Deep-leaning using PSPNet, U-net and Yolo toward automated ultrasound differential diagnosis -Application to breast tumors

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1. Introduction

The diagnosis and treatment of human cancerous diseases has become a pressing clinical issue of greater interest worldwide. For instance, extensive research has demonstrated the importance of early detection in reducing cancer mortality. In particular, computer vision technology has attracted much attention in recent years. In this study, we utilized deep learning (DL) for breast cancer detection and semantic segmentation. Specifically, U-Net,[1)] PSPnet,[2)] and YOLO[3)] were executed in a novel way to enable differentiation between benign and malignant tumors with high accuracy.

2. Methods

To achieve the high accuracy in segmentation and/or detection, we devised the way to perform the 3 current state-of-the-art DL models as follows.

2.1 U-Net

Four experiments were conducted with the U-Net architecture. All the experiments were evaluated by calculated its Intersection over Union (IoU) value. Detectability was also evaluated as a new trial.

In Experiment 1, two models were constructed: benign-only and malign-only models. In Experiment 2, several difficult images were excluded by students who were novices in ultrasound imaging. In Experiment 3, the two models trained in Experiment 1 were fed untrained mutual data. In Experiment 4, benign and malignant data used in Exp. 1 were mixed as a single dataset and three models were trained as new trials: (i) for both type tumors simultaneously; (ii) and (iii) with either the absence of masks for benign or malignant data, focusing exclusively on either malignant or benign cases.

2.2 PSPnet

Four experiments were conducted with the PSPnet, renowned for its PSP-module capable of capturing contextual data. The performance was evaluated with IoU, precision, pixel accuracy, and recall metrics.

In Experiment 1, PSPnet was trained with benign data only (349 images); in Experiment 2, with malignant data only (168 images); in Experiment 3,

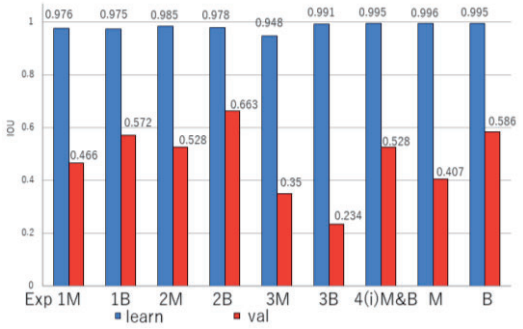

Fig. 1. IoU of U-Nets.

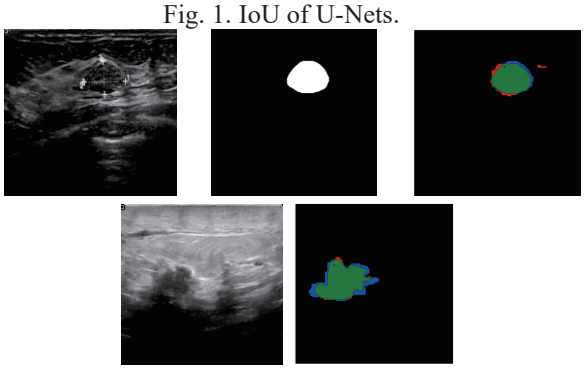

Fig. 2. Examples of segmentation with U-Net for (upper) benign; (below) malignant tumors. Left, original image; middle, ground truth (GT); right, result of matching area with GT (green), not occupied (blue) and overflowed (red) with respect to GT.

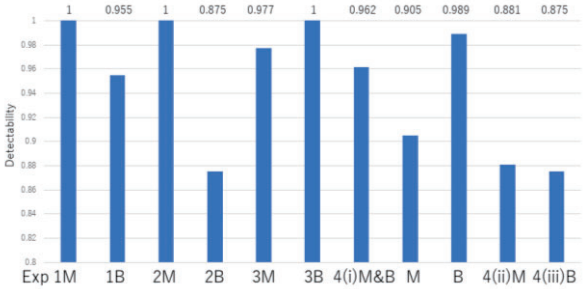

Fig. 3. Detection and differentiation with U-Net.

with both data as usual. In Experiment 4, an augmented dataset was created by randomly rotating the images within a range of -15 to 15 degrees, comprised of 1795 images totally (benign 1220 and malign 575). And, a loss function known as focal loss[4)] was used.

2.3 YOLO

Three types of models were performed using YOLOv5: (1) the malignant-only model, (2) the benign-only model, and (3) the mixed model. For the

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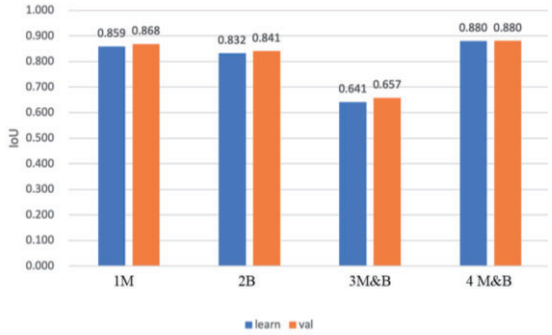

Fig. 4. IoUs of PSPnets.

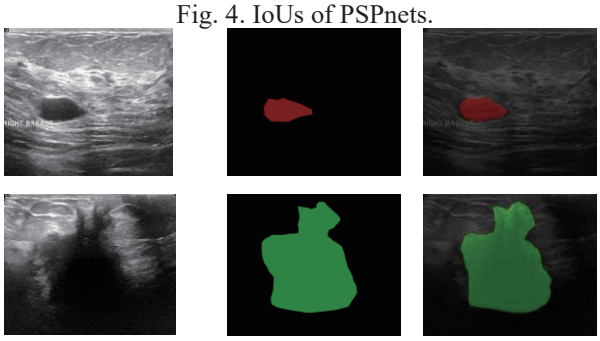

Fig. 5. Examples of segmentations with PSPnet for (upper) benign and (below) malignant tumors. Left: original image; middle: GT; right: result.

mixed model, three specific types were performed similarly to with U-Nets as follows: (i) A model that differentiate between malignant and benign tumors, training both datasets as usual. (ii) A model that modifies the training data to differentiate and detect only malignant tumors. In this case, the benign data was trained with unlabeled data, focusing solely on training for malignant cases. (iii) A model that detects only benign tumors inversely to (ii).

3 Results

3.1 U-Net

Figs. 1 and 2 respectively show the IoU results and the examples of segmentation results. With other version modules, both the training and evaluation data exhibited higher IoU values than those our previously reported[5] and the tendency remained consistent. Malignant was more difficult than begin; Exp 1 < Exp 2; 3M > 3B.[5] The results of 4(ii) and (iii) are omitted since the hyperparameters have not been optimized yet. Fig. 3 shows the detectability, in which 4(ii) and 4(iii) are tentative. However, high capabilities of U-Net about the detection/differentiation were confirmed.

3.2 PSPnet

PSPnet exhibited high performance superior to U-Net. See the IoU values shown in Fig. 4 and the segmentation results in Fig. 5. For the open data, all the IoUs were higher than those with U-Net, particularly for the mixed data. PSPnet demonstrated a commendable level of generalization ability with no over-fitting. With an augmented dataset, the

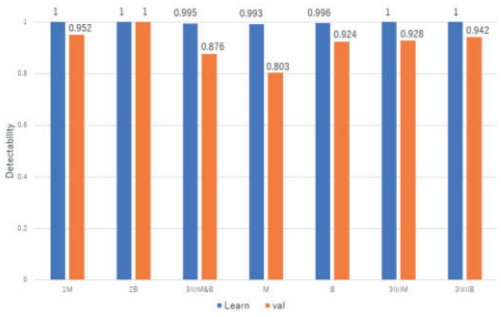

Fig. 6. Detection and differentiation with YOLOs.

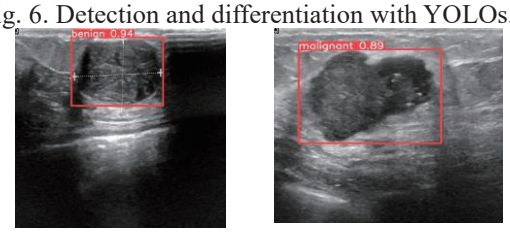

Fig. 7. Examples of YOLO (left: benign, right: malignant tumor)

performance became high significantly. Considering the inherent imbalance between benign and malignant data properties and data number, the focal loss function played a vital role in mitigating the imbalance and enhancing the performance of the model. The precision, pixel accuracy and recall exceeded 90%, indicating the effectiveness in accurately identifying both tumor regions.

3.3 YOLO

Figs. 6 and 7 respectively show the detectability/differentiation and the samples of results. Particularly, the proposed usage of YOLO achieved the higher differentiability than the usual usage. The misdetection rate of 3(ii) and 3(iii) were very low, i.e., 0.057 and 0.119, respectively, similarly to that of 3(i), i.e., 0.037 and 0.117, respectively.

4. Conclusions

The new methods for the U-net, PSPnet and YOLO were considerably effective in increasing the detection and differentiability of tumors.

References

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