

02_Validation_Dataset_Insights

02 — Validation Dataset Insights

Folder Location

```
1  DATASET/Offroad_Segmentation_Training_Dataset/val/
2    └── Color_Images/      (289 PNG files)
3    └── Segmentation/     (289 PNG files)
```

What's Inside

| Property | Details |
|--------------------|--|
| Total Image Pairs | 289 (RGB + mask) |
| Image Format | .png |
| Naming Convention | cc0000016.png , cc0000019.png , etc. — same cc prefix style as training, but different IDs (no overlap with train) |
| Color Images | Synthetic desert RGB scenes (same style as training) |
| Segmentation Masks | Identical format to training — raw pixel values that get remapped to 0–9 |
| Image-Mask Pairing | Same filename in both subfolders |

Validation vs Training — Key Differences

| Aspect | Training Set | Validation Set |
|--------------------|--------------------------------------|---|
| Image Count | 293 | 289 |
| Split Ratio | ~50.3% | ~49.7% |
| Image IDs | cc0000012 – cc0000XXX (one range) | cc0000016 , cc0000019 ... (different IDs, non-overlapping) |
| Purpose | Model learns from this | Model is evaluated on this (unseen during gradient updates) |
| Same Scene Domain? | Yes — same desert biome | Yes — same desert biome but different specific locations |

Notable: The train/val split is nearly 50-50 (~293 vs ~289). This is an **unusually even split** — most real projects use 80/20 or 70/30. This means less training data but stronger validation signal.

How Validation is Used in Training (`train_segmentation.py`)

During each epoch, the training script:

1. **Trains** on the train set (with gradient updates)
2. **Evaluates** on the val set (no gradients) — computes val loss
3. **Calculates full metrics** on BOTH train and val sets using `evaluate_metrics()`:
 - **Mean IoU** (Intersection over Union) — main hackathon metric (80 points)
 - **Mean Dice Score** (F1 per class)
 - **Pixel Accuracy** (% correct pixels)



Python

```
1 # From train_segmentation.py main():
2 val_iou, val_dice, val_pixel_acc = evaluate_metrics(
3     classifier, backbone_model, val_loader, device, num_classes=10
4 )
```

Metrics Tracked Per Epoch

| Metric | Formula | Why It Matters |
|-----------------------|---|--|
| IoU (Jaccard) | Intersection / Union per class, then averaged | Primary hackathon score — measures overlap between prediction and ground truth |
| Dice (F1) | $2 * \text{Intersection} / (\text{Pred} + \text{GT})$ per class | Alternative overlap metric; more forgiving than IoU |
| Pixel Accuracy | Correct pixels / Total pixels | Simple but misleading if classes are imbalanced (sky/landscape dominate) |

Hackathon scoring: IoU = **80 points** out of 100. This is THE metric to optimize.

Key Observations

1. **Validation set has ground truth masks** — this means you can fully evaluate locally before submitting
2. **50/50 split is generous for validation** — consider combining train+val and doing your own 80/20 split, or using k-fold cross-validation for better training
3. **Same domain but different locations** — the val set tests same-biome generalization (desert → different desert area)
4. **No model checkpointing in default script** — the provided `train_segmentation.py` does **not** save the best model (by val IoU). It only saves the final epoch's model. You should add `if val_iou > best_iou: save_checkpoint`
5. **Val loss is computed but not used for early stopping** — another improvement opportunity

Suggestions for Better Validation

- **Add best-model saving:** Save checkpoint when `val_iou` improves
- **Add early stopping:** Stop if val loss doesn't improve for N epochs
- **Consider re-splitting:** Merge train+val (582 total) → re-split 80/20 (466 train, 116 val) for more training data
- **Watch for overfitting:** With only 293 training images and no augmentations, the model will likely overfit fast