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U-Net Tuning Hyperparameter for Segmentation in Amniotic Fluid Ultrasonography Image

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***Abstract*— Ultrasound Amniotic Fluid (AF) images generally have image quality similar to other 2-D ultrasound images, which have noise, blurry edges, artifacts, and low contrast. Some of the confusing factors in pocket AF segmenting comprise (a) reverberation artifact, (b) AF mimicking region, (c) floating matters, and (d) incomplete or missing boundary. Obtaining the Region of Interest (ROI) area of amniotic fluid requires a segmentation method that can identify each object in more detail. Based on the problems in AF segmentation, the contribution of this research focuses on the development of segmentation methods in AF using the U-Net semantic segmentation model using the architecture of the Roonerberger. This paper analyzes several uses of hyperparameters to determine the performance of the U-NET model architecture, especially for segmenting AF. The hyperparameter tuning is in the optimizer, loss function, learning rate, and the number of epochs. The best performance of U-Net in segmenting amniotic fluid with a combination of RMSprop optimizer parameters, the Loss function is Binary cross entropy, learning rate value is 0.00001 with Epoch of 33 with DSC of 0.88 and IoU of 0.79, the accuracy of 0.87, precision of 0.93, recall of 0.88.**

Keywords—*Amniotic Fluid, Segmentation, U-Net, Tuning Hyperparameter*

I. INTRODUCTION

Examination of amniotic fluid is an examination that must be carried out by doctors when the womb enters the second trimester [1]. Amniotic fluid is found in the amniotic cavity, aims to protect the fetus if there is pressure on the umbilical cord, collisions with the uterine wall, and help the growth and development of fetal movements and maintain body temperature in the baby [2]. Amniotic Fluid Volume (AFV) gradually increased to about 20 ml at week 10, then increased to 630 ml at 22 weeks gestation and 770 ml at 28 weeks gestation. [3]. During pregnancy age above 39 weeks, the volume of amniotic fluid decreased sharply with an average volume of 515 ml. The condition of AFV is used as an indicator of the health of fetal development. [4]. Determining AFV is needed as a reference to determine the condition of fetal development. An accurated of AFV measurement, a segmentation model is needed to determine the amniotic fluid area. Determination of the amniotic fluid area on ultrasound images has difficulties because the boundary between the fluid area and other areas is not as blury edge as shown in Fig. 1.

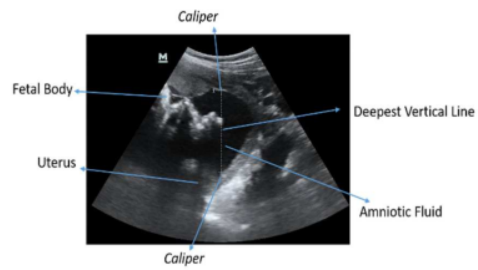


Fig. 1. Part of the amniotic fluid cavity

In general, amniotic fluid ultrasound images have almost the same image quality as other 2-D ultrasound images, which have noise, blurry edges, artifacts, and low contrast [5]. Amniotic fluid images have low contrast and there is a lot of noise around the object or organ you want to observe. In addition, the effect of sound reflection on objects will cause noise that can make it difficult to identify objects. Some of the confusing factors in pocket AF segmenting include: (a) reverberation artifact, (b) AF mimicking region, (c) floating matters, and (d) incomplete or missing boundary [6].

Obtaining the area or ROI (Region Of Interest) of amniotic fluid requires a segmentation method to identify each object in more detail. Several studies about the segmentation of amniotic fluid ultrasound images include the pixel classification method based on local gray level rectangle window sampling. [7]. This research limits the training set of pixels based on environmental information with the rectangle window sampling method used to determine the characteristics of each pixel in its specific environment. Feature extraction is no longer based on the global characteristics of the object but rather on retrieving the value of each pixel in the object area using a sampling window. This study also combines local first-order statistical methods and gray level information in the window to obtain the characteristics of each pixel. Based on this method, the average DSC is 84% and Intersection of Union (IoU) is 72.7%. Then research using the Pixel Classification Method Using Local Window Information and Distance Angle Pixels[8]. This study proposes a pixel classification model to separate amniotic fluid from other objects with a specified window size limit and combine it with several feature extractions such as gray-level, gray-level local variance, and distance angle pixels. Researched by Ayu, et al [8] showed an average DSC value of 87.6% and an average IoU of 76.8%. Research with the deep learning method approach has been carried out by several studies such as [9] using the method a dual path network, whose primary path is AF-net, and the secondary path is an auxiliary segmentation network, with amount DSC 85.9%. Then further research related to deep learning by developing the AF-net method is a variation of U-net combined with three complementary concepts - atrous convolution, multi-scale side-input layer, and side-output layer with a DSC of 87.7% [6].

Based on the problems in AF segmentation, the contribution of this research focuses on the result segmentation methods in AF using the U-Net semantic segmentation model approach with the architecture of the Roonerberger[10]. This paper analyzes several uses of hyperparameters to determine the performance of the U-NET model architecture, especially for segmenting AF. The hyperparameter tuning like the optimizer, loss function, learning rate and the number of epochs. Roonerberger's architecture has been widely used in segmenting medical images [11]–[15] with satisfactory segmentation results. The U-Net model is one of the methods used in semantic segmentation. The U-Net architecture is formed from the Encoding and Decoding process on the input image, namely the amniotic fluid image. The feature extraction process is carried out through convolutional layers, from low-dimensional features to high-dimensional features. U-Net is divided into two important parts: (1) the contraction or downsampling path formed by the common convolutional process and (2) the expansion or upsampling path, transposing the 2D convolutional layer. Experiments in this study were conducted by tuning hyperparameters such as epoch, learning rate, loss function, and optimizer. This hyperparameter tuning is carried out to determine the best parameters for AF segmentation.

II. PROPOSED MODEL

A. Data Acquisition

The Ultrasound image data is taken from the patient's examination recording with the image format of jpg. 2D ultrasound image data of amniotic fluid was obtained by Surya Husadha Hospital Bali and Kasih Medika Clinic Bali. Image data are taken from Voluson S8 USG machine and transducer with a frequency of 3.5Hz, lateral resolution corresponding 3 mm to 0.2 m, with a gain of 0-8 Hz. Gain is the brightness setting on the ultrasound machine. The higher gain value is set at the time of inspection, the resulting image will have a very high brightness. The data criteria are images with a single pregnancy and pregnant women who are not in a condition of obesity with a gestational age of 13-37 weeks. At the data acquisition stage, data labeling is considered as ground truth by two Gynecologists and the total number of images used is 95.

B. Pre-Processing Data

The initial process in preprocessing is cropping which is done automatically. This automatic cropping is done by cutting the image size in weight and height from 800 × 600 pixels to 550.98 × 400.98 pixels using the imcrop library in Matlab. The purpose of cropping is to remove unused information, such as text or patient data descriptions. The cropped image is used as input for the segmentation process.

C. U-Net Architecture

The amniotic fluid image is a RGB image then number of the first convolutional layers for input is 3. The input image is 256×256, and the convolutional application adds depth to the images. We use convolutional blocks for each filter in this architecture with sizes 64, 128, 256, and 512. The convolutional block consists of two convolutional processes with a kernel size of 3×3 followed by one batch normalization process. The ReLU activation function is used in each convolutional layer. The green arrow in Fig. 2 shows the maximum merge process using a 2×2 kernel. The gray arrow indicates proced used to save the feature map from an encoder to decoder.

The first process is to initialize a variable named skip_connection_x to perform the bridging procedure between this encoder and decoder. *The output of conv_block is then added to the skip_connection_x variable, which is used later in the decoder stage.* This decoder process has the primary function namely to produce the desired semantic segmentation map. The decoder loops over all filter sizes used. Where in the looping process there is an upsampling layer with a window size 2×2. After that the output from the upsampling process is then combined or connected with the value in the skip connection stored in the skip_connection_x variable. At the end of this decoder process, the convolution process is carried out is using a window size of 1×1 using the sigmoid activation function. This process produces a final output in the form of segmentation results in the form of a binary mask from the amniotic fluid image.

D. Optimizer

An optimizer is an algorithm or method used to minimize the loss function or to maximize production efficiency. The optimizer is a mathematical function related to the development of parameters such as weight and biases. The optimizer can help in changing the value of the weight and learning rate on the neural network to reduce losses. There are several optimizers used in deep learning such as:

1. Gradient Descent

Gradient descent (GD) is an optimization algorithm based on the convex function and tweaks its parameters iteratively to minimize reduced loss function by moving in the direction opposite to that of the steepest ascent [16]. The advantages of gradient descent are easy to understand and implement and the disadvantages are very slow computation or computations caused by gradient calculations for the entire data set in one update and require large memory and high computation. One of the developments of the GD algorithm is the Stochastic Gradient Descent (SGD), where this SGD updates the parameters one by one each training example $x^{(i)}$ and label $y^{(i)}$, where the equation is in (1).

$$\theta = \theta - \eta . \nabla_\theta J(\theta; x^{(i)}; y^{(i)}) \qquad (1)$$

Where θ is weight, η is learning rate, J is amount training sampel.

The advantage of the SGD optimizer is frequently updates model parameters, requires less memory, and allows the use of large data sets as it has to update only one example at a time.

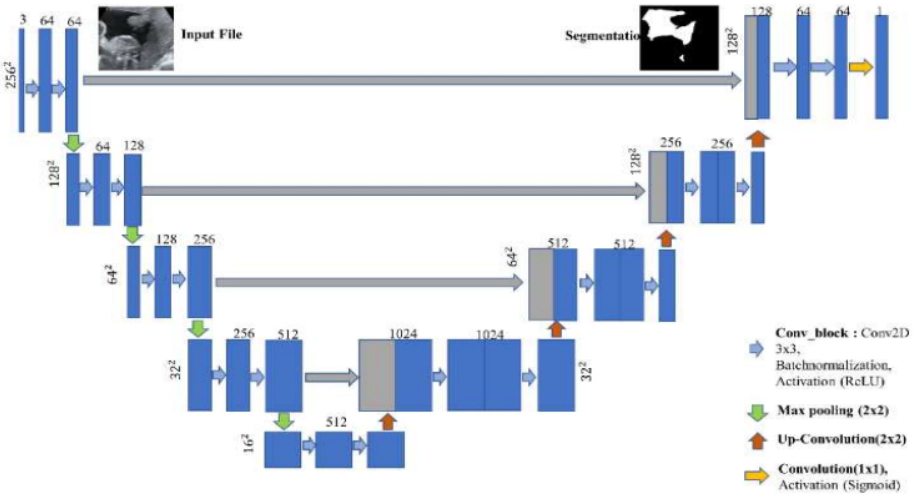


Fig. 2. U-Net Architecture[10]

2. Adadelta

Adadelta is an extension of Adagrad that seeks to reduce its aggressive, monotonically decreasing learning rate [17]. Instead of accumulating all past squared gradient, adadelta restricts the window of accumulated past gradient to some fixed size w. Adadelta it is not necessary to set the default learning rate because it has been removed from the update rule. The advantage of Adadelta is that it does not require a learning rate. Where the equation is in (2).

$$\theta_{t+1} = \theta_t + \Delta_{\theta t} \tag{2}$$

3. RMSprop

RMSprop is an unpublished, adaptive learning rate method proposed by Geoff Hinton. RMSprop is a special version of Adagrad where the learning rate is the exponential average of the gradients, not the cumulative sum of the squared gradients [16]. RMS-Prop basically combines momentum with AdaGrad. In RMS-Prop the RMS-Prop learning rate is adjusted automatically and selects a different learning rate for each parameter. Where the equation for RMS-Prop is in (4).

$$\theta_{t+1} = \theta_t - \frac{\eta}{\sqrt{E[g^2]t + \in}}\, g_t \tag{3}$$

$$\sqrt{E[g^2]t} = 0.9\, E[g^2]_{t-1} \tag{4}$$

RMSprop also divides the learning rate by the mean of the exponentially decreasing squared gradient. Hiton suggest γ *to be set to* 0.9, while a good default value for the learning rate η is 0.001.

4. Adam

Adaptive Moment Estimation (Adam) is a method that calculates the adaptive learning rate for each parameter. In addition to storing the exponentially decaying average of past squared gradient v_t, like Adadelta and RMSprop, Adam also stores the exponentially decreasing average of past gradient m_t [18]. Adam observes the value of the bias towards zero, especially during the initial time step and especially when the decay rate is small (i.e 1 and close to 1). The equation for Adam can be seen in equation (7).

$$m_t = \beta_1 m_{t-1} + (1 - \beta_1)\, g_t \tag{5}$$

$$v_t = \beta_2 v_{t-1} + (1 - \beta_2)\, {g_t}^2 \tag{6}$$

$$\theta_{t+1} = \theta_t - \frac{\eta}{\sqrt{\hat{v}_t} + \in}\, \hat{m}_t \tag{7}$$

Where m_t and v_t are estimate of the first moment (the mean) and the second moment (the uncentered variance) of the gradients [16]. Default values 0.9 for β_1, 0.999 for β_2, and 10^{-8} for $\in$.

5. Nadam

Nadam (Nasterov-accelerated Adaptive Moment Estimation) optimizer merupakan kombinasi Adam dan NAG. In order to incorporate NAG into Adam, modifications to the momentum m_t are needed. The equations for Nadam is (8).

$$\theta_{t+1} = \theta_t - \frac{\eta}{\sqrt{\hat{v}_t} + \in}\left(\beta_1 \hat{m}_t + \frac{(1 - \beta_1) gt}{1 - \beta_1^t}\right) \tag{8}$$

E. Loss Function

The loss function is used to measure the error between the predicted output and a given target value. The goal is almost always to minimize the minimize loss function. Where the lower the loss, the better the model. A loss function tells us how far the algorithm model is from realizing the expected result. The word "loss" means the penalty or penalty received by the model for failing to deliver the desired result. The use of the loss function is based on the purpose of the developed model. In the model classification, the loss functions that are used include Binary Cross-Entropy (BCE), Hinge Loss (HL), and Squared Hinge Loss (SHL). BCE Loss is used for binary classification models, in which the model only has two classes, with equation (9).

$$loss(x,y) = -\sum x\,.\log(y) \quad (9)$$

F. Learning Rate dan Epoch

Learning rate is one of the training parameters to calculate the weight correction value during the training process. This learning rate value has the range of zero (0) to (1). The higher the learning rate, the faster the training process will run. Greater the learning rate the network accuracy will decrease, but if the learning rate is getting smaller, the network accuracy will be greater or increase with the consequence that the training process will take longer. Epoch represents the number of iterations that must be done on the data set. The epoch represents one cycle of the deep learning algorithm learning from the entire training dataset. One epoch means that a deep learning algorithm has learned from the all training dataset.

G. Evaluate Performance Method

Performance evaluation for segmentation uses the Dice Similarity Coefficient (DSC) and Intersection of Union (IoU). Meanwhile, to determine the performance of the Optimizer on the loss function, learning rate, and epoch, we use the confusion matrix.

Therefore, DSC has an interval of values at [0, 1]. In addition it is defined in Eq. (10) [8]. Furthermore, Jaccard Coefficient/ IoU is the number of intersections in pixels *A* to *B* divided by union *A* and *B* as shown in equation. (11)[8].

$$DSC = \frac{2|A \cap B|}{|A| + |B|} \quad (10)$$

$$Jaccard/IoU = \frac{|A \cap B|}{|A \cup B|} \quad (11)$$

Where: *A* is a segmented pixel, and *B* is pixel label/ground truth.

The parameters used to measure the performance loss function, learning rate, epoch using accuracy, precision and recall, measure as shown in equation (12) - (14) [1].

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FP} + \text{TN} + \text{FN}} \quad (12)$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \quad (13)$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \quad (14)$$

TP is True Positive (a positive label that is predicted as an actual label), FP is False Positive (negative label but predicted as a positive label), TN is True Negative (negative data that predicted correctly), and FN is False Negative (a positive label but predicted as negative label).

III. EKSPERIMENT AND RESULT

The U-Net method in this study was carried out based on tuning hyperparameters such as epoch, learning rate, loss function, and optimizer. The Hyperparameter tuning used to find out the best parameters that used for segmenting amniotic fluid. In the first step, checked by testing several optimizer methods such as Stochastic Gradient Descent (SDG), Adam, Nadam, RMSprop, AdaDelta, and AdaMax with several learning rate values, the number of batches is 2, and the epoch is 1 to 40. Table 1 shows the test results of the six optimizer methods above.

TABLE I. COMPARISON OF PERFORMANCE OF OPTIMIZER METHOD ON U-NET MODEL FOR AMNIOTIC FLUID SEGMENTATION

Optimizer	Performance Metric (Val)					
	loss	**acc**	**recall**	**precision**	**IoU**	**DSC**
Stocastic Gradient Descent (SGD)	0,45	0,80	0,83	0,86	0,5466	0,70
RMSprop	**0,41**	**0,87**	**0,87**	**0,93**	**0,78**	**0,88**
AdaDelta	0,69	0,50	0,69	0,59	0,39	0,56
AdaMax	0,32	0,87	0,87	0,93	0,79	0,86
Nadam	0,36	0,88	0,89	0,92	0,81	0,85
Adam	0,31	0,88	0,89	0,92	0,78	0,85

*acc: accuracy

Table 1 shown that the RMSprop method achieved the best performance with DSC and IoU values on the test data of 0.88 and 0.78. From these results, hyperparameter tuning is then carried out on the model with the RMSprop optimizer by conducting experiments on the Loss Function method used are Binary Crossentropy, Hinge, and Squared Hinge. The purpose of this second experiment is to find out the Loss Function method with the best accuracy with the RMSprop optimizer. Table 2 shows the model's performance against several loss function methods being tested.

TABLE II. COMPARISON OF RESULTS TO THE LOSS FUNCTION METHOD USED IN THE METHOD U-NET

Loss Function	Performance Metric					
	loss	***acc***	***recall***	***precision***	**IoU**	**DSC**
Binary cross entropy	0,41	0,87	0,87	0,93	**0,79**	**0,88**
Hinge	0,40	0,78	0,98	0,75	0,70	0,82
Squared Hinge	0,39	0,59	0,97	0,61	0,59	0,73

From the results shown in the Table 2, the Loss Function method is Binary Cross Entropy, can provide the best results by achieving a DSC value of 0.88 (88%) and an IoU of 0.79 (79%). From these two experimental results, best combination between optimizer method and Loss Function method is RMSprop and, also Binary Cross Entropy. The next Hyperparameter tuning is carried out to determine the value of Learning Rate and best number of epochs from the two combinations of the above methods on the U-Net model. The Learning Rate was observed at values of 0.00001, 0.0001, 0.001, and 0.1. Table 3 shows performance results of the U-Net model on Learning Rate parameter tuning.

TABLE III. COMPARISON OF RESULTS TO THE LEARNING RATE VALUE METHOD USED ON THE U-NET METHOD

Performance Metric	**RMSprop + Binary_crossentropy**			
	Learning Rate			
	0,00001	**0,0001**	**0,001**	**0,01**
Val_IoU	**0,79**	0,78	0,77	0,78
Val_DSC	**0,88**	0,85	0,87	0,86
Val_acc	0,87	**0,88**	0,86	0,88
Val_precision	**0,93**	0,92	0,94	0,84
Val_recall	0,88	**0,89**	0,83	0,89
Val_loss	0,41	0,31	0,34	**0,28**

*Val: validation

A learning Rate value of 0.00001 can give the best results on the U-Net model, with a DSC value of 0.88 and an IoU value of 0.79. The three results of the Hyperparameter Tuning, it was found that the combination of the RMSprop optimizer, the Loss Function Binary Cross-Entropy Method, and the Learning Rate 0.00001 became the best parameters that could be tuned in the U-Net model to segment the amniotic fluid. Finally, to find out the Epoch value needed until this model converges, it is done by checking the number of Epochs with a limit of up to 100 and also using the Early Stopping method to monitor when there is no longer any performance improvement. Figure 3 shows the plot between the number of epochs and the validation loss in the U-Net model from the results of this Hyperparameter Tuning.

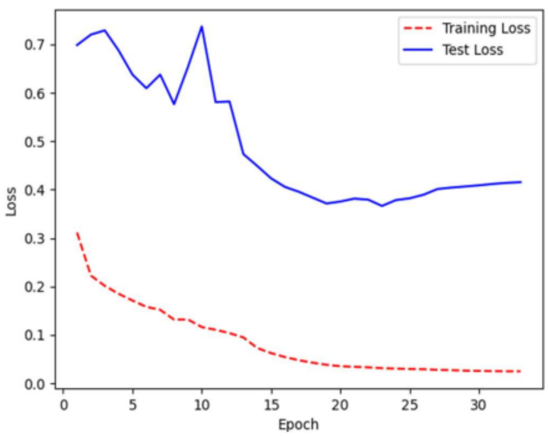
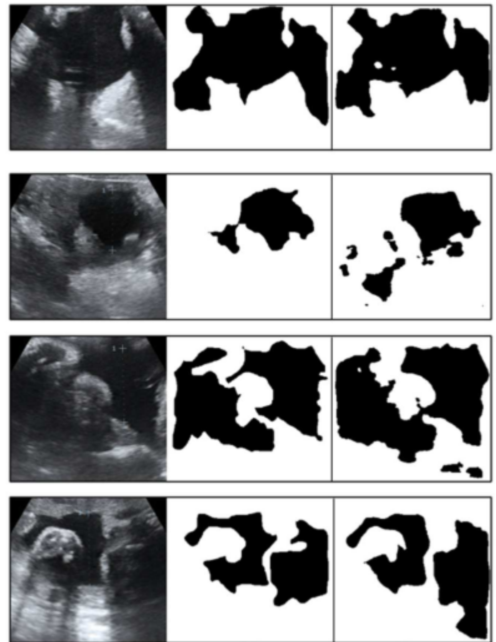


Fig. 3. Plot between Epoch value and Loss value in U-Net model

From Fig. 3 where the value of epoch 33 and above, there is no change in the value of the validation loss so that the early stopping method ends the training process on the 33rd epoch obtained U-Net in one of the image data validations. Fig. 4 shows the results of segmentation using U-Net based on the best Tuning Hyperparameter. In Fig. 4, the first column (a) shows the ultrasound image of the amniotic fluid, the second column (b) shows the ground truth, and the third column (c) shows the segmentation results of the U-Net method.



(a) (b) (c)

Fig. 4. Amniotic fluid segmentation results in the U-net model

In Fig. 4 can be seen an example of the segmentation results based on U-NET with the hyperparameters. In the third column (c) shown the amniotic fluid segmentation results are almost close to the ground truth image (b), where the results of this segmentation show an average DSC value of 0.88.

IV. CONCLUSION

The conclusion in this paper is based on experimental results on the tuning parameters of the U-Net model, show the best performance of U-Net in segmenting amniotic fluid is the combination of the RMSprop optimizer parameter, the Loss function is Binary cross-entropy, the learning rate value is 0.00001 with an Epoch of 33 with DSC of 0.88 (88%) and IoU of 0.79, the accuracy of 0.87, precision of 0.93, recall of 0.88. Experiments with Hyperparameter Tuning showed improved results on DSC from several previous studies [8] and [9] and the proposed model is able to segment Amniotic Fluid with research data. Future research is carried out to improve segmentation results by developing methods, especially which can analyze segmentation with a limited amount of data.

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REFERENCES

[1] P. D. W. Ayu, S. Hartati, A. Musdholifah, and D. S. Nurdiati, "Amniotic fluid classification based on volume and echogenicity using single deep pocket and texture feature," *ICIC Express Lett.*, vol. 15, no. 7, pp. 681–691, 2021.

[2] M. H. Beall, J. P. H. M. van den Wijngaard, M. J. C. van Gemert, and M. G. Ross, "Amniotic Fluid Water Dynamics," *Placenta*, vol. 28, no. 8–9, pp. 816–823, 2007.

[3] R. A. Brace and E. J. Wolf, "Normal amniotic fluid volume changes throughout pregnancy," *Am. J. Obstet. Gynecol.*, vol. 161, no. 2, pp. 382–388, 1989.
[4] W. Dc and L. Rock, "Dubil2013," vol. 16, no. May, 2013.
[5] M. I. Martínez-León, "Fetal imaging," *J. Ultrasound Med.*, vol. 33, no. 5, pp. 745–757, 2014.
[6] H. C. Cho *et al.*, "Automated ultrasound assessment of amniotic fluid index using deep learning," *Med. Image Anal.*, vol. 69, p. 101951, 2021.
[7] P. D. W. Ayu and S. Hartati, "Pixel Classification Based on Local Gray Level Rectangle Window Sampling for Amniotic Fluid Segmentation," *Int. J. Intell. Eng. Syst.*, vol. 14, no. 1, pp. 420–432, 2021.
[8] P. D. W. Ayu, S. Hartati, A. Musdholifah, and D. S. Nurdiati, "Amniotic fluid segmentation based on pixel classification using local window information and distance angle pixel," *Appl. Soft Comput.*, vol. 107, p. 107196, 2021.
[9] S. Sun, J. Y. Kwon, Y. Park, H. C. Cho, C. M. Hyun, and J. K. Seo, "Complementary Network for Accurate Amniotic Fluid Segmentation from Ultrasound Images," *IEEE Access*, vol. 9, pp. 108223–108235, 2021.
[10] O. Ronneberger, P. Fischer, and T. Brox, "U-net: convolutional networks for biomedical image segmentation," *Lect. Notes Comput. Sci.*, vol. 9351, pp. 234–241, 2015.
[11] H. Shin, R. Agyeman, M. Rafiq, M. C. Chang, and G. S. Choi, "Automated segmentation of chronic stroke lesion using efficient U-Net architecture," *Biocybern. Biomed. Eng.*, vol. 42, no. 1, pp. 285–294, Jan. 2022.
[12] J. Li *et al.*, "Study on strategy of CT image sequence segmentation for liver and tumor based on U-Net and Bi-ConvLSTM," *Expert Syst. Appl.*, vol. 180, p. 115008, Oct. 2021.
[13] M. Han *et al.*, "Automatic segmentation of human placenta images with u-net," *J. EEE Access*, vol. 7, pp. 180083–180092, 2019.
[14] C. Chu, J. Zheng, and Y. Zhou, "Ultrasonic thyroid nodule detection method based on U-Net network," *Comput. Methods Programs Biomed.*, vol. 199, p. 105906, Feb. 2021.
[15] K. bing Chen, Y. Xuan, A. jun Lin, and S. hua Guo, "Lung computed tomography image segmentation based on U-Net network fused with dilated convolution," *Comput. Methods Programs Biomed.*, vol. 207, p. 106170, Aug. 2021.
[16] S. Ruder, "An overview of gradient descent optimization algorithms," pp. 1–14, 2016.
[17] M. D. Zeiler, "ADADELTA: An Adaptive Learning Rate Method," 2012.
[18] D. P. Kingma and J. L. Ba, "Adam: A method for stochastic optimization," *3rd Int. Conf. Learn. Represent. ICLR 2015 - Conf. Track Proc.*, pp. 1–15, 2015.

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