CS 7643 Milestone Report: Learning Costmap Generation from RGB & Depth for Mobile Robot Navigation

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Abstract

We aim to learn traversability costmaps directly from RGB + Depth images and assess them with both perception metrics and planner-level outcomes. Since the proposal, we implemented the end-to-end data pipeline (NYU and KITTI), dataset loaders, training/evaluation scripts, losses/metrics, and configuration files, and we report preliminary NYU/KITTI results for UNet, ViT, and a Hybrid CNN+Transformer. The report clarifies our hypotheses, details the methodology and evaluation protocol, and outlines the plan toward planner-in-the-loop assessment.

1 Introduction

Problem Motivation. Safe autonomous navigation requires reliable costmaps marking free space and obstacles for planners (e.g., A*, RRT*). Classical pipelines generated from depth/LiDAR can be brittle across domains and sensors. We study learning costmaps from RGB + Depth (RGBD) to improve robustness while preserving planner compatibility.

InputsOutputs Training Conditions. Input is a single RGBD image $I \in \mathbb{R}^{H\times W\times 4}$; output is a local, egocentric costmap $C \in [0,1]^{64\times 64}$. We also evaluate a binarized occupancy map by thresholding C. Supervision uses costmaps derived from depth-based heuristics. Optimization uses Adam with a composite objective of L1 and Dice losses (and an optional boundary-aware term).

Datasets and splits (paired .npz). NYU: 523 train, 131 val. KITTI: 438 train, 433 val. All pairs are standardized to 4-channel inputs and 64×64 targets.

Goal. Compare classical depth-to-cost mapping with UNet, ViT, and Hybrid CNN+Transformer models, measuring MAE, IoU, PrecisionRecallF1 on held-out splits and, later, planner performance. **Planner status:** Planner-in-the-loop evaluation with A* and RRT* is *not yet performed in this milestone* and is planned as future work.

2 Related Work

Our proposal emphasized learning traversability or BEV maps from vision and connecting predictions to planning utility. *TerrainNet* [3] fuses semantic and geometric cues for high-speed off-road traversability and stresses boundary fidelity and planning-aware metrics. A simplified U-Net for Mars rovers [4] highlights efficiency for resource-limited platforms. Transformer-based BEV mapping such as Trans4Map [5] improves global consistency; camera-only pipelines [6, 7] show promise without LiDAR but can be sensitive to depth errors and calibration. Preference-conditioned costmaps [8] offer flexibility that is complementary to our fixed traversability objective. We ground our models in foundational dense prediction with U-Net [1] and ViT [2]. Compared to prior work, our focus is a unified pipeline that standardizes supervision from depth-derived costmaps on indoor/outdoor datasets, compares UNet, ViT, and Hybrid encoders under identical training and

metrics, and evaluates perception quality with a planned extension to planner-level outcomes (A*, RRT*).

3 Methodology (Tentative Technical Approach)

3.1 Data Processing and Labels

We implemented scripts to prepare NYU and KITTI, discover RGBDepth pairs, and generate targets. Depth is projectedprocessed into an egocentric grid and converted to a normalized costmap $C \in [0,1]^{64\times64}$. The same heuristic is used across datasets to ensure label consistency.

3.2 Models

We compare three families with a common lightweight decoder to a 1-channel output. The **UNet** baseline uses an encoder–decoder with skip connections. The **ViT** variant employs patch embedding, a transformer encoder, and a convolutional upsampling decoder. The **Hybrid** model combines a CNN stem with a transformer bottleneck followed by a CNN decoder to fuse local and global context. All models produce a 64×64 map (resize applied if needed).

3.3 Objective and Metrics

Training loss uses $\mathcal{L} = \lambda_{\ell_1}\,\mathcal{L}_{\ell_1} + \lambda_d\,\mathcal{L}_{\text{Dice}}(+\lambda_b\,\mathcal{L}_{\text{boundary}})$. Evaluation reports Mean Absolute Error (MAE) on continuous cost and IoU, Precision, Recall, and F1 on a binarized map (threshold τ=0.5 by default).

3.4 Evaluation Protocol

We train per-dataset (NYU, KITTI) and evaluate on held-out validation splits. Optional cross-domain tests (NYU→KITTI and vice versa) assess generalization. For this milestone, we report *perception metrics only*; planner-in-the-loop evaluation (A*, RRT*) of predicted costmaps is future work.

3.5 Hypotheses

We test three hypotheses. **H1 (Modality):** RGBD inputs outperform RGB-only for IoU and MAE when holding architecture and schedule fixed. **H2 (Architecture):** the Hybrid model achieves higher IoU than pure UNet or ViT at similar parameter budgets. **H3 (Objective):** combining L1 with Dice improves IoU over L1-only by emphasizing occupied regions and boundaries.

4 Baseline Results & Trials of Your Method

This section satisfies the milestone's requirement to report baseline and preliminary results. We trained/evaluated UNet, ViT, and Hybrid models on NYU and KITTI using identical splits, losses (L1+Dice), and threshold τ=0.5 for binarized metrics.

4.1 Baselines

We include a classical depth-to-cost baseline (thresholding, morphology, distance transform) and simple sanity checks (all-free and all-obstacle predictions) to contextualize metric behavior.

4.2 Quantitative Results

Summary. On NYU, *ViT* achieves the best overall performance across MAE/IoU/F1, with *Hybrid* close behind and *UNet* trailing by 5–6 IoU points. On KITTI, *Hybrid* attains the best MAE (0.174) and IoU (0.527) with strong precision, while recall is lower; *UNet* with transfer learning from NYU yields the best F1 (0.651) and improves over the KITTI-only UNet by +1.96 IoU points and +1.3 F1 points; *ViT* reaches the highest recall (0.723) and competitive F1 (0.650). The trends suggest indoor

Table 1: NYU validation metrics. Threshold τ=0.5.

Method	MAE ↓	IoU ↑	Precision	Recall	F1	Params (M)
UNet	0.0139	0.9168	0.9526	0.9607	0.9566	4.2
ViT	0.0063	0.9750	0.9880	0.9860	0.9870	–
Hybrid	0.0088	0.9680	0.9830	0.9840	0.9840	–

Table 2: KITTI validation metrics. Threshold τ=0.5.

oprule Method	MAE ↓	IoU ↑	Precision	Recall	F1	Params (M)
UNet (KITTI only)	0.2083	0.4803	0.6148	0.6989	0.6384	4.2
UNet (NYU → KITTI TL)	0.2015	0.4999	0.6313	0.6956	**0.6514**	4.2
ViT	0.1890	0.4940	0.5990	**0.7230**	0.6500	–
Hybrid	**0.1740**	**0.5270**	**0.7090**	0.5850	0.6360	–

scenes (dense depth, regular geometry) favor global context from transformers, while outdoor KITTI benefits from Hybrid's local+global fusion and from cross-domain pretraining.

4.3 Implementation Notes

UNet. Architecture based on milesial/Pytorch-UNet with light edits. Training used Adam, L1+Dice loss, and a final `sigmoid` applied prior to L1/Dice and thresholding for metrics ($\tau = 0.5$). A transfer-learning run (pretrain on NYU, fine-tune on KITTI) improved KITTI metrics: IoU +1.96 pts (0.4803 → 0.4999), F1 +1.3 pts (0.6384 → 0.6514), and MAE from 0.2083 → 0.2015. Profiled model: **4.2M** params, **6.72 GFLOPs**, **1.75 ms/frame** on Tesla V100 (~571 FPS).

ViT. Patch embedding with transformer encoder and a convolutional upsampling decoder to a 1-channel output. Same optimizer and loss. ViT excelled on NYU (MAE 0.0063, IoU 0.975, F1 0.987) and achieved the highest recall on KITTI (0.723), indicating stronger sensitivity to thin/fragmented obstacles but with some over-segmentation (lower precision).

Hybrid. CNN stem with a transformer bottleneck and CNN decoder for local/global fusion. Heads match UNet/ViT for a fair comparison. Hybrid is competitive on NYU and leads MAE/IoU on KITTI (MAE 0.174, IoU 0.527) with high precision (0.709). Lower recall than ViT suggests potential benefit from boundary or focal terms and augmentation targeted at outdoor clutter.

4.4 Qualitative Results

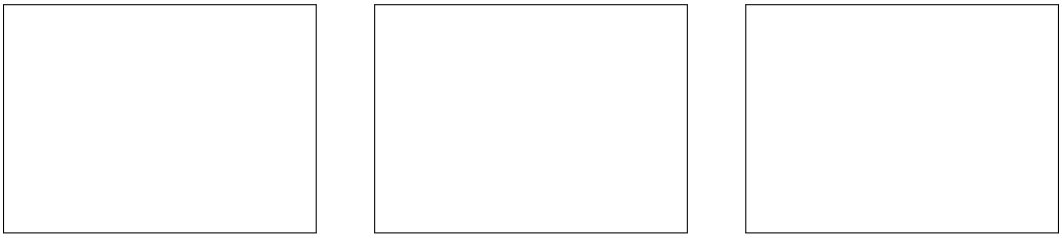
Include side-by-side panels: RGB, Depth, baseline costmap, predicted costmap, and binarized occupancy overlay.

4.5 Problem Decomposition and Experimental Plan

Our three hypotheses translate into concrete experiments. For **H1 (Modality)**, we will hold the architecture and training schedule fixed and compare RGBD versus RGB-only inputs on both NYU and KITTI, reporting MAE, IoU, precision/recall, and F1 at τ=0.5 alongside PR curves to analyze calibration across thresholds. For **H2 (Architecture)**, we will match parameter budgets across UNet, ViT, and Hybrid by adjusting base channel widths and transformer depth, then compare accuracy, FLOPs, and latency; this isolates representational differences from capacity. For **H3 (Objective)**, we will ablate L1 versus L1+Dice and optionally add a boundary-aware term; we expect L1+Dice to improve occupied-region fidelity and thin obstacles. Training follows the same splits used here (NYU: 523/131; KITTI: 438/433). Risks include domain shift and class imbalance outdoors; we mitigate with transfer learning (NYU→KITTI) and augmentation (random brightness/contrast, flips, small perspective jitter). Success criteria are: (i) NYU F1 $\geq$ 0.98 for the best model; (ii) KITTI IoU $\geq$ 0.53 with F1 $\geq$ 0.65; and (iii) real-time feasibility on a single GPU ($\leq$ 10 ms/frame for 256×256 RGBD).

4.6 Classical Baseline and Training Setup

The classical depth-to-cost baseline thresholds depth to mark obstacles, applies morphology to close holes and dilate by a robot footprint, and computes a distance transform to produce a continuous cost map normalized to $[0, 1]$. This provides an interpretable, planner-compatible reference and informs error modes (such as thin obstacles, sensor noise, etc.). All learning models use Adam, L1+Dice loss, and `sigmoid` activation before regression and thresholding; metrics default to $\tau{=}0.5$ with PR curves computed for sensitivity analysis. Unless otherwise noted, we train with batch sizes tuned per GPU memory, cosine or step LR schedules around 1e-3 initial rate, and early stopping on validation F1. We profile params, FLOPs, and latency to quantify deployability; UNet runs at 1.75 ms/frame on a V100 at $\sim$571 FPS, while ViT/Hybrid trade a modest latency increase for improved accuracy.



Left: RGB; middle: depth; right: predicted costmap (Hybrid). A draft teaser illustrating inputs and outputs. Full qualitative panels will include baseline and binarized overlays.

Figure 1: Draft teaser figure illustrating the input modalities and an example predicted costmap.

5 Next Steps

Near-term (1–2 weeks). Run a classical depth-to-cost baseline and add it to Tables 1–2; perform a hyperparameter sweep (lr, batch size, λ_d, data augmentations); and enable boundary or focal terms to raise KITTI recall for Hybrid without sacrificing precision.

Mid-term (3–4 weeks). Conduct ablations for H1–H3: modality (RGB vs RGBD), architecture (UNet vs ViT vs Hybrid at matched parameters), and objective (L1 vs L1+Dice vs +Boundary); run cross-domain tests (NYU$\rightarrow$KITTI and KITTI$\rightarrow$NYU) including transfer learning; and add calibration analysis (precision–recall across thresholds).

Endgame. Perform planner-in-the-loop evaluation (A* on grids, RRT* in continuous space) using predicted costmaps; report success, collisions, path cost, and planning time; finalize error analysis (thin obstacles, distant clutter), profile models (params, FLOPs, latency), and complete writing.

Reproducibility

Code and configuration files are in the repository. Training and evaluation live in `src/train/train.py`; datasets in `src/data/dataset_npz.py`; losses and metrics are configured via YAML in `configs/`. Example configs include `train_nyu_unet.yaml`, `train_nyu_hybrid.yaml`, `train_kitti_unet.yaml`, and `train_kitti_hybrid.yaml`. Processed pair counts are NYU 523/131 and KITTI 438/433. We evaluate MAE on continuous costs and IoU/precision/recall/F1 at $\tau{=}0.5$ by default, with threshold sweeps for PR curves.

References

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Appendix (Figures Only)

Figure 2: Qualitative examples (placeholder): RGB, Depth, classical baseline costmap, predicted costmap, binarized occupancy overlay.