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SEMANTIC SEGMENTATION OF FETAL BRAIN ULTRASOUND IMAGES BASED ON A GENERAL FULLY CONVOLUTIONAL DISCRIMINATOR

Abstract. *The fetal central nervous system (CNS) is one of the most common fetal congenital diseases in the world. It is of great significance to use deep learning methods to provide doctors with reliable auxiliary diagnosis methods. The area outside the skull halo in fetal brain ultrasound images contains a lot of irrelevant information and has fuzzy boundaries, which is not conducive to the classification or recognition tasks of ultrasound images. This paper aims to study the effect of generative adversarial networks based on universal fully convolutional discriminators on the automatic segmentation results of skull halo in fetal brain ultrasound images. This paper proposes a method for automatic segmentation of skull halo in fetal brain ultrasound images using a generative adversarial network based on a universal fully convolutional discriminator. Inspired by the concept of generative adversarial networks, a new semantic segmentation network based on a universal discriminator is constructed. To verify the universality of the discriminator, the semantic segmentation network uses both Deeplab_v2 and Attention U-net networks as generators to generate probability maps of segmentation results. A universal fully convolutional discriminator is also designed to let it learn to distinguish whether the probability map input to the discriminator network is real data or segmentation results. Experimental results on the dataset of automatic measurement of fetal head circumference in ultrasound imaging demonstrate the effectiveness of the algorithm. Compared with the baseline of Deeplab_v2, the segmentation accuracy is significantly improved, and the Attention U-net also has a similar improvement. Generative adversarial network based on universal fully convolutional discriminator can effectively improve the accuracy of automatic segmentation of skull halo in fetal brain ultrasound images.*

Keywords: *Fetal Central Nervous System, Generative Adversarial Networks, Deeplab_V2, Attention U-Net.*

Introduction. The fetal central nervous system (CNS) is one of the most common congenital disorders in fetuses worldwide. With the continuous advancement of ultrasound technology, ultrasound examination of the fetal brain, known for its non-invasive nature, real-time capabilities, and cost-effectiveness, has become the preferred imaging modality for routine prenatal check-ups. However, the development of the fetal CNS is a highly complex process, and the pathological features of the fetal brain are particularly subtle and difficult to discern. Clinically, conducting fetal ultrasound examinations requires a comprehensive knowledge base and extensive practical experience. Experienced doctors can efficiently use ultrasound for diagnosis; however, in underdeveloped regions, there is a lack of experienced specialists and advanced ultrasound imaging equipment.

Therefore, it is highly significant to use deep learning methods to provide doctors with a reliable auxiliary diagnostic tool.

Literature Review. In recent years, deep learning (DL), particularly convolutional neural networks (CNNs), has rapidly become a research hotspot in medical image analysis. In 2015, Long et al. [1] introduced the Fully Convolutional Network (FCN) at CVPR 2015, achieving a major breakthrough in image semantic segmentation through end-to-end learning. This has led to increased research and improvements in the field. Due to the high performance of CNNs in various image processing tasks [2], there has been a growing body of research and achievements in fetal ultrasound image processing within the deep learning domain. Yu Z et al. [3] proposed a deep learning-based method for recognizing standard fetal ultrasound planes; Baumgartner et al. [4] used deep learning

methods to achieve real-time detection of standard planes to aid doctors as a clinical diagnostic tool. Currently, utilizing deep learning methods for fetal disease diagnosis will become the next research focus and challenge. Ye Hai et al. [5] proposed a fetal brain ultrasound image segmentation algorithm based on a fully convolutional network. Cerrolaza et al. [6] discussed the application of fully convolutional networks in skull segmentation of fetal 3D ultrasound images. Zahra Sobhaninia et al. [7] presented a multi-scale and deep neural network for estimating fetal biometric parameters. This network outperforms single-task networks in segmentation and ellipse optimization tasks.

However, the above methods insufficiently utilize boundary information in fetal brain images, and segmentation accuracy needs further improvement. To address these issues, this paper proposes a semantic segmentation network for fetal brain ultrasound images based on a generic fully convolutional discriminator. This network uses a discriminator to optimize local features of the segmentation network, fully utilizing boundary information and reducing data set requirements, effectively addressing the issue of limited medical image datasets. In this paper, the segmentation network is used as the generator in the GAN [8] framework. Unlike traditional generators that train to generate images from noise vectors, our segmentation network outputs a probability map of semantic labels for a given input image. In the discriminator network, we use a generic fully convolutional network. Experimental results on an automatic measurement dataset of fetal head circumference in ultrasound imaging have demonstrated the effectiveness and accuracy of the proposed semantic segmentation framework based on a generic fully convolutional discriminator GAN.

Purpose. This paper aims to study the effect of generative adversarial networks based on universal fully convolutional discriminators on the automatic segmentation results of skull halo in fetal brain ultrasound images.

Materials and Methods. This paper draws on the idea of generative adversarial networks and designs a generalized semantic segmentation network with a fully convolutional discriminator. The overall network structure is shown in Figure 1. The entire network structure consists of two modules: a semantic segmentation network and a discriminant network. Through this overall network structure, we can understand how this paper uses generative adversarial networks for training and obtains semantic segmentation results through generative adversarial learning.

First, drawing on the idea of generative adversarial networks, this paper uses semantic segmentation networks as generative networks. To verify the versatility of the designed discriminator, this paper selects Deeplab_v2 [9] and Attention U-net [10], 2 networks as segmentation networks for training. At the same time, using the idea of generative adversarial learning, a discriminator is designed to conduct adversarial learning on the segmentation network, and the parameters of the segmentation network are continuously optimized, so as to achieve the purpose of optimizing the segmentation results. The advantage of this design is that it does not need to increase the network depth of the segmentation network, but can improve the segmentation accuracy, and does not need to add various post-processing methods like other segmentation networks to improve the segmentation accuracy.

This paper uses two segmentation networks, DeepLab-v2 and Attention U-net, to conduct experiments to verify the generalization ability of the designed discriminator.

The specific operations are as follows:

(1) Using DeepLab_v2 as the segmentation network

The DeepLab_v2 framework uses the ResNet-101[11] network. The pre-trained model is a model pre-trained using the MS COCO dataset [12]. However, the conditional random fields (CRFs) proposed in DeepLab_v2 are not used to optimize the segmentation results. Instead, the last classification layer is deleted in this paper, and the last step size of the two convolutional layers is changed from 2 to 1, so that the resolution of the output feature map is actually 1/8 of the input image size. Finally, the upsampling layer and Softmax output are used to match the size of the input image. In other words, given an image of size $H \times W \times 3$, the input of the segmentation network can output a probability map of size $H \times W \times C$, where C is the number of semantic segmentation categories.

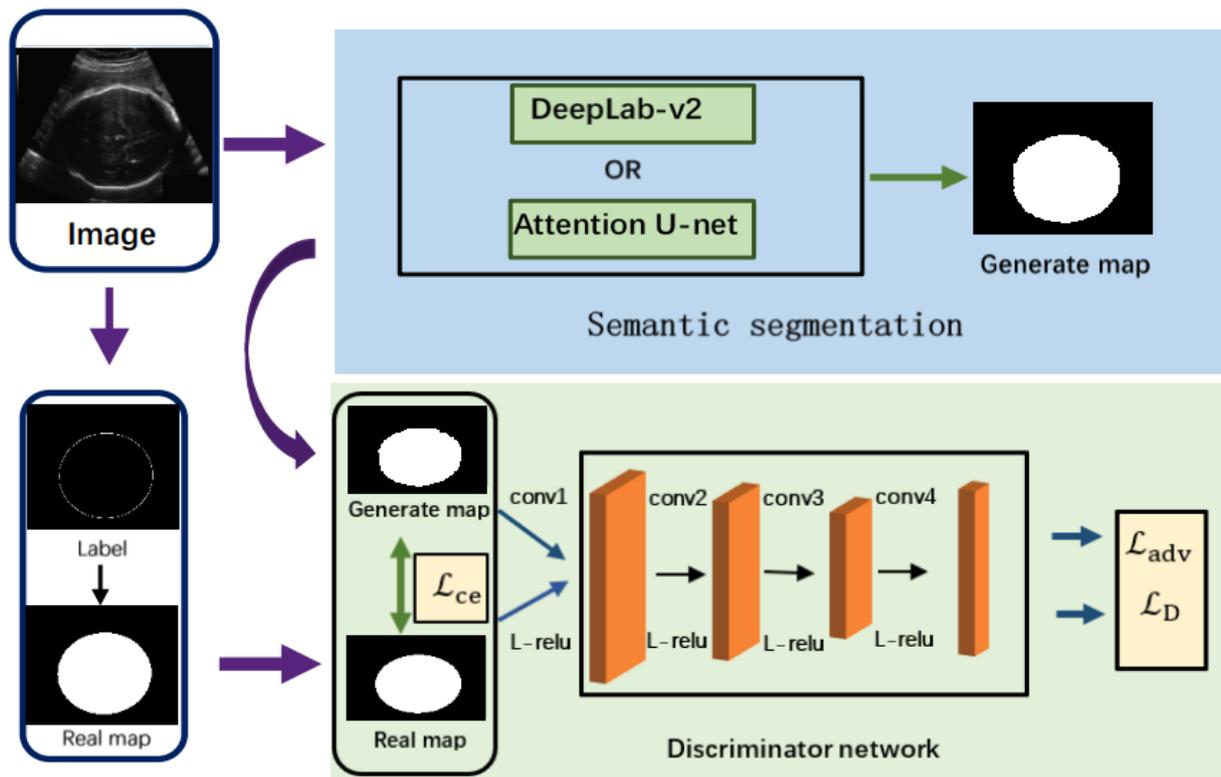


Figure 1 – An overview of the proposed semantic segmentation network based on a generative adversarial network with a generic full convolutional discriminator

In deeplab_v2, Hollow Convolution and Atrous spatial pyramid pooling are used to expand the perceptual field of view, thereby improving the segmentation accuracy of the segmentation network.

(2) Using U-net Attention as the segmentation network

The Attention U-Net model is improved on the basis of the U-Net[13] model and also adopts a U-shaped structure. The difference between the two models is that Attention U-Net adds an attention module based on U-Net, and this attention module is used for skip connection. The original U-Net simply concatenates the features of the same layer of the downsampling layer directly to the upsampling layer, while the improved Attention U-Net uses the Attention module to process the feature map of the same layer of the downsampling layer and the feature map of the upper layer of the upsampling layer respectively, and then concatenates them with the feature map of the upsampling layer.

The discriminative network is based on FCN. The discriminative network consists of four convolutional layers with 4×4 kernels. Each convolutional layer is followed by a Leaky-ReLU [14] layer with a parameter of 0.2. The expression of Leaky-ReLU is:

$$y_i = \begin{cases} x_i & \text{if } x_i \geq 0 \\ \frac{x_i}{\alpha_i} & \text{if } x_i < 0 \end{cases} \quad (1)$$

where α_i is a fixed parameter in the interval $(1, +\infty)$.

Finally, an upsampling layer is added to the last layer to scale the output to the large of the input mapping, thus constituting a fully convolved discriminator network, which allows the input image to be of arbitrary size.

This is done as follows, the discriminator network takes the segmentation probability map or the real data probability map generated by the segmentation network as input and outputs a spatial probability map of size $H \times W \times 1$. The discriminator outputs each pixel p of the map, when $p=1$, it

means that the pixel is from the real data label, when $p=0$, it means that the pixel is from the segmentation network.

In this paper, we are borrowing the idea of generative adversarial network to implement, for the generative network in GAN, we replace it with a segmentation network, in designing a fully convolutional discriminative network to optimize the segmentation network.

Given an input image X_n of size $H \times W \times 3$, denote the segmentation network by $S(\bullet)$ and $S(X_n)$ denotes the predictive probability map of size $H \times W \times C$, where C is the number of categories. We denote the full convolutional discriminator by $D(\bullet)$, which uses a probability map of input size $H \times W \times C$, where the discriminator network has two possible inputs: segmentation prediction $S(X_n)$ or real data vector Y_n . and outputs a predicted probability map of size $H \times W \times 1$ to discriminate whether the input probability map is from the segmentation network or from the real data.

Discriminative network: To train the discriminative network, the loss of spatial cross-entropy of the two classes is \mathcal{L}_D is minimized:

$$\mathcal{L}_D = -\sum_{h,w}(1-y_n) \log(1 - D(S(X_n))^{(h,w)}) + y_n \log(D(Y_n)^{(h,w)}). \quad (2)$$

Segmentation networks: we train segmentation networks by minimizing a multi-task loss function:

$$\mathcal{L}_{seg} = \mathcal{L}_{ce} + \lambda_{adv}\mathcal{L}_{adv}. \quad (3)$$

Among them \mathcal{L}_{ce} and \mathcal{L}_{adv} denote spatial multi-class cross entropy loss, adversarial loss, respectively. λ_{adv} are the weights of the adversarial loss function.

Given an input image, which has real data at Y_n and predictions at $S(X_n)$, the cross-entropy loss can be obtained:

$$\mathcal{L}_{ce} = -\sum_{h,w} \sum_{c \in C} Y_n^{(h,w,c)} \log(S(X_n)^{(h,w,c)}). \quad (4)$$

We do this by means of a loss \mathcal{L}_{adv} of an adversarial learning process to give a fully convolutional discriminative network $D(\bullet)$:

$$\mathcal{L}_{adv} = -\sum_{h,w} \log(D(S(X_n))^{(h,w)}). \quad (5)$$

Using this loss, we train the segmentation network to maximize the probability of the predictions produced in the segmentation network to deceive the discriminator.

At the same time, the experiment verifies the effectiveness of the algorithm according to the following results. As shown in Figure 2, the segmentation results obtained from the experiments conducted on Deeplab_v2 network based on and not based on full convolutional discriminator with fetal head circumference dataset. Where the first column is the fetal head circumference image, the second column is the segmented image manually labeled on the fetal head circumference image, the third column is the segmented image obtained by training the Deeplab_v2 network without full convolutional discriminator based, and the fourth column is the segmented image obtained by training the Deeplab_v2 network based on the full convolutional discriminator.

As can be seen from Figure 2, when the discriminator is not used, although the results of fetal head circumference segmentation are very good, but for and manually labeled, its edge is still lacking. But when the discriminator is used, the segmentation results, it can be clearly seen that the edge is very close to the manual labeling, from which it can also be seen that the connection of a full convolutional discriminator can optimize the segmentation boundaries, for the edge of the information can be better utilized, and this discriminator structure for the segmentation of fetal ultrasound images is very advantageous.

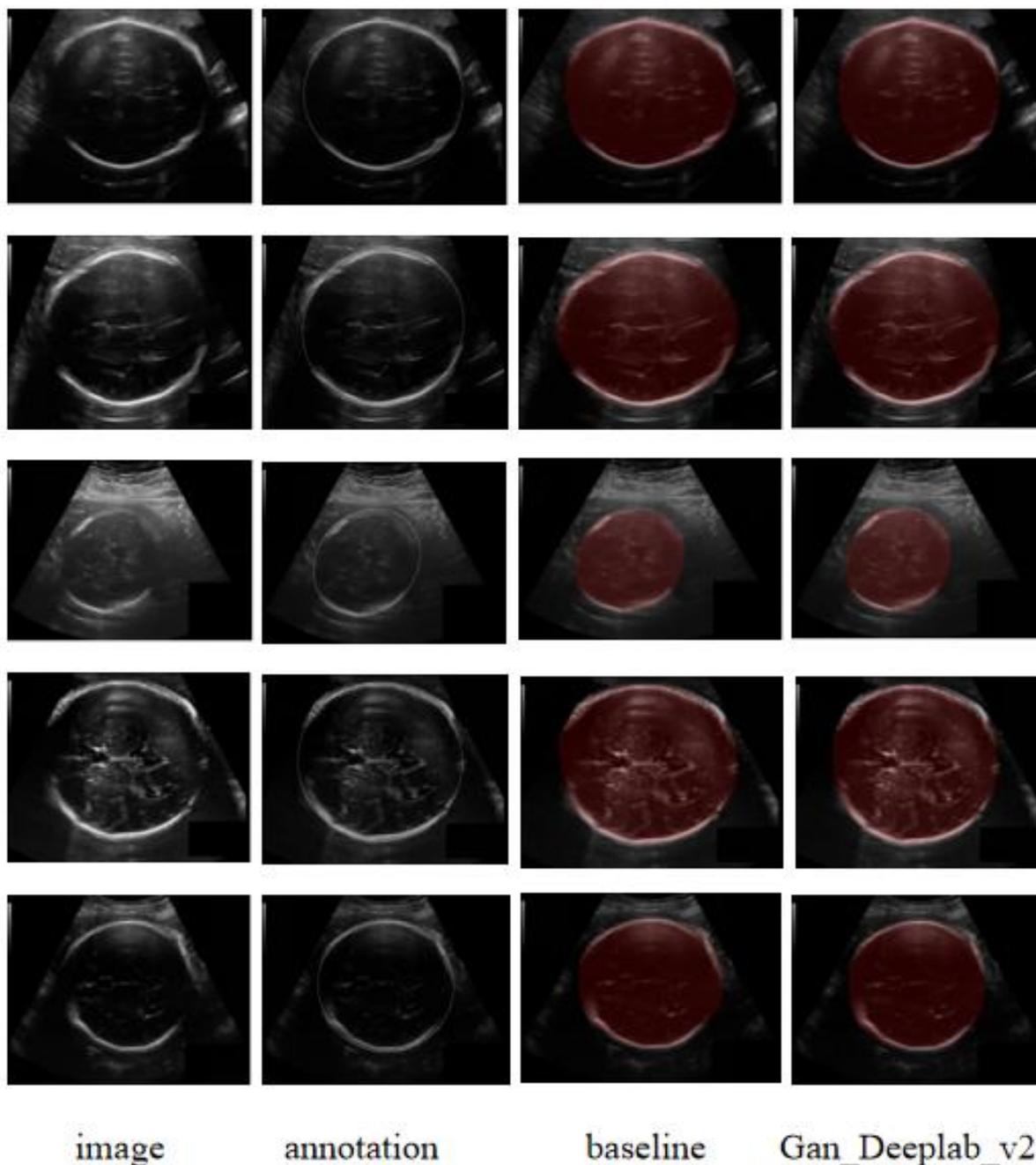


Figure 2 – Comparison of Deeplab_v2 network based and not based on full convolutional discriminator under fetal head circumference dataset

Table 1 shows the comparison of the results of Deeplab_v2 and Deeplab_v2's baseline, based on the full convolutional discriminator, with the fetal head circumference dataset. From the data in the table, after using the discriminator, comparing with Deeplab_v2's baseline, the IOU for the fetal head circumference validation set improves by 3.2% to 94.2%, and the DICE improves by 2.1% to 97.0%. This can be seen, this network for fetal head circumference dataset training and recognition segmentation effect is very good, at the same time, we are based on the idea of generative adversarial network, add the discriminator to optimize the segmentation results of this method, can be very good to improve the segmentation results, for the segmentation of the boundaries of the improvement is greater, the same discriminator can reduce the segmentation of the network for the dataset requirements, so this discriminator is very suitable for fetal ultrasound. This discriminator is very suitable for fetal ultrasound images, and this structure is also suitable for other medical images.

Table 1 – Results derived from fetal head circumference validation set under Deeplab_v2 network

Method	IOU (%)	Dice (%)
Baseline	91.0	94.9
GAN_Deep plab_v2	94.2	97.0

As shown in Figure 3, the segmentation results obtained from the experiments conducted on Attention U-net network based and not based on full convolutional discriminator with fetal head circumference dataset. Wherein the first column is the fetal head circumference image, the second column is the segmentation image manually labeled on the fetal head circumference image, the third column is the segmentation image obtained by training the U-net network, the fourth column is the segmentation image obtained by training the Attention U-net network not based on the full convolutional discriminator, and the fifth column is the segmentation image obtained by training the Attention U-net network based on the full convolutional discriminator.

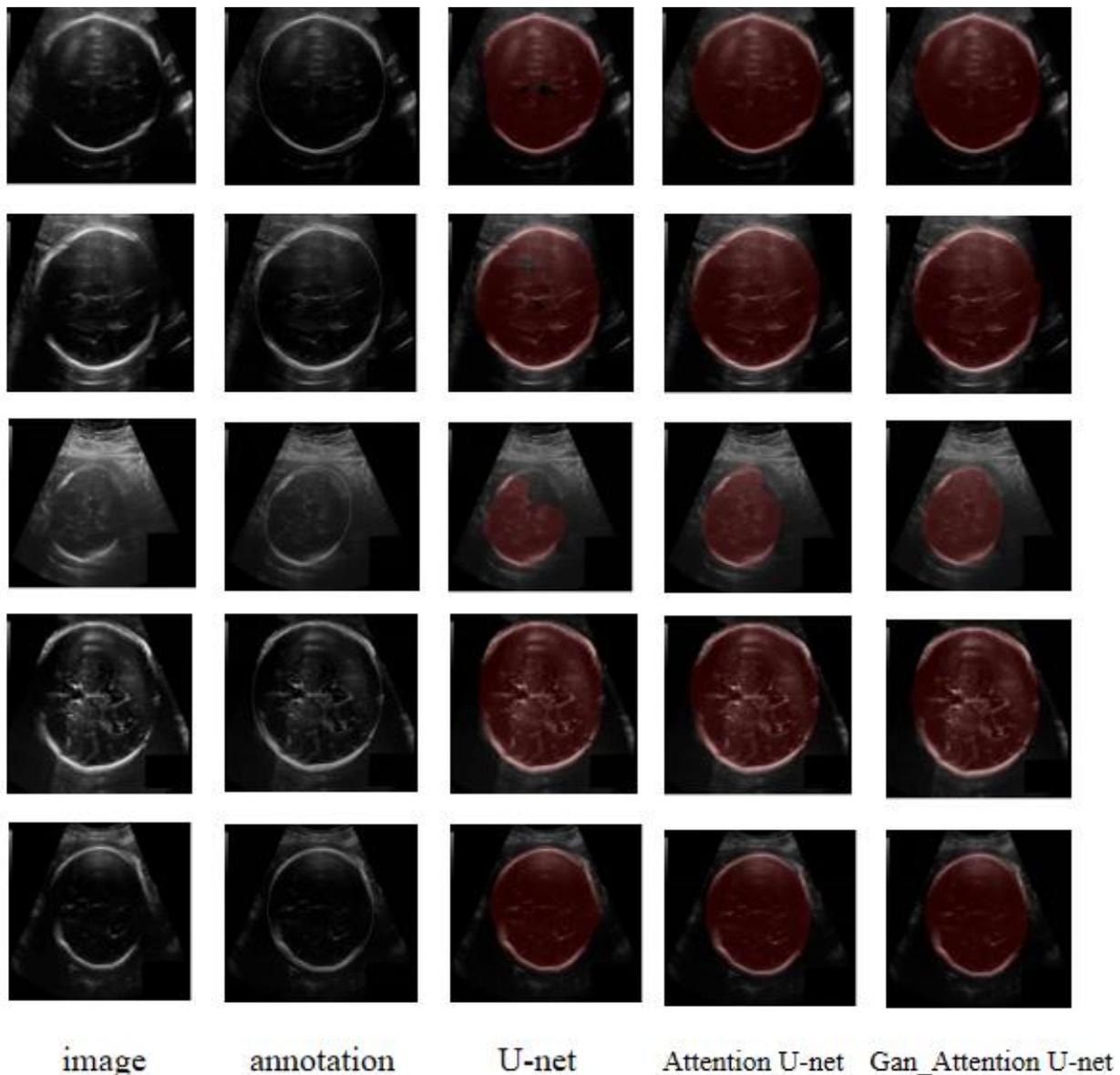


Figure 3 – Comparison of Attention U-net network with and without full convolutional discriminator based on fetal head circumference dataset

As can be seen from Fig.3, the segmentation results obtained by using U-net directly are not good, and some of them have problems with poor class recognition and poor results of edge segmentation. By adding an attention mechanism, the segmentation results are directly greatly improved, but there are still some edges of the image of fetal head circumference where the segmentation is not very good. After adding a discriminator to the network, the segmentation results can be clearly seen that the corresponding segmentation boundaries have been greatly improved, making them closer to the manually labeled segmented images.

Table 2 shows the comparison of the results of U-net family of networks under fetal head circumference dataset. From the data in the table, it can be seen that after using an attention mechanism, comparing to U-net, the IOU of the fetal head circumference validation set is improved by 10% to 89.2% and the DICE is improved by 7% to 94% . After continuing to add a full convolutional discriminator, comparing to U-net, the IOU of the fetal head circumference validation set improves by 11% to 90.2%, and the DICE improves by 7.6% to 94.6% ; comparing to Attention U-net, the IOU of the fetal head circumference validation set improves by 1%, and the DICE improves by 0.6%. This can be seen that adding a full convolutional discriminator can continue to increase the segmentation accuracy even further, and at the same time can optimize the segmentation edges to be closer to the results of manual segmentation. This can be a good solution to the problem of blurred boundaries in fetal ultrasound images.

Table 2 – Results derived from fetal head circumference validation set under U-net series network

Method	IOU (%)	Dice (%)
U-net	79.2	87.0
Attention U-net	89.2	94.0
GAN Attention U-net	90.2	94.6

As shown in Figure 4, the segmentation results obtained from experiments conducted with Deeplab_v2 and Attention U-net networks, under the fetal head circumference dataset. Where the first column is the fetal head circumference image, the second column is the segmentation image obtained by training the Deeplab_v2 network without full convolutional discriminator, the third column is the segmentation image obtained by training the Deeplab_v2 network with full convolutional discriminator, the fourth column is the segmentation image obtained by training the Attention U-net network without full convolutional discriminator, and the fifth column is the segmentation image obtained by training the Attention U-net network with full convolutional discriminator. Attention U-net network training with full convolutional discriminator.

From Figure 4 and combining with Table 2, Table 3, it can be seen that Deeplab_v2 and Attention U-net networks after using the discriminator, the IOU of Deeplab_v2 is improved by 3.2% and the DICE is improved by 2.1%; Attention U-net network's IOU is improved by 1.0% and the DICE is improved by 0.6%. It can be seen that the use of discriminators for segmentation networks will have different degrees of improvement; at the same time, the discriminators are significantly better than Attention U-net for Deeplab_v2, which can also be concluded that for the deeper the semantic segmentation network, the discriminators play a better role in the semantic segmentation network, and the segmentation effect will be improved more. By adding a full convolutional discriminator, this can improve the segmentation results of fetal ultrasound images by using a deeper network when processing fetal ultrasound images.

Conclusions. This paper presents a semantic segmentation network for fetal brain ultrasound images based on a generalized fully convolutional discriminator. The proposed method uses the scheme of Generative Adversarial Networks (GANs), which consists of a segmentation network and a discriminator. In this paper then Deeplab_v2 and Attention U-net are used as the segmentation network to verify the generalization of this full convolutional discriminator.

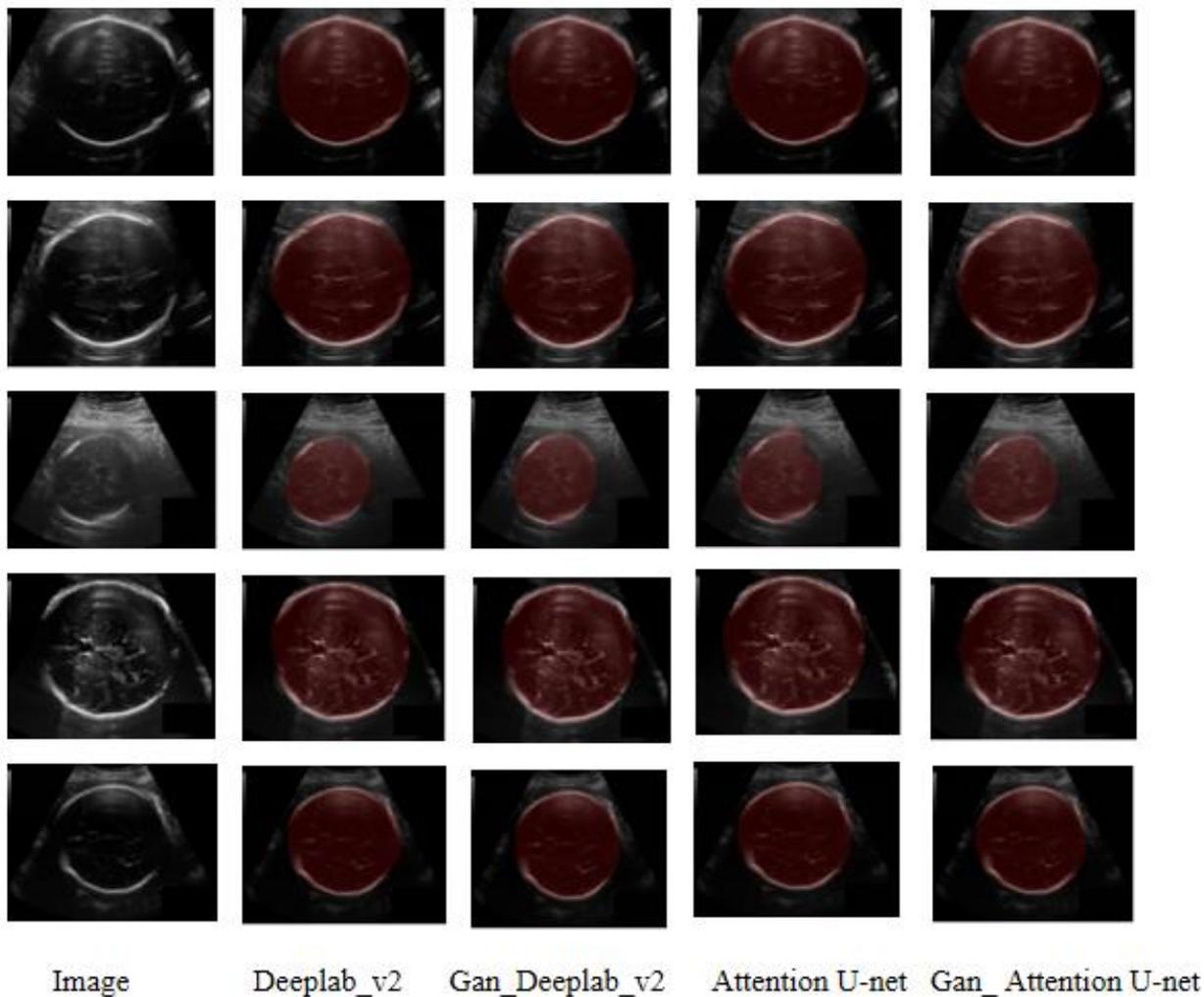


Figure 4 – Comparison of Deeplab_v2 and Attention U-net network under fetal head circumference dataset

The discriminator uses a fully convolutional network to distinguish between the input map which is a probability map of the real data and the probability map of the segmentation result of the segmentation network. Through the generative confrontation between this discriminator and the segmentation network, the discriminator continuously optimizes the model parameters of the segmentation network, so as to improve the segmentation accuracy of the segmentation network. And in this process of adversarial learning, the network depth of the segmentation network does not increase. A large number of experiments were conducted on the fetal head circumference data set to verify the effectiveness of the algorithm, and also proved that the scheme of adding a fully convolutional discriminator is very suitable for fetal ultrasound images, which can further optimize the edge segmentation of fetal ultrasound images and reduce the data requirements of the segmentation network.

References

1. Long, J., Shelhamer, E., & Darrell, T. (2015). Fully convolutional networks for semantic segmentation. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (pp. 3431–3440). <https://doi.org/10.48550/arXiv.1411.4038>.
2. Litjens, G., Kooi, T., Bejnordi, B. E., Setio, A. A. A., Ciompi, F., Ghafoorian, M., van der Laak, J. A. W. M., van Ginneken, B., & Sánchez, C. I. (2017). A survey on deep learning in medical image analysis. *Medical Image Analysis*, 42, 60–88. <https://doi.org/10.1016/j.media.2017.07.005>.

3. Yu, Z., Ni, D., Chen, S., et al. (2016). Fetal facial standard plane recognition via very deep convolutional networks. In 2016 38th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC) (pp. 1–4). IEEE. <https://doi.org/10.1109/EMBC.2016.7590780>.
4. Baumgartner, C. F., Kamnitsas, K., Matthew, J., Fletcher, T. P., Smith, S., Koch, L. M., Kainz, B., Rueckert, D., & Glocker, B. (2017). SonoNet: Real-time detection and localization of fetal standard scan planes in freehand ultrasound. *IEEE Transactions on Medical Imaging*, 36(11), 2204–2215. <https://doi.org/10.1109/TMI.2017.2712367>.
5. Ye, H., Feng, K.-P., & Xie, H.-N. (2019). Fetal brain ultrasonic image segmentation algorithm based on fully convolution network. *Modern Computer*, (27), 43–47.
6. Cerrolaza, J. J., Sinclair, M., Matthew, J., et al. (2018). Deep learning with ultrasound physics for fetal skull segmentation. In 2018 IEEE 15th International Symposium on Biomedical Imaging (ISBI 2018) (pp. 564–567). IEEE. <https://doi.org/10.1109/ISBI.2018.8363639>.
7. Sobhaninia, Z., Rafiei, S., Emami, A., Karimi, N., Najarian, K., & Samavi, S. (2019). Fetal ultrasound image segmentation for measuring biometric parameters using multi-task deep learning. In 2019 41st Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC) (pp. 6545–6548). IEEE. <https://doi.org/10.1109/embc.2019.8856981>.
8. Goodfellow, I., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., Courville, A., & Bengio, Y. (2014). Generative adversarial nets. In Z. Ghahramani, M. Welling, C. Cortes, N. D. Lawrence, & K. Q. Weinberger (Eds.), *Advances in Neural Information Processing Systems* (Vol. 27). <https://proceedings.neurips.cc/paper/2014/hash/f033ed80deb0234979a61f95710dbe25-Abstract.html>.
9. Chen, L.-C., Papandreou, G., Kokkinos, I., Murphy, K., & Yuille, A. L. (2018). DeepLab: Semantic image segmentation with deep convolutional nets, atrous convolution, and fully connected CRFs. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 40(4), 834–848. <https://doi.org/10.48550/arXiv.1606.00915>.
10. Oktay, O., Schlemper, J., Folgoc, L. L., Lee, M. C. H., Heinrich, M., Misawa, K., Mori, K., McDonagh, S., Hammerla, N. Y., Kainz, B., Glocker, B., & Rueckert, D. (2018). Attention U-Net: Learning where to look for the pancreas [Preprint]. arXiv. <https://doi.org/10.48550/arXiv.1804.03999>.
11. He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition* (pp. 770–778). <https://doi.org/10.48550/arXiv.1512.03385>.
12. Lin, T.-Y., Maire, M., Belongie, S., Hays, J., Perona, P., Ramanan, D., Dollár, P., & Zitnick, C. L. (2014). Microsoft COCO: Common objects in context. In D. Fleet, T. Pajdla, B. Schiele, & T. Tuytelaars (Eds.), *Computer Vision – ECCV 2014* (pp. 740–755). Springer. https://doi.org/10.1007/978-3-319-10602-1_48.
13. Ronneberger, O., Fischer, P., & Brox, T. (2015). U-Net: Convolutional networks for biomedical image segmentation. In N. Navab, J. Hornegger, W. M. Wells, & A. Frangi (Eds.), *Medical Image Computing and Computer-Assisted Intervention – MICCAI 2015* (pp. 234–241). Springer. https://doi.org/10.1007/978-3-319-24574-4_28.
14. Maas, A. L., Hannun, A. Y., & Ng, A. Y. (2013). Rectifier nonlinearities improve neural network acoustic models. In *Proceedings of the 30th International Conference on Machine Learning, Deep Learning Workshop*. https://ai.stanford.edu/~amaas/papers/relu_hybrid_icml2013_final.pdf.

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Лі Юйлун*аспірант кафедри комп'ютерних наук,**Національний університет біоресурсів і природокористування України*ORCID: <https://orcid.org/0009-0004-2039-6919>E-mail: liyulong@dgut.edu.cn**СЕМАНТИЧНА СЕГМЕНТАЦІЯ УЛЬТРАЗВУКОВИХ ЗОБРАЖЕНЬ МОЗКУ ПЛОДА НА ОСНОВІ ЗАГАЛЬНОГО ПОВНІСТЮ ЗГОРТКОВОГО ДИСКРИМІНАТОРА**

Анотація. Ураження центральної нервової системи (ЦНС) плода є одним з найпоширеніших вроджених захворювань плода у світі. Використання методів глибокого навчання має велике значення для забезпечення лікарів надійними допоміжними методами діагностики. Область за межами ореолу черепа на ультразвукових зображеннях головного мозку плода містить багато нерелевантної інформації та має нечіткі межі, що не сприяє вирішенню задач класифікації або розпізнавання ультразвукових зображень. Метою роботи є дослідження впливу генеративних змагальних мереж на основі універсальних повністю згорткових дискримінаторів на результати автоматичної сегментації ореолу черепа на ультразвукових зображеннях головного мозку плода. У статті запропоновано метод автоматичної сегментації ореолу черепа на ультразвукових зображеннях головного мозку плода з використанням генеративної змагальної мережі на основі універсального повністю згорнутого дискримінатора. На основі концепції генеративних змагальних мереж побудовано нову семантичну мережу сегментації на основі універсального дискримінатора. Для перевірки універсальності дискримінатора мережа семантичної сегментації використовуються мережі Deeplab_v2 та Attention U-net як генератори для генерації карт ймовірностей результатів сегментації. Універсальний повністю згортковий дискримінатор також розроблено для того, щоб він міг навчитися розрізняти, чи є карта ймовірностей на вході мережі дискримінатора реальними даними або результатами сегментації. Експериментальні результати на наборі даних автоматичного вимірювання окружності голівки плода при ультразвуковому дослідженні демонструють ефективність алгоритму. Порівняно з базовою лінією Deeplab_v2, точність сегментації значно покращилася, і Attention U-net також має аналогічне покращення. Генеративна змагальна мережа на основі універсального повністю згорткового дискримінатора може ефективно підвищити точність автоматичної сегментації ореолу черепа на ультразвукових зображеннях мозку плода.

Ключові слова: центральна нервова система плода, генеративні змагальні мережі, Deeplab_v2, Attention U-net..