Gastric Cancer Detection from X-ray Images Using Effective Data Augmentation and Hard Boundary Box Training

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Abstract—X-ray examination is suitable for screening of gastric cancer. Compared to endoscopy, which can only be performed by doctors, X-ray imaging can also be performed by radiographers, and thus, can treat more patients. However, the diagnostic accuracy of gastric radiographs is as low as 85%. To address this problem, highly accurate and quantitative automated diagnosis using machine learning needs to be performed. This paper proposes a diagnostic support method for detecting gastric cancer sites from X-ray images with high accuracy. The two new technical proposals of the method are (1) stochastic functional gastric image augmentation (sfGAIA), and (2) hard boundary box training (HBBT). The former is a probabilistic enhancement of gastric folds in X-ray images based on medical knowledge, whereas the latter is a recursive retraining technique to reduce false positives. We use 4,724 gastric radiographs of 145 patients in clinical practice and evaluate the cancer detection performance of the method in a patient-based five-group cross-validation. The proposed sfGAIA and HBBT significantly enhance the performance of the EfficientDet-D7 network by 5.9% in terms of the F1-score, and our screening method reaches a practical screening capability for gastric cancer (F1: 57.8%, recall: 90.2%, precision: 42.5%).

Index Terms—Gastric cancer, X-ray images, data augmentation, negative sample training, convolutional neural networks, computer-aided diagnosis.

I. INTRODUCTION

GASTRIC cancer is the third most common cancer affecting people in Japan [1]. Advanced gastric cancer has a poor prognosis, but early prognosis before metastasis is good, and thus, early detection and appropriate treatment are important. Gastric cancer is generally diagnosed by radiography or endoscopy. In radiography which is widely used in Japan for mass screening, diagnosis is made by reading the shape of the stomach and atrophy of the mucosa [2], [3]. If an abnormality is diagnosed, a re-examination, such as an endoscopy, is performed. The sensitivity of endoscopy is reported to be 95.4%, which is better than that reported for other techniques [4]. In contrast, radiography can be performed by radiographers, which allows for a large number of images to be taken simultaneously, making it suitable for screening. However, this diagnosis is difficult, especially for inexperienced physicians, because 1) it is subjective and highly dependent on the physician’s reading experience, 2) there are reproducibility issues, 3) it is effort-intensive, and 4) it takes a much longer time to acquire diagnostic skills than other diagnostic imaging methods, such as CT, MRI, and PET/CT [5]. Moreover, according to statistics, the sensitivity of gastric radiography is 85.5% [4]. To address these problems, an automatic diagnostic system that can accurately and quantitatively evaluate gastric abnormalities from gastric X-ray images needs to be developed.

One of the fundamentals of gastric X-ray diagnosis is to find inflammation on the surface of the gastric mucosa [6]. Healthy gastric folds are thin, smooth, and parallel, but gastric diseases, such as inflammation, infection, ulcers, and tumors, can change the thickness and size of gastric folds, resulting in irregular bends, depressions, and tears in the lining (mucosa) [7]. In the 1990s, a method for effectively extracting the pattern of gastric folds by applying binarization as a preprocessing step and a method for estimating the gastric region based on the position of the barium reservoir were proposed [8], [9]. In the 2010s, more empirical studies focusing on gastric folds began to emerge [10]–[13]. Ishihara et al. calculated numerous statistical features (7,760 per case) for H. pylori infection, one of the major causes of gastric cancer, by focusing on post-infection mucosal patterns and gastric folds. Their support vector machine based on the data of 2,100 patients, eight per person, yielded a sensitivity (SE) of 89.5% and a specificity (SP) of 89.6% [12]. In addition, Abe et al. designed their own features based on the symptoms of gastric folds and showed that conventional classifiers, such as LDA and SVM, perform better in lesion site detection (precision 89.3%, recall 100%) [13]. Although the design of the handcrafted features appeared reasonable, the number of images for performance validation was very small (88 images, including 13 abnormalities); moreover, the images were taken in a research environment (controlled geometry). Thus, the performance in a real environment needs to be further validated.
In the past decade, convolutional neural networks (CNNs) have achieved great success in the task of image classification, which has dramatically changed the traditional schema of machine learning. The greatest advantage of CNNs and other deep learning techniques is that they can automatically capture efficient features for the target task, making them a promising technology for diagnosing gastric cancer, where appropriate disease characteristics are difficult to define. For a CNN-based diagnostic technique for gastric X-rays, Ishihara et al. achieved SE of 89.5% and SP of 93.5% using 2,100 patient images (16,800 images in total) [14]. Togo et al. achieved a precision of 98.3% and a recall of 96.2% for 815 patients (6,520 images) using double-contrast barium X-ray images of the upper gastrointestinal tract [15]. On the other hand, in a study of gastric endoscopy, Wu et al.'s system based on 24,549 images achieved SE of 94.0% and SP of 91.0% [16]. Li et al.'s diagnostic system for early gastric cancer using 2,429 images of gastric magnification endoscopy with narrow-band imaging achieved SE of 91.2% and SP of 90.6% [17]. Although these methods have achieved excellent results, from a practical viewpoint, a system capable of detecting ROIs (i.e., candidate lesion sites) is desired to eliminate medical oversights. These methods are based on the assumption that the ROIs for diagnosis are indicated in advance, which leaves some practical issues. In addition, as none of the abovementioned methods describe the details of the dataset, the same patient images can be mixed in the training and test data. In such cases, test data that is very close to the training data is evaluated, resulting in only superficially high scores compared to the intrinsic ability.

To address these issues, Kanayama et al. constructed a system for 130,000 gastrointestinal endoscopic images under the condition that the same patient was not divided into the training and evaluation sets, and reported an average precision of 0.596 for lesion detection. They further generated 20,000 high-definition lesion images from 1,315 narrow-field-of-view images of the lesion through their own generative adversarial network (GAN) [18], and added these images to the training set [19]. Although the accuracy of this method was numerically inferior to that achieved in the previous method, this method is newer and more sophisticated than the previous method and can represent the essential value of the current diagnostic and lesion extraction accuracy when using image-based machine learning technology. Moreover, CNN-based integrated methods that can rapidly detect multiple objects in an image and classify them (e.g., region-based CNN (R-CNN)) [20], Faster R-CNN [21], single-shot multitbox detector (SSD) [22], YOLOv3 [23], and EfficientDet [25] have been successfully applied in various fields, including medicine.

Li et al. analyzed 1,231 chest X-ray images with R-CNN and achieved an average disease localization accuracy 26.9% by using IoU = 0.5 for eight lung diseases [26]. For 13,684 gastrointestinal endoscopic images, Hirasaawa et al. found that the SSD-based system achieved 92.2% SE and 30.6% SP [27]. Zhang et al. used Faster R-CNN for automatic detection of metastatic lymph nodes in upper abdominal CT enhanced at a diagnostic time of 10-15 s/case; they achieved an AUC of 0.925 [28]. Laddha et al. used YOLOv3 for an automatic detection of gastric polyps and achieved mAP of 0.916 [29]. Kanei et al. used a patch-based CNN for detecting chronic atrophic gastritis from gastric X-ray images [30]. They trained image patches of the inside and outside of the stomach and performed a diagnosis through a majority vote of each estimated result in the stomach region. The performance was further improved by increasing the number of training patches in a self-training manner, and finally, a harmonic mean of 95.5% for sensitivity and specificity was obtained for the test data of different patients. Although this method does not provide the lesion location, and thus, does not facilitate interpretation of the results when used, it is a practical diagnostic aid for gastritis that achieves high accuracy while maintaining low cost of annotations for training.

In order to realize practical gastric cancer screening from X-ray images, we previously proposed a practical screening method [31]. We devised our stochastic gastric image augmentation (sGAIA) based on medical knowledge, which significantly improved the performance of object detection models, such as Faster R-CNN. The screening method with the proposed sGAIA can indicate the suspected location of the gastric cancer to the doctors, thus contributing significantly to screening in the field. The recall and precision of sGAIA are 92.3% and 32.4%, respectively. Thus, the recall is approximately 7% higher than that achieved by radiologists (85.5%), and the ratio of true detection to false detection is maintained constant at 1:3 in a box-by-box evaluation using patient cases different from the training set. Thus, sGAIA has achieved practically useful accuracy, but further performance improvements are required. Moreover, it requires more annotated training samples and is very costly, especially for medical data that require a high level of expertise.

This paper proposes a more practical gastric cancer screening method that includes two new proposals: stochastic functional gastric image augmentation (sфGAIA), which is a modification of sGAIA, and hard boundary box training (HBBT), which explicitly includes undetected regions that have not been trained in object detection techniques. To suppress the high-confidence false positives predicted by the object detector, HBBT registers each of those boxes as an "hard-sample" class, and retrains the model until the predetermined convergence conditions are met. We investigated 4,608 gastric X-ray images obtained from 140 patients in a clinical setting and confirmed the practicality and effectiveness of the proposed method by evaluating the gastric cancer detection performance with a patient-based cross-validation strategy.

The contributions of this study are as follows:

- Proposal of sфGAIA, which is a probabilistic augmentation of gastric folds region enhancement based on medical findings.
- Proposal of HBBT, which can significantly reduce the false-positive proposals by recursive training with hard-sample class assignment.
- Our gastric cancer screening system based on EfficientDet with the proposed sфGAIA and HBBT achieved practical performance (recall = 90.2%, precision = 42.5%, F1 = 57.8%).
II. METHODS

This paper proposes a practical gastric cancer screening system using gastric X-ray images with limited labeled data. Our system provides suspicious regions from gastric X-ray images. The overall structure of the proposed system is shown in Fig. 1. This study has been approved by the Institutional Review Board of Tokai University Hospital (No. 20R-033, date of approval: Jun. 12th, 2020).

The important technical proposals in the system are (1) sfGAIA: probabilistic data augmentation for effective detection of gastric fold regions for lesion detection, and (2) HBBT: a training method that iteratively assigns an hard-sample class to bounding box regions that are falsely detected with a high confidence score to avoid detection.

The proposed system uses sfGAIA as online data augmentation for training the backbone network, EfficientDet [25], which achieves high speed, efficiency, and accuracy by using EfficientNet [24] as its backbone. This yields high performance with few parameters and appropriately balances the layer size, width, and image size. The input is 2048 × 2048 pixels, and the output is a bounding box surrounding the presumed cancer region in the image and its confidence score.

A. Stochastic functional gastric image augmentation (sfGAIA)

The proposed sfGAIA is an improved version of our previous proposal, sGAIA [31]. The proposed sfGAIA and sGAIA are probabilistic online data augmentation methods, which can create various images that highlight gastric folds in X-ray images based on medical knowledge to detect inflammation on the gastric mucosal surface. The former sfGAIA improved the detection of gastric cancer by 6.9% in terms of the F1-score (recall 92.3%, precision 32.4%) on a Faster R-CNN model with ResNet-101 as the backbone, validating its practical screening performance. However, in sGAIA, the emphasis probability of each pixel $p(x,y)$, which is important for an effective augmentation, was determined subjectively as a discrete value based on the results of preliminary experiments. Thus, this method needs to be validated and improved.

A schematic of the proposed sfGAIA process is shown in Fig. 2. Like sGAIA, sfGAIA comprises the following four steps, with only step 2 being different.

- (Step 1) Calculation of edge strength
  First, a contrasting enhanced image of the original gastric X-ray image $I(x,y)$, $I_e(x,y)$, is generated by equalizing the histogram of a grayscale image. Then, its gradient and high-frequency component, $\nabla I_e(x,y)$, and $H_e(x,y)$, respectively, are obtained. Each of them is normalized into $[0,1]$, and the normalized edge strength $E(x,y)$ is calculated as follows. Here, $\overline{I}$ is the value of $x$ normalized to $[0,1]$.

$$E(x,y) = \frac{(\nabla I_e(x,y) + H_e(x,y))}{2}.$$  

- (Step 2) Calculation of edge enhancement probability
  The candidate edge regions for the gastric folds are selected probabilistically for each pixel. The proposed sfGAIA differs from sGAIA in this step. In sfGAIA, the probability map $p(x,y)$ of the gastric folds, edge is obtained from the edge intensity $e = E(x,y)$ of each pixel by using the probability defined below.

$$p(x,y) = p(e) = p(E(x,y)) = \frac{1}{1 + \exp(-\gamma E(x,y) + \theta)}.$$  

Here, the parameters $\gamma$ and $\theta$ are hyperparameters of sfGAIA, respectively, defining the gradient of the function and adjusting the probability of running the augmentation of $E(x,y)$ to be 50%. They were determined based on the diagnostic performance of the validation data. Fig. 3 compares the enhancement selection probability $p(e)$ based on the feature intensity $e$ for sfGAIA and sGAIA. In this way, we obtain a reasonable probability of pixel enhancement. Note that, in sGAIA, the probability $p(e)$ is subjectively determined based on preliminary experiments, as described above.

- (Step 3) Determination of gastric fold edge region
  According to the probability map $p(x,y)$, we determine a binary gastric fold edge region. As this region is noisy, we perform a morphological opening operation to eliminate numerous small, isolated regions. Let $G(x,y)$ be a binary mask representing the gastric fold edge regions obtained using this process.

- (Step 4) Enhancement of gastric edge region
  Finally, an enhanced gastric fold edge image $A(x,y)$ is obtained as follows:

$$A(x,y) = I_e(x,y) + \alpha G(x,y) + \beta.$$  

Here, $\alpha$ and $\beta$ are hyperparameters. According to the results of preliminary experiments, the value of $\alpha$ ranges from 0.9 to 1.0 and that of $\beta$ ranges from -15 to -5. Based on this, the proposed sfGAIA probabilistically enhances the location and intensity of the gastric fold region each time. Thus, it produces a different enhanced gastric image for each trial and is highly compatible with online data augmentation in training deep neural networks. Another significant advantage of the proposed sfGAIA is that it does not require any additional runtime.

B. Hard boundary box training (HBBT)

The diagnostic support system for gastric X-ray images is a one-class detection problem that targets only positive (i.e., malignant) regions. However, the task we are dealing with has many regions with similar image features, making it difficult to distinguish even for experts. Given a very large number of training images, the recently developed deep learning-based object detection algorithms can achieve the desired detection performance for the task, but this is difficult in situations where the labeled supervisory data are limited. The images in Fig. 4 are typical false positives indicated by experts in the experiments conducted using a vanilla detection model (i.e., EfficientDet-D7 without the proposed HBBT). They indicate that many of these false-positive detections fall into five major
categories. However, it is difficult to clearly define and control these characteristics in advance.

Especially in a fine-grained task, such as our current target, it is very important to reduce such hard negatives that have high image similarity but are not the target. As described above, in general recognition problems, various training techniques, including adversarial learning, have been applied to reduce the number of hard negatives and increase the generalizability of the models, but their application to object detection models is not common. This might be because the general object detection model learns only the object to be detected and does not explicitly focus on the background.

Therefore, we propose HBBT, which is a very simple and effective to suppress false positives by referring to self-training and the concept of AdaBoost [33]. In general, training negative samples, which are more prone to false positives among the training data, is effective in constructing detectors with few false positives. In our HBBT, we name the false-positive boundary boxes detected by the model hard boundary boxes, assign an hard-sample label to them, and train the model as a two-class detection problem. Here, this newly added hard-sample class label is treated as a negative example. The training is repeated until an optimal F1-score of the validation data is achieved.

III. EXPERIMENTS

A. Datasets

The image set used in this study comprised 4,724 gastric X-ray images (1,117 images with 1,504 lesion annotations by radiologists and 3,607 images without lesions) of 145 patients in clinical settings provided by Tokai University School of Medicine, Japan. A total 116 images of five randomly selected patients (49 of them with 49 annotated boxes) were used as the validation data to determine the hyper parameters and decision to terminate HBBT, and the remaining 4,608 images of 140 patients were used to train and evaluate the proposed method.

Each image was in 8-bit grayscale and had a resolution of 2,048 × 2,048 pixels. Based on each annotation of the
gastric cancer site given by the expert, the smallest rectangle surrounding it was defined as a bounding box that required detection. A patient-based five-group cross-validation was used for training and evaluation. Precision, recall, and F1-score were used as the performance indicators of this system. The system provided candidate lesion bounding boxes and their associated confidence scores were above a predefined detection threshold $\alpha$.

### B. Details of the detection model

We used EfficientDet-D7 as a detection model for gastric cancer with an input resolution of 1,536 × 1,536 pixels. A difference from the original image size was the margin for the random crop performed during training. This model used EfficientNet-B7 as the backbone (384 channels in the feature map, 8 layers of BiFPN, and 5 layers of classification/rectangle heads). The learning rate was 0.001, the batch size was 32, and the number of trainings was 100. As an optimization method, momentum SGD [34] was used, and the exponential decay rate of the first-order moment was set to 0.9. To build a robust lesion detector in terms of various lesion sizes, shapes, and resolutions, we used RandAugment [32], which is a state-of-the-art augmentation method that randomly applies 14 types of data augmentation, excluding color augmentation, to the training data, and treated the model as a baseline for performance.

### C. Experimental conditions

1) **Determination of hyperparameters in sfGAIA:** In this section, we show how to determine the hyperparameters of the proposed sfGAIA (i.e., $\theta$ and $\gamma$ of $p(x, y)$). For $\theta$, we set $\theta = 0.55$ so that the probability of the inflection point of the sigmoid function was 50% based on the intensity distribution of the validation images. For $\gamma$, which characterizes the slope of $p(e)$, we selected $\gamma = 4$ from 2, 4, 6, 8, and 10 (Table I) from the detection performance on validation images.

2) **Detection of malignant regions:** In order to confirm the effectiveness of the proposed system with sfGAIA and HBBT, we conducted comparison experiments using the following combinations of conditions. As there is no directly comparable gastric cancer detection literature, we applied Laddha et al.’s method [29] for detecting gastric polyps as a reference.

- **Model selection and baseline.** We selected two object detection models for this task: ResNet-101+Faster R-CNN (model 1) and EfficientDet-D7 (model 2). The first model has been widely used in the literature including sGAIA. The second model has recently demonstrated state-of-the-art object detection performance and is one of the most advanced models currently available. As mentioned earlier, we applied RandAugment [32] as an online data augmentation to the model and used it as the baseline for each model (i.e., baseline model 1 and 2, respectively). As this task involved a grayscale image, we omitted color augmentation. Based on the detection performance of the validation dataset, we selected four types of augmentations out of 13, with an intensity level of 3 (i.e., $M = 4$ and $N = 3$ according to their notation).

- **Selection of proposed method** We compared the performance of each model with and without the proposed method. Regarding data augmentation, we chose either RandAugment, conventional sGAIA (+sGAIA), or the proposed sfGAIA (+sfGAIA). Regarding the proposed HBBT, this was annotated as use (+HBBT) or not.

### Table I

**Detection performance in validation images for determining hyperparameter $\gamma$.**

| $\gamma$ | precision | recall | F1-score |
|---------|-----------|--------|----------|
| 2       | 35.7      | 89.6   | 51.1     |
| 4       | 39.6      | 91.7   | 55.3     |
| 6       | 31.2      | 91.7   | 46.6     |
| 8       | 32.8      | 89.6   | 48.0     |
| 10      | 30.3      | 89.6   | 45.3     |
Fig. 5 shows an example of augmented images obtained using the proposed sfGAIA. The left-most image is the original and the others are images by sfGAIA. Fig. 6 compares the cancer detection with and without the proposed sfGAIA and HBBT on EfficientDet-D7 network. Here, input images (a), detection results with RandAugment (baseline model 2) (b), and those with the proposed sfGAIA+HBBT (c) are observed. The detection performance of gastric cancer regions from gastric X-rays is summarized in Table II. We confirmed that each of the proposed sfGAIA and HBBT improved the lesion detection performance for both baseline models and outperformed the previously proposed methods, such as sGAIA and Laddha’s methods. The detection results showed that the proposed methods decrease the number of areas that the doctor has to check.

V. Discussions

Our proposed gastric cancer screening support system utilizing the proposed techniques, sfGAIA and HBBT, achieved recall of 90.2%, precision of 42.5%, and F1-score of 57.8% (Table II). These results are significantly better than those achieved using the baseline methods, including RandAugment; a cutting-edge general data augmentation strategy, as well as the existing methods (i.e., sGAIA and those proposed by Laddha et al.). The ability of the proposed method to detect cancer was higher than that of the doctor’s reading (~85%), and in terms of percentage, more than two out of five detection results presented by the system were related to cancer, indicating that the system is practical enough for onsite screening and puts little burden on doctors.

The proposed sfGAIA probabilistically highlights the gastric folds pixel-by-pixel, as shown in Fig. 5, and emphasizes the portion of the folds that should be emphasized based on medical findings. sGAIA was shown to be highly effective in a previous paper [31], and in this experiment, we also introduced one of the most advanced augmentation methods, RandAugment, to each baseline model and compared their performances. In this experiment, we found that the proposed sfGAIA achieved 6.0% and 2.7% better performance in terms of the F1-score than RandAugment on baseline models 1 and 2, respectively. This confirms the importance of probabilistic augmentation based on medical knowledge. sfGAIA further improves the F1-score by 1.2% over sGAIA in a stand-alone comparison (baseline 2). It determines the pixel enhancement probability \( p(e) \) for each pixel in generating an enhanced image to a discrete value based on subjectivity from preliminary experiments. In contrast, in sfGAIA, \( p(e) \) is determined as a continuous function based on the diagnostic performance of the validation data, which is considered the reason why more appropriate and different types of enhanced images were generated to emphasize the gastric folds.

Even a good object detection algorithm exhibits limited accuracy when the training data are limited. The proposed HBBT is a very simple and direct method that recursively...
relearns the false-positive regions of the detector, but achieves a 2.9% improvement in the F1-score (baseline model 2) on its own. HBBT encourages training to reduce the number of false positives, which improves the ability of the model itself to detect the ROIs. As the final model detection is determined by the threshold for the confidence of the bounding box, HBBT reduces not only the number of false positives but also that of false negatives (middle case of Fig. 6). When combined with sfGAIA, it achieves an extremely large improvement of +10.9% for baseline 1 and +5.9% for baseline 2. Because of its simple mechanism, HBBT is a general-purpose learning method that can be used not only for gastric cancer detection, as in this study, but also in general applications.

As sfGAIA is an online data augmentation method and
HBBT is a training method, they do not affect the execution time of the inspection. The processing time required to process one X-ray image is approximately 0.512 s, which makes the proposed method suitable as a practical screening system for gastric X-ray images. The example of the detection results shown in Fig. 6 indicates that the proposed method can correctly detect the mucosal surface without being affected by its irregularity, as shown in the upper row. In addition, the proposed method can correctly detect small areas, as shown in the middle case in the figure. In contrast, as shown in the bottom row, there are some cases in which the proposed method detects the wrong regions. This result almost covers the ROI, but is misaligned, so we evaluate it as a false-positive.

The detection of a gastric cancer region from the X-ray images is inherently difficult, not only for automatic diagnosis systems but also for experts. Despite these difficulties, our system achieves a significant improvement in detection performance. The final result of 42.5% precision at 90.2% recall is considered sufficient for screening, but there is still room for improvement. In the future, we would like to examine the results more closely with the help of experts to improve the system further.

VI. CONCLUSIONS

This paper proposes a practical screening system for gastric cancer from X-ray images by using the following two proposed methods: (1) sfGAIA and (2) HBBT. The detection performance of the proposed method (sfGAIA + HBBT on EfficientDet-D7 network) was 90.2% for recall and 42.5% for precision, which exhibited a 5.9% improvement in F1-score compared to the same network with RandAugment, which is a cutting-edge augmentation method. This result can be attributed to the fact that sfGAIA can obtain more valid probabilities for highlighting gastric folds than the previous sfGAIA and that HBBT can learn negative samples, which are more likely to be false positives in the training data. As sfGAIA is an online data augmentation method and HBBT is a learning method, they do not affect the execution time of the examination and thus are useful screening systems for gastric X-ray images.

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