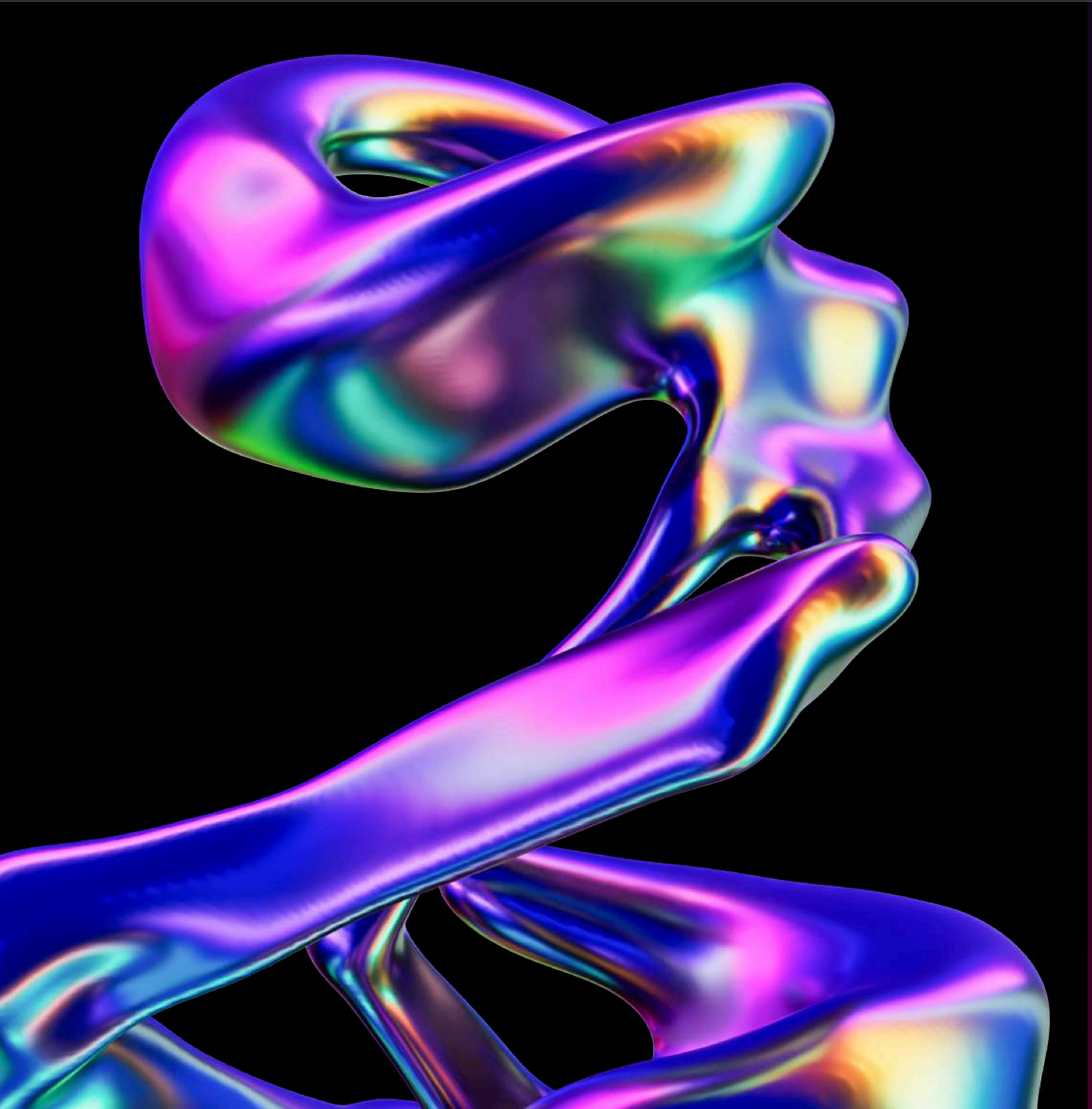

NUCLEUS

Nuclear Contamination Leak and Exploration Utility System

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Guide: Dr. Suvidha Rupesh Kumar

INTRODUCTION

Need for Safer and Efficient Solutions in nuclear facilities

- Hazardous environments like nuclear facilities require advanced solutions.
- Challenges include high radiation levels, extreme conditions, and confined spaces.
- Current manual and remote systems are inefficient, inaccurate, and expose humans to risks.

Focus of the Study

- Development of an autonomous robotic mobile chasis attached with a robotic arm to address challenges in nuclear facilities.
- RTAB-Map algorithm used for SLAM (Simultaneous Localization and Mapping).
- The system generates detailed 3D maps and localizes itself in complex, dynamic environments.

INTRODUCTION

Advanced Features

- Integration of radiation and thermal sensors for precise nuclear leakage detection.
- Capable of performing targeted intervention tasks autonomously or under operator guidance.

Research Question

- How can an autonomous robotic arm improve safety, precision, and operational efficiency in hazardous nuclear environments?

Significance of the Research

- Addresses critical safety concerns in nuclear operations.
- Reduces human exposure to radiation.
- Enhances efficiency in inspection and repair tasks.

PROBLEM STATEMENT

Risks in nuclear environments: radiation exposure, confined spaces, manual interventions. Inefficiencies in existing inspection and repair systems.

Current limitations: low autonomy, inefficiencies, and safety concerns.

Need for a Robust Solution:

a. Autonomous navigation and mapping.
b. Advanced leakage detection.
c. Reduced human exposure and increased operational efficiency.

RESEARCH CHALLENGES

1. **Material Selection: Testing materials for durability in extreme radiation and temperature conditions.**
2. **Mobility and Localization: Integration of precise SLAM for navigating confined nuclear spaces.**
3. **Sensor Integration: Ensuring accuracy and reliability of radiation and thermal sensors.**
4. **Precision Control: Coordinating robotic arm movement and chassis mobility.**

RESEARCH OBJECTIVES

1. Durable Materials: Test chassis and robotic arm materials for radiation resistance.
2. Enhanced SLAM: Improve RTAB-Map for better mapping and self-localization.
3. Dataset Creation: Collect RGB and thermal images using Intel RealSense D435i.
4. Path Planning with Federated Learning: Develop a model to dynamically select path planning algorithms.
5. User-Friendly Control: Design a ROS-based GUI for efficient operation and monitoring.

PROPOSED SYSTEM INTRODUCTION

The ever-growing need for safer and more efficient solutions in hazardous environments, such as nuclear facilities, has driven significant advancements in robotics.

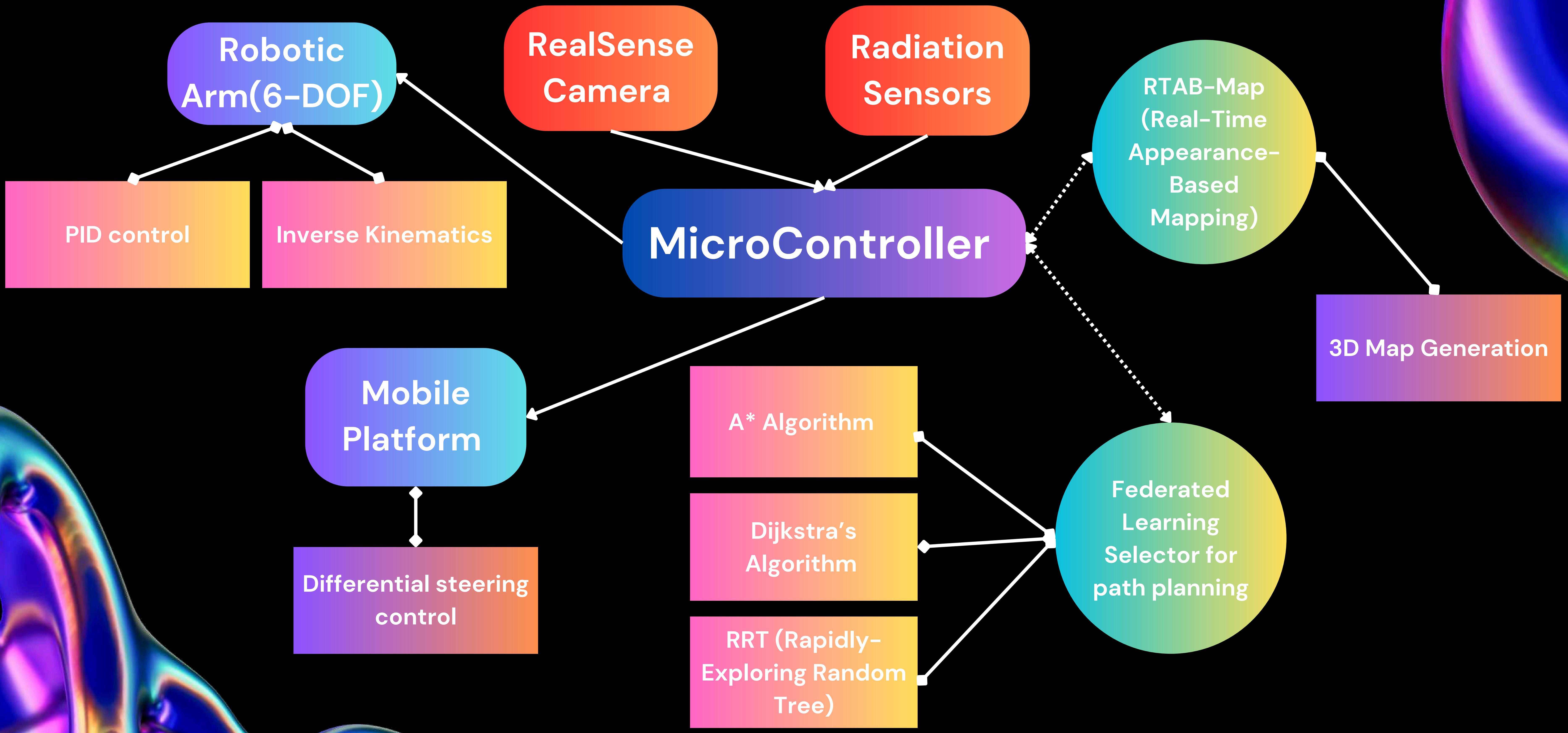
Challenges in Nuclear Facilities: High radiation levels, Extreme environmental conditions, Confined spaces posing risks to human workers

Limitations of Current Methods: Manual labor is inefficient and risky, Remote-operated systems lack precision, Prolonged human exposure increases health risks

Objective of the Study: Development of an autonomous robotic arm system to improve safety and efficiency in nuclear environments

Integration of SLAM, thermal and radiation sensors for precise inspection and intervention

PROPOSED SYSTEM DIAGRAM



PROPOSED SYSTEM MODULES

The system consists of the following key modules:

1. Mobile Platform (Chassis) – Autonomous navigation system
2. Robotic Arm (6-DOF) – High-precision manipulator
3. Sensor Suite – Thermal and radiation sensors for anomaly detection
4. SLAM Module (RTAB-Map) – Real-time mapping and localization
5. Path Planning Module – Dynamic navigation strategy
6. Federated Learning Selector – Adaptive path selection using AI
7. Gazebo Simulation Testing – Virtual validation of the system

PROPOSED SYSTEM MODULES

Mobile Platform (Chassis)

Purpose: Provides mobility in nuclear environments

Features:

- Autonomous navigation for confined spaces
- Differential drive system for high maneuverability
- Integration with SLAM for obstacle avoidance

Key Components:

- Motors & Wheels: High-torque motors for movement
- Power System: Battery-powered for extended operation

Robotic Arm (6-DOF)

Purpose: Conducts inspection and intervention tasks

Features:

- 6 Degrees of Freedom (DOF) for precise movement
- Inverse Kinematics (IK) control for smooth operation
- Gripper or tool attachment for sample collection

Algorithm Used:

- Jacobian Matrix for IK – Computes arm movements efficiently
- PID Controller for smooth and stable arm motion

Sensor Suite (Thermal + Radiation)

Purpose: Detects nuclear leakages and abnormal heat signatures

Key Sensors:

- Intel RealSense D435i (thermal imaging)
- Geiger Counter & Radiation Sensors (real-time radiation monitoring)

Data Processing:

- Thermal anomaly detection using OpenCV
- Radiation mapping using ROS visualization tools

SLAM Module (RTAB-Map)

Purpose: Enables the robot to map and localize itself

Algorithm: RTAB-Map (Real-Time Appearance-Based Mapping)

- Loop Closure Detection – Prevents mapping errors
- Graph-Based Optimization – Reduces drift in large environments

Process:

- Collects camera data
- Generates a real-time 3D map
- Updates localization continuously

Path Planning & Federated Learning Selector

Purpose: Selects the best path planning algorithm dynamically

Algorithms Considered:

- A Algorithm* – Finds shortest path
- Dijkstra's Algorithm – Guarantees safest route
- RRT (Rapidly-Exploring Random Tree) – For unknown environments

Federated Learning Approach:

- Uses historical navigation data to improve path selection over time
- Adapts to different nuclear facility layouts dynamically

PROPOSED SYSTEM MODULES

Gazebo Simulation Testing

Purpose: Validates system performance before deployment

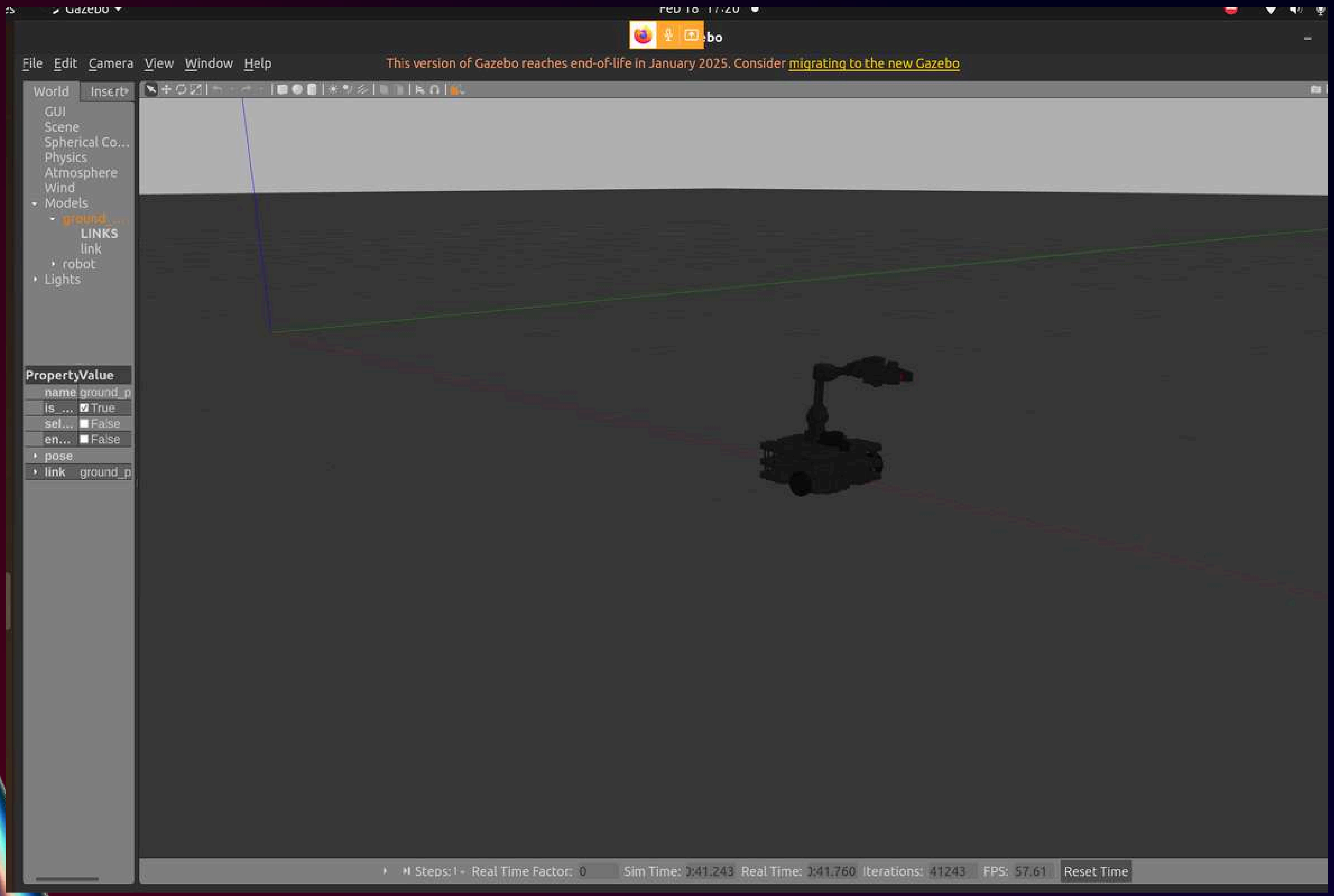
Features:

- Simulated nuclear facility environment
- Testing robotic arm manipulation
- Evaluating SLAM-based navigation
- Assessing radiation detection accuracy

Results:

- Successful mapping of hazardous areas
- Efficient path optimization using federated learning
- Autonomous detection and intervention with minimal human involvement

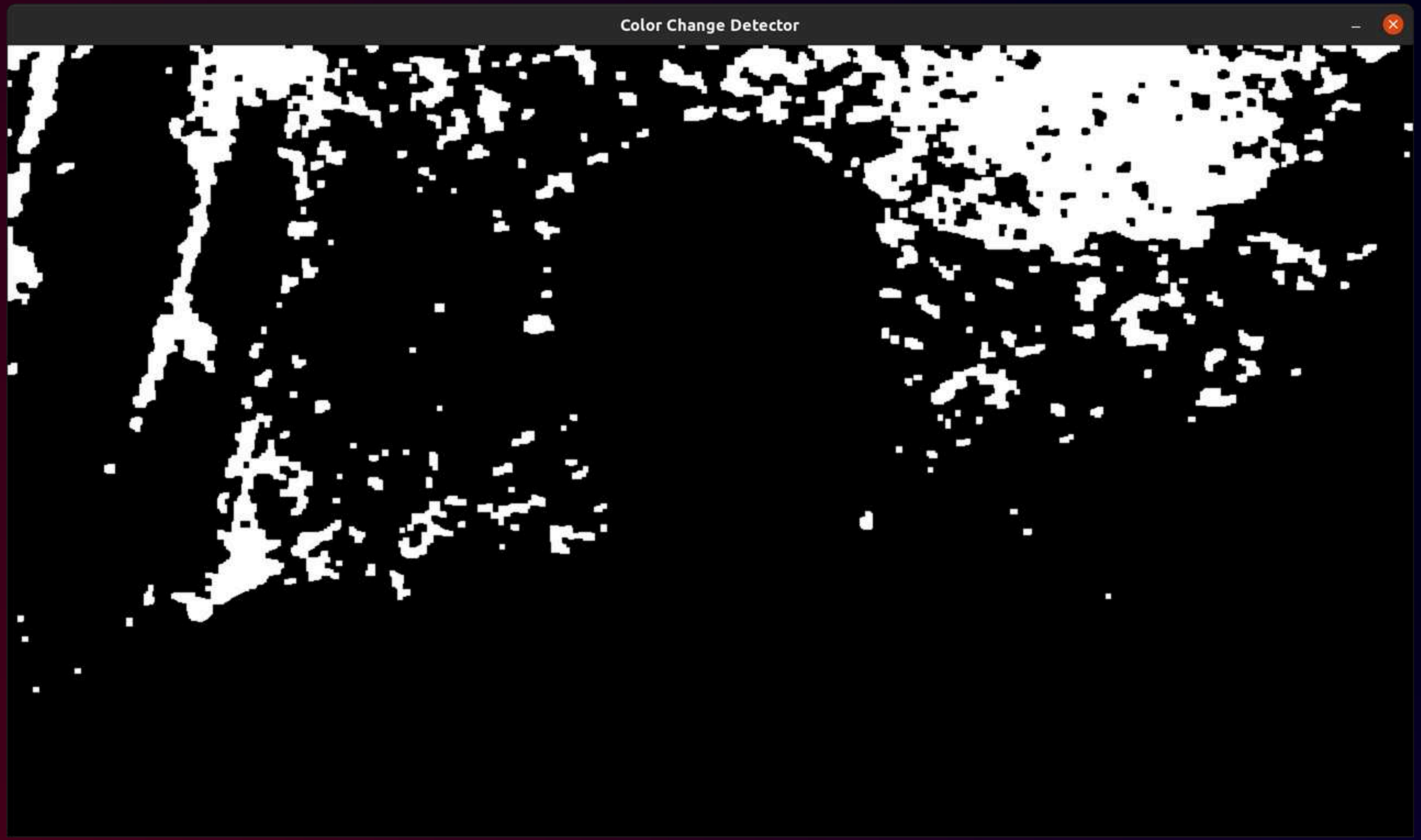
RESULTS



CHASSIS DESIGN: THE ROBOT'S CHASSIS IS A COMPACT, MOBILE BASE DESIGNED FOR STABLE NAVIGATION IN HAZARDOUS NUCLEAR ENVIRONMENTS. IT IS EQUIPPED WITH DIFFERENTIAL DRIVE WHEELS FOR PRECISE MOVEMENT AND MANEUVERABILITY IN CONFINED SPACES.

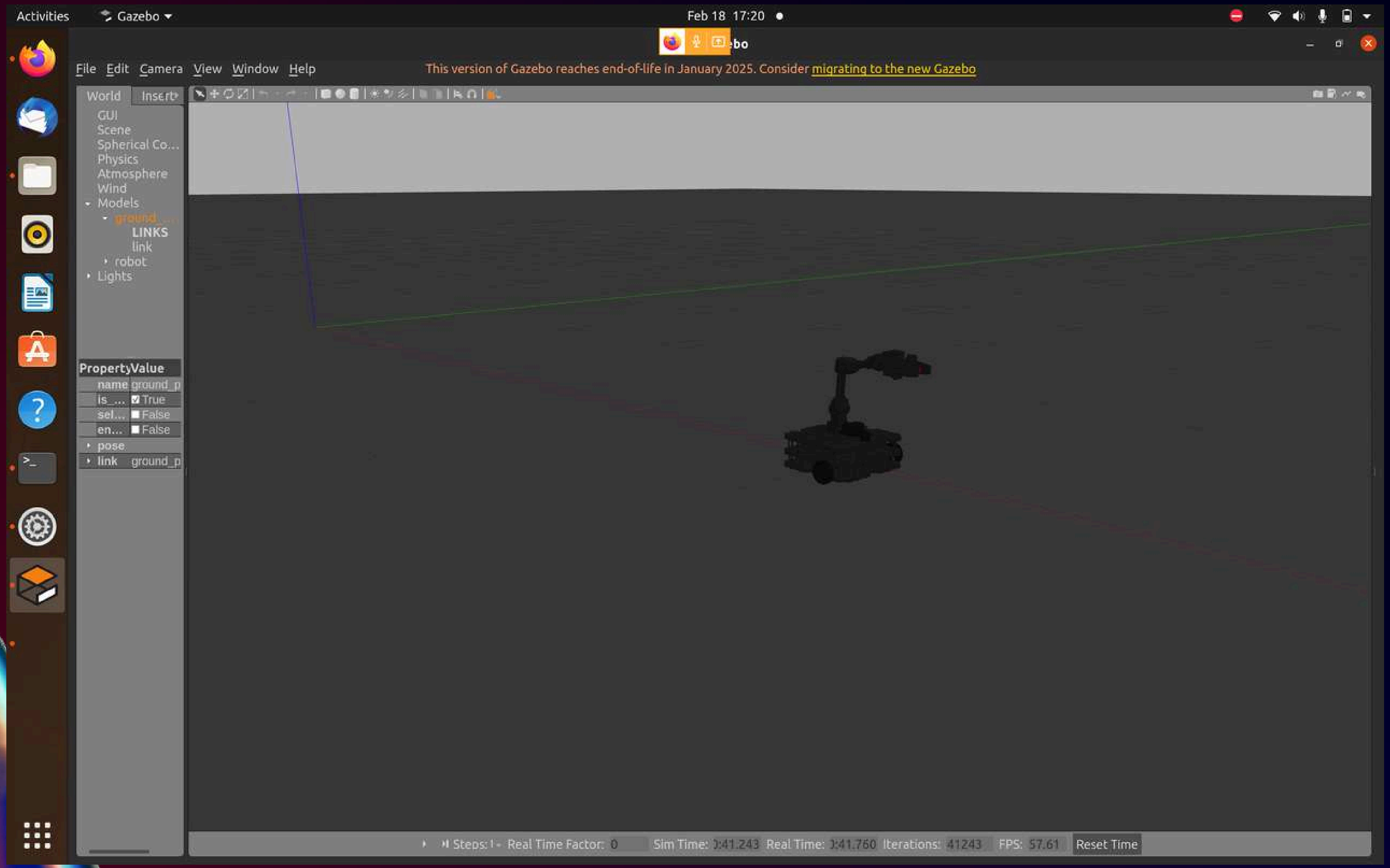
ROBOTIC ARM: THE ROBOTIC ARM IS A LIGHTWEIGHT, MULTI-DOF MANIPULATOR MOUNTED ON THE CHASSIS, CAPABLE OF PERFORMING INSPECTION AND INTERVENTION TASKS. IT IS DESIGNED WITH A END-EFFECTOR FOR HANDLING DELICATE OPERATIONS SUCH AS SEALING MINOR LEAKS OR PLACING SENSORS. THE ARM'S MOVEMENT IS CONTROLLED USING INVERSE KINEMATICS AND ROS-BASED MOTION PLANNING, ALLOWING IT TO INTERACT WITH THE ENVIRONMENT BASED ON REAL-TIME SENSOR FEEDBACK.

RESULTS



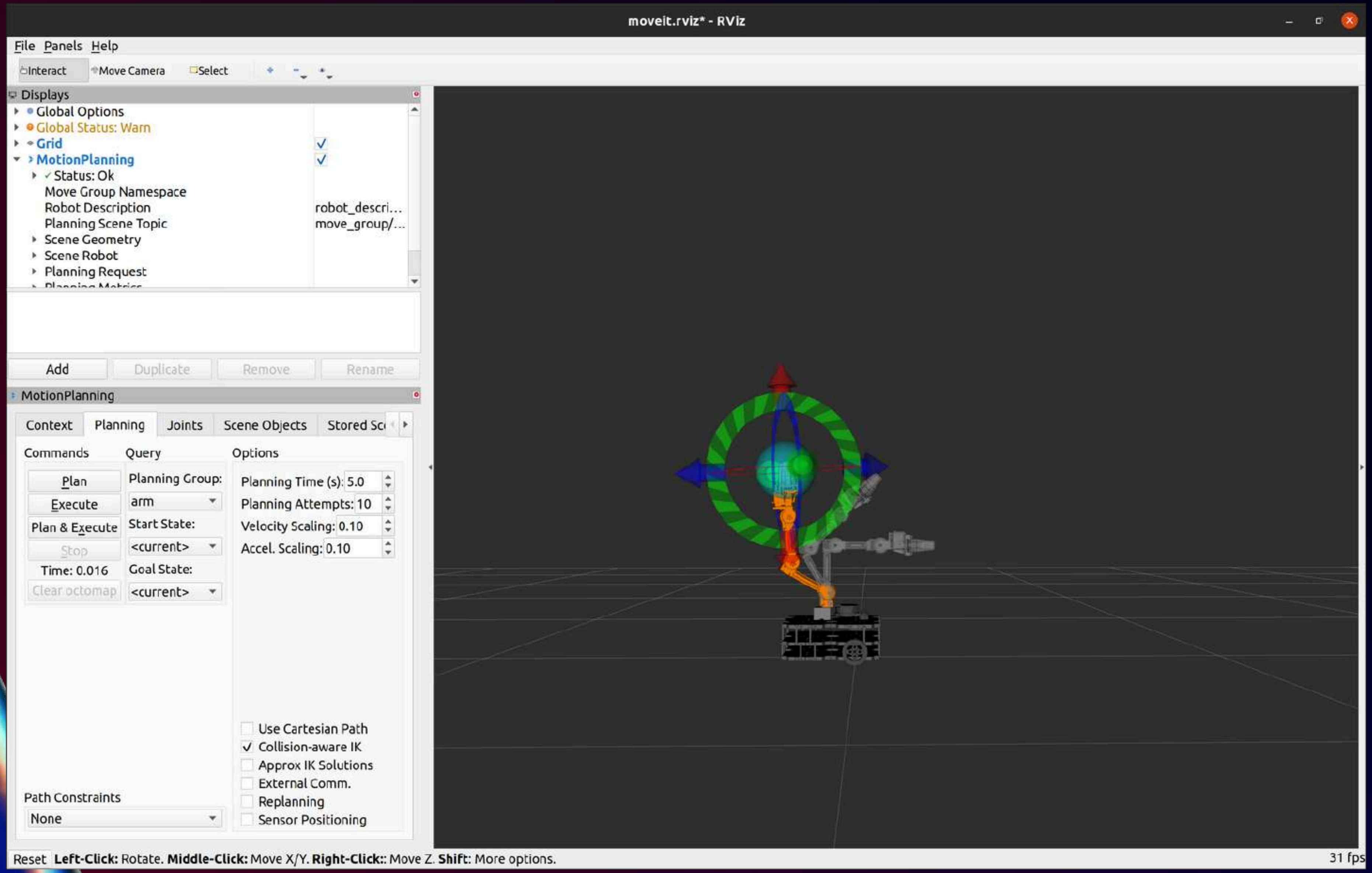
- WHEN A SPARK-LIKE COLOR (YELLOWISH TONES) APPEARS, A BOOLEAN TRUE IS PUBLISHED TO THE /COLOR_LEAKAGE_DETECTED TOPIC.
- IF NO SPARK IS DETECTED, THE SCRIPT CONTINUOUSLY PUBLISHES FALSE.
- THE PROCESSED MASK VISUALLY HIGHLIGHTS THE DETECTED AREA IN A SEPARATE OPENCV WINDOW.
- THE DETECTION IS SMOOTHED USING MORPHOLOGICAL OPERATIONS, REDUCING NOISE AND FALSE POSITIVES.
- THE DETECTION LOOP RUNS IN REAL-TIME, PROCESSING FRAMES CONTINUOUSLY UNTIL THE USER EXITS BY PRESSING 'Q'.
- THE ROS-BASED PUBLISHER ENABLES INTEGRATION WITH OTHER ROBOTIC COMPONENTS FOR AUTOMATED RESPONSE UPON SPARK DETECTION.

RESULTS



- WHEN A LEAKAGE (SPARK) IS DETECTED, THE ROBOT STOPS IMMEDIATELY BY PUBLISHING A ZERO-VELOCITY COMMAND (TWIST).
- THE DETECTION SIGNAL IS RECEIVED FROM THE /COLOR_LEAKAGE_DETECTED TOPIC, ALLOWING REAL-TIME RESPONSE TO COLOR CHANGES.
- THE ROBOT CONTINUOUSLY CHECKS FOR NEW DETECTION UPDATES WITHIN A 10 HZ CONTROL LOOP.
- ROS LOGS PROVIDE REAL-TIME UPDATES, DISPLAYING "LEAKAGE DETECTED! STOPPING THE TURTLEBOT..." OR "NO LEAKAGE DETECTED. RESUMING NORMAL OPERATION..." ACCORDINGLY.
- THE SYSTEM RUNS AUTONOMOUSLY IN A LOOP, ENSURING THE ROBOT REACTS DYNAMICALLY TO ITS ENVIRONMENT.
- THE MOTION CONTROL LOGIC INTEGRATES WITH THE ROBOT'S NAVIGATION STACK, MAKING IT ADAPTABLE FOR FURTHER ENHANCEMENTS LIKE OBSTACLE AVOIDANCE OR ARM MOVEMENTS UPON DETECTION.

RESULTS



- THE ROBOTIC ARM IS CONTROLLED USING MOVEIT, ALLOWING FOR PRECISE MOTION PLANNING AND EXECUTION.
- RVIZ IS USED FOR VISUALIZING THE ARM'S MOVEMENTS, ENSURING ACCURATE POSITIONING BEFORE EXECUTION.
- THE ARM FOLLOWS PLANNED TRAJECTORIES TO INTERACT WITH THE ENVIRONMENT BASED ON SENSOR INPUTS.
- THE INTEGRATION ENABLES REAL-TIME MANIPULATION, ALLOWING THE ARM TO RESPOND DYNAMICALLY TO DETECTED LEAKAGES.
- COLLISION AVOIDANCE IS HANDLED THROUGH MOVEIT'S PLANNING ALGORITHMS, PREVENTING UNINTENDED CONTACT WITH OBSTACLES.
- THE ARM'S MOVEMENT CAN BE TRIGGERED AUTONOMOUSLY UPON LEAKAGE DETECTION OR MANUALLY THROUGH RVIZ.
- THE SYSTEM SUPPORTS INVERSE KINEMATICS, ENABLING SMOOTH AND EFFICIENT END-EFFECTOR CONTROL.

RESULTS

TO TRAIN THE MODEL FOR OPTIMAL PATH PLANNER SELECTION, A CUSTOM DATASET WAS PREPARED USING DEPTH IMAGES CAPTURED FROM A SIMULATED ENVIRONMENT WITHIN GAZEBO. THE ROBOT WAS ALLOWED TO NAVIGATE THROUGH VARIOUS NUCLEAR CHAMBER SCENARIOS WITH DIVERSE OBSTACLE ARRANGEMENTS. EACH DEPTH IMAGE WAS LABELED WITH THE MOST SUITABLE PATH PLANNING ALGORITHM (A* OR DIJKSTRA) BASED ON PERFORMANCE METRICS SUCH AS PATH LENGTH, TIME TO GOAL, AND OBSTACLE DENSITY. OVER 2000 DEPTH IMAGES WERE COLLECTED AND MANUALLY CLASSIFIED, ENSURING A BALANCED DISTRIBUTION BETWEEN THE TWO CLASSES. THE LABELED DATA WAS THEN PREPROCESSED, RESIZED, AND NORMALIZED TO SERVE AS INPUT TO A CONVOLUTIONAL NEURAL NETWORK (CNN) FOR SUPERVISED LEARNING

RESULTS

pjt2.ipynb

File Edit View Insert Runtime Tools Help

+ Code + Text

```
import cv2

# Read the image
image = cv2.imread('yoyo.jpeg.jpe

# Convert the image to grayscale
grayscale_image = cv2.cvtColor(ima

# Save the grayscale image
cv2.imwrite('grayscale_image.jpg'
```

True

```
import cv2
import numpy as np

# Load the grayscale depth image
image_path = "grayscale_image.jpg"
depth_img = cv2.imread(image_path_

# Normalize the image (0 = Free,
occupancy_grid = np.zeros_like(dep

# Define thresholds
free_threshold = 200   # Pixels al
occupied_threshold = 50   # Pixels
```

labels.csv

image_name	path_found	start_x	start_y	goal_x	goal_y	obstacle_ratio	path
planned_path.png	1					99.86	0

Show 10 per page

- THE PLANNED PATH IMAGE (PLANNED_PATH.PNG) IS USED FOR TRAINING A CNN MODEL.
- TO TRAIN THE MODEL EFFECTIVELY, WE NEED A STRUCTURED DATASET WITH LABELED PARAMETERS.
- LABELS PROVIDE GROUND TRUTH INFORMATION ABOUT THE ROBOT'S MOVEMENT, PATH COMPLEXITY, AND ENVIRONMENT.

RESULTS

image_name	path_found	start_x	start_y	goal_x	goal_y	obstacle_ratio	path_length	grid_size
planned_path1.png	1	10	20	90	80	32.5	113.14	100x100

Parameter	Description
Image Filename	Name of the image file (e.g., `planned_path_1.png`)
Start Position (X, Y)	Robot's starting coordinates on the occupancy grid
Goal Position (X, Y)	Target destination coordinates
Path Length	Total number of steps in the path
Number of Turns	Number of directional changes in the path
Obstacle Density	Percentage of the grid occupied by obstacles
Path Complexity	A measure of how many detours/zigzags the path has
Optimality Score	A heuristic-based score indicating path efficiency

RESULTS

PERFORMANCE METRICS OF PATH PLANNING ALGORITHMS

METRIC	A*	DIJKSTRA	OVERALL
PRECISION	0.93	0.92	MACRO AVG.: 0.925
RECALL	0.96	0.99	MACRO AVG.: 0.975
F1-SCORE	0.92	0.96	MACRO AVG.: 0.94
SUPPORT	238	256	TOTAL: 494

CONCLUSION

The proposed system successfully integrates a CNN-based classification model, reinforcement learning techniques, and real-time perception tools to dynamically select optimal path planning algorithms based on environmental complexity. By leveraging depth and RGB images captured through Intel RealSense D435i and utilizing SLAM with RTAB-Map, the robot effectively navigates and executes leakage detection and maintenance tasks.

Simulation results demonstrate that the adaptive decision-making framework significantly outperforms static planning strategies in terms of accuracy, efficiency, and robustness. The integration of the ROS ecosystem with Gazebo and MoveIt enables a seamless simulation and control environment for both navigation and manipulation. Furthermore, the system's modular design and real-time adaptability underline its potential applicability across various hazardous domains, including disaster response, space exploration, and deep-sea missions.

Future enhancements, such as sensor fusion, multi-agent coordination, and real-world deployment, will further elevate the system’s reliability and scalability. Ultimately, this research lays a strong foundation for intelligent, autonomous robotics in high-risk environments, minimizing human exposure and maximizing operational precision.

FURTURE WORK

Extend to Multiple Depth Images

- Process and convert multiple depth images into occupancy grids.
- Automate batch labeling for all images.
- Compare results for different environments and obstacle distributions.

Fine-Tune CNN for Path Prediction

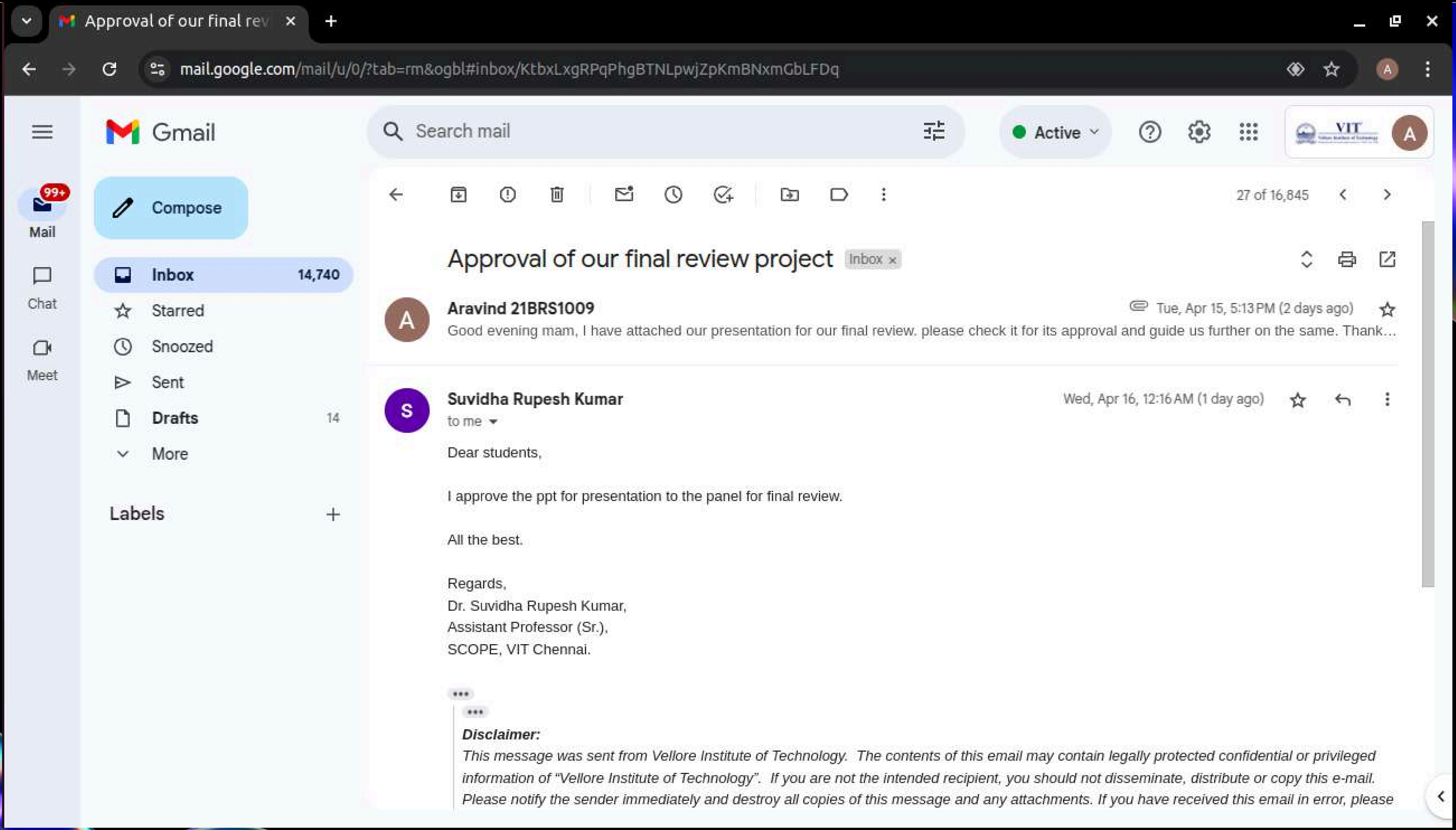
- Train CNN with a larger dataset of planned paths.
- Optimize hyperparameters like learning rate, batch size, and number of layers.
- Use data augmentation (rotation, scaling) to improve model generalization.
- Evaluate model performance using validation loss, accuracy, and confusion matrix.

FUTURE WORK

Integrate CNN with ROS for Real-Time Path Planning

- Convert trained CNN into a ROS-compatible inference model.
- Implement ROS nodes to take real-time depth images, process them into occupancy grids, and predict the best path.
- Deploy the model on a ROS-based TurtleBot manipulator for nuclear environment navigation.
- Use ROS topics/services to communicate planned paths to the robot's motion planner.

GUIDE APPROVAL



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