POLYP SEGMENTATION MODEL USING UNET AND PSPNET

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https://datasets.simula.no/kvasir-seg/

POINTS COVERED

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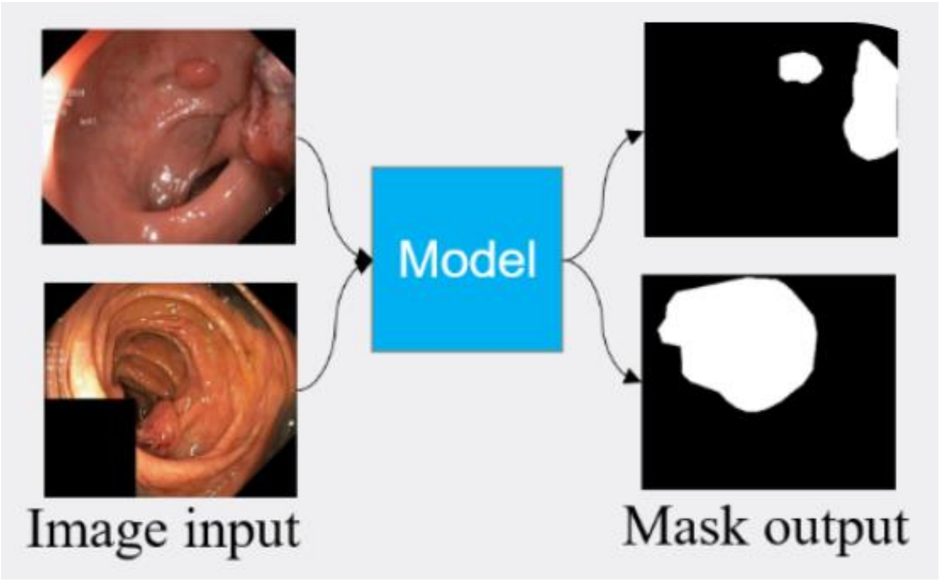
INTRODUCTION

- Pixel-wise image segmentation is crucial in medical image analysis.
- Accurate polyp segmentation aids in effective diagnosis and treatment.
- Kvasir-SEG dataset to tackle polyp segmentation challenges.
- Kvasir-SEG: Open-access dataset of gastrointestinal polyp images and segmentation masks.
- Annotations by experienced gastroenterologists.
- Facilitates result replication, method comparison, and advancement in polyp segmentation.

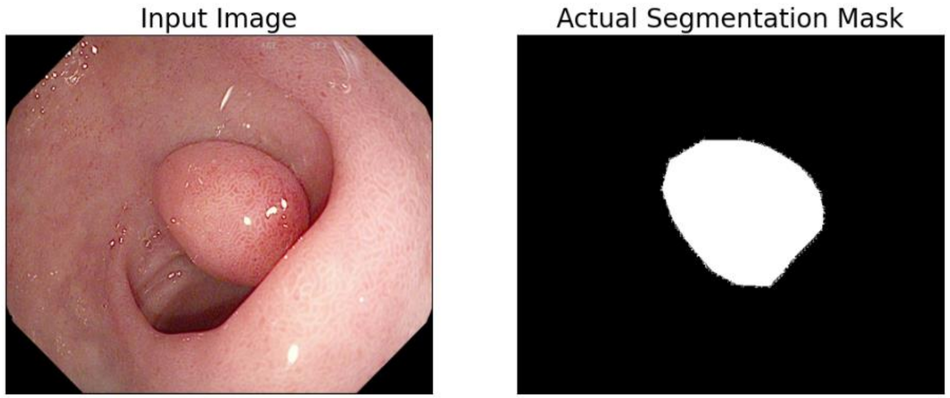
MOTIVATION

- Human GI Tract: Explore GI tract anatomy and importance in digestion.
- Early Polyp Detection: Critical for preventing GI diseases, especially colorectal cancer.
- Colorectal Cancer: Global health concern, high prevalence, and public health impact.
- Polyps as Precursors: Polyps as precursors to colorectal cancer.
- Colonoscopy's Role: Gold standard for detecting, assessing, and removing polyps.
- Polyp Miss Rates: Challenges in detection, potential for oversight, highlighting segmentation's importance.



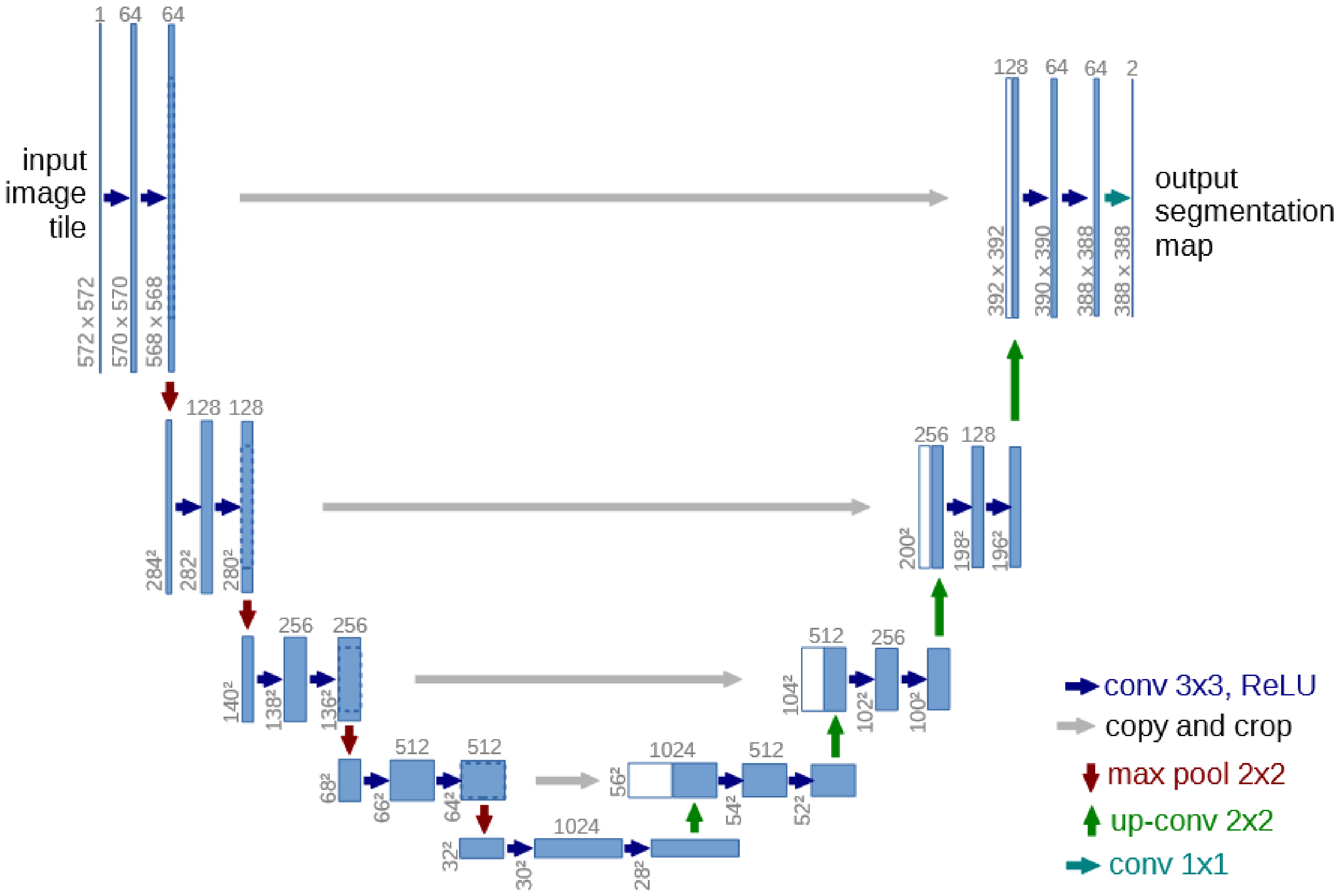
Source: https://www.awadelrahman.com/polypseg.html

DATA SOURCE



- Kvasir-SEG dataset consists of:
  - 1000 polyp images and their corresponding masks from Kvasir Dataset v2.
  - Images exhibit varying resolutions, ranging from 332x487 to 1920x1072 pixels.
  - Both images and masks are meticulously organized in separate folders, ensuring consistent filenames.
  - The dataset utilizes JPG compression, offering easy accessibility and online browsing capabilities.
  - Annotations have been verified and validated by experienced gastroenterologists.
  - Kvasir-SEG serves as a valuable resource for researchers and practitioners in the field of medical image segmentation.
  - The dataset is open-access, fostering collaborative research and innovation in polyp segmentation methodologies.

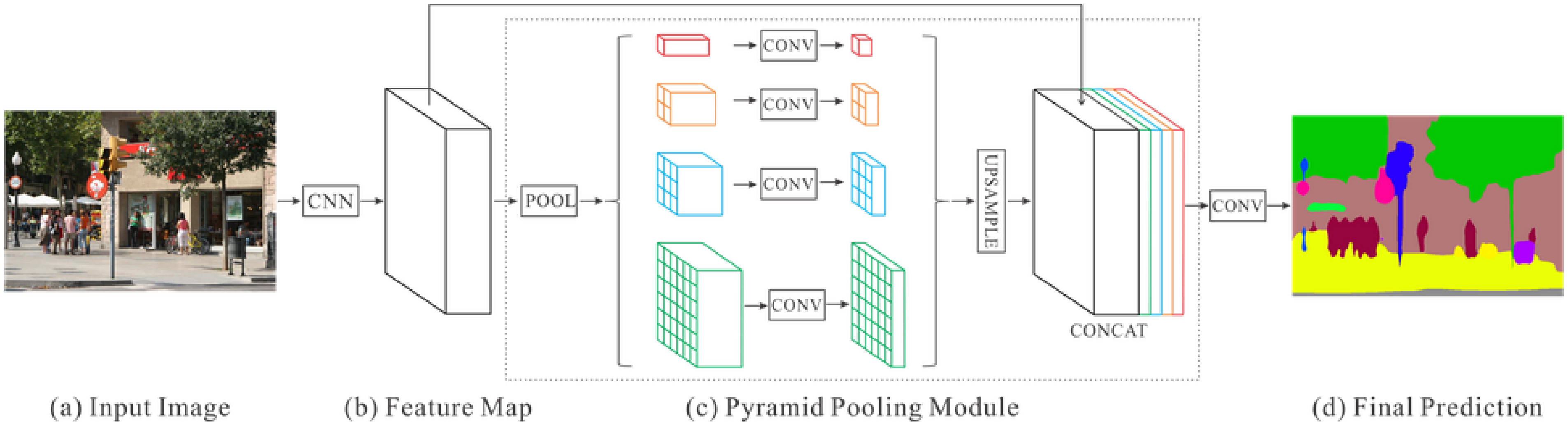
MODEL ARCHITECTURE - UNET



Source: https://arxiv.org/abs/1505.04597

MODEL ARCHITECTURE - PSPNET

Pyramid Scene Parsing Architecture



Source: https://arxiv.org/abs/1612.01105

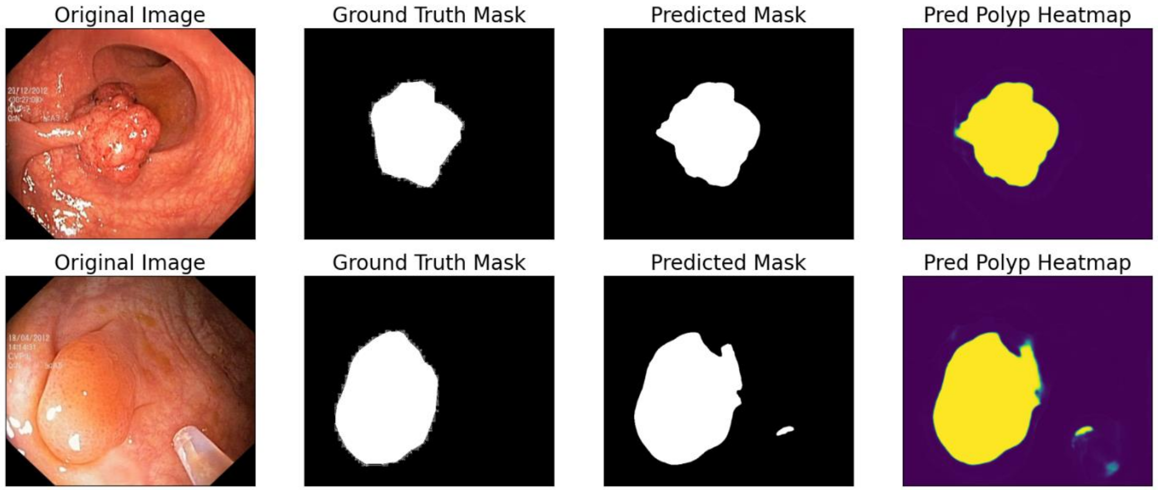
MODEL TRAINING – UNET AND PSPNET

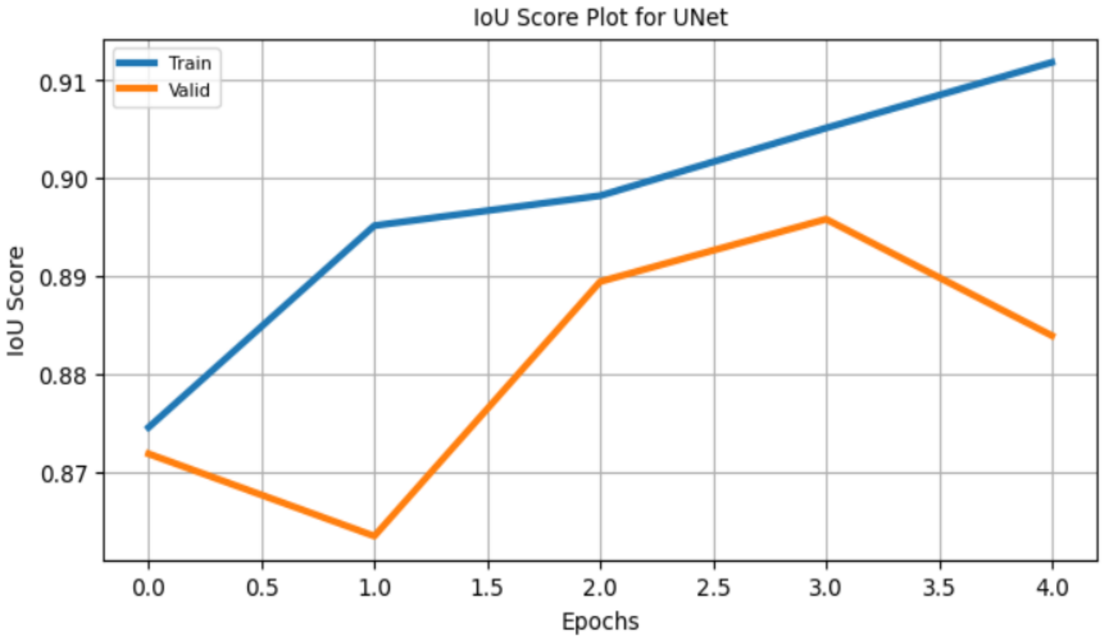
- Train/Valid Split – 90/10
- Set architecture: UNet (with 'resnet50' encoder) and PSPNet (with similar setup).
- Create datasets: Utilize Kvasir data for training and validation.
- Apply preprocessing: Normalize and augment data for model readiness.
- Define loss and metrics: Implement Dice Loss, IoU, and F-score.
- Optimize: Utilize Adam optimizer with a learning rate of 0.0001.
- Scheduler: Implement Cosine Annealing Warm Restarts.
- Training: Run training loops for 5 epochs.
- Track progress: Monitor training and validation logs.
- Model checkpoint: Save models after each epoch for future use.

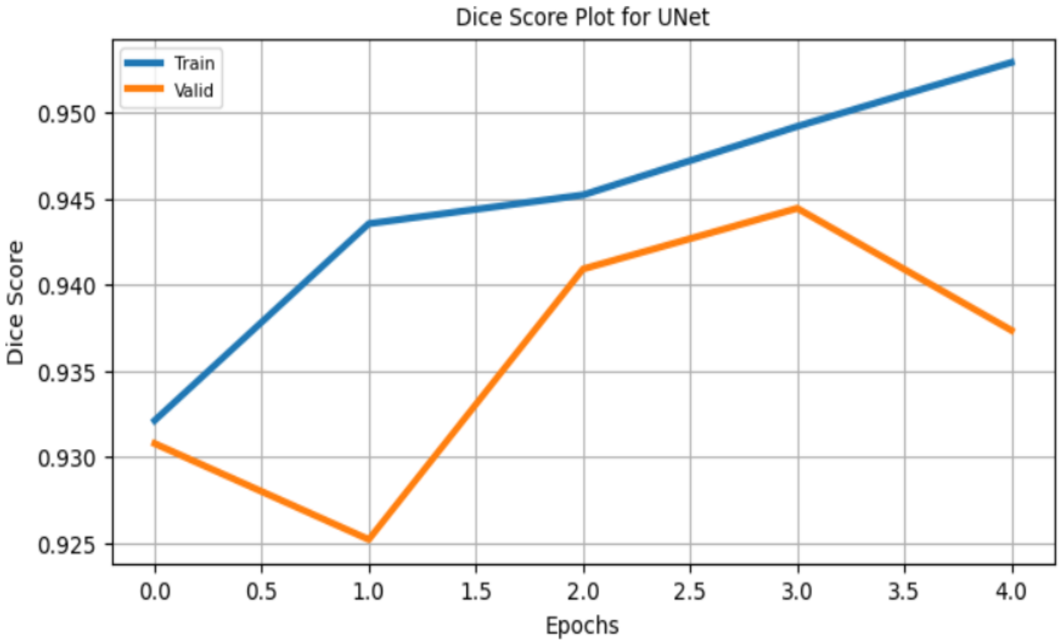
MODEL EVALUATION

- UNet and PSPNet architectures assessed on validation data.
- Metrics include IoU, Dice Loss, and Dice Score.
- UNet Evaluation:
  - Utilize smp.utils.train.ValidEpoch for validation.
  - Configure model, loss, metrics, and device.
  - Execute validation epoch with test_epoch_unet.run(val_dataloader_unet).
  - Metrics accessed from valid_logs_unet.
- PSPNet Evaluation:
  - Similar process as UNet for PSPNet.
  - Configure model, loss, metrics, and device.
  - Execute validation epoch with test_epoch_pspnet.run(val_dataloader_pspnet).
  - Metrics accessed from valid_logs_pspnet.
- Metrics:
  - IoU Score: Measures mask overlap.
  - Dice Loss: Quantifies predicted-true mask dissimilarity.
  - Dice Score: Represents segmentation accuracy.

RESULTS - UNET



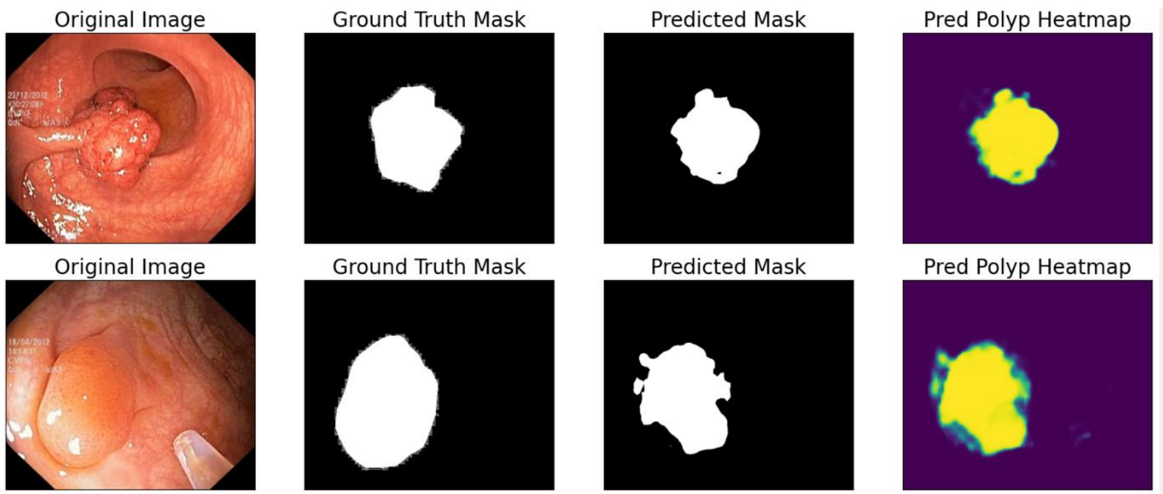


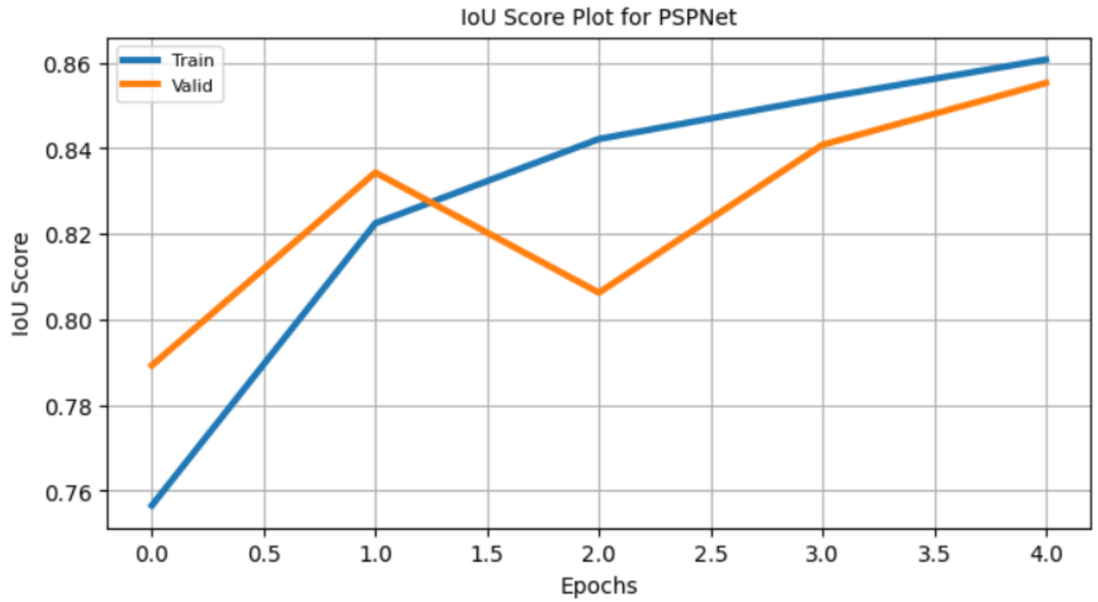


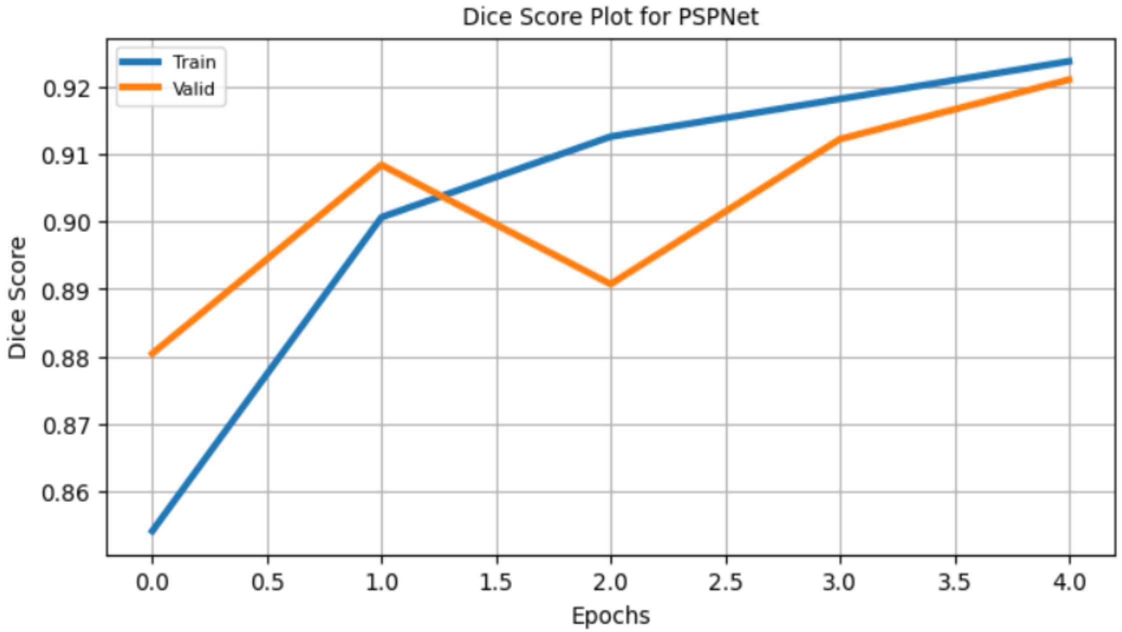
Evaluation on Validation Data for UNet:

- Mean IoU Score: 0.8897
- Mean Dice Loss: 0.0705
- Mean Dice Score: 0.9374

RESULTS - PSPNET







Evaluation on Validation Data for PSPNet:

- Mean IoU Score: 0.8600
- Mean Dice Loss: 0.0828
- Mean Dice Score: 0.9210

COMPARATIVE ANALYSIS

	Dice Loss (Epoch 0)	Dice Loss (Epoch 1)	Dice Loss (Epoch 2)	Dice Loss (Epoch 3)	Dice Loss (Epoch 4)
UNet	0.153295	0.098130	0.077641	0.065151	0.056876
PSPNet	0.156990	0.105502	0.092216	0.085852	0.079802

	IoU Score (Epoch 0)	IoU Score (Epoch 1)	IoU Score (Epoch 2)	IoU Score (Epoch 3)	IoU Score (Epoch 4)
UNet	0.874588	0.895190	0.898244	0.905154	0.911858
PSPNet	0.756549	0.822493	0.842161	0.851748	0.860717

	F-Score (Epoch 0)	F-Score (Epoch 1)	F-Score (Epoch 2)	F-Score (Epoch 3)	F-Score (Epoch 4)
UNet	0.932122	0.943563	0.945232	0.949217	0.952936
PSPNet	0.854204	0.900609	0.912532	0.918100	0.923667

CONCLUSION

- **Project Overview**: "Polyp Segmentation Model using UNet and PSPNet" evaluation reveals insights into segmentation capabilities of both architectures.
- **UNet Performance**: UNet excels with Mean IoU Score of 0.8897, strong overlap, Mean Dice Loss of 0.0705, precise accuracy, and Mean Dice Score of 0.9374, capturing polyp regions effectively.
- **PSPNet Performance**: PSPNet competes well with Mean IoU Score of 0.8600, significant overlap, Mean Dice Loss of 0.0828, accurate segmentation, and Mean Dice Score of 0.9210, confident polyp region identification.
- **Model Comparison**: UNet slightly edges PSPNet in IoU and Dice Scores, showcasing robust segmentation capabilities.
- **Structured Approach**: Project's systematic data preparation, model training, and evaluation underscore tailored architecture selection and strong training processes.
- **Comprehensive Pipeline**: Developed pipeline advances polyp segmentation methodologies, aiding accurate detection and diagnosis in medical imaging.
- **Implications**: UNet and PSPNet contribute significantly to medical imaging, elevating polyp segmentation and enhancing diagnostic precision.

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THANK YOU!