**Introduction:**

The project focuses on building a machine learning model that can detect and classify objects in the environment, such as pedestrians, vehicles, traffic signs, and obstacles. The model will be deployed in autonomous vehicle systems to enhance safety and decision making in real-time driving scenarios. The project aims to address challenges such as detecting objects in different lighting conditions, road types, and varying environmental factors.

Objectives:

**1. Develop an Accurate and Robust Machine Learning Model**

Train a YOLO model to detect and classify objects such as:

1-Pedestrians

2-Vehicles (cars, trucks, motorcycles)

3-Traffic signs (stop signs, speed limits,…)

4-Obstacles (road debris, construction barriers, …)

Ensure high precision and recall to minimize false positives/negatives.

**2. Handle Diverse Environmental Conditions**

Improve detection under varying:

Lighting conditions (day, night, fog, rain)

Road types (urban streets, highways, rural roads)

Weather conditions (snow, glare, shadows)

**3. Enhance Safety and Decision-Making**

Provide reliable object detection to:

Prevent collisions with pedestrians/obstacles.

Improve path planning by accurately identifying traffic signs and lane markings.

Assist in adaptive cruise control and emergency braking.

**4. Deployment in Deployment systems**

Deploying on streamlit.

**5. Evaluation and Benchmarking**

Test the model on standard Bdd dataset.

Compare performance against state-of-the-art models.

Conduct real-world testing in simulated and controlled environments.

**6. Scalability and Future Improvements**

Design the system to allow continuous learning (updating the model with new data).

**Milestone 1: Data Collection, Exploration, and Preprocessing**:

1-Data Collection:

We used Bdd dataset instead of kiti as it contains weather conditions, light Conditions and other features that wasn’t found in kiti dataset

2- Exploration:

Class Distribution (Instance Count)

|  |  |
| --- | --- |
| **Notes** | **Class** |
| Dominant class (needs balancing?) | 713,211Car |
| Critical for path planning | 528,643 Lane |
| Key for urban driving | Traffic Light 186,117 |
| Semantic segmentation focus | Drivable Area 125,723 |
| Pedestrian safety priority | Person 91,349 |
| Rare but high-risk | Truck 29,971 |
| Urban scenarios | Bus 11,672 |
| Vulnerable road user | Bike 7,210 |
| Motorcyclists/cyclists | Rider 4,517 |
| Small but critical | Motor 3,002 |
| Extremely rare (consider augmentation) | Train 136 |

**Data Quality**

-Image Resolution

* Detect Unique image resolutions
* Bounding Box Processing

**-Bias Detection**

* Spatial Bias (Center Coordinates)
* Analysis: Plot (x\_center, y\_center) per class to detect

|  |  |  |
| --- | --- | --- |
| **Scene Type distribution:** | **Time of Day distribution:** | **Weather Distributions:** |
| gas stations: 27 | daytime: 36728 | clear: 37344 |
| city street: 43516 | night: 27971 | snowy: 5549 |
| undefined: 361 | dawn/dusk: 5027 | undefined: 8119 |
| tunnel: 129 | undefined: 137 | rainy: 5070 |
| parking lot: 377 |  | partly cloudy: 4881 |
| residential: 8074 |  | overcast: 8770 |
| highway: 17379 |  | foggy: 130 |

**3-Preprocessing**

* Parse the JSON annotation files.
* Extract category, bounding boxes.
* Convert to YOLO format.
* Map categories to class IDs (you may need to create a consistent class list across both datasets).
* Save images and corresponding YOLO .txt files.

**Milestone 2 (object detection)**

using the pretrained model (yolo) to detect objects

Milestone 3 deployment

Milestone 4 mlops

Challenges and Its Solutions:

We faced a problem when working with BDD dataset that it has imbalanced data so we had to make data augmentation and it toke so much time and more resources

Business Impact For Autonomous Vehicles:

**Enhanced Road Safety**  
• **Reduction in Accidents & Collisions**

Real-time detection of road debris, animals, and stalled vehicles prevents accidents

• **Eliminating Distracted Driving**

System remains vigilant even when driver is fatigued or distracted

• **Preventing Drunk & Reckless Driving**

Autonomous systems can override dangerous maneuvers

• **Improved Performance in Low-Visibility Conditions**

Better than human vision in fog, rain, and darkness due to multi-sensor fusion

• **Compliance with Traffic Laws**

Ensures adherence to speed limits, stop signs, and dynamic signals

**Increased Driving Efficiency**  
• **Smoother Traffic Flow**

Predictive braking & adaptive cruise control reduce "phantom traffic jams"

Potential Improvement in future work:

Handling More Complex Road Conditions

Adverse Weather & Lighting Adaptations

Polarized cameras to reduce glare from wet roads.

Detecting off-road obstacles (animals, fallen trees) for rural driving.