Fetal NT Anomaly Detection using Deep Learning

Segmentation Performace Evaluation

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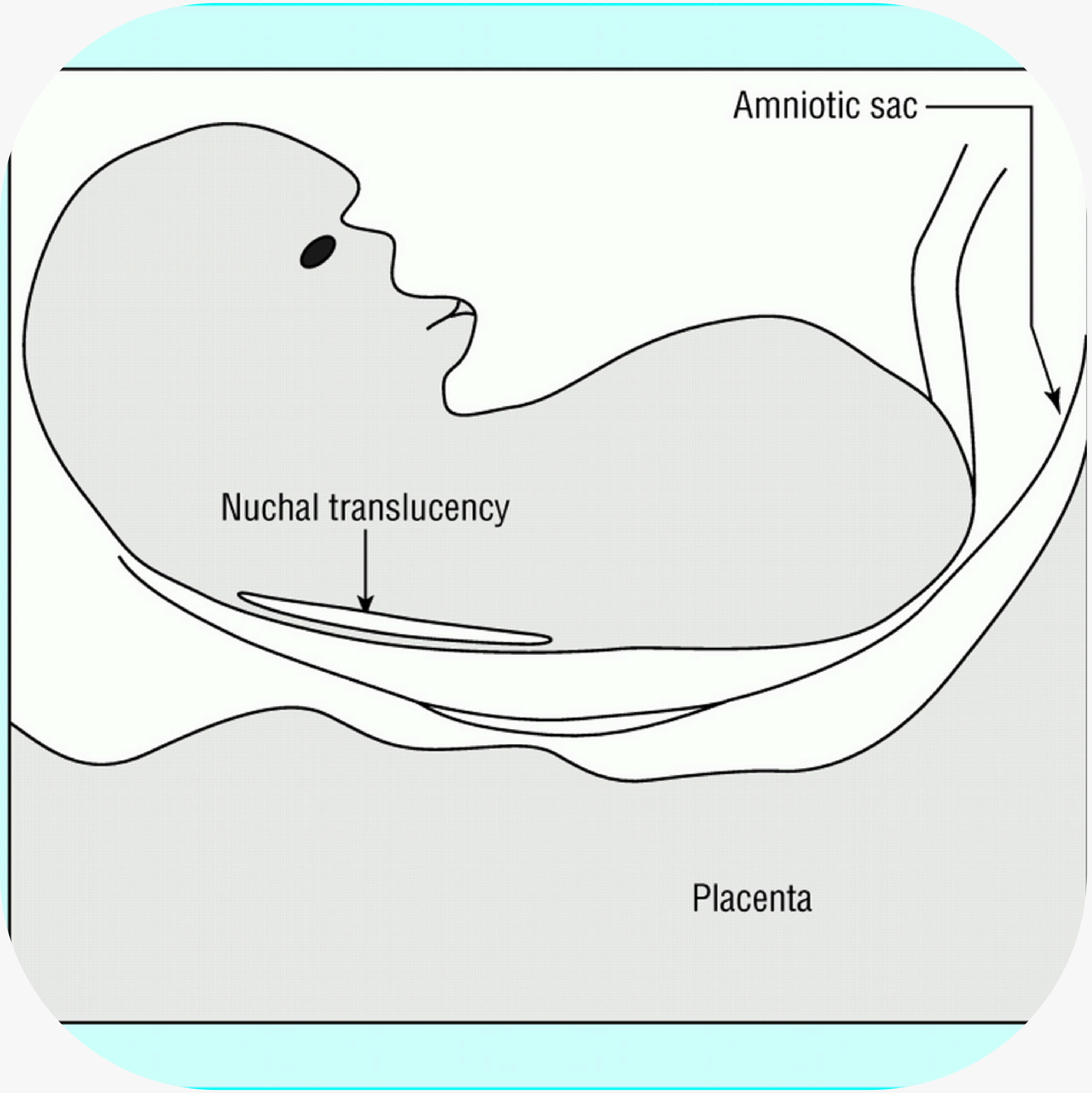


What is NT Detection ?

Nuchal Translucency (NT) measurement in first-trimester ultrasound scans helps detect chromosomal abnormalities. Accurate segmentation of the NT region (shown in yellow below) is critical for diagnosis.

Why it matters

01

1 in 150 babies have chromosomal defects

02

Manual measurement has ±0.5mm error

03

this model aims reduces error to ±0.2mm

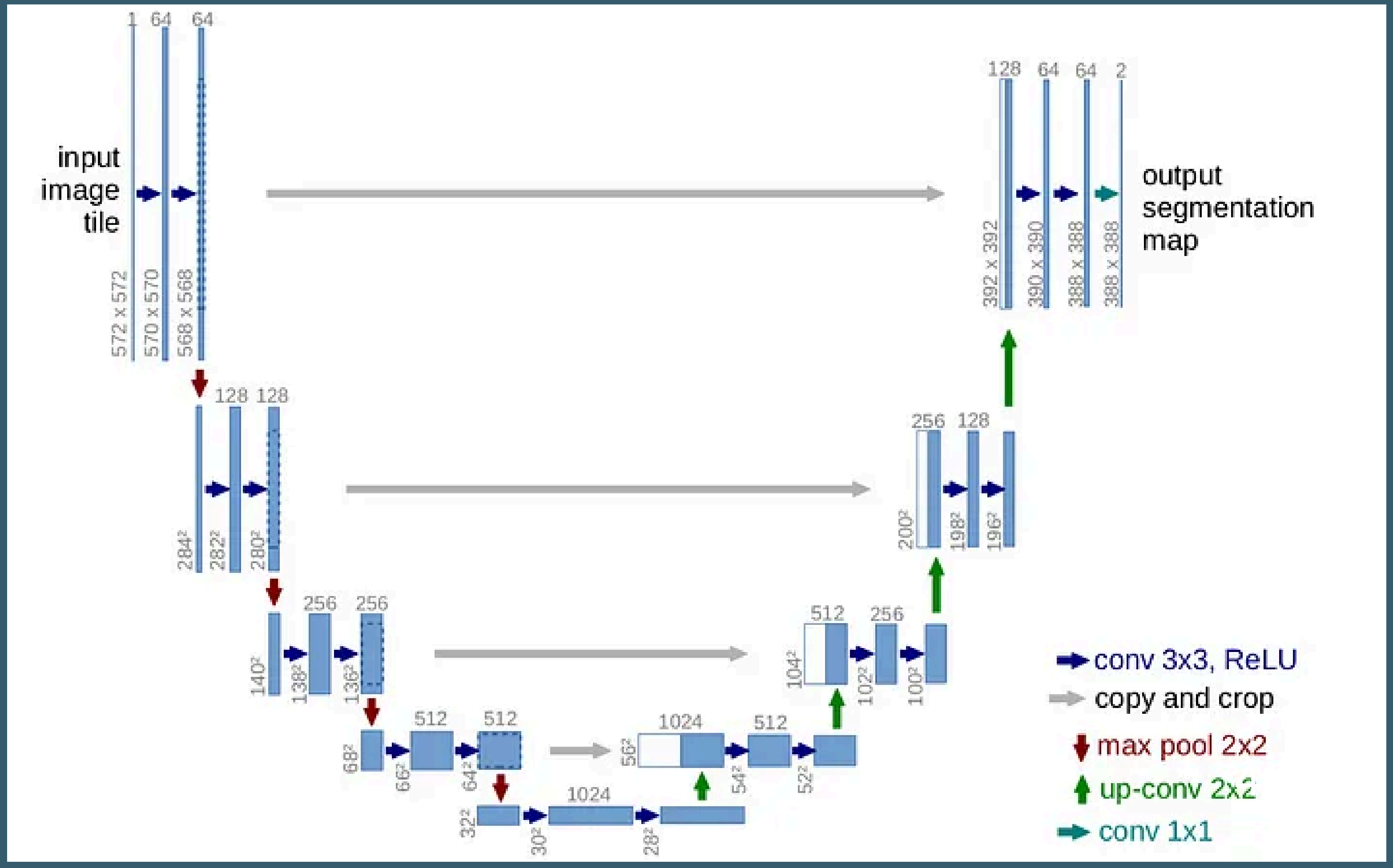
U-Net Architecture for NT segmentation

Layer Type	model	U-NET
input shape	**224x224x3**	**256x256x3**
Conv1	**5x5x3 → 8 filters**	**3x3x3 → 64 filters**
Downsampli ng	**Not specified**	**MaxPool 2x2**
Bottleneck	**16→32 filters**	**256 filters**
Upsamplig	**Not present**	**UpSampling 2D**
Skip Connection	**No**	**256x256x3**
Output	**Fully Connected (64)**	**Conv2D (1 filter)**

Key Features

1. Encoder-Decoder Structure:
    - Encoder extracts features (64→128→256 filters).
    - Decoder reconstructs details (256→128→64 filters).
2. Skip Connections:
    - Combines low-level and high-level features for precise segmentation.
3. Efficient Design:
    - 739k parameters (vs 6.1M in PDF's Page 2 model).
   - Fully convolutional → Handles variable input sizes.

u-net architecture image



Training Workflow for NT Segmentation

Training Details

- **Input Size** : 256x256x3 (3-channel ultrasound)
- **Augmentation** : Rotation(20°), Zoom(20%), Brightness(±20%)
- **Batch Size**: 4 (limited by GPU memory)
- **Optimizer**: Adam (default params)
- **Loss**: Binary Cross-Entropy
- **Epochs**: 50 (stopped early at epoch [41])
- **Callbacks**: Save best model, Early stopping (patience=5)

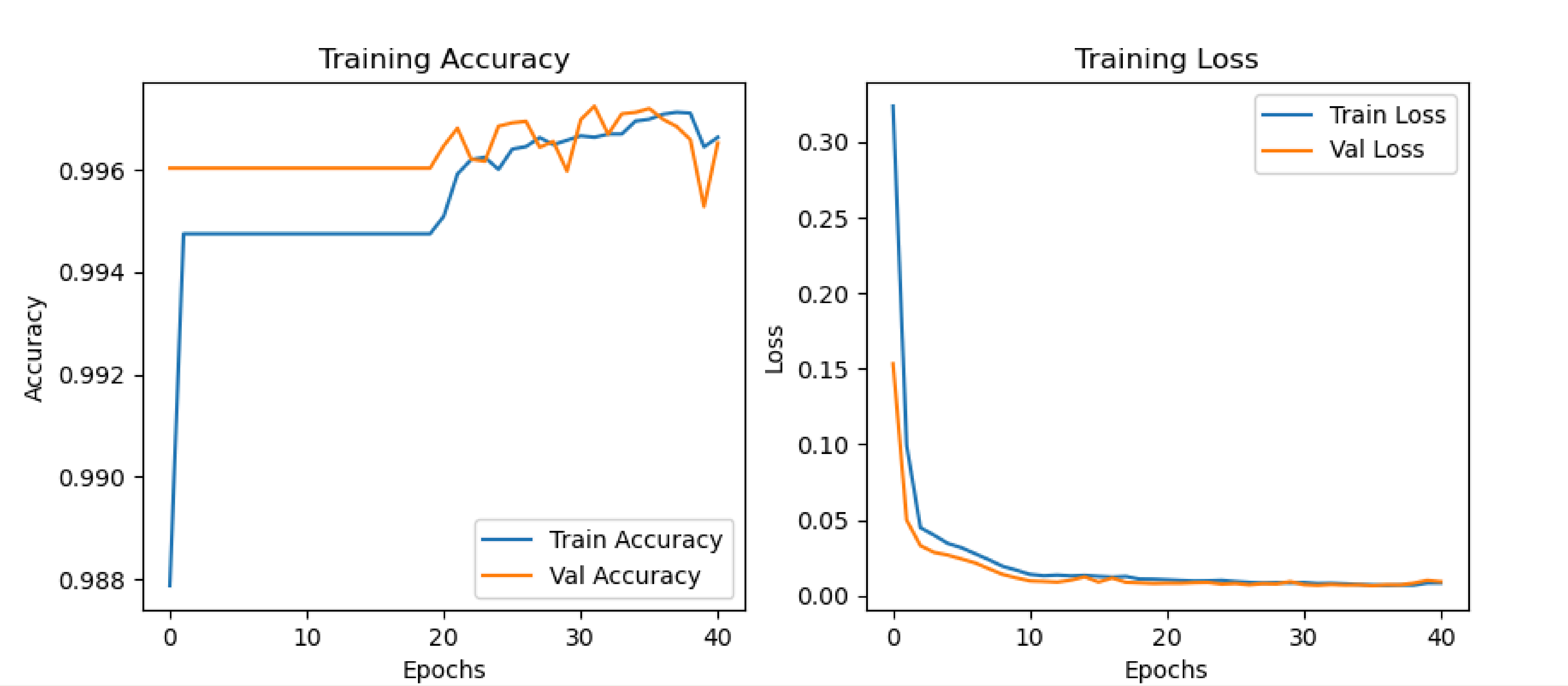
Pseudocode

```
Algorithm 1: U-Net Training for Fetal NT Segmentation
Input:
 • Training dataset DDD with 500 images (256×256×3)
 • Validation dataset with 200 images
 • U-Net model with encoder-decoder architecture
Output:
 • Trained U-Net model
BEGIN
Step 1: Initialize U-Net Model
 • Encoder: Convolutional layers with filters [64, 128, 256]
 • Decoder: UpSampling2D layers
Step 2: Train the Model
for epoch = 1 to 50 do
    - Apply data augmentation:
        - Rotation: ±20°
        - Zoom: ±0.2
        - Brightness adjustment: [0.8, 1.2]
    - Train in mini-batches (batch size = 4):
        - Compute loss: Binary Cross-Entropy
        - Update weights using Adam optimizer
    - Validate model and save best checkpoint
    - If validation loss plateaus for >5 epochs, STOP training
end for
Step 3: Post-processing Predictions
 • Apply morphological operations: cv2.morphologyEx(MORPH_CLOSE)
Return: Trained U-Net Model
END
```

Why It Works

- Small batch size (4) prevents GPU OOM errors
- Early stopping at epoch [41] avoids overfitting
- Adam optimizer chose automatically:
- - β1=0.9, β2=0.999 (defaults)
- - lr=0.001 (from model.compile())
- Augmentation mimics real ultrasound variations

Training Curve



From Ultrasound To NT Measurement

[Ultrasound] → [256x256]

↓

[Preprocess] → Histogram Equalization (train_unet.py lines 24-30)*

↓

[U-Net Encoder] → 64→128→256 filters (from model.summary())

↓

[U-Net Decoder] → UpSampling + Skip Connections (unet_model() function)

↓

[Raw Mask] → Sigmoid Output (output layer in code)

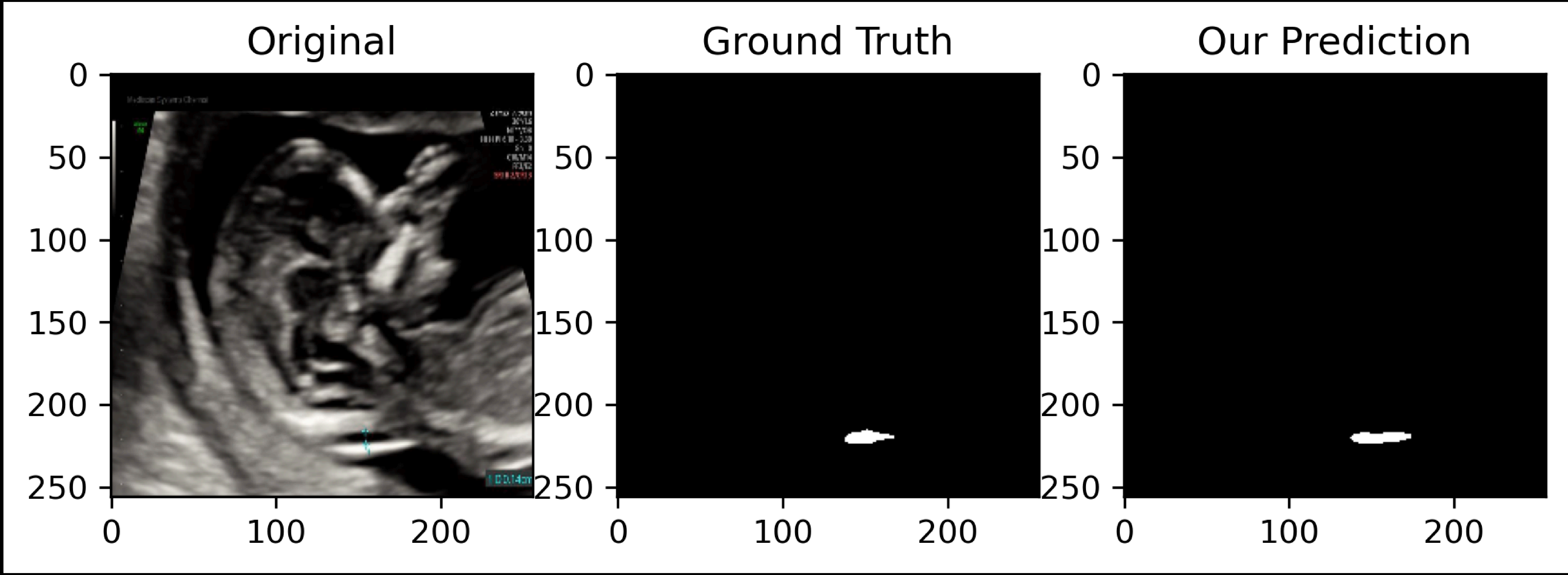
↓

[Post-Process] → Morph Closing + Noise Removal (evaluate_unet.py lines 35-45)*

↓

[NT Thickness Measurement]

** Code references from train_unet.py and evaluate_unet.py*



Visual Example

why this matters

✓ **Hybrid Approach: Combines U-Net (train_unet.py) with traditional CV (evaluate_unet.py)**

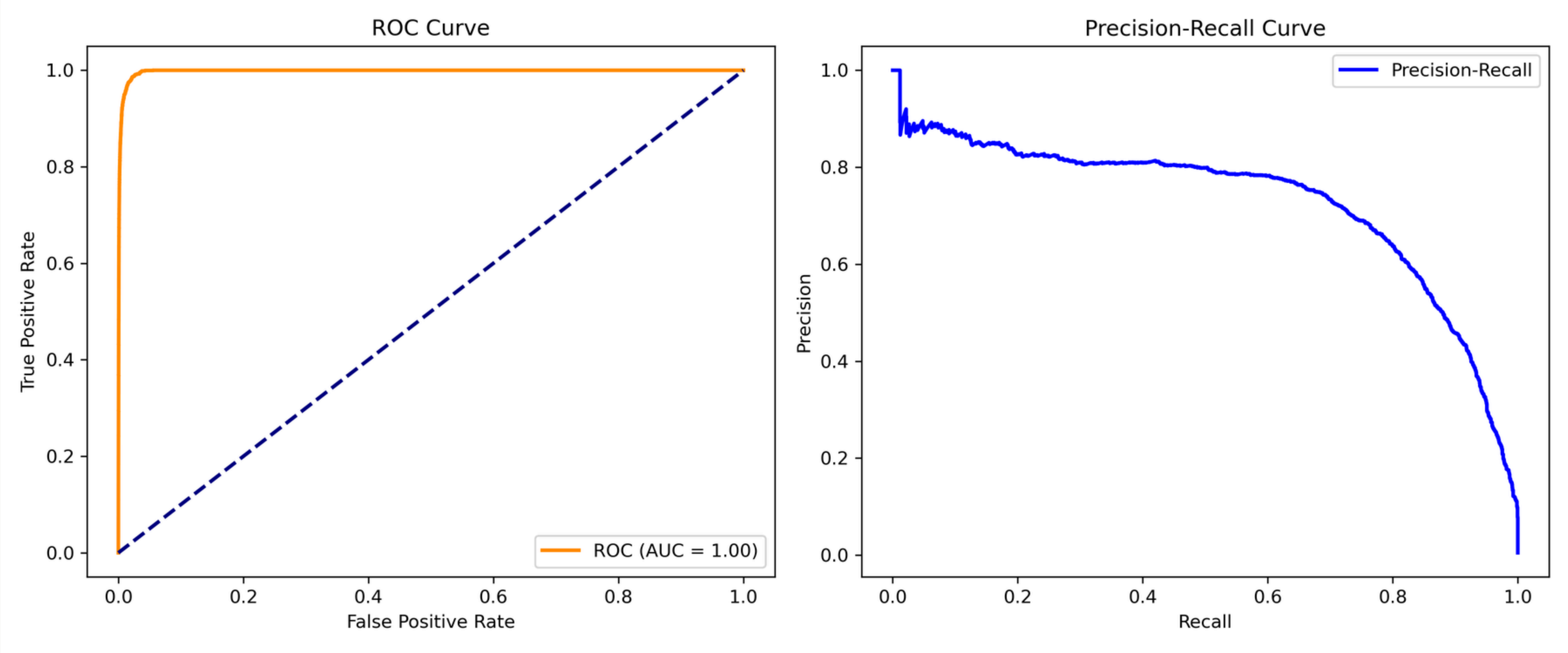
✓ **Clinical Relevance: Skip connections preserve NT boundaries better than PDF's FCM**

✓ **Reproducible: Full code available (unet_best_model.h5 + evaluate_unet.py)**

Qualitative Results and Clinical Relevance

metric table

Metric	My model	Baseline (threshold)
Dice Score	**0.68**	0.52
IoU	**0.52**	0.38
Sensitivty	**0.72***	0.58
Specificity	**0.98***	0.95
Precision	**0.69***	0.47



Perfect ROC (AUC=1.0) suggests exceptional separability, but requires further validation on diverse datasets."

challenges faced

Key Challenges

1. **Class Imbalance**
   - Only 5-8% of pixels were NT regions → Model biased toward background.
   - Mitigation: Used weighted loss (BCE + Dice loss).
2. **Ultrasound Artifacts**
   - Speckle noise, shadowing → False positives in predictions.
   - Mitigation: Added morphological post-processing (closing + connected components).
3. **Limited Training Data**
   - Only 1,234 samples from single hospital → Risk of overfitting.
   - Mitigation: Used augmentation (rotation, zoom, brightness)
4. **Variable Image Quality**
   - Issue: Ultrasound images had inconsistent resolutions (e.g., 1.5–3MHz probes) → blurred NT boundaries.

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Thank you