

# Research Summary



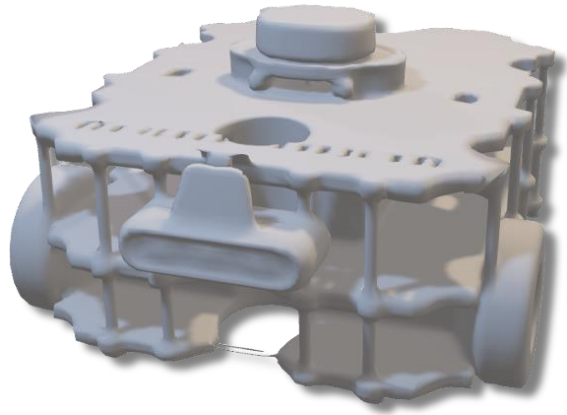
Hanyang University, Department of Automotive engineering



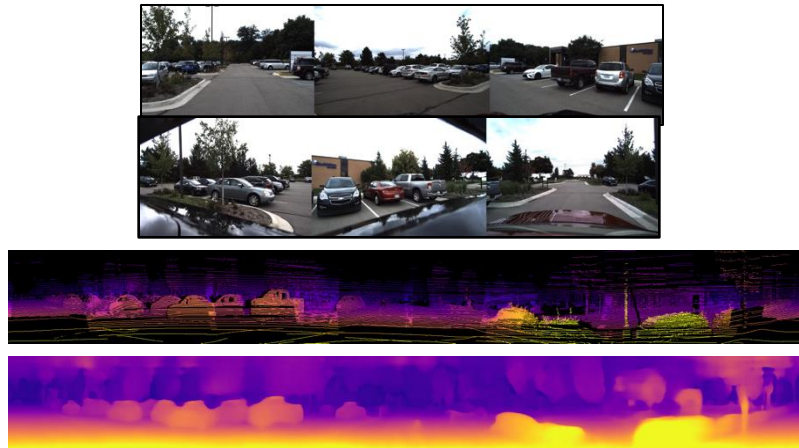
Chungwoo Lee

# Contents

- **From Simulation to Reality:  
VLN on TurtleBot3**



- **Variance-Integrated  
Panodepth for Cylindrical  
Depth Estimation**



- **Autonomous PickingBot  
using LIDAR**



# From Simulation to Reality: VLN on TurtleBot3



# From Simulation to Reality: VLN on TurtleBot3

- **Simulation-Centric Evaluation**

- ◆ Most VLN studies are conducted in [synthetic, simulation-based environments](#), utilizing [synthetic images](#).
- ◆ Real-world evaluations are severely limited due to the absence of [precise evaluation metrics](#).

- **Fundamental Issues with Simulation**

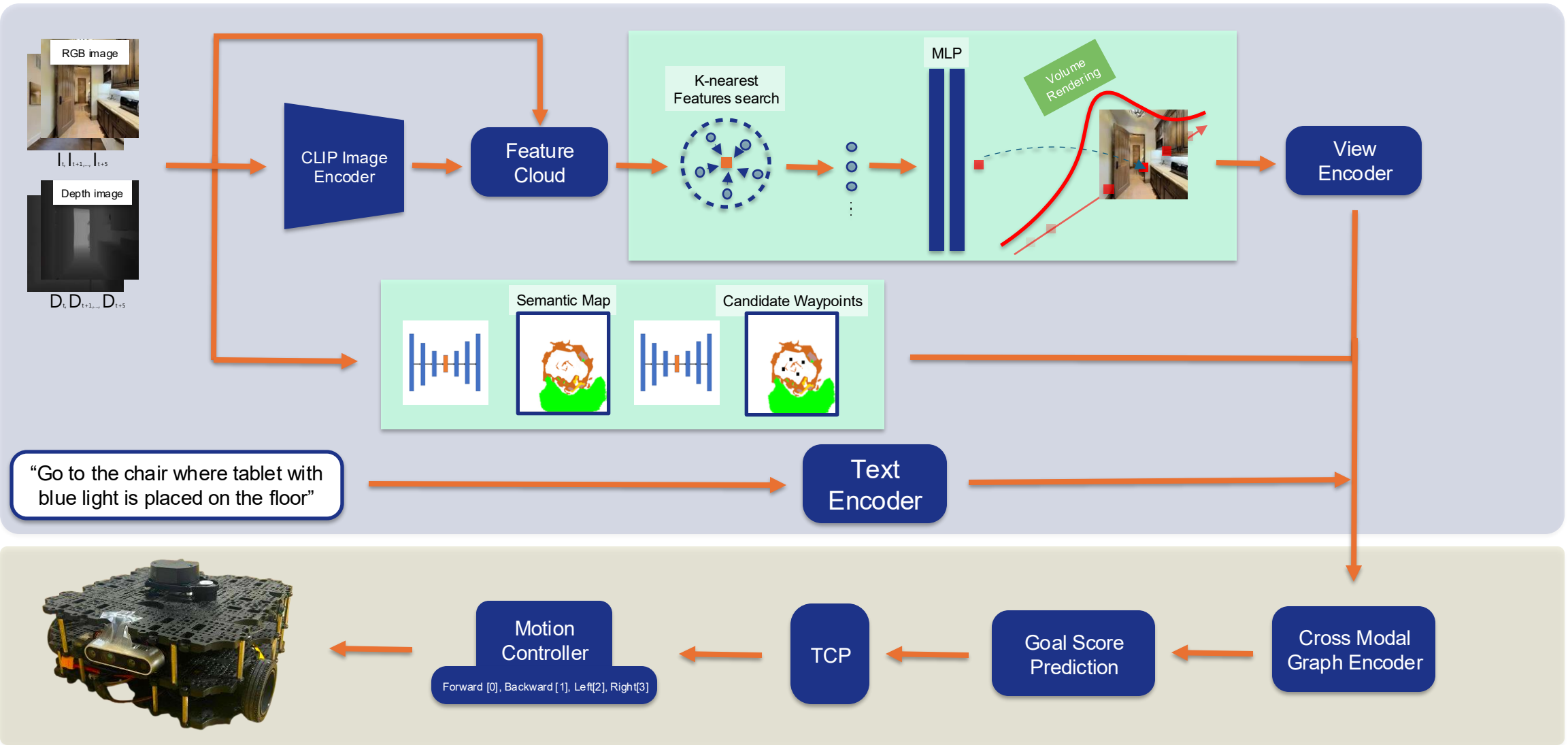
- ◆ Simulation environments inherently differ from real-world conditions, presenting fundamental discrepancies.
- ◆ Limitations of synthetic datasets:
  - ▶ Lack of environmental complexity.
  - ▶ Absence of sensor noise.
  - ▶ Simplified lighting conditions.
  - ▶ Failure to reflect real-world physical constraints.

- **Sensor Constraints**

- ◆ Most robots rely on [monocular cameras](#), which complicates the implementation of [360-degree panoramic cameras](#).
- ◆ The limited field of view of [monocular cameras](#) leads to [performance degradation](#) in navigation tasks.



# System Overview



# Experimental Result

---

- **Baseline Performance**

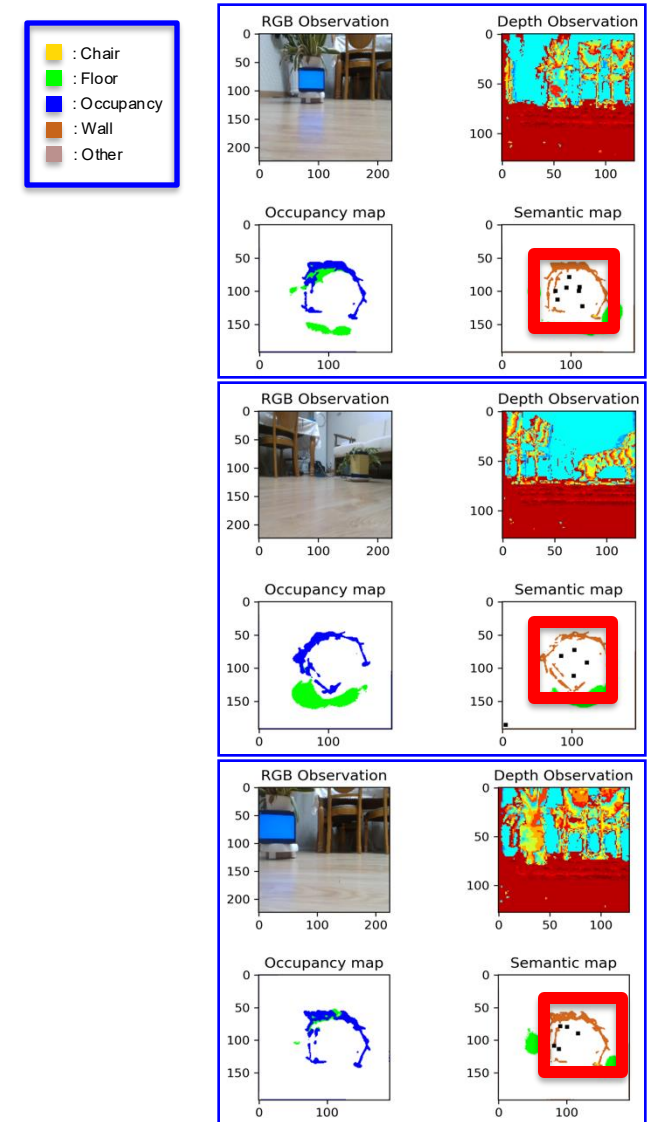
- ◆ Success rate (SR): 43.3% (13/30)
- ◆ The camera and LiDAR on the Locobot were mounted at the mid-thigh height of an adult male.
- ◆ Viewpoints from the pre-trained VLNCE dataset clearly distinguished between the ceiling and the floor, aiding in navigation accuracy.

- **Proposed Model Performance**

- ◆ Success rate (SR): 45% (18/40).
- ◆ In experiments using the TurtleBot3 Waffle, the camera and LiDAR were mounted lower, closer to the ground.
- ◆ The proposed model used past RGB-D data embeddings to improve the consistency of the traversable map.
- ◆ Significant improvements in the consistency of the traversable map were visually confirmed during the experiments.

# Result

- **Temporal Context Integration**
  - ◆ Use **sequential RGB-D frames (past + current)** instead of single-frame inputs.
  - ◆ Add **Positional Encoding** to each frame to capture temporal order effectively.
- **Feature Extraction Enhancement**
  - ◆ Process all frames through the **HNR Model** to generate a **Temporal Feature Map** that integrates spatial and temporal information.
- **Temporal Attention Mechanism**
  - ◆ Employ **Attention Mechanism** to dynamically weigh past frames based on their relevance to the current frame.
  - ◆ **Ensure effective utilization of temporal dependencies.**
- **Improvement Assessment**
  - ◆ **Observe the consistency** of the segment map during navigation
  - ◆ **Verify that the map remains stable and accurate** when the target point is temporarily out of view
  - ◆ **Compare with the baseline model** to ensure enhanced map continuity and better utilization of temporal dependencies





## Experiment1

💡: Go to the chair near where the tablet emitting blue light is located.



» X10

## Experiment2

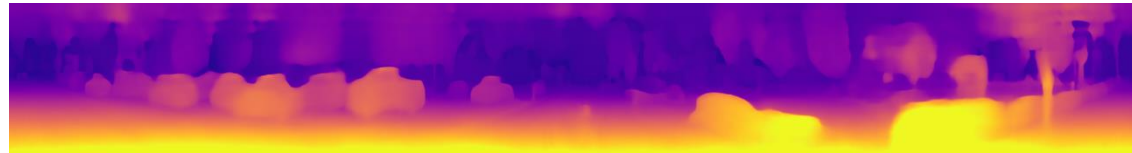
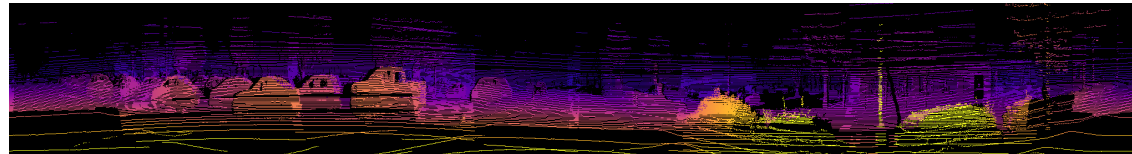
💡: Go near the place where a tablet emitting blue light is placed near the plant.



» X20



# Variance-Integrated Panodepth for Cylindrical Depth Estimation



# Variance-Integrated Panodepth for Cylindrical Depth Estimation

## ◆ Limitations of Monocular Depth Estimation:

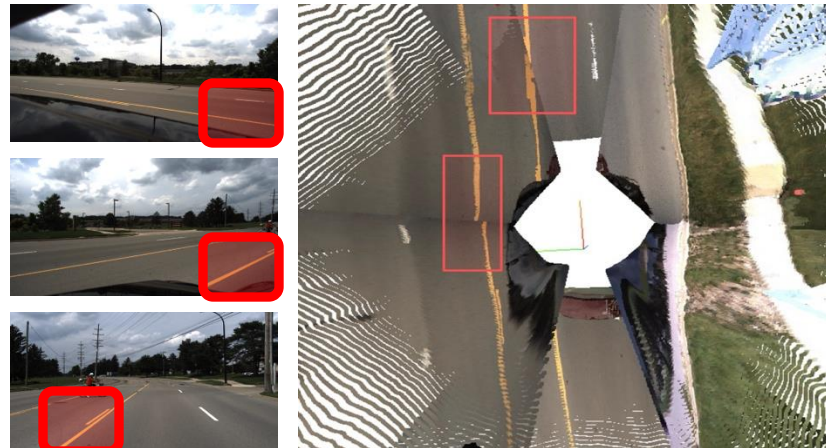
- ▶ Using only the front camera does not fully capture depth information of the surrounding, allowing only relative depth estimation.

## ◆ Limitations of Surround View Monocular Depth Estimation

- ▶ Recently, studies have been proposed using surround-view cameras, but scale misalignment issues arise in the overlapping areas between cameras.

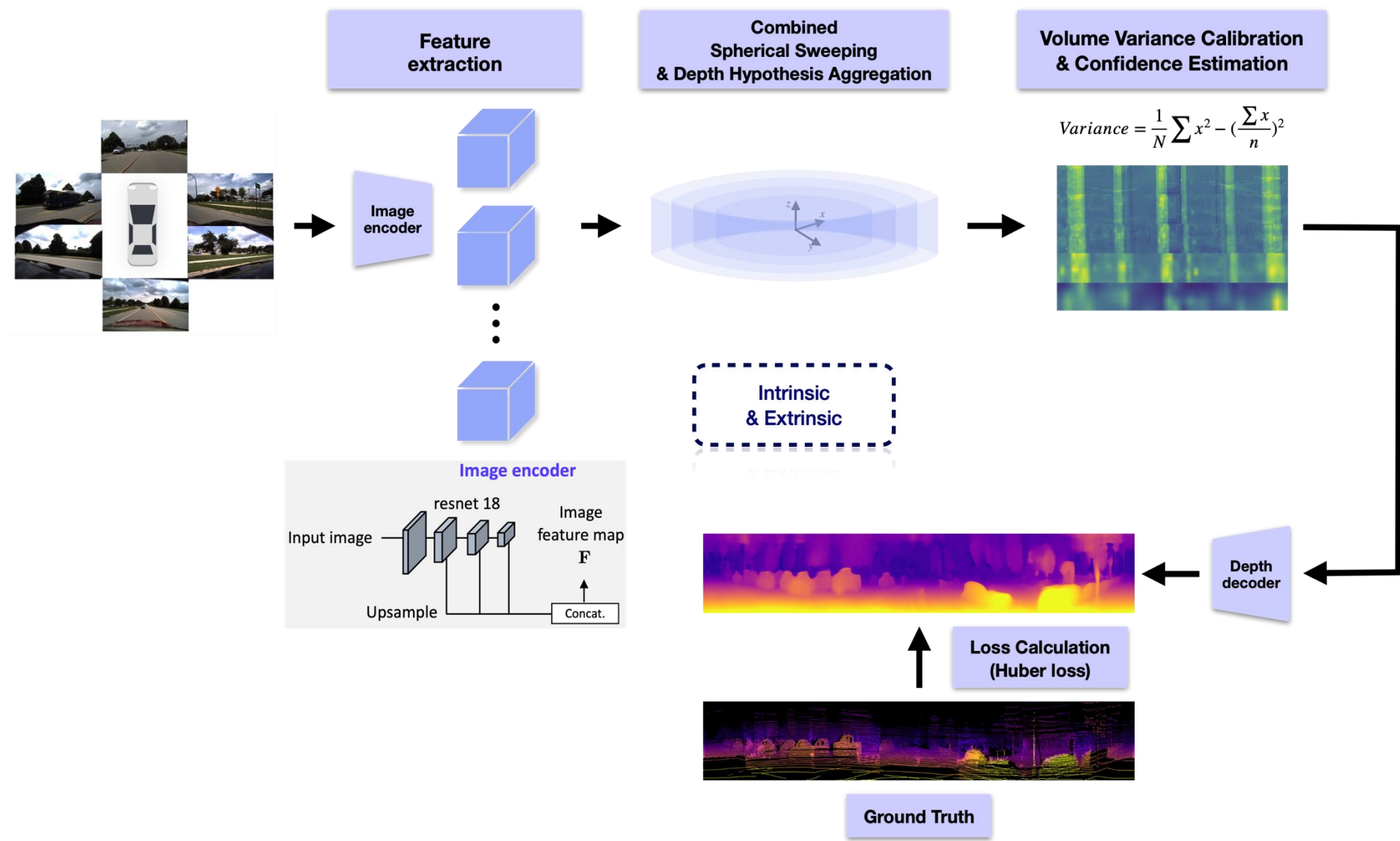
## ◆ Variance-Integrated Panodepth

- ▶ To address the limitations of insufficient boundary information and scale misalignment, Panodepth is proposed using a cylindrical projection method.



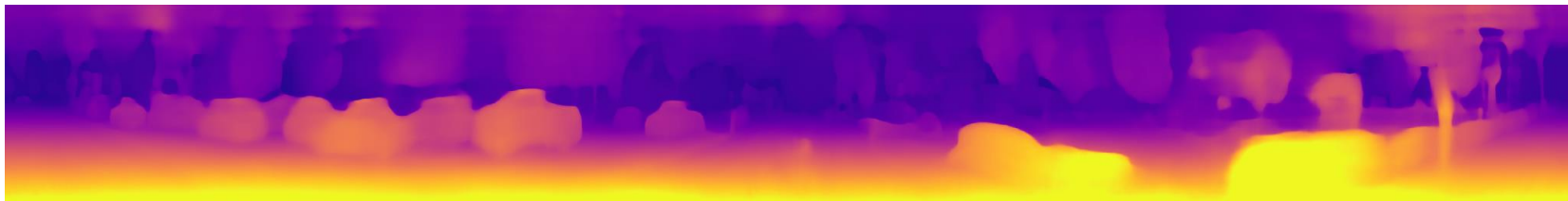
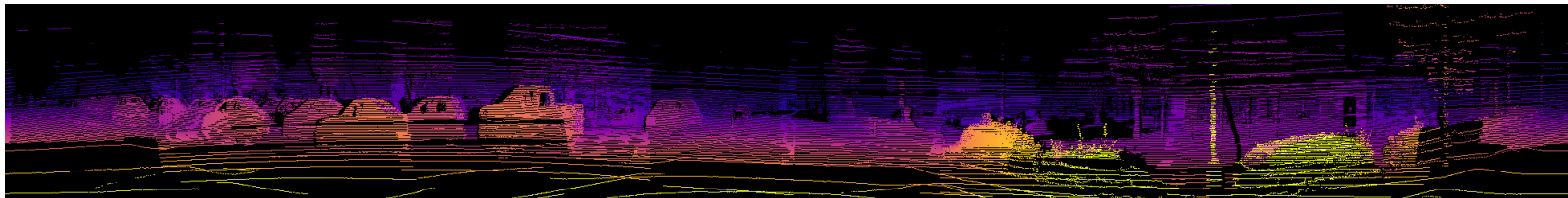
Scale misalignment on overlap areas

# Variance-Integrated Panodepth for Cylindrical Depth Estimation



# Variance-Integrated Panodepth for Cylindrical Depth Estimation

---

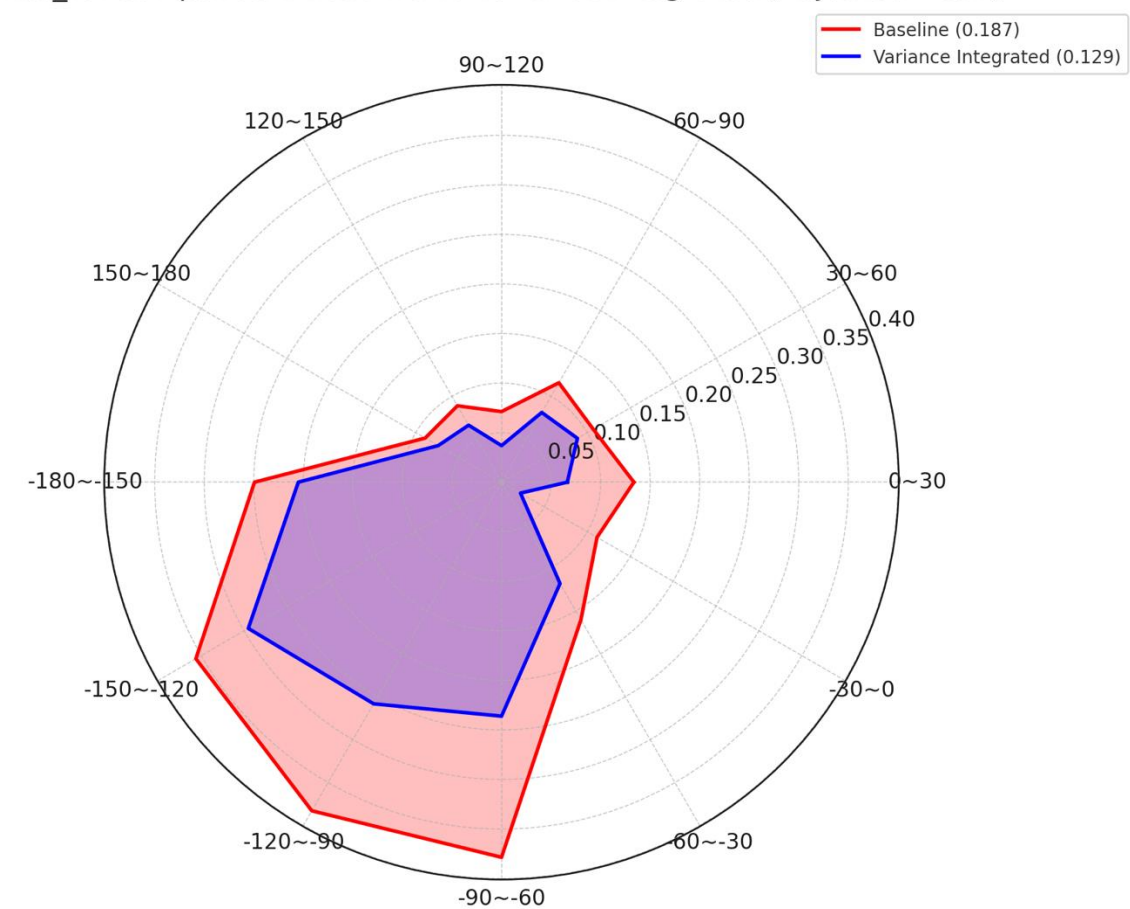


*Ground Truth(GT) and estimated depth map results generated from 6 surround view images.*



# Variance-Integrated Panodepth for Cylindrical Depth Estimation

Abs\_rel Comparison: Baseline vs Variance Integrated (Adjusted Mean)



Angle-wise comparison of Abs\_rel between Baseline (Cylindrical Sweeping) and Variance-Integrated Method

	AbsRel	SqrRel	RMSE	RMSElog	SiLog	A1	A2	A3
Cylindrical Sweeping	0.187	4.217	14.543	0.362	34.597	0.798	0.866	0.927
Variance Confidence	0.129	2.778	13.532	0.341	32.71	0.832	0.871	0.934

Performance comparison between the Baseline (Cylindrical Sweeping) model and the model with added Variance Confidence

- **Smoother and More Robust Results**
  - ◆ Integrating the Variance Confidence method into Cylindrical Sweeping leads to smoother, more reliable depth predictions.
- **Reduced Error Metrics**
  - ◆ The variance-integrated approach helps minimize errors and improve overall accuracy.
- **Enhanced Stability**
  - ◆ Improved consistency and stability, as demonstrated in the radial comparison.

# Variance-Integrated Panodepth for Cylindrical Depth Estimation

---

## Conclusions & Future Works

- ◆ Improvement in consistency of **Boundary Information** and Consistency in **Overlap Regions**
- ◆ **Model Lightweighting** and **Computational Efficiency Improvement**
  - ▶ By applying a method that divides the cylindrical coordinate system in half for projection, both lightweighting and computational efficiency can be enhanced.
- ◆ **Adaptive Depth Hypothesis Adjustment**
  - ▶ Research on adjusting the depth hypothesis on a **pixel-wise** basis, rather than at fixed intervals.
  - ▶ Placing denser hypotheses in areas close to the actual depth based on **the predicted depth score**.
  - ▶ Possibility of placing **sparse depth hypotheses** in distant locations.

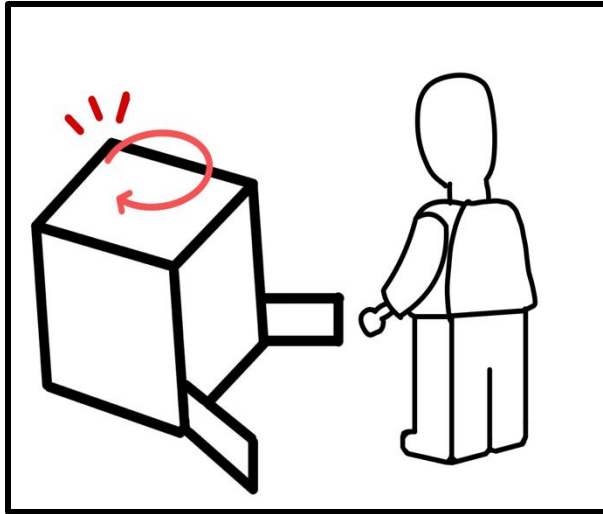


# Autonomous PickingBot using LIDAR

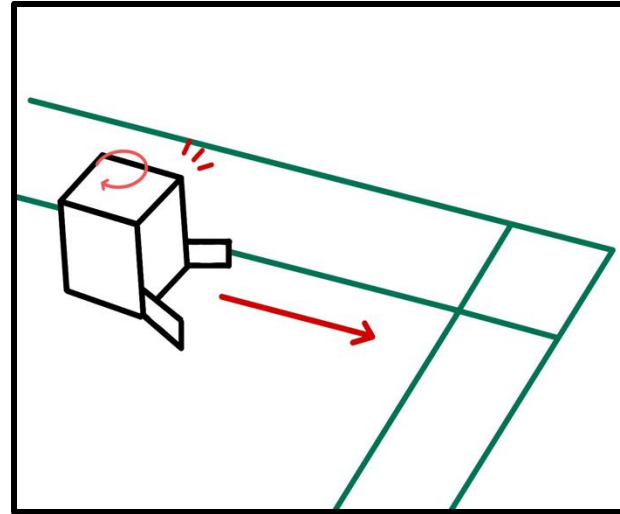


# Autonomous PickingBot using LIDAR

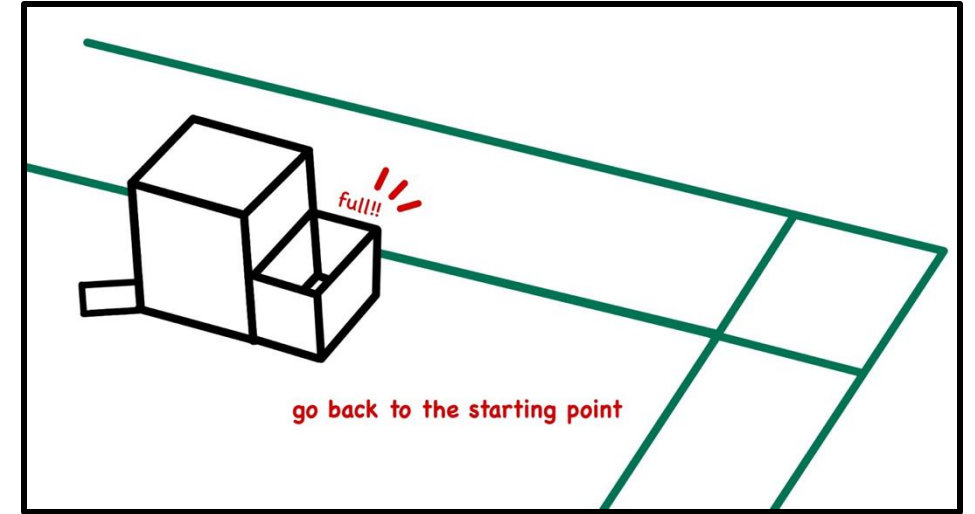
## ► Core Features of the Shuttlecock Collecting Robot



Obstacle  
Avoidance



Driving Along  
a Predefined  
Path



Returning to the Starting  
Point When the  
Shuttlecock Basket Is Full

# Introduction

---

- **Project Background:**

- ◆ **Accumulation of Shuttlecocks**

- During badminton practice, shuttlecocks often pile up in specific areas of the court.

- ◆ **Manual Collection Challenges**

- The inconvenience of picking up shuttlecocks by hand was a major drawback, prompting the development of an autonomous robot.

- **Key Techniques:**

- ◆ **Google Cartographer with 2D LIDAR**

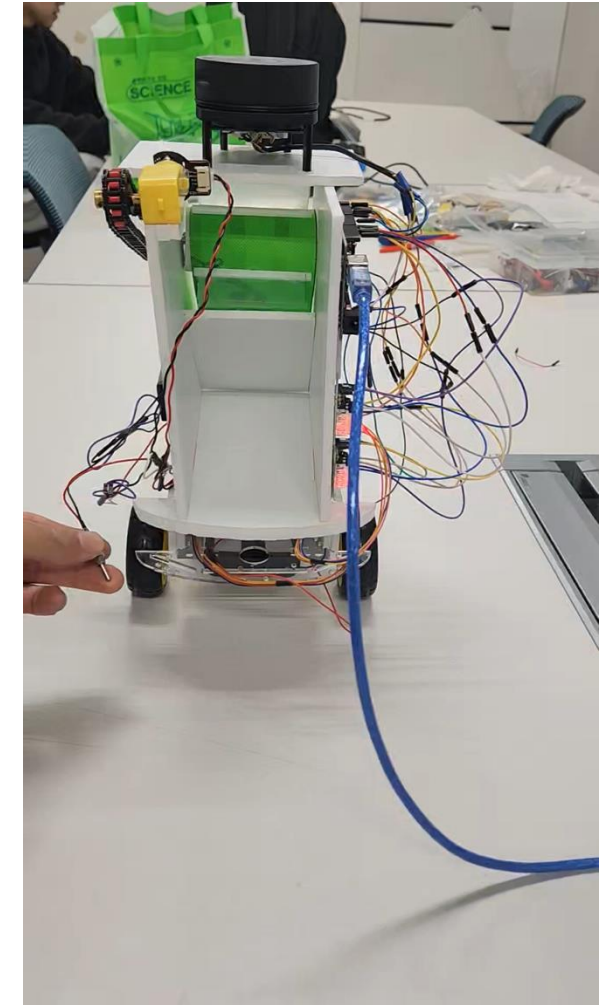
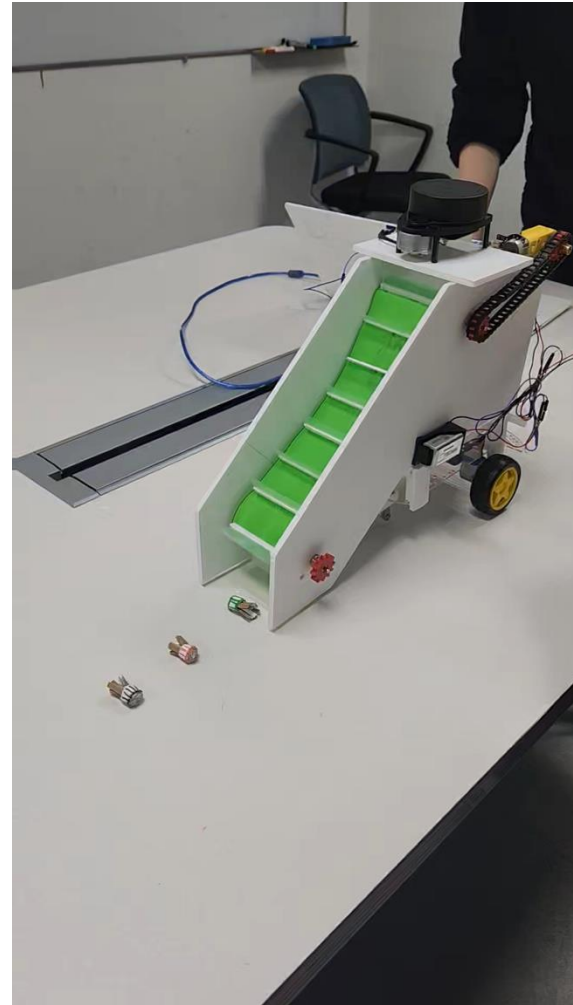
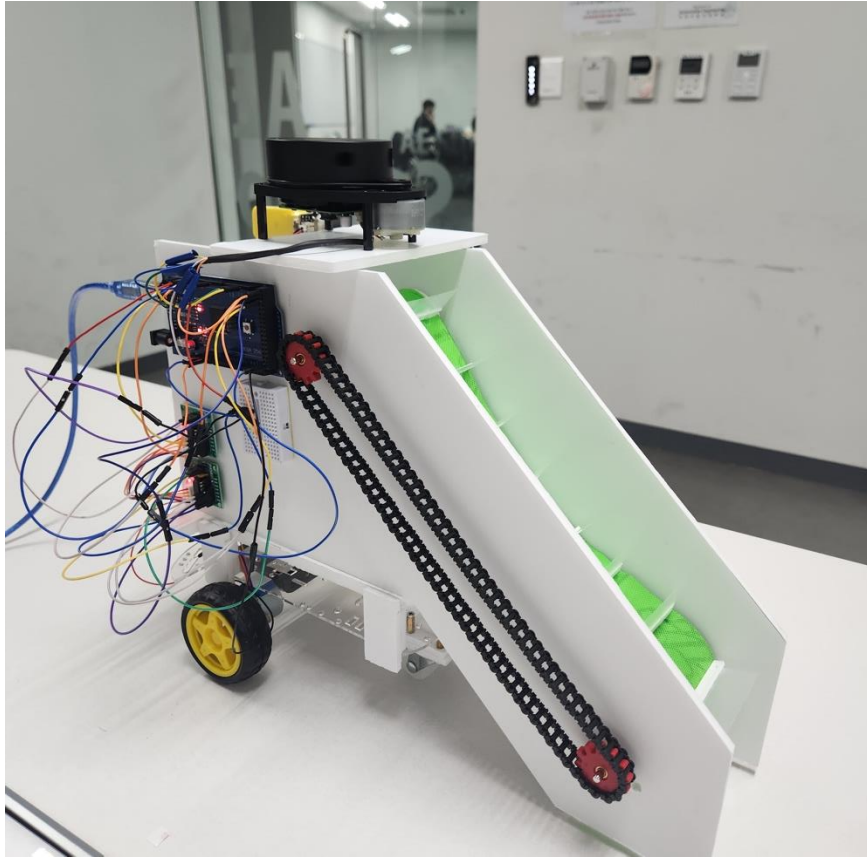
- ▶ Real-time localization and map generation

- ◆ **LIDAR-Based Obstacle Detection**

- ▶ Dynamically adjusts driving paths to avoid obstacles.

*(By automating shuttlecock collection on the badminton court, the PickingBot significantly improves convenience. Future integration of computer vision aims to offer more precise detection and advanced autonomy.)*

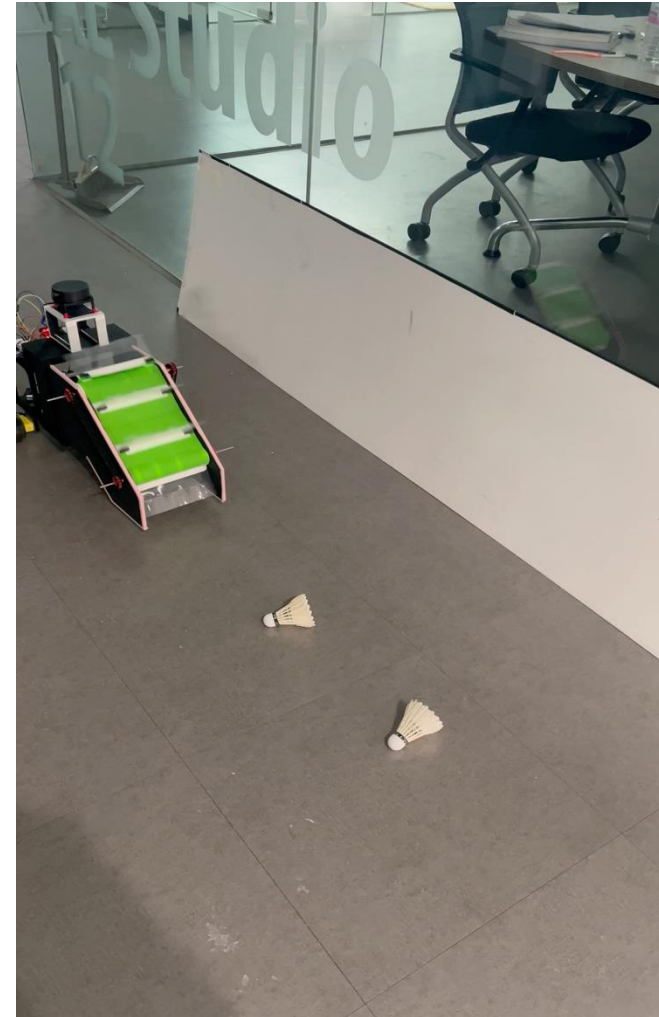
# Autonomous PickingBot using LIDAR



*<Functional Prototype: Shuttlecock Collection Robot with LIDAR-Based Navigation>*

# Autonomous PickingBot using LIDAR

---



<Live Test: MintonBot Navigating and Collecting Shuttlecocks Using LIDAR>

**Thank you**