NEURAL SEGMENTELLO

REFINING USER INPUT FOR HIGH-PRECISION OBJECT SEGMENTATION

«AILab: Computer Vision and NLP»
Project Presentation
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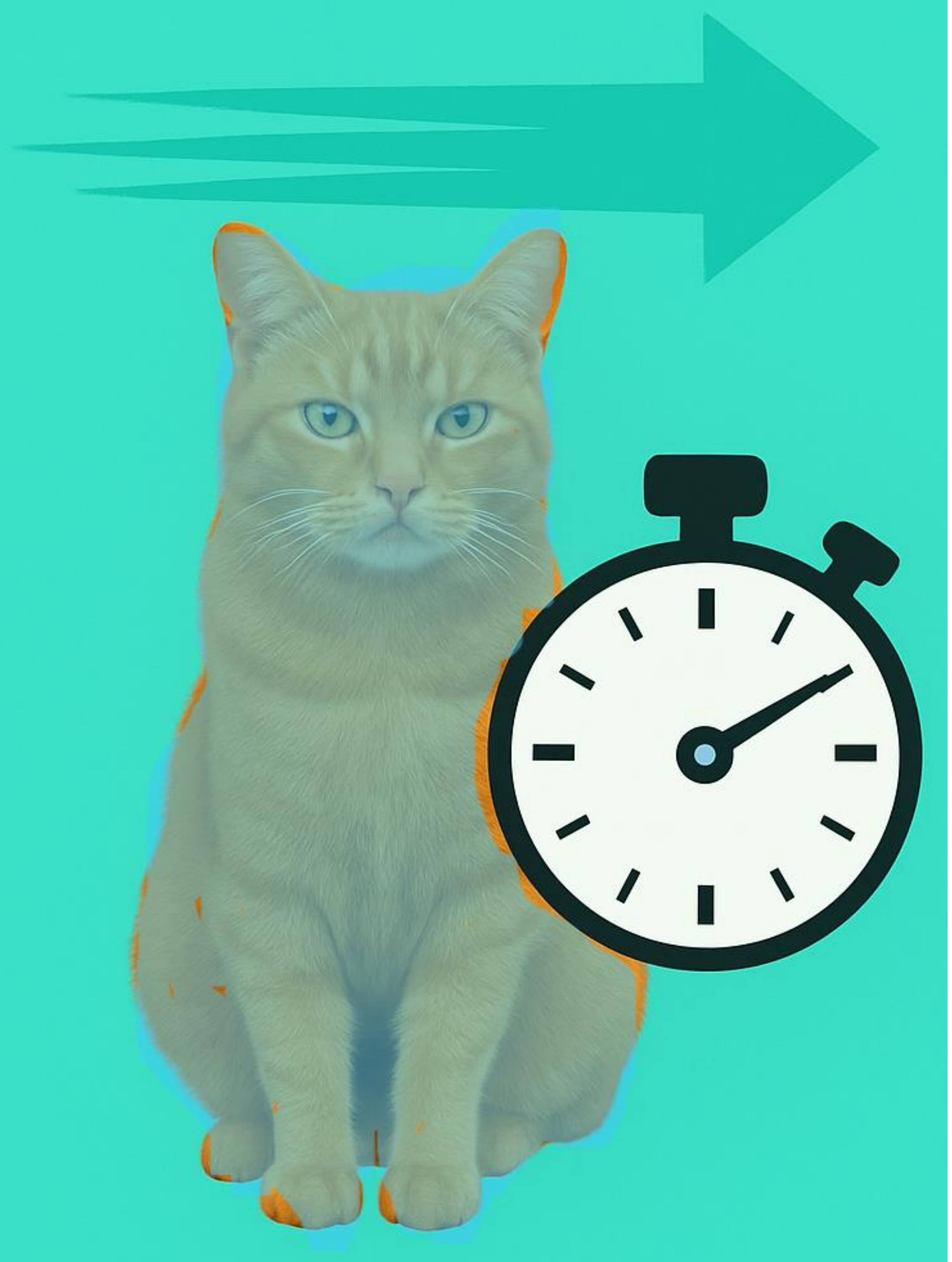
INTRODUCTION & CONTEXT

- Interactive object segmentation aims to accurately isolate objects within an image using minimal human input.
- This project focuses on refining a **coarse binary mask**, mimicking a user-drawn brush stroke, into a **high-precision segmentation mask**.
- Our approach bridges **human intuition** and **deep learning capabilities**, reducing annotation effort without sacrificing accuracy.



FAST VS ACCURATE-WHY NOT BOTH?

Precise segmentation is time-consuming and demands expert knowledge

A single brush stroke is fast, intuitive – but too rough to be used directly

What if neural networks could refine it into pixel-perfect masks?

WHAT NEURALSEGMENTELLO AIMS TO ACHIEVE 🎯

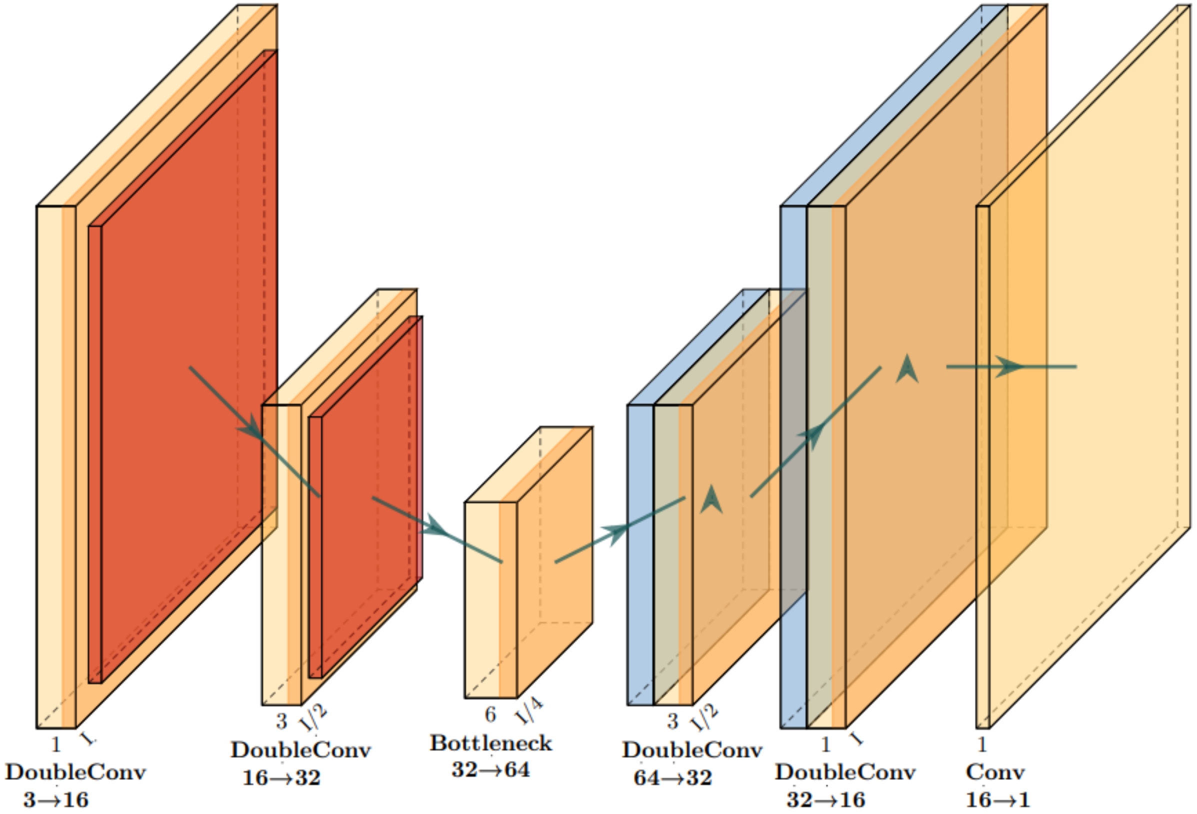
1. Design and train lightweight U-Net architectures for refining coarse user masks.
2. Experiment with architectural variants: → residual connections, attention-based decoding.
3. Evaluate using segmentation-specific losses: → Binary Cross-Entropy, Dice, Boundary Loss.
4. Ensure reproducibility via:

- Fixed seeds and config files
- Reduced dataset and public codebase

DATASET & USER INPUT SIMULATION

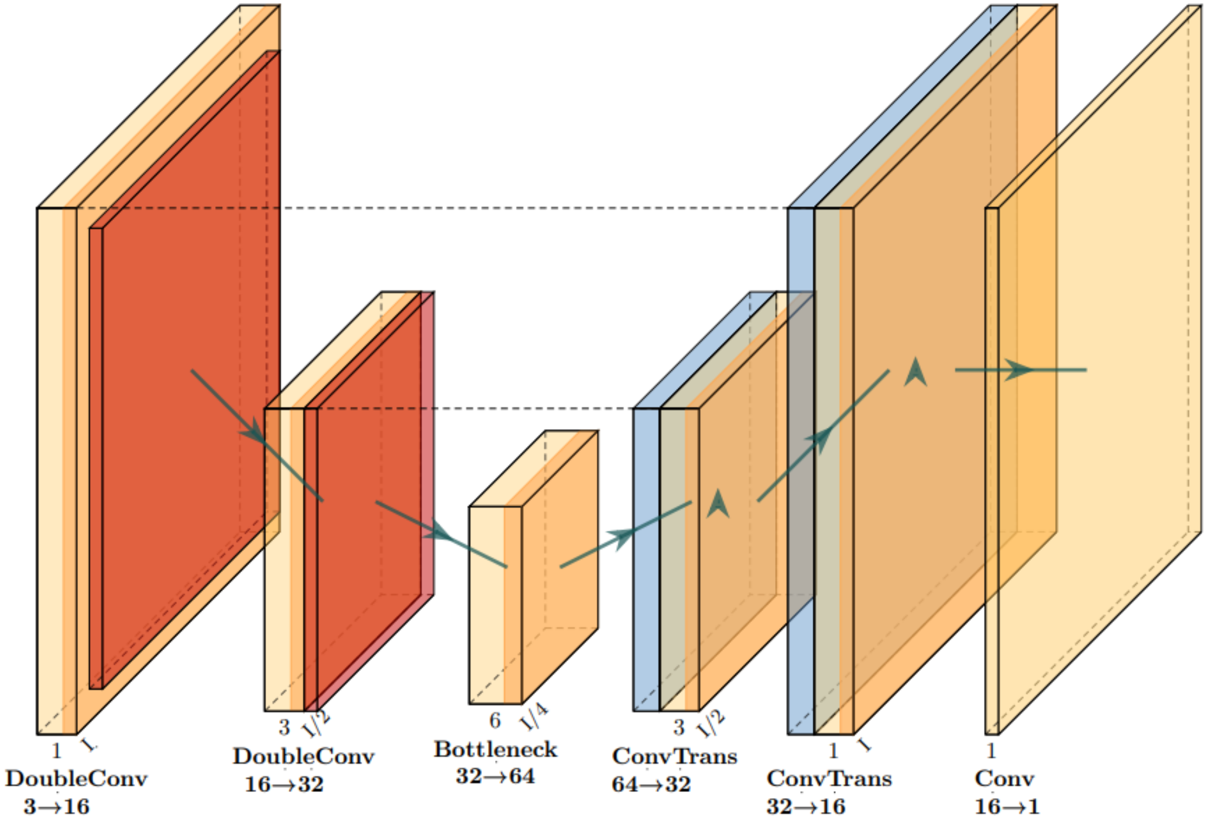
- We use a subset of the Microsoft COCO Common Objects in Context dataset a large-scale benchmark with over 200,000 annotated images.
- To simulate realistic user input, we generated synthetic brush strokes by introducing random circular occlusions and Gaussian blurring.

OUR MODELS



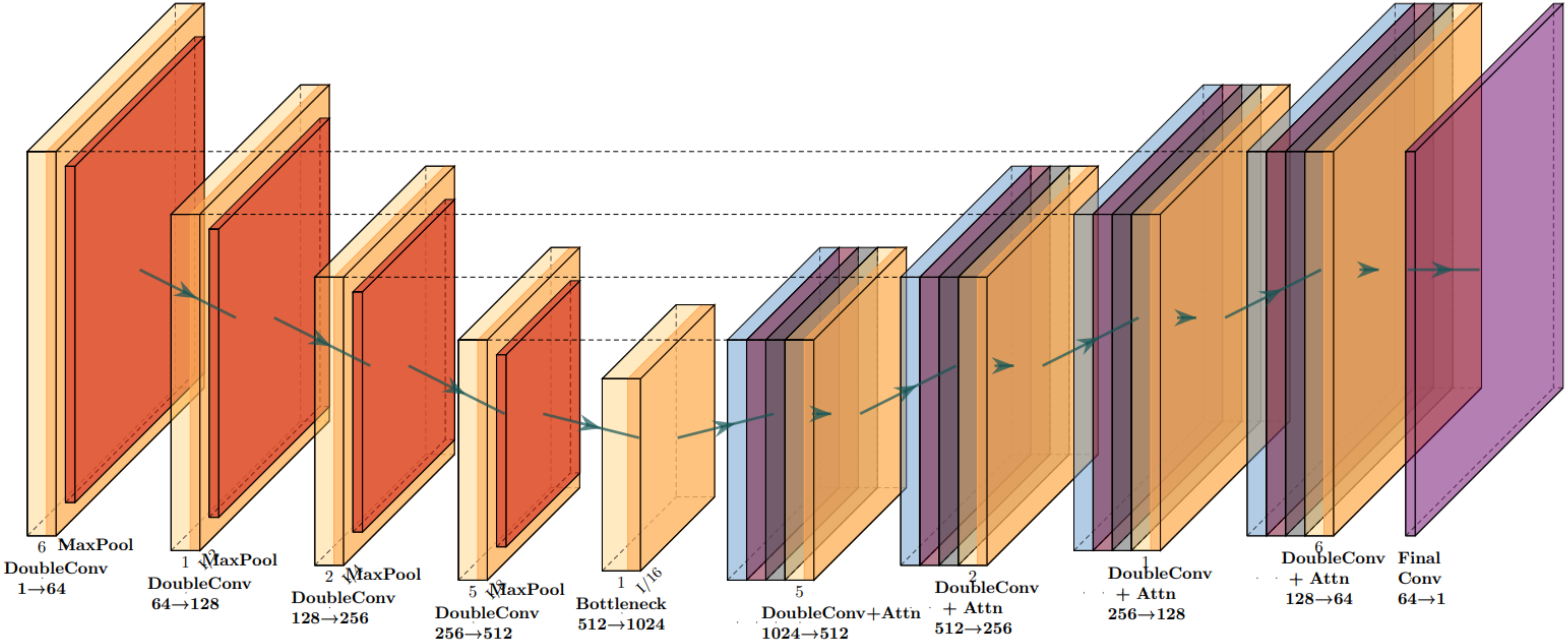
U-Net Tiny: A compact version of the U-Net model with reduced feature dimensions, designed to balance performance and computational efficiency.
Explored in tiny16-32, tiny16-128.

OUR MODELS



U-Net Tiny with Residual Connections: Incorporates residual connections within both encoder and decoder blocks to improve gradient flow and facilitate faster convergence.
Explored in res16-32, res16-128, res32-256.

OUR MODELS



U-Net with Attention Mechanisms: Integrates attention modules within the decoder to enhance focus on semantically relevant regions guided by the coarse input. Explored in attn32-256.

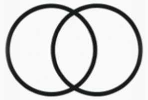
UNDERSTANDING OUR LOSS FUNCTIONS

BINARY CROSS ENTROPY

- Treats segmentation as pixel-wise classification
- Penalizes incorrect predictions at the individual pixel level
- Sensitive to class imbalance

$$L_{BCE} = -[y\log(p) + (1-y)\log(1-p)]$$

DICE LOSS



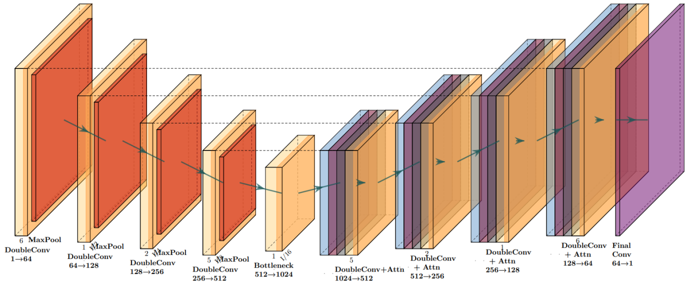
- Measures overlap between prediction and ground truth
- Optimizes global object-level accuracy
- Especially useful for imbalanced classes

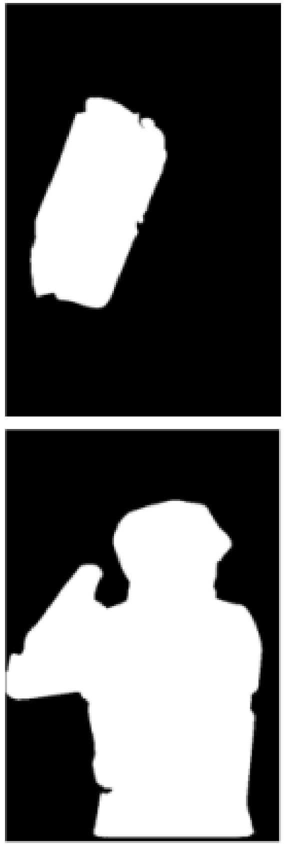
$$L_{Dice} = 1 - \frac{2|P \cap G|}{|P| + |G|}$$

BOUNDARY LOSS

- Focuses on the alignment of object boundaries
- Penalizes misalignment even if global mask is mostly correct
- Useful for fine detail segmentation (edges, contours)

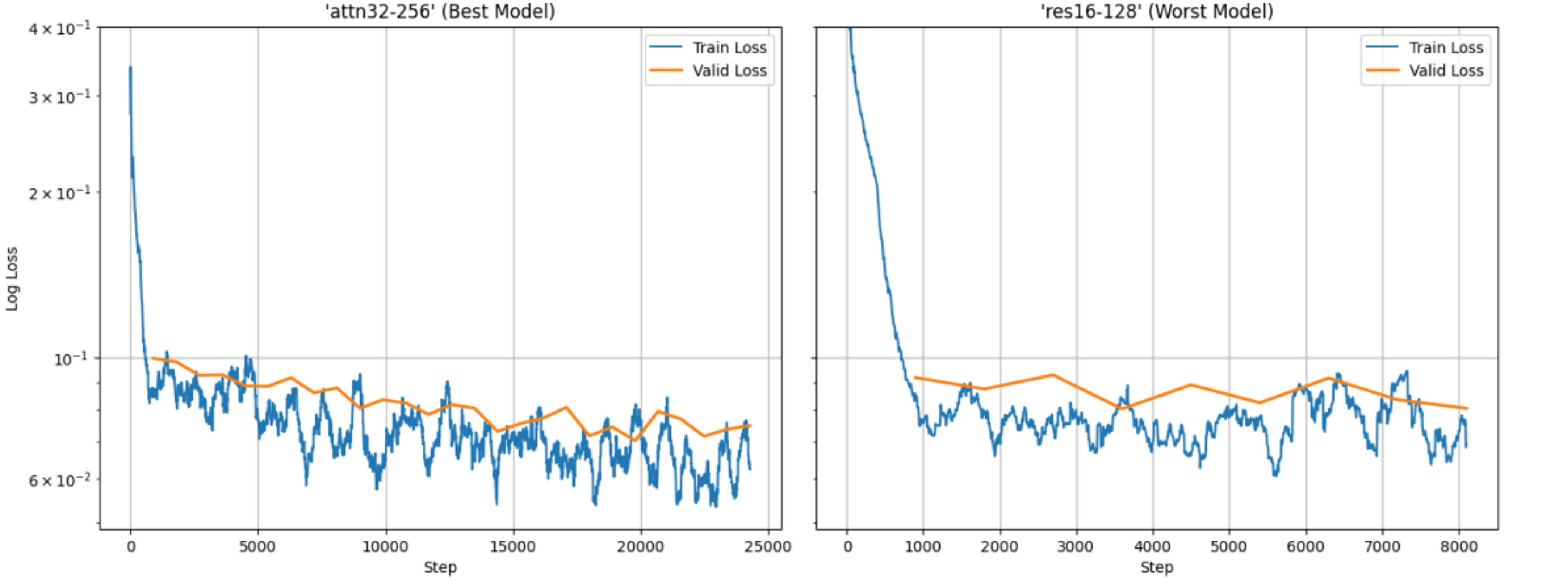
A QUALITATIVE LOOK AT OUR MODEL'S PERFORMANCE





This is how our attention-based U-Net inspired model performs on these two images from the MS COCO Dataset.

BY THE NUMBERS: EVALUATING PERFORMANCE



Model Name	Pixel Accuracy	IoU	Boundary IoU	Hausdorff Distance
tiny16-32_bce-dice	0.9839	0.8609	0.1566	43.10
res16-32_bce-dice	0.9840	0.8611	0.1581	42.73
tiny16-128_bce-dice	0.9833	0.8528	0.1485	46.29
res16-128_bce-dice	0.9830	0.8534	0.1416	43.64
tiny16-128_bce-dice-bound	0.9864	0.8796	0.2207	40.66
res16-128_bce-dice-bound	0.9857	0.8749	0.2082	42.17
res32-256_bce-dice-bound	0.9859	0.8654	0.2040	43.03
attn32-256_bce-dice-bound	0.9866	0.8792	0.2210	40.77

- Showcases refined masks from **coarse user input**
- Attention-based and deep residual models yield the **sharpest contours**
- All models drastically improve over initial brush stroke

THANK YOU FOR YOUR ATTENTION!