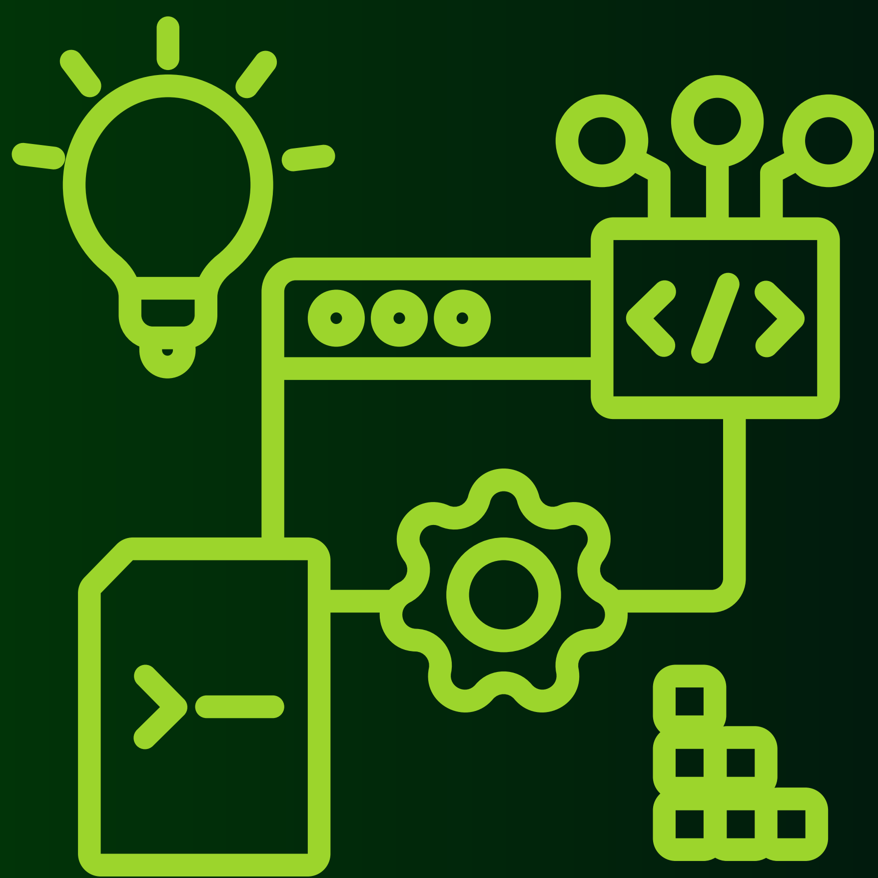
MACHINE LEARNING

IMAGE SEGMENTATION OF MARTIAN CRATERS USING U-NET CNN



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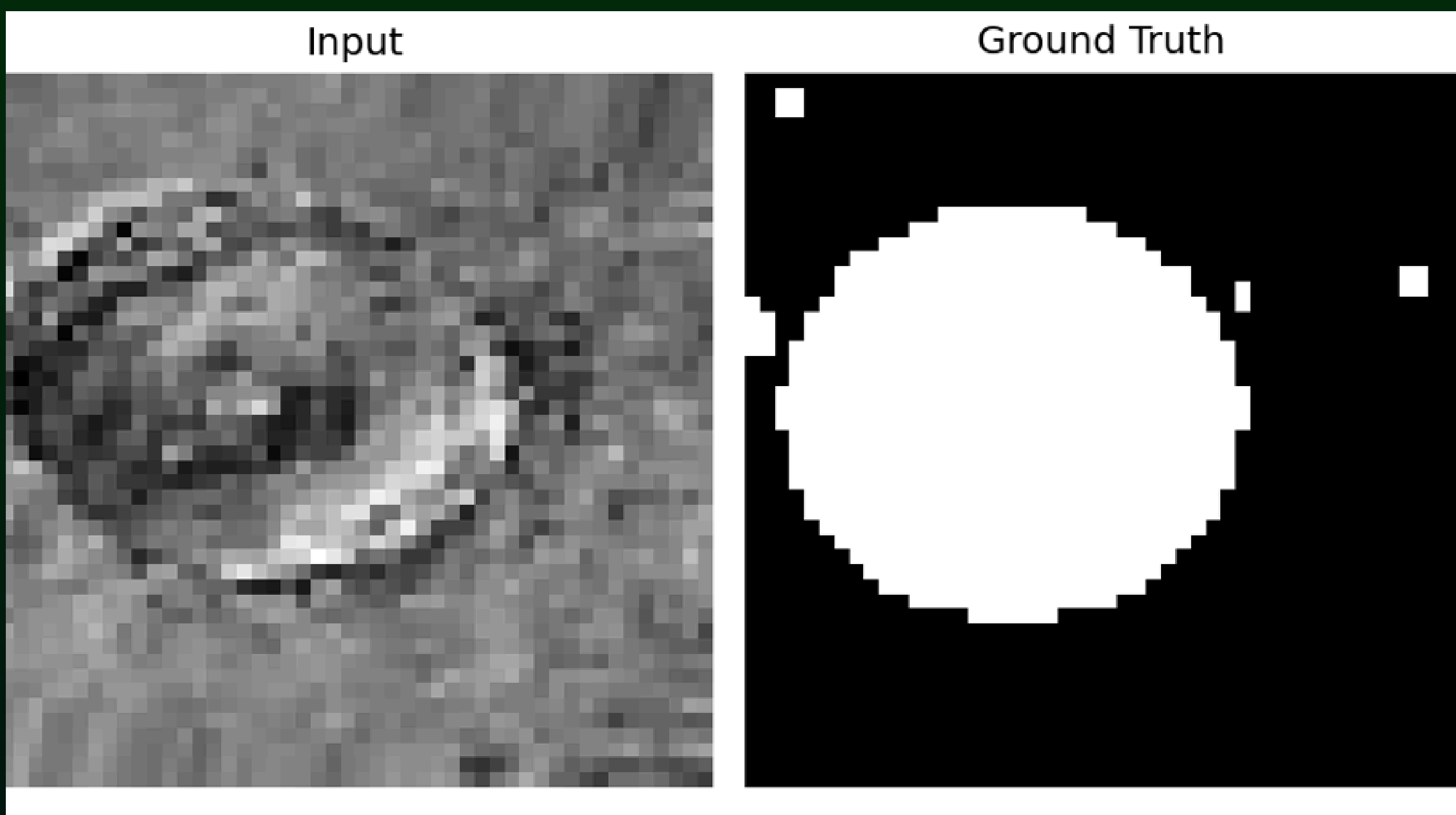
PROBLEM DEFINITION AND DATA OVERVIEW

PROBLEM

- Identify and segment craters on Martian surface
- Input: Grayscale images (48x48 px)
- Output: Binary mask indicating crater pixels

DATA

- Full image + full segmentation mask.
- Imbalanced: background >> crater pixels
- Pixel-level classification:
  - 1 → crater pixel
  - 0 → background



Mars image + ground truth mask

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EVALUATION METRICS: BALANCED ACCURACY & VALIDATION LOSS

BALANCED ACCURACY

- Crater segmentation is imbalanced: many more background pixels than crater pixels.
- Standard accuracy would favor the majority class (background).
- Balanced Accuracy = (Sensitivity + Specificity) / 2 → Gives equal importance to both classes.
- Fairer metric for imbalanced binary classification, especially when crater pixels are rare.

VALIDATION LOSS

- Measures the model's binary cross-entropy error on the validation set.
- Helps us detect overfitting:
  - ↓ training loss + ↑ validation loss → overfitting
- Used for:
  - Early stopping
  - Saving best model (ModelCheckpoint)

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SOLUTION OVERVIEW

APPROACH

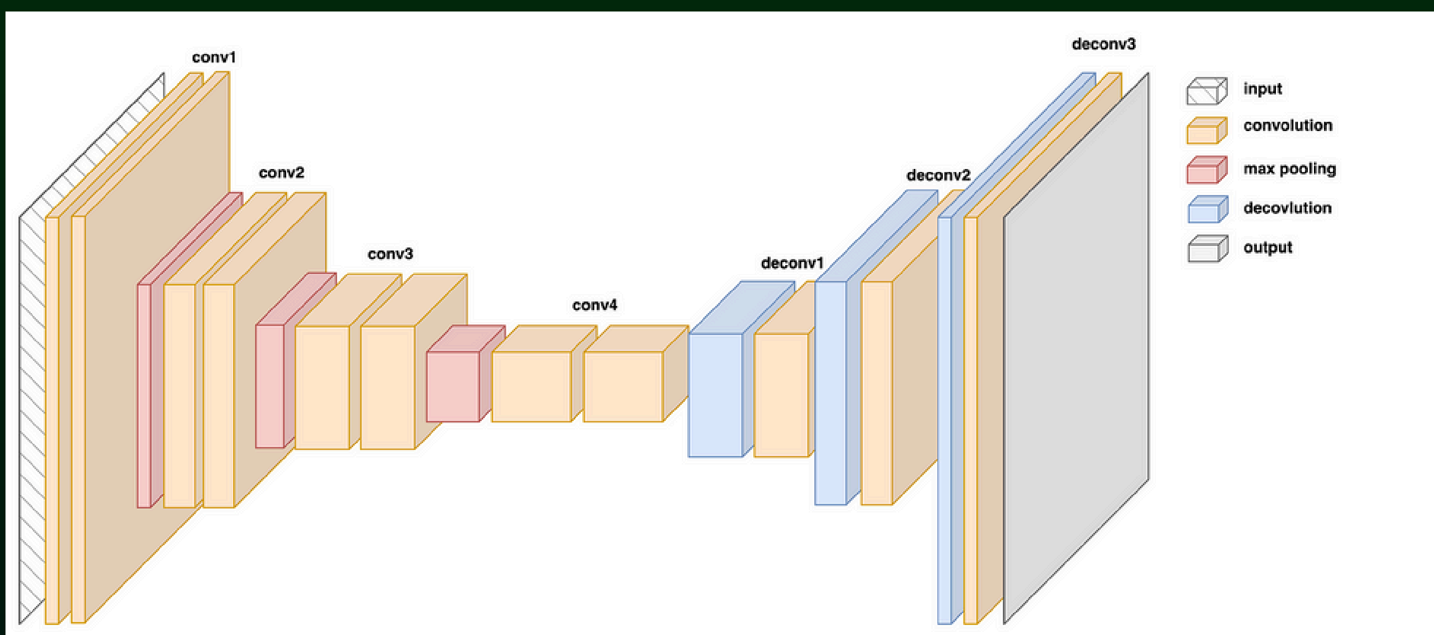
- Train U-Net on full images (48x48)
- Binary classification (per pixel)
- Binary cross-entropy loss
- Balanced Accuracy as a metric
- Data augmentation for robustness

U-NET DETAILS

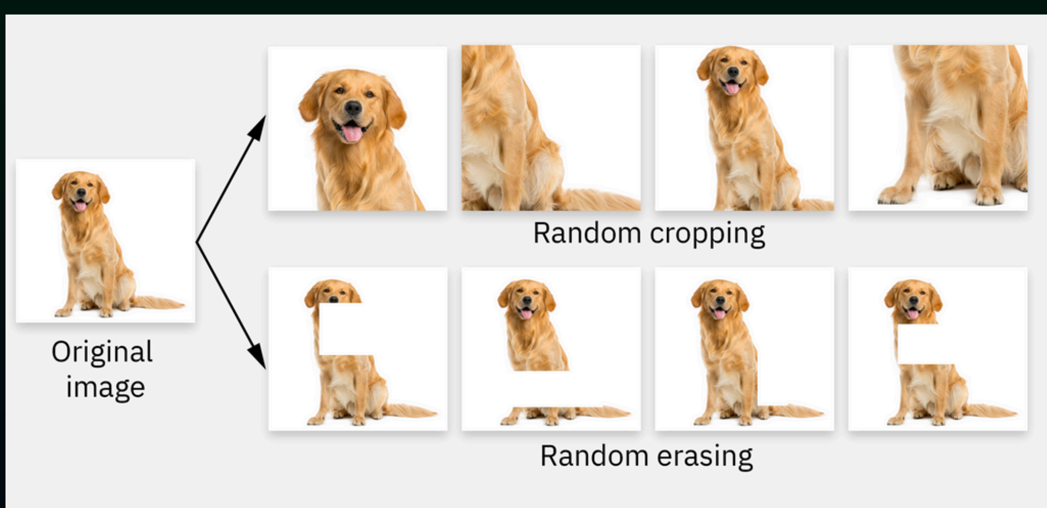
- Encoder: 3 conv + pool blocks
- Bottleneck: 128 filters
- Decoder: 3 upsampling + concat blocks
- Output: 1-channel sigmoid mask (48x48)

DATA AUGMENTATION

- Augment factor: 2×
- Random rotation (±20°), zoom (up to 30%)
- Helps generalize with limited data



U-NET Architecture Illustration



Data Augmentation General Illustration

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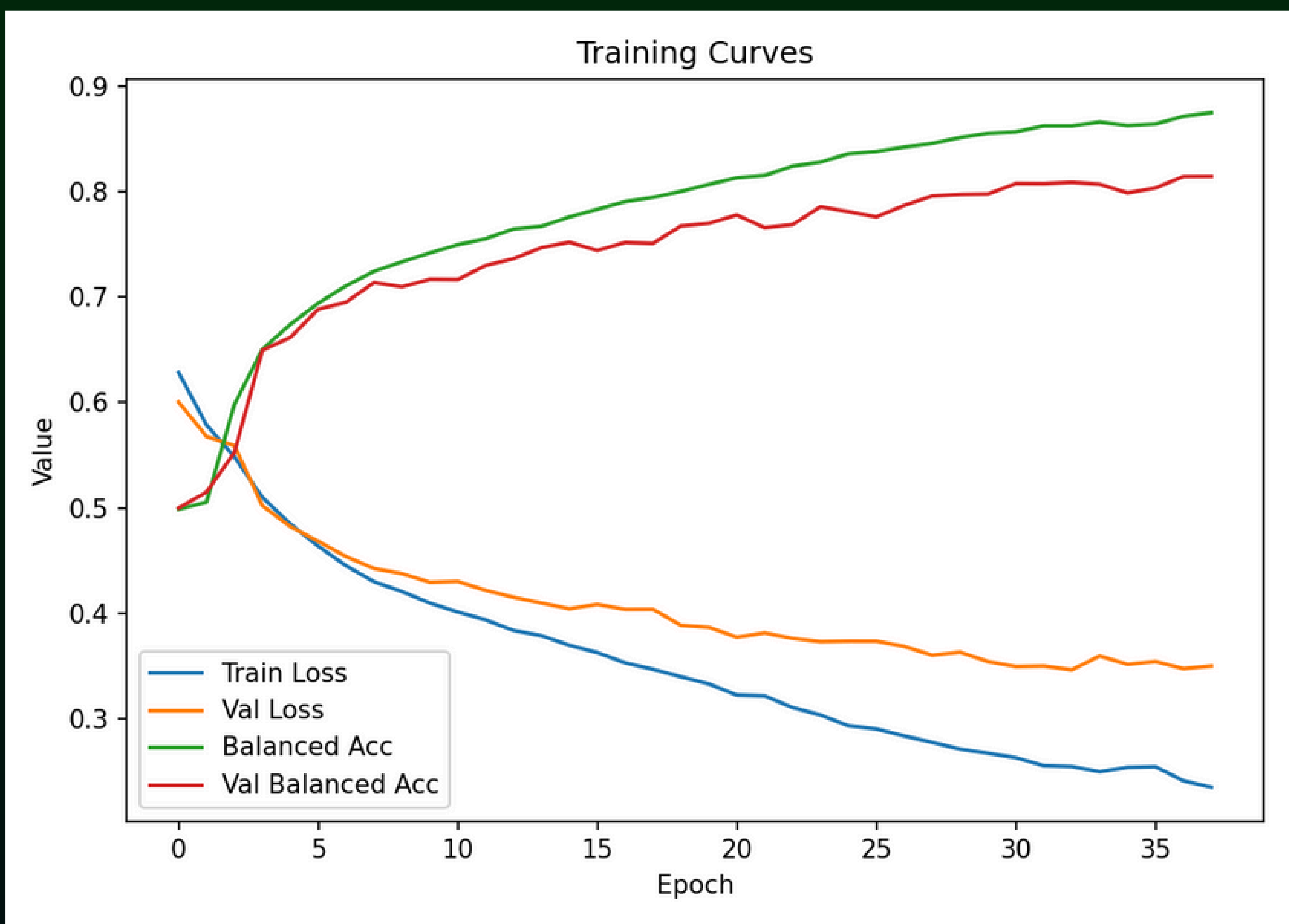
TRAINING SETUP AND CURVES

CONFIGURATION

Epochs: 48
Batch size: 32
Optimizer: Adam (LR = 5e-4)
20% validation split
EarlyStopping & ModelCheckpoint

PERFORMANCE OVER TIME

Balanced accuracy improves across epochs
Validation loss monitored for early stopping



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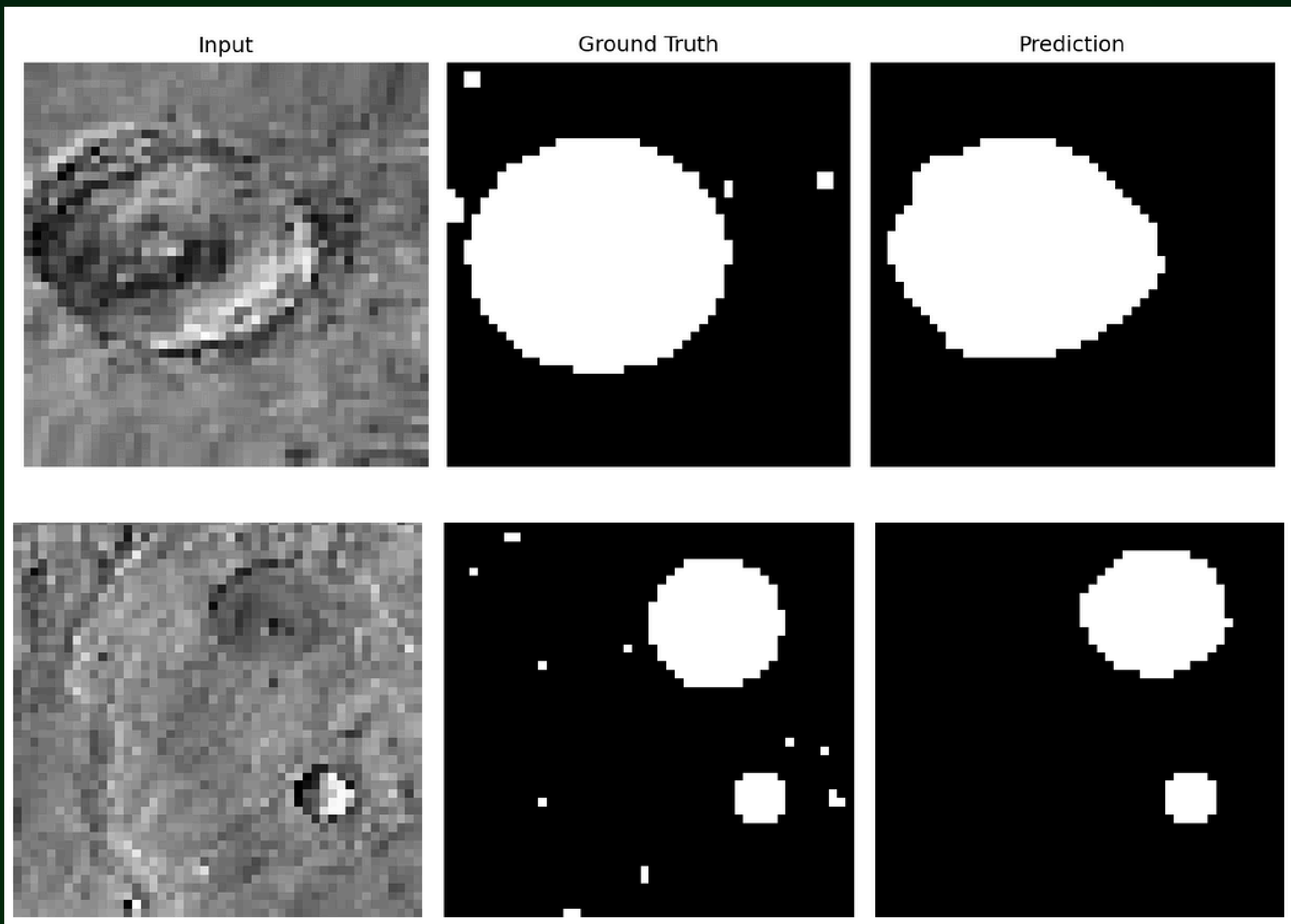
RESULTS

QUALITATIVE RESULTS

Visual comparison: Input, Ground Truth (only for val) and Prediction.



U-NET Architecture Illustration

QUANTITATIVE RESULTS

FINAL METRICS	
BAL ACCURACY	0.8867
VAL LOSS	0.3383

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KEY TAKEAWAYS

- U-Net performs well even on small 48×48 images.
- Augmentation improves robustness, especially when training data is limited.
- Balanced Accuracy prevents misleading results from class imbalance.
- Predictions sometimes struggle at crater edges (uncertain boundaries).

TO EXPLORE

- Augmentation choices (rotation, zoom, flips, brightness, etc.)
- Learning rate schedules and optimizers
- Network depth / number of filters in U-Net
- Batch size and training epochs
- Different loss functions (Dice loss, Focal loss)

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