TRANSPARENCY STRATEGY-BASED DATA AUGMENTATION FOR BI-RADS CLASSIFICATION OF MAMMOGRAMS

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ABSTRACT

Image augmentation techniques have been widely investigated to improve the performance of deep learning (DL) algorithms on mammography classification tasks. Recent methods have proved the efficiency of image augmentation on data deficiency or data imbalance issues. In this paper, we propose a novel transparency strategy to boost the Breast Imaging Reporting and Data System (BI-RADS) scores of mammograms classifier. The proposed approach utilizes the Region of Interest (ROI) information to generate more high-risk training examples from original images. Our extensive experiments were conducted on our benchmark mammography dataset. The experiment results show that the proposed approach surpasses current state-of-the-art data augmentation techniques such as Upsampling or CutMix. The study highlights that the transparency method is more effective than other augmentation strategies for BI-RADS classification and can be widely applied for our computer vision tasks.

Index Terms— Mammogram, deep learning, data augmentation, abnormality detection, BI-RADS classification.

1. INTRODUCTION

Breast cancer has currently become the most common cancer, based on statistics of the International Agency for Research on Cancer (IARC) in December 2020 [1]. The American Cancer Society (ACS) stated that the average hazard proportion of a woman in the United States developing breast cancer during her life was about 13% [2]. WHO estimated that 2.3 million women were diagnosed with breast cancer, and there were about 685,000 deaths worldwide in 2020 [3]. The recommendation of experts for women at high risk of breast cancer is to take diagnostic screening annually to detect cancer earlier and receive effective treatments beforehand. Mammography is a prevalent X-ray examination for breasts and is employed in computer-aided diagnosis (CADx) systems to assist radiologists in assessing breast cancer risk. In particular, the BI-RADS score is used as a risk evaluation and quality assurance tool that supplies a widely accepted lexicon and reporting schema for breast imaging [4]. This standard consists of seven assessment levels: BI-RADS 0 (incomplete), BI-RADS 1 (negative), BI-RADS 2 (benign), BI-RADS 3 (probably benign), BI-RADS 4 (suspicious for malignancy), BI-RADS 5 (highly suggestive of malignancy), and BI-RADS 6 (known biopsy-proven malignancy). However, malignancy cases are much less than benign cases, leading to data issues consisting of data deficiency and data imbalance.

Recently, several data augmentation strategies have been proposed to boost further training efficiency [5, 6, 7, 8]. There are some deep learning techniques for medical image synthesis, but mainly using generative adversarial network (GAN) [5, 8]. The potential of GANs for images processing issues is enormous because they can be trained to mimic any datasets. However, results from [8] reveal that GANs for medical imaging problems are much inferior to other basic ideas. Some basic augmentation techniques such as cropping, filtering, flipping, noise injection are simple to apply but still adequate for model performance improvement [5]. Two combination methods including [6, 7] could achieve remarkable results because a new image is generated by integrating some original images. Additionally, we observed that lesion areas in medical imaging, especially in mammograms, play an essential role, but most current images generating works have not focused on them. This motivates us to propose a new basic augmentation technique, called Transparency, for mammography BI-RADS classification. We did extensive experiments to show that our approach has outstanding performance compared to CutMix [6] in mammograms.

Our main contribution in this work is developing a transparency data augmentation technique that can generate new compelling images based on original images. A new image focuses on lesion areas without losing global image context by blurring the original image except for lesion areas. The new image would still have the same distribution as the original one and a deep focus on lesions. Our method is easy to apply to any medical dataset whose images have lesion

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One limitation of mammograms is that they contain a large black area without valuable information. Hence, we implement a breast detection model based on YOLOv5 [9] to crop the breast out of the original image. First, we used the labeling tool to label 2,000 images from the internal dataset. Then a dataset is built with 1,600 samples for training and 400 samples for validation. The medium YOLOv5 [9] achieved the mAP of 0.995 for breast detection during testing. The crop samples for validation. The medium YOLOv5 [9] achieved the mAP of 0.995 for breast detection during testing.

The CutMix augmentation strategy [6] was applied to mammograms to increase the number of unusual samples. The key idea behind the CutMix algorithm is to create a new pattern by merging the interpolation of both images and two labels. In this study, we simply moved the lesion region from image A \((x_A, y_A)\) with abnormal bounding boxes \(Box = (x_{min}, x_{max}, y_{min}, y_{max})\) and ground truth labels \(y_A \in \{\text{"BIRADS 3"}, \text{"BIRADS 4"}, \text{"BIRADS 5"}\}\). A mask \(M \in \{0; 1\}^{W \times H}\) is created by reducing the background pixel value to 0 and keeping the box pixels to 1 as

\[
M_{ij} = \begin{cases} 1; & \text{if} \ (x_{min} \leq i \leq x_{max}) \& (y_{min} \leq j \leq y_{max}) \\ 0; & \text{if} \ (x_{min} > i > x_{max}) \& (y_{min} > j > y_{max}) \end{cases}.
\]

We then generate the new sample \((x', y')\) through the equation

\[
x' = M \odot x_A + \bar{M} \odot x_B, \\
y' = y_A,
\]

where \(\odot\) denotes element-wise multiplication, image \(B \ (x_B, y_B)\) with \(y_B \in \{\text{"BIRADS 1"}, \text{"BIRADS 2"}\}\).

The key idea behind the CutMix algorithm is to create a new pattern by merging the interpolation of both images and two labels. We denote that \(x \in R^{W \times H \times C}\) and \(y\) correspond to a mammography sample and its label where \(W, H, C\) are width, height, and channels of this sample, respectively. First, we extract the lesion area from image \(A \ (x_A, y_A)\) with abnormal bounding boxes \(Box = (x_{min}, x_{max}, y_{min}, y_{max})\) and ground truth labels \(y_A \in \{\text{"BIRADS 3"}, \text{"BIRADS 4"}, \text{"BIRADS 5"}\}\). A mask \(M \in \{0; 1\}^{W \times H}\) is created by reducing the background pixel value to 0 and keeping the box pixels to 1 as

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Before putting the data into the models, we define a data loader that loads the data and generates more samples based on the Transparency algorithm. So deep learning models can see about 28,000 images instead of 25,373 original images. In comparing several data augmentation techniques that use information from abnormal bounding boxes, such as Mixup, Cutout, CutMix, the advantages of the proposed approach are using the whole breast image, utilizing informative lesion location, and adjusting the weight of region needed to focus. See Figure 2 for more details.

### 2.2. Deep Learning BI-RADS Classification

We implemented a deep learning end-to-end model to classify BI-RADS on mammograms in this work. Our network consists of two main components: (i) an extraction feature based on the Efficientnet-B2 [10] architecture, the output of which is a feature representation for each sample image, and (ii) a fully connected layer as a classifier to predict results from computed representations. Figure 3 illustrates an overview of the proposed architecture.

### 3. RESULTS

#### 3.1. Dataset

We evaluate the effectiveness of the proposed approach on our private dataset. It was retrospectively collected from Hanoi Medical University Hospital from 2018 to 2020. The dataset includes 36,614 screening mammogram images that come with their BI-RADS classification; each image was annotated by a team of three radiologists specializing in breast imaging for global labels (BI-RADS 1 to 5). These images were divided into three groups by global label stratification method [11]: training set (25,373), validation set (5,398), and test set (5,393). In the dataset, 2,503 images were remarked on three local labels (lesions), including Discrete Mass, Spiculated Mass, Stellate Mass with bounding boxes. The number of lesions on BI-RADS 3 & 4 & 5 occupies almost a total of mass images that contains local labels. Descriptions of three sets on our internal dataset are provided in Table 1.

#### 3.2. Training Methodology & Evaluation Metrics

This study was built on PyTorch version 1.8.1\(^1\), and using a PC with an Nvidia GTX 1080 GPU. We trained the feature extractors using SGD optimizer [12] with a momentum of 0.9 and cosine annealing learning rate [13]. The cross-entropy function was used to calculate the error. For model evaluation, we used F1-score on the 5-class BI-RADS level. F1-score is the harmonic mean of precision and recall. For multi-class problems, F1-score macro, which is defined as the mean of class-wise F1-scores could be used. In our experiments, the results are appraised on image-level for BI-RADS classification.

\(^1\)https://pytorch.org/
The classification models for different augmentation method are trained with the same network architecture (EfficientNet-B2 [10]) and a fixed image size of $1024 \times 768$. The number of epochs was set to 50, and the training process stopped in case there was no improvement in F1-score of the validation set after 15 consecutive epochs by an early stopping callback. The performance of different techniques is assessed on the test set with the same evaluation metrics and network architecture.

### 3.3. Experimental Results

We evaluate the effectiveness of the proposed approach and compare its performance with two other data augmentation techniques: baseline and CutMix [6]. The base model is trained on the initial dataset, with all images cropped with the breast detector and flipped before being included in the model. Table 2 reports the experimental result on our benchmark dataset. Compared to the base model, both CutMix [6] and the proposed Transparency approaches achieved better classification performance, about 3.66% and 4.28% higher F-1 scores at the image level, respectively. In particular, the classification results of BI-RADS 3, 4, 5 increased approximately from 4% to 8% in CutMix [6] and from 1% to 10% for all BI-RADS classes in the proposed approach. In addition, we also observed that our method performed better than the CutMix algorithm for several label classes such as BI-RADS 1, BI-RADS 2, and BI-RADS 3.

### 4. CONCLUSION

Resolving data imbalance is one of the most challenging problems in machine learning, especially in medical image analysis, where anomalous patterns are rare and hard to collect. This study introduced a Transparency strategy-based technique that creates diseased samples by adjusting the pixel values. Experimentally, the proposed approach shows strong evidence that it could improve the BI-RADS classification task on mammogram exams. Our approach is simple and can be applied for various tasks in medical imaging, especially for lesion detection and classification problems.

#### Compliance with Ethical Standards

Our work follows all applicable ethical research standards and laws. The study has been reviewed and approved by the hospital’s institutional review board (IRB). The need for obtaining informed patient consent was waived because this work did not impact clinical care.

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