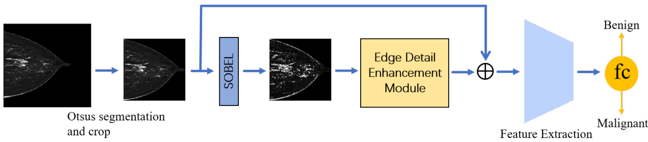

Figure 1. *This figure shows the architecture of the EEFL-Net model. Mammography images are first segmented and normalized by the Otsu method. Then, the key edges in the image are enhanced by the Sobel edge detection module. After that, image detail features are enhanced by the EDEM. These features are combined with the original image and fed into the CNN for feature extraction and finally, the highest probability value is determined by the fully connected layer to arrive at a diagnosis.*

niques, neural networks have been widely used to assist radiologists in interpreting mammograms [13], resulting in a series of methods that do not rely on ROI labeling. For example, Shen et al [14]. improved a weakly supervised localization network to enhance the performance of the network through dense prediction as well as redundant cropping and channel attention mechanisms. Multiscale learning methods enhance the network's ability to learn tumor features by capturing richer multiscale semantic information, but this also brings higher computational costs. Xie et al [15] preserve local semantic information through multiscale pooling, but the fusion of information may still lead to confusion when making predictions.

Compared with these approaches, our proposed model is more concise and efficient in design. It not only successfully overcomes the dependence on ROI or segmentation annotation data, but also avoids the complex multi-stage training process, thus improving classification accuracy while reducing the need for large amounts of annotated data and simplifying the overall training process.

Methodology

In this section, we exhaustively describe our enhanced edge feature learning network (EEFL-Net) for mammogram classification. The network includes an image preprocessing module, an edge detection module, an edge detail enhancement module, and a classifier.

Overview of EEFL-Net

The comprehensive architecture of the proposed method is illustrated in Fig.1, which includes the following elements:

EEFL-Net is trained using only raw mammogram images and their corresponding classification labels. For a given input image x_{input}, we first increase the proportion of pixels with meaningful content in the image by automatically localizing the breast region through edge detection and Otsu segmentation and removing the excess black background. Next, we crop the image by selecting an appropriate bounding box based on segmentation lines or specific rules to obtain the cropped image x, which is then resized to a specific size required by the network input.

Subsequently, we introduce the Sobel edge detection module, which identifies edges in an image by applying the Sobel operator, which highlights the location of edges by calculating the horizontal and vertical gradients of the image brightness. This approach is particularly effective in capturing high-frequency information in images such as contours and lines.

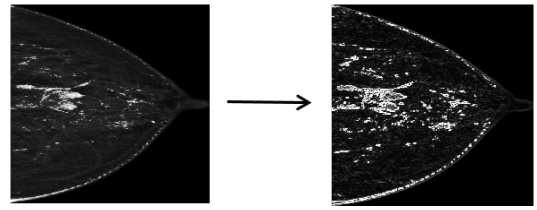

Figure 2. *Example of results obtained after convolution of images with Sobel-filter. Input (left) and edge-enhanced images (right).*

We introduce the edge detail enhancement module (EDEM), which combines ordinary convolution and difference convolution to enhance the representation and generalization of features.EDEM performs a finer-grained analysis of the image, reinforcing small variations and texture information in the image, which enhances the network's ability to recognize complex lesion features.

We use a simple yet effective CNN architecture for deep feature extraction of mammography images. Using this feature extractor, the system can automatically learn and capture abstract and high-level features in the image, which play a crucial role in the analysis and recognition of mammography images. In this paper, f_e denotes the feature extractor. For a given image x, we obtain the feature map:

$$z = f_e(x|\phi), \tag{1}$$

in this context, $z \in \mathbb{R}^{C\times H\times W}$ denotes the feature map, where H and W correspond to the column and row indices, C denotes the channel dimensions, and ϕ refers to the parameters of the network that was pre-trained on the ImageNet dataset [16].

Finally, we use a fully connected layer to synthesize the malignancy likelihood of each set of local features to compute the final malignancy probability. In particular, we consider mammography image classification as a binary classification task to predict the presence of malignant lesions in mammography images. The malignancy probability is derived using a neuron in the network as described in Equation:

$$p = \sigma\left(\omega \cdot z + b\right), \tag{2}$$

where σ denotes the sigmoid activation function, ω and b stand for the weights and biases of the linear regression layer, and $\cdot$ signifies the operation of matrix multiplication.

With these well-designed steps, EEFL-Net can process and analyze mammograms efficiently, providing strong technical support for the early diagnosis of breast cancer.

Edge Detection Module

When radiologists diagnose tumor features, they usually give priority to the edge feature information of the tumor. Inspired by this, this study employs an edge detection module based on the Sobel operator to extract image features. The Sobel edge detection module is specifically designed to identify and enhance edge information in an image. The module highlights the location of edges by calculating the horizontal and vertical gradients of image brightness. Specifically, the Sobel operator convolves the image using two 3×3 convolution kernels to compute the magnitude of

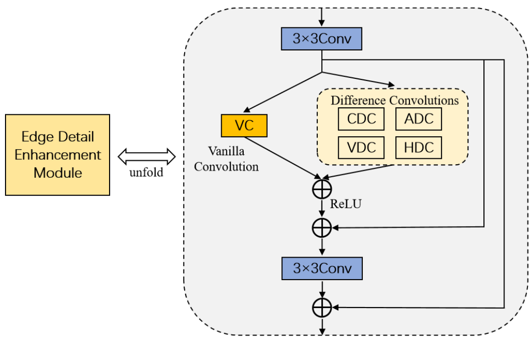

Figure 3. *Edge Detail Enhancement Module contains five parallel deployed convolution layers including VC, CDC, ADC, HDC, and VDC.*

the gradient in the horizontal and vertical directions, respectively. The formulas for these convolution kernels are as follows:

$$G_x = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix}, \quad G_y = \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix}. \tag{3}$$

The gradient magnitude is then obtained by computing the square root of the sum of the squares of these two gradients:

$$G = \sqrt{G_x^2 + G_y^2}. \tag{4}$$

The sample results of the edge-enhanced image are shown in Fig 2, in which the tumor edge features become more obvious and prominent. By applying the edge enhancement technique, the subtle edges and contours in the image are enhanced, which makes the tumor region more clearly defined and provides important information for subsequent image analysis and processing.

Edge Detail Enhancement Module

In this paper, we design an edge-detail-enhanced convolution module (EDEM), whose core goal is to enhance the model's ability to capture high-frequency information (e.g., edges and contours) by integrating well-designed a priori knowledge into traditional convolutional layers. The module is innovative in that it fuses ordinary and differential convolution (DC), including center differential convolution (CDC), angular differential convolution (ADC), horizontal differential convolution (HDC), and vertical differential convolution (VDC). These differential convolutions capture high-frequency information such as edges and contours in an image by calculating the differences between pixels, which is crucial for enhancing edge details. We accomplish this by deploying five convolutional layers - including four differential convolutions and one ordinary convolution - in parallel. The design of these convolutional layers allows the model to explicitly encode a priori information, such as gradient information, which enhances the model's ability to capture image details.

To simplify the model and reduce the number of parameters and computational cost, we employ a reparameterization technique. Specifically, our formula (with the bias term omitted for simplified representation) is as follows:

$$\begin{aligned} F_{\text{out}} &= \text{EDEM}(F_{\text{in}}) = \sum_{i=1}^{5} F_{\text{in}} * K_i \\ &= F_{\text{in}} * \left(\sum_{i=1}^{5} K_i \right) = F_{\text{in}} * K_{\text{cvt}}, \end{aligned} \tag{5}$$

Where EDEM$(\cdot)$ denotes our proposed EDEM operation, K_i ($i = 1:5$) represents the convolution kernel for VC, CDC, ADC, HDC, VDC, respectively, and $*$ denotes the convolution operation, and K_{cvt} denotes the transformation kernel that combines the parallel convolutions together.

Fig 3 visualizes the process of the reparameterization technique, which reduces five parallel convolutional layers to one standard convolutional layer. This technique exploits the additivity of convolution by summing multiple convolution kernels at corresponding positions to obtain an equivalent convolution kernel that produces the same final output. This approach not only simplifies the model structure but also reduces the number of parameters and computational cost of the model while maintaining the performance of the model.

EXPERIMENT

Datasets

In this paper, we conducted experiments using two public datasets and one private dataset:

INbreast [23]: The INbreast dataset contains 410 full-field digital mammograms derived from 115 different cases. These images were randomly divided, of which 80% were used for training and 20% for testing.

CBIS-DDSM [24]: The CBIS-DDSM dataset contains 3,071 mammogram images, of which we used 80% for model training and the remaining 20% for testing.

Experimental Setups

During the preprocessing stage, the original mammography images were processed by a background removal module to retain only the breast area, which was then resized to a fixed dimension. To mitigate overfitting, we employed data augmentation techniques. The normalized and cropped images were initially scaled to the range of [0,1], followed by histogram equalization and random contrast adjustment for each training epoch. Furthermore, our data augmentation pipeline for breast X-ray images included random horizontal and vertical flipping, as well as random rotation between -25 and +25 degrees. These augmentation methods help to enhance the model's generalization capabilities.

The code for this study was developed based on the PyTorch framework and executed on an RTX 3080 GPU. We selected DenseNet-169 as the base model and made necessary adjustments, including replacing the final classification layer and integrating a spatial embedding module, an aggregated pooling section, and a fixed-size linear regression layer. In the experiments, the Convolutional Neural Network (CNN) part was initialized with weights pre-trained from ImageNet and then fine-tuned with a small learning rate. These pre-trained weights were directly sourced from the PyTorch vision library.

For the EEFL-Net model, we employed the Adam optimizer for training. The initial learning rate for both the logistic regression layer and the CNN part was set to 10^{-5}, and the learning rate

Table 1: Performance comparisons of previous state-of-the-art methods on different dataset

Dataset	Methods	ROI	AUC	Acc	Sensitivity	Specificity	Precision
INbreast	Pre-trainedCNN+Randomforest [17]	YES	0.760	0.910	-	-	-
	CAD-Faster-RCNN [18]	YES	0.950	-	-	-	-
	CAD-YOLO [19]	YES	0.948	0.956	0.971	0.924	-
	RGP [20]	NO	0.934	0.919	-	-	-
	GGP [20]	NO	0.924	0.922	-	-	-
	EEFL-Net	NO	0.939	0.950	0.952	0.983	0.933
CBIS-DDSM	Multi-View Hypercomplex CNN [21]	YES	0.843	0.867	-	-	-
	DenseNet-169 [22]	NO	0.764	0.703	-	-	-
	RGP [20]	NO	0.838	0.762	0.774	0.818	0.792
	GGP [20]	NO	0.823	0.767	0.796	0.784	0.801
	EEFL-Net	NO	0.854	0.779	0.855	0.764	0.804

was decayed by a factor of 0.95 after every 10 epochs. Additionally, we set the regularization loss parameter λ to 1×10^{-5}. During training, we used a batch size of 8 and terminated the training after 150 epochs.

The total loss function for the EEFL-Net model is:

$$\mathscr{L} = -\frac{1}{N}\sum_{n=1}^{N}\left(c_n\left[t_n \log p_n + (1-t_n)\log(1-p_n)\right]\right) + \frac{\lambda}{2}\|\theta\|^2, \tag{6}$$

where, c_n denotes the artificial rescaling factor for the loss function, $t_n \in \{0,1\}$ stands for the true label of the mammography x_n, p_n denotes the predicted probability of a malignant tumor, λ is the regularization term controlling the model's complexity, and θ signifies the parameter of EEFL-Net.

Experiment Results

Comparative Experiments

In this paper, we validate the effectiveness of EEFL-Net by completing the experimental EEFL-Net on two public datasets and comparing it to a large number of baseline models. Performance metrics for all methods were assessed using categorical AUC, Acc, sensitivity, specificity, and precision.

Our experimental results, as shown in Table 1 , indicate that our performance is comparable to those methods that utilized ROI annotated data; in contrast, our results significantly outperform other methods that did not employ ROI annotations.

On the INbreast dataset, our experiments did not utilize ROI annotations, demonstrated that EEFL-Net achieved improvements of 0.2% in Acc, 0.5% in AUC, and 0.6% in specificity. Similarly, on the CBIS-DDSM dataset, also without ROI annotations, EEFL-Net surpassed previous methods with significant improvements: AUC by 5.3%, sensitivity by 1.7%, and precision by 2.4%.

All experimental results for the baseline methods were obtained from the original papers corresponding to each method. EEFL-Net achieved the highest performance scores on two public datasets compared to these methods, demonstrating its effectiveness and robustness.

Ablation Experiments

In this study, we validate the effectiveness of the Sobel edge detection module and edge detail enhancement module (EDEM) in the mammography image recognition task through a series of ablation experiments. The detailed results of these experiments have been presented in Table 2, providing a solid data base for further analysis and summarization.

Table 2. Comparison of auc and accuracy for different networks on Inbreast database.

Methods	AUC	Acc
Densenet-169	0.902	0.896
DenseNet-169+SOBEL	0.913	0.902
Densenet-169+EDEM	0.931	0.915
Densenet-169+SOBEL+EDEM	0.929	0.950

First of all, edge information plays a crucial role in images, especially in medical image analysis, where tumor edge features are essential for distinguishing between benign and malignant tumors.The Sobel Edge Detection Module effectively highlights the edge locations and enhances high-frequency information in the image, such as contours and lines, by calculating the horizontal and vertical gradients of the image luminance. This enhancement allows the model to more accurately identify and locate tumor regions, laying the foundation for subsequent processing steps.

Second, EDEM enhances the model's ability to capture image details by combining ordinary and differential convolution. This fine-grained processing reinforces small changes and texture information in the image, improving the network's ability to recognize complex lesion features.The design of EDEM allows the model to explicitly encode a priori information, such as gradient information, which enhances the model's ability to capture image details.

Through the experimental results, we can see that the addition of Sobel edge detection and EDEM results in a significant improvement in the AUC and accuracy of the model compared to using only Densenet-169. This finding provides empirical support for edge enhancement to improve recognition performance.

Taken together, this study successfully enhanced the model's performance in the mammography image recognition task by integrating the Sobel edge detection module and the EDEM, significantly improving the AUC and accuracy.

Conclusions

In this section, we propose an enhanced edge feature learning network (EEFL-Net) for mammogram classification. This network effectively improves the ability to distinguish benign and malignant tumors by combining Sobel edge detection and edge detail enhancement. Experimental results on multiple datasets show that EEFL-Net outperforms existing techniques in key performance metrics, even in the absence of ROI annotations. In addition, our model reduces the number of parameters and computational cost by fusing differential convolution and ordinary convolution, as well as employing reparameterization techniques, while maintaining high performance. Overall, EEFL-Net provides an effective new tool for medical image analysis and early diagnosis of breast cancer. In the future, we will continue to optimize the network structure and validate its performance on a wider range of datasets to facilitate the translation of this technology to clinical applications.

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