Deep Curriculum Learning in Task Space for Multi-Class Based Mammography Diagnosis

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ABSTRACT

Mammography is used as a standard screening procedure for the potential patients of breast cancer. Over the past decade, it has been shown that deep learning techniques have succeeded in reaching near-human performance in a number of tasks, and its application in mammography is one of the topics that medical researchers most concentrate on. In this work, we propose an end-to-end Curriculum Learning (CL) strategy in task space for classifying the three categories of Full-Field Digital Mammography (FFDM), namely Malignant, Negative, and False recall. Specifically, our method treats this three-class classification as a “harder” task in terms of CL, and create an “easier” sub-task of classifying False recall against the combined group of Negative and Malignant. We introduce a loss scheduler to dynamically weight the contribution of the losses from the two tasks throughout the entire training process. We conduct experiments on an FFDM datasets of 1,709 images using 5-fold cross validation. The results show that our curriculum learning strategy can boost the performance for classifying the three categories of FFDM compared to the baseline strategies for model training.

Keywords: Curriculum learning, Full-Field Digital Mammography, Deep learning

1. INTRODUCTION

Breast cancer is the second leading cause of cancer death in women. As of 2021, breast cancer takes up 12\% of new annual cancer cases globally.\textsuperscript{1} Full-Field Digital Mammography (FFDM), also known as the digital mammography, is a mammography screening technique that enables the manipulation of images in such a way that it is more convenient for the radiologists to evaluate the areas of concerns with computer-aided detection (CAD) systems. Meanwhile, over the past decade, it has been shown that deep learning techniques have succeeded in reaching near-human performance in a number of tasks,\textsuperscript{2–4} and its application in mammography is one of the topics that medical researchers most concentrate on.\textsuperscript{5}

Curriculum learning\textsuperscript{6} (CL), as a major machine learning regime, is a learning strategy where an “easy-to-hard” curriculum is designed to train the model. CL is particularly intriguing in medical fields, since medical knowledge can serve as an important contributing factor to the definition of “easy” and “hard” in terms of CL.\textsuperscript{3,4} Such a curriculum can be designed with respect to both the input space and the output (task) space. CL in the input space sorts the training samples from the “easier” ones to “harder” ones.\textsuperscript{3,4} And CL in the output (task) space\textsuperscript{7} treats the original task as a “harder” task, and learns “easier” sub-tasks prior to learning the original “harder” task. In classification tasks with multiple (≥ 3 classes) classes, CL in task space creates “easier” classification sub-tasks out of the original “harder” task, usually by grouping classes with similarities,\textsuperscript{7} and thus reducing the number of total classes and the difficulty of the task.

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In this work, we propose an end-to-end curriculum learning in task space strategy on classifying three categories of the Full-Field Digital Mammography (FFDM), namely Malignant, Negative, and False recall (shown in Figure 1). Our method treats the original three-class classification task as a “harder” task in terms of CL, and create an “easier” sub-task of classifying the false recall cases against the combined group of the negative and the malignant cases. We introduce a loss scheduler to dynamically weight the contribution of the two tasks to the loss that the machine learning model learns from throughout the training process. We conduct experiments using an FFDM dataset of 1,709 images using 5-fold cross validation. The results show that our curriculum learning strategy can boost the model’s performance compared to the baseline training strategies.

2. METHOD

2.1 Study Cohort and Dataset

In this IRB-approved study, we used a cohort of 1,709 FFDM images (349 Malignant cases, 653 Negative cases and 707 False recall cases). The FFDM images were retrospectively collected at our institution and reviewed by expert radiologists. Sample images from the three classes are shown in Figure 1. We conducted our experiments with 5-fold cross validation. Within each iteration of cross validation, one fold of the data was used as a hold-out test set. 80% and 20% of the remaining four folds were used as training and validation set respectively. The data partitioning scheme is described with more details in Table 1. Note that the numbers in Table 1 are within ±1 range, since the five folds do not evenly split the data samples.

|                   | Malignant | Negative | False recall | Total |
|-------------------|-----------|----------|--------------|-------|
| Training set      | 226       | 425      | 460          | 1,111 |
| Validation set    | 53        | 98       | 106          | 280   |
| Test set          | 45        | 130      | 141          | 341   |
| Total             | 349       | 653      | 707          | 1,709 |

Table 1: The number of images in each class for each partition of the 5-fold cross validation. Note that the numbers are within ±1 range, since the five folds do not evenly split the data samples.

2.2 Curriculum in Task Space

Curriculum learning seeks a certain “easy-to-hard” order of the learning procedure. The order can be in terms of the input samples or the learning tasks. Here in this study, while we focus on the original three-class classification of the FFDM images, we treat it as a “harder” task and create an “easier” sub-task of binary classification. In this sub-task, the goal is to classify False recall against the combined group of Malignant and Negative cases.

Consider an image-label pair \((x_i, y_i)\), where \(x_i\) represents the image and \(y_i \in \{0, 1, 2\}\) (with 0, 1, and 2 representing False recall, Negative, and Malignant respectively) is the ground truth label of the image. Let \(f(x_i)^{(c)}\) be the probability that the predicted label is \(c\) with \(f(\cdot)\) being the machine learning model and \(c \in \)
\{0, 1, 2\}. We compute the cross entropy loss for the original “harder” task of the three-class classification as in Equation (1), where \(y_{i,c}\) is the \(c^{th}\) element in the one-hot representation of the label \(y_i\).

\[
\mathcal{L}_{\text{hard}}(x_i, y_i) = -\sum_c (y_{i,c} \cdot \log(f(x_i)^{(c)}))
\] (1)

For the created “easier” task, to group the Negative and Malignant classes together against the False recall class, we assign \(x_i\) a new label \(z_i = 1\) if \(y_i \neq 0\) where 1 is the indicator function, which means that \(z_i\) will only be 0 if \(y_i = 0\), or else \(z_i = 1\). In terms of the prediction, we treat the probability of \(z_i = 0\), or else \(z_i = 1\).

\[
\mathcal{L}_{\text{easy}}(x_i, z_i) = - \left( z_i \cdot \log(f(x_i)^{(0)}) + (1 - z_i) \cdot \log(1 - f(x_i)^{(0)}) \right)
\] (2)

\[
\mathcal{L}(x_i, y_i, z_i) = \lambda \cdot \mathcal{L}_{\text{easy}}(x_i, z_i) + (1 - \lambda) \cdot \mathcal{L}_{\text{hard}}(x_i, y_i)
\] (3)

We compute the final loss as a weighted sum of \(\mathcal{L}_1(x_i, y_i)\) and \(\mathcal{L}_2(x_i, z_i)\) as shown in Equation (3). We introduce a loss scheduler to dynamically weight the contribution of the losses from the two tasks throughout the entire training process, which is done by designing a specific function for the \(\lambda\) in Equation (3) with respect to the current training epoch number. In this work, we investigate the loss schedulers listed in Table 2 and Figure 2. In practice, \(\lambda\) can be any function. Note that in Figure 2 and Table 2 all loss schedulers have \(\lambda = 1\) at the beginning of training, and \(\lambda = 0\) after when the current epoch number, \(e\), is larger than a preset hyperparameter \(L\). This is to make the training focus on the “easier” task in the beginning of training, while transitioning to focusing on the “harder” task (original three-class classification) as training progresses.

![Figure 2: Seven different types of loss scheduler.](image)

**Table 2:** Functions of different types of loss scheduler with current epoch number, \(e\), less than the preset hyperparameter \(L\), \((\lambda = 0\) when \(L \leq e \leq E\))

| Loss scheduler type | Function (with \(0 \leq e < L\)) |
|---------------------|----------------------------------|
| Cosine              | \(\lambda(e) = (\cos(e\pi/L) + 1)/2\) |
| Linear              | \(\lambda(e) = 1 - e/L\) |
| Concave quadratic   | \(\lambda(e) = -(e/L)^2 + 1\) |
| Convex quadratic    | \(\lambda(e) = L^{-2} \cdot (e - L)^2\) |
| Exponential         | \(\lambda(e) = e/L, \ e = 10^{-3}\) |
| Logarithm           | \(\lambda(e) = \log(1 + L - e)/\log(1 + L)\) |
| Step                | \(\lambda(e) = 1\) |

![Table 3: Comparison of the different methods’ performance. “LS: X” stands for a certain type of loss scheduler. The bold numbers correspond to the highest value for each metric.](image)

|                | Accuracy | Balanced accuracy | Average AUC | Binary task accuracy | Binary task AUC |
|----------------|----------|-------------------|-------------|----------------------|-----------------|
| Aboutalib et al.\(^5\) (baseline) | 0.489    | 0.458             | 0.658       | 0.598                | 0.633           |
| LS: exponential | 0.491    | 0.468             | 0.658       | 0.623                | 0.641           |
| LS: convex quadratic | 0.510    | 0.474             | **0.672**   | 0.607                | 0.648           |
| LS: linear      | 0.480    | 0.476             | 0.655       | 0.614                | 0.635           |
| LS: cosine      | 0.501    | 0.464             | 0.653       | 0.611                | 0.645           |
| LS: concave quadratic | 0.508    | 0.492             | 0.671       | **0.633**            | 0.647           |
| LS: logarithm   | 0.511    | **0.494**         | 0.668       | 0.617                | 0.644           |
| LS: step        | **0.515**| 0.483             | 0.669       | 0.622                | **0.655**       |
3. RESULTS

We evaluate our method on 1,709 FFDM images using 5-fold cross validation. The results shown in Table 3 are means over the five partitions. We use the VGG16\(^2\) as the backbone of the convolutional neural network (CNN) model. We present the results for different loss schedulers and compare our methods with Aboutalib et al.’s method\(^5\) (baseline) which is a deep learning method on the same three-class classification task as ours. Our model evaluation metrics include the accuracy and the AUC for the three-class classification, and the balanced accuracy by averaging the accuracies of the three classes, which reduces the effect induced by data imbalance. In addition, to further evaluate the methods’ overall ability to distinguish False recall, we also show the accuracy and AUC of the binary “easier” task mentioned in Section 2.2. All experiments are implemented in PyTorch framework and run on an Nvidia TESLA V100 GPU from Pittsburgh Supercomputing Center.

4. DISCUSSION

In this work, we proposed a curriculum learning strategy in task space for FFDM image classification of the three classes of Malignant, Negative, and False recall. We designed a loss scheduler to weight the contribution of the original “harder” three-class classification task and the created “easier” binary classification task.

According to the results, CL in task space with most forms of the loss scheduler outperform the baseline, which attributes to the fact that the loss schedulers focus more on the “easier” task during the first stage of the training process \((0 \leq e < L)\), while Aboutalib et al.’s method\(^5\) (baseline) only uses the basic learning strategy. In addition, the three concave loss schedulers, namely the concave quadratic, logarithm and step function, perform better than the other ones. This is partially because these three concave loss scheduler put reasonably more weight than others on the “easier” task, which provides more help on understanding the “harder” task (see Figure 2).

5. NEW OR BREAKTHROUGH WORK TO BE PRESENTED

As far as we know, this work is one of the newest studies that develop a learning strategy with regard to curriculum learning in task space on FFDM image classification. Our method demonstrates that by scheduling the learning from an “easier” sub-task to the original “harder” task, the model’s performance to classify the three classes of the FFDM images will be further improved from the baseline learning strategies. We believe that such curriculum learning methods will expand the possibilities of artificial intelligence (AI) studies and its applications in future medical imaging research.

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