

Efficient Fetal Ultrasound Image Segmentation with MFP-Unet: A Deep Learning Approach

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Received July 10, 2025; revision requested August 5, 2025; accepted October 19, 2025

Background and purpose: Fetal ultrasound image segmentation is a crucial component of prenatal diagnosis, enabling the accurate measurement of key biometric parameters and the early detection of abnormalities. Manual segmentation is prone to variability due to factors such as operator skill, image quality, and acquisition conditions. This study compares conventional and deep learning-based segmentation methods, proposing an enhanced Multi-Feature Pyramid U-Net (MFP-Unet) to improve accuracy, robustness, and clinical applicability.

Methods: We utilised the HC18 Grand Challenge Dataset, which comprises 1,334 ultrasound images from 551 pregnancies without growth abnormalities. The proposed MFP-Unet integrates multi-scale feature pyramid fusion, dilated convolutions, and attention gates into the U-Net framework. Performance was compared with Dilated U-Net, U-Net, RU-Net, Attention U-Net, and R2U-Net using Dice Coefficient, Intersection over Union (IoU), and mean Average Precision (mAP). Preprocessing included Niblack's adaptive thresholding and custom region extraction for femur length images.

Results: MFP-Unet achieved the highest accuracy across all parameters: HC IoU = 90% (Dice = 0.95), FL IoU = 93% (Dice = 0.97), BPD IoU = 88% (Dice = 0.93), and overall mAP = 0.92. The architecture formed smoother anatomical boundaries, enhanced robustness to image variability, and compact measurement variations associated with other methods.

Conclusions: The MFP-Unet approach shows strong promise for use in clinical fetal ultrasound analysis, offering reliable and precise biometric measurements that can aid in timely interventions and enhance prenatal care outcomes. Future research should validate performance on multi-centre datasets and explore real-time deployment.

Key words: Deep learning; Fetal ultrasound segmentation; Multi-Feature Pyramid U-Net; Biometric measurement; Prenatal care

Advanced Ultrasound in Diagnosis and Therapy 2026; 03: 216-222

DOI: [10.26599/AUDT.2026.250052](https://doi.org/10.26599/AUDT.2026.250052)

Ultrasound remains the most widely used imaging technique in prenatal diagnostics because it is affordable, portable, radiation-free, and readily available. Clinically, it plays a central role in monitoring fetal growth, estimating gestational age, and identifying both normal and abnormal conditions in utero [1-4]. Despite these advantages, ultrasound has limitations. Image interpretation can vary among operators; soft tissue contrast is often limited, and imaging becomes particularly challenging in cases with low amniotic fluid levels. These factors can affect the accuracy of measurements. Reliable assessment of fetal growth depends on precise estimation of key biometric indicators such as biparietal diameter (BPD), head circumference (HC),

abdominal circumference (AC), and femur length (FL) [5]. Traditionally, these measurements are taken manually from two-dimensional (2D) scans, but the process is time-intensive and susceptible to variability between and within observers, as well as to changes in image quality and fetal positioning [6,7]. These challenges have driven interest in developing automated and robust segmentation methods for fetal biometric evaluation. Over the past decade, both traditional image-processing techniques and recent deep-learning methods have been explored. Commercial software like SonoBiometry can produce semi-automated measurements with high accuracy, although manual corrections are sometimes still required [8]. Classical methods such as thresholding and

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edge detection tend to perform poorly under diverse imaging conditions. In contrast, machine learning (ML) and deep learning (DL) –based solutions have demonstrated greater adaptability, with convolutional neural networks (CNNs) and their extensions leading much of the recent progress [9–11]. The introduction of U-Net by Ronneberger et al. [12] was a turning point for biomedical segmentation, combining an encoder–decoder framework with skip connections to preserve spatial detail. Since then, numerous adaptations—such as recurrent convolutional U-Nets (RU-Net) [13,14], recurrent residual U-Net (R2U-Net) [13], and attention U-Net [15,16] have aimed to further enhance feature extraction and segmentation accuracy. Feature pyramid networks [17,18] and multi-task learning strategies [19–22] have further advanced segmentation accuracy, especially in challenging modalities like ultrasound. In fetal ultrasound, deep learning methods have achieved human-level performance for HC and BPD estimation [23–27]. Techniques such as the Difference-of-Gaussian method [27], probabilistic boosting trees [28,29], and attention-gated CNNs [30–32] have shown that integrating anatomical priors with deep features improves robustness. However, existing methods often struggle to balance local detail preservation with global anatomical context, leading to either boundary inaccuracies or missed structures. To address these gaps, we propose the Multi-Feature Pyramid U-Net (MFP-Unet), which combines dilated convolutions for large receptive fields, multi-scale feature pyramid fusion for contextual richness, and attention gates for structure-focused learning. This architecture is designed to deliver accurate, consistent segmentation of HC, BPD, and FL in varied imaging conditions. In this study, we evaluate MFP-Unet against established segmentation models, demonstrating its superiority across multiple performance metrics and its potential for clinical integration.

Dataset

We used the publicly available HC18 Grand Challenge Dataset [19], which contains 1,334 two-dimensional fetal ultrasound images from 551 pregnancies without growth abnormalities. Images were acquired on Voluson E8 or Voluson 730 ultrasound machines (GE Healthcare) and annotated by clinical experts for head circumference (HC) measurement. The dataset was split into 75% for training and 25% for testing, ensuring no overlap of patient data between sets.

Preprocessing

We applied preprocessing tailored to each biometric parameter:

HC and AC: Niblack’s adaptive thresholding was

used to highlight contour regions.

FL: A custom region extraction method was implemented to remove background noise and enhance femur edges.

All images were resized to 256×256 pixels, normalized, and augmented via rotation, flipping, and scaling to improve generalization.

Proposed Architecture

The MFP-Unet extends the classical U-Net with three main enhancements:

Dilated Convolutions: Increase receptive field size without additional parameters, capturing broader contextual information.

Multi-Scale Feature Pyramid Fusion: Aggregates features from multiple resolution levels to balance local detail and global context.

Attention Gates: Suppress irrelevant background noise while highlighting salient anatomical features in skip connections.

Figure 1 shows the proposed MFP-Unet architecture, highlighting the integration of dilated convolutions, multi-feature pyramid fusion, and attention mechanisms.

Segmentation Pipeline

We implemented a multi-stage segmentation workflow to robustly delineate fetal anatomy and extract biometric measurements (Fig. 2). First, a fetal-anatomy detector localizes the region of interest in the ultrasound frame. The pipeline then uses dual input channels: the original ultrasound image and a preprocessed channel generated by Niblack’s adaptive thresholding (for HC/AC) or custom region extraction (for FL). These inputs are fed into the Attention MFP-Unet, which outputs pixel-level segmentation masks. Post-processing involves morphological cleaning, skeletonization for femur measurements, and ellipse fitting via gradient descent for HC and AC. Final biometric parameters (HC, BPD, AC, FL) are calculated from the processed shapes and compared with expert annotations. Figure 2 illustrates the complete segmentation pipeline, from image acquisition to final measurement extraction.

Implementation Details

All models were developed in Python 3.8 using the TensorFlow 2.8 framework with the Keras API. Training was carried out on a workstation equipped with an NVIDIA RTX 3090 GPU (24 GB VRAM). For optimization, we employed the Adam algorithm with a learning rate of 0.0001, using binary cross-entropy as the loss function and a batch size of 16. Each model was trained for a maximum of 200 epochs, with early stop-

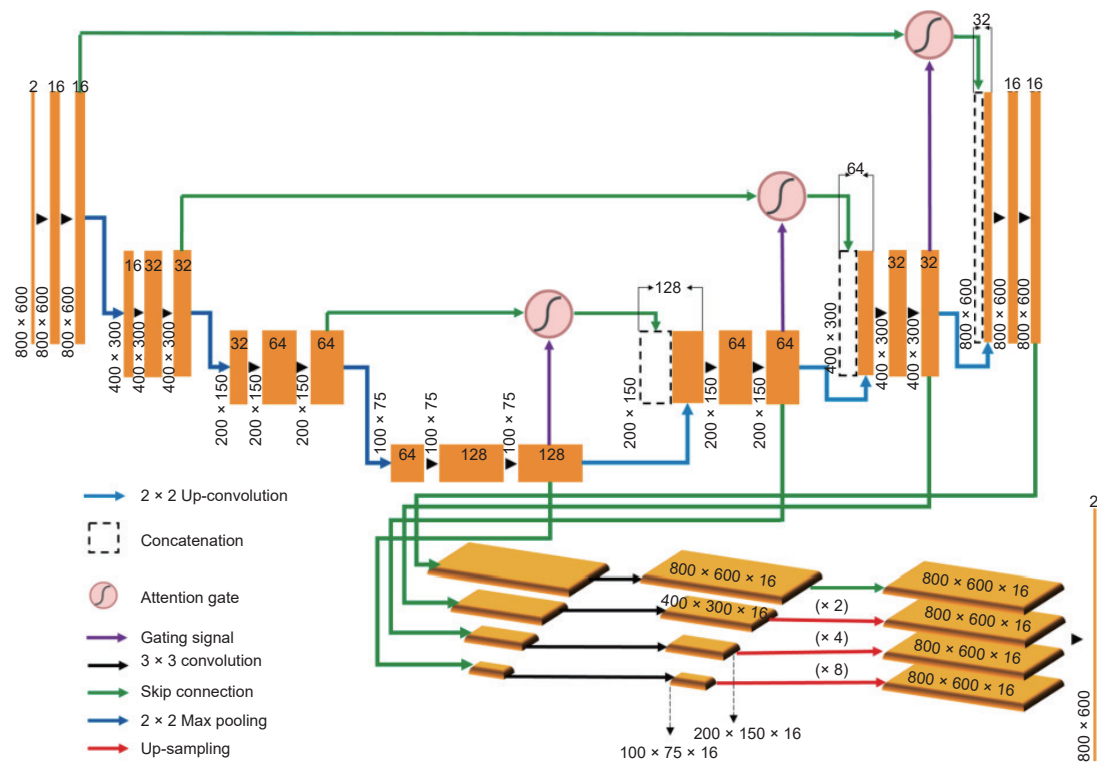


Figure 1 Proposed attention MFP-Unet architecture with dilated convolution blocks, multi-scale feature pyramid fusion, and attention gates in skip connections.

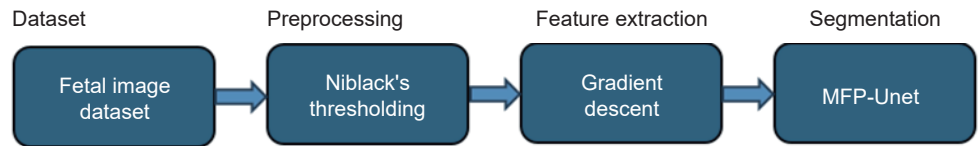


Figure 2 Segmentation pipeline for fetal biometric analysis: (1) anatomy detection; (2) preprocessing and dual-channel input preparation; (3) Attention MFP-Unet segmentation; (4) post-processing with morphological cleaning, skeletonization, and ellipse fitting.

ping applied when validation loss ceased to improve.

Mean Average Precision (mAP) — captures detection performance across a range of IoU thresholds.

Performance Evaluation

The proposed MFP-Unet was benchmarked against five established segmentation models: U-Net, Dilated U-Net, Attention U-Net, RU-Net, and R2U-Net. Table 1 summarises the evaluation metrics and formulas used in this study. Evaluation was based on three widely recognised metrics in medical image segmentation: Segmentation performance was evaluated using:

Intersection over Union (IoU) — quantifies the degree of overlap between predicted and reference segmentation masks.

Dice Coefficient — provides a balanced measure of precision and recall, emphasizing boundary accuracy.

Dataset and Experimental Design

This study utilized the publicly available dataset from van den Heuvel et al. [19], comprising 1,334 two-dimensional ultrasound images of fetal head circumferences collected from 551 pregnant women during routine examinations at the Radboud University Medical Center, Nijmegen, The Netherlands (May 2014–May 2015). All fetuses were assessed as healthy and without growth abnormalities. Images were acquired using Voluson E8 and Voluson 730 ultrasound systems (GE Healthcare), with pixel dimensions varying according to scanning settings. Data were split into 75% for training and 25%

Table 1 Mathematical definitions of these metrics, along with their role in this study.

Metric	Formula	Role of the study
IoU	$\text{IoU} = \text{TP} / (\text{TP} + \text{FP} + \text{FN})$	Assesses how closely predicted regions align with the reference segmentation.
Dice	$\text{Dice} = 2\text{TP} / (2\text{TP} + \text{FP} + \text{FN})$	Measures segmentation boundary accuracy by balancing precision and recall.
mAP	Mean of precision values across IoU thresholds	Evaluates overall detection accuracy under varying overlap requirements.

for testing, ensuring subject exclusivity between sets.

MFP-Unet Architecture

The proposed Multi-Feature Pyramid U-Net (MFP-Unet) is designed to enhance the standard U-Net's segmentation accuracy through several innovations:

Dilated Convolutions: Increase the receptive field while keeping the parameter count manageable.

Multi-Feature Pyramid Fusion: Merges multi-scale feature maps, integrating local details with global context.

Depth Equalization: Harmonizes concatenated feature map depths, preventing data loss.

Fixed-Dimension Upsampling: Aligns feature resolutions before semantic classification.

These modifications allow MFP-Unet to effectively capture structural details at multiple scales, improving robustness across varied image resolutions.

Attention MFP-Unet

To further refine segmentation, Attention Gates (AGs) were incorporated into skip connections. AGs selectively highlight relevant spatial regions by:

1. Applying 1×1 convolutions and ReLU activation to encoder-decoder feature maps.
2. Passing features through a sigmoid activation to compute attention coefficients.
3. Upsampling coefficients using trilinear interpolation.
4. Multiplying them by the original feature maps to emphasize salient anatomical regions.

This targeted focus is particularly beneficial for fetal

ultrasound segmentation, where subtle anatomical boundaries must be preserved.

Segmentation Workflow

1. **Fetal Anatomy Detection:** A CNN localizes the target organ in each frame.

2. **Dual-Channel Preprocessing:** The original image is paired with a processed channel generated using Niblack's thresholding, defined as:

$$T(a,b) = \mu(a,b) + k \cdot \sigma(a,b) \quad (1)$$

where $\mu(a,b)$ and $\sigma(a,b)$ are the local mean and standard deviation, and k is a sensitivity constant.

3. **Segmentation:** The Attention MFP-Unet processes the two-channel input to produce a binary mask.

4. **Post-processing:** Morphological operations, skeletonization (for FL), and ellipse fitting (for HC and AC) are applied.

Figure 3 shows the segmentation and biometric parameters of abdomen, fetal head, and femur.

This figure presents representative segmentation outputs from the proposed method, illustrating clear delineation of anatomical structures. The example masks for the abdomen, fetal head, and femur demonstrate precise boundary tracing, enabling the reliable calculation of Head Circumference (HC), Biparietal Diameter (BPD), Abdominal Circumference (AC), and Femur Length (FL).

The confusion matrix in figure 4 summarizes classification performance for fetal organ identification. High diagonal values indicate strong agreement between pre-

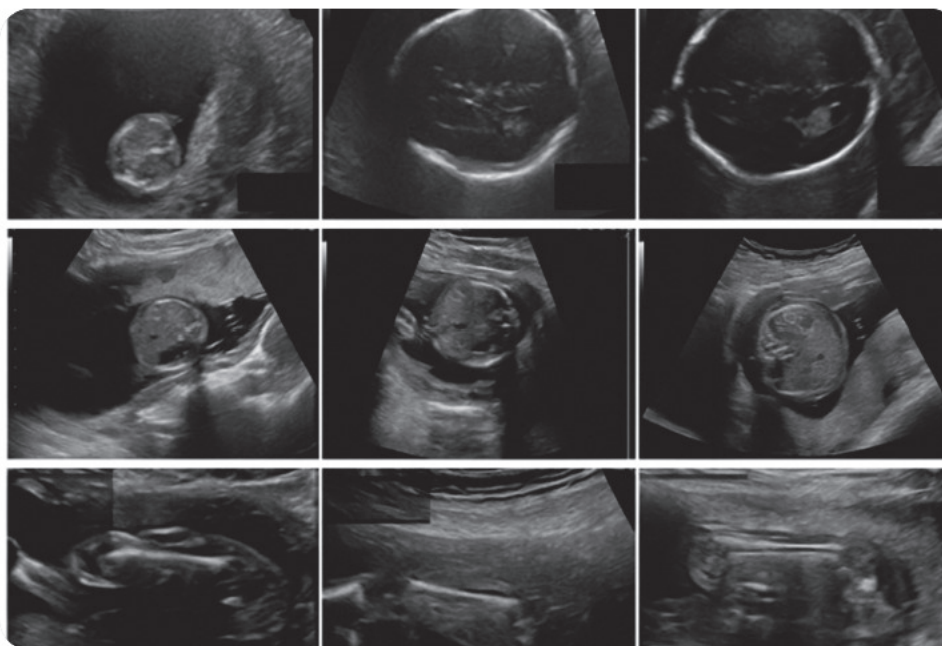


Figure 3 Segmentation and Biometric Parameters of Abdomen, Fetal Head, and Femur.

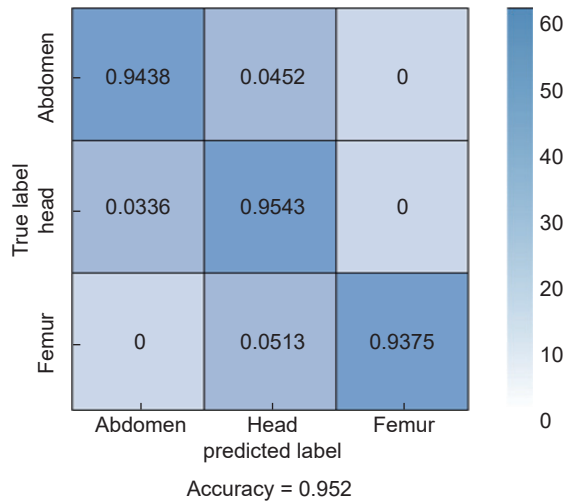


Figure 4 Classification Network on Test Set – Confusion Matrix.

dicted and ground truth classes, with minimal misclassification. This step ensures that segmentation is applied to correctly identified regions, further improving downstream biometric accuracy.

Fetal Biometry Extraction

Ellipse fitting is optimized using gradient descent:

$$\theta_{j+1} = \theta_j - \alpha \frac{\partial J(\theta)}{\partial \theta} \tag{2}$$

Here θ_j is the parameter set at iteration j , α is the learning rate, and $J(\theta)$ is the cost function.

From the optimized ellipse: BPD is measured as the semi-minor axis, HC and AC are derived from the ellipse perimeter, and FL is computed from the length of

the skeletonized femur contour.

This process ensures sub-millimetre accuracy, with iterative refinement reducing measurement error at each step.

Results and Discussions

The findings indicate that MFP-Unet outperforms conventional U-Net-based models, providing more accurate segmentation for every fetal biometric parameter assessed. The observed improvements in IoU, Dice Coefficient, and mAP are consistent with previous findings that multi-scale feature fusion and attention mechanisms enhance the delineation of complex anatomical boundaries [15,16]. Compared to Attention U-Net, the MFP-Unet achieved a higher Dice score (0.95 vs. 0.94 for HC and 0.97 vs. 0.96 for FL), highlighting its ability to preserve fine structural details while maintaining global context. These results also align with earlier studies on fetal head segmentation using deep learning, where incorporating multi-level features improved robustness under variable imaging conditions [9-11]. Notably, the integration of gradient descent-based ellipse fitting reduced measurement variability, addressing a key limitation of manual biometry noted in prior clinical research [5-7]. Together, these findings suggest that MFP-Unet can offer more consistent and clinically reliable measurements, potentially streamlining prenatal assessments in routine practice. Table 2 demonstrates that the proposed MFP-Unet consistently outperforms all baseline models, achieving the highest IoU, Dice, and mAP values across HC, BPD, and FL.

Table 3 shows a high correlation ($R \geq 0.95$) between

Table 2 Various techniques using our dataset are compared to the performance of the proposed segmentation method.

Model	HC IoU (%)	HC Dice Coeff.	BPD IoU (mm)	BPD Dice Coeff.	FL IoU (mm)	FL Dice Coeff.	Overall Seg. mAP
U-net	85.0	0.90	0.82	0.88	0.88	0.92	0.87
Dilated U-net	87.0	0.92	0.84	0.90	0.90	0.94	0.89
Attention U-net	89.0	0.94	0.86	0.92	0.92	0.96	0.91
RU-net	86.0	0.91	0.83	0.89	0.89	0.93	0.88
R2U-net	88.0	0.93	0.85	0.91	0.91	0.95	0.90
MFP-Unet	90.0	0.95	0.88	0.93	0.93	0.97	0.92

Notably: HC: IoU = 90.0%; Dice = 0.95; BPD: IoU = 88.0%; Dice = 0.93; FL: IoU = 93.0%, Dice = 0.97; Overall mAP: 0.92

Table 3 Fetal Biometry Parameters from Proposed Method: Training vs Test Sets

Set	Parameter	Correlation coefficient t (R)	Slope (a)	Intercept (b, mm)
Training	Biparietal Diameter (BPD)	0.98	1.02	−0.05
	Head Circumference (HC)	0.96	1.03	0.1
	Abdominal Circumference (AC)	0.97	1.00	−0.01
	Femur Length (FL)	0.99	1.01	−0.02
Testing	Biparietal Diameter (BPD)	0.97	1.01	−0.03
	Head Circumference (HC)	0.95	1.02	0.12
	Abdominal Circumference (AC)	0.96	0.99	0.02
	Femur Length (FL)	0.98	1.00	0.01

predicted and reference biometric measurements for both training and test sets, confirming accuracy and generalizability.

Training Behaviour

In figure 5, the training accuracy increased rapidly and approached 1.0 by the final epochs. Validation accuracy plateaued at ~0.9 after 25 epochs, indicating stable generalization.

In figure 6, the training loss steadily declined towards zero, while validation loss decreased but displayed minor fluctuations, suggesting slight variability in unseen data performance.

Conclusion

Accurate segmentation of fetal ultrasound images plays a pivotal role in ensuring dependable biometric measurements and improving the quality of prenatal care. In this work, we introduced an enhanced segmentation framework — MFP-Unet — that combines multi-feature pyramid fusion, dilated convolutions, and attention mechanisms to capture both fine structural details and broader anatomical context. Across all tested metrics — IoU, Dice Coefficient, and mAP — the proposed model consistently outperformed widely used architectures, delivering precise delineation of fetal head, abdomen, and femur. These improvements translated directly into more reliable calculations of head circumference, biparietal diameter, abdominal circumference, and femur length, closely matching expert annotations. The integration of gradient descent-based ellipse fitting

and dual-channel preprocessing further strengthened measurement accuracy, offering a complete end-to-end solution from image input to biometric output. This makes the method well-suited for clinical use, where consistency and speed are equally important. Looking ahead, expanding the approach to larger, more diverse datasets and exploring its adaptation for 3D ultrasound volumes could make it even more robust. With further refinement, MFP-Unet has the potential to support real-time decision-making during routine fetal scans, assisting clinicians in early detection and intervention.

Acknowledgment

Not applicable.

Authors' Contributions

A.Usha Ruby conceived of and designed the study; GeorgeChellin Chandran.J drafted the manuscript; A.UshaRuby and George Chellin Chandran.J performed statistical design and analysis; A.Usha Ruby and George Chellin Chandran.J performed the research; the data for the work. All authors read and approved the final manuscript.

Funding

Not applicable.

Data Availability

The datasets used or analyzed during the current study available from the corresponding author on reasonable request.

Declarations

Ethics approval and consent to participate

Ethical clearance to conduct this study was sought from the Excellency in Research Ethics and Science (ERES) committee. The patients/participants provided their written informed consent to participate in this study.

Conflict of interest

The authors report no potential conflicts of interest related to this work.

Consent for publication

Not applicable.

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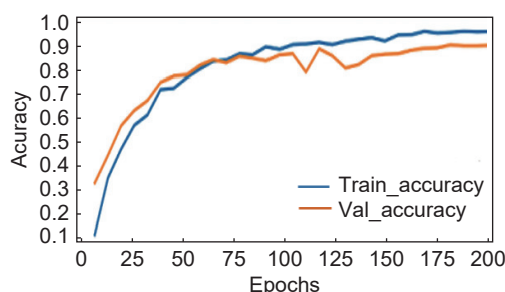


Figure 5 Accuracy during training and validation.

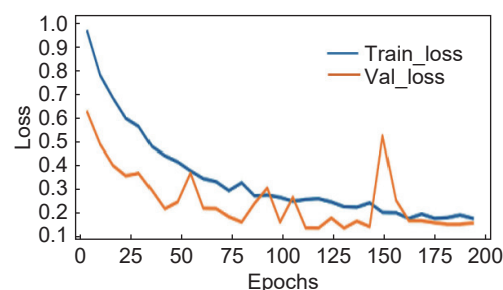


Figure 6 Training and validation loss

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