Project #4: Real-Time Object Detection for Autonomous Vehicles

Project Description

Our project aims to develop a **real-time object detection** model for autonomous vehicles. The model will identify and classify objects like pedestrians, vehicles, and traffic signs from live video feeds. This system will be integrated into autonomous driving platforms to improve safety and navigation by providing accurate, low-latency environmental perception. It will address the critical challenge of maintaining high performance under diverse conditions, including varying lighting and weather.

Group Members & Roles

1. **AbdElRahman Ahmed Mohamed**: Data Scientist
2. **Ahmed Ashraf**: Machine Learning Engineer
3. **Elsayed Aboulila**: Machine Learning Engineer
4. **Mohamed Ashraf**: MLOps Engineer
5. **Nizar Hussien**: Project Manager/Team Lead

> ➢ Team roles are flexible and can change based on the project's needs. Each member's contribution, regardless of their initial title, helps the team achieve a professional and perfect outcome by adapting to new challenges and leveraging individual strengths.

Team Leader: Nizar Hussien

Tools & Technologies

1. **Programming Languages:** Python
2. **Machine Learning Frameworks:** TensorFlow, PyTorch
3. **Object Detection Models:** YOLO, SSD
4. **Data Handling:** NumPy, Pandas, OpenCV
5. **MLOps:** MLflow, Kubeflow, TensorFlow Serving
6. **Cloud Platform:** Amazon Web Services (AWS) or Google Cloud Platform (GCP)
7. **Version Control:** Git

Milestones & Deadlines

1) **Milestone 1:** Data Collection & Preprocessing**:** 05/11/2025
2) **Milestone 2:** Model Development & Training**:** 15/11/2025
3) **Milestone 3:** Deployment & Real-Time Testing**:** 22/11/2025
4) **Milestone 4:** MLOps & Monitoring**:** 28/11/2025
5) **Milestone 5:** Final Documentation & Presentation**:** 30/11/2025

> ➢ The deadlines are **flexible** and may be adjusted based on the project's progress.

Objectives

Milestone 1 objective: Data Collection & Preprocessing

1. Data Collection

The main objective is to collect visual data like images and videos from trusted resources and real-world environments in various states, weather conditions, lighting conditions, and object types (vehicles, pedestrians, traffic signs, etc.).

2. **Data Exploration**

Performing Exploratory Data Analysis to understand data distribution, object frequency, visual variability to make sure that we cover all driving critical conditions.

3. **Data Preprocessing**

It's about cleaning and normalizing data to prepare it for model training stage. This includes resizing frames, removing duplicates, correcting annotations, and applying augmentations to improve model robustness in real-time environments.

Milestone 2 objective: Model Development and Training

1. **Model Selection and Architecture Design**

Evaluate and select suitable Machine learning models that balance detection accuracy and inference speed for real-time performance.

2. **Model Implementation**

Configure the model structure, define hyperparameters, and implement the training pipeline using the preprocessed dataset from Milestone 1.

3. **Model Training and Optimization**

Train the model using appropriate loss functions and optimizers, applying techniques to improve robustness and reduce overfitting.

4. **Performance Evaluation**

Continuously monitor training metrics to ensure the model meets real-time and accuracy requirements for autonomous driving.

Milestone 3 objective: Deployment & Real-Time Testing

1. **Model Deployment**

Integrate the trained object detection model into the autonomous vehicle's perception framework or an edge-computing platform Ensure compatibility, efficient memory usage, and low-latency inference.

2. **System Optimization**

Apply model compression, quantization, or pruning techniques if necessary to improve inference speed and energy efficiency without significant accuracy loss.

3. **Real-Time Testing**

Conduct real-time detection tests using live video feeds or onboard camera data to assess performance in various environmental and traffic conditions.

4. **Performance Validation**

Evaluate the system using metrics such as frame rate (FPS), detection latency, and accuracy under dynamic conditions. Identify potential limitations and areas for further improvement in robustness and scalability.

Milestone 4: MLOps & Monitoring

1. **Model Monitoring**

Implement real-time monitoring tools to track key performance metrics during live operation.

2. **Data and Performance Feedback Loop**

Collect new data from real-world scenarios to detect data drift and trigger automated retraining or fine-tuning processes, ensuring continuous improvement of model accuracy and robustness.

3. **Scalability and Maintenance**

Design the MLOps infrastructure to support large-scale deployments across multiple vehicles and environments, ensuring consistent performance and simplified model maintenance.

KPIs (Key Performance Indicators)

Our project's success will be measured against a set of key performance indicators (KPIs) across four critical areas: Data Quality, Model Performance, Deployment & Scalability, and Business Impact. These metrics will ensure we deliver a robust and effective solution for real-time object detection in autonomous vehicles.

1. Data Quality

➢ Our goal is to ensure the highest possible data quality to support a high-performing model.

- **Percentage of Missing Values Handled:** We aim to achieve between **85-95%** missing value handling by leveraging comprehensive, pre-annotated datasets like KITTI and COCO. This approach minimizes data gaps and provides a solid foundation for training.
- **Data Accuracy After Preprocessing:** The bounding box and class annotations will be meticulously verified to ensure an accuracy of **85-95%**. This guarantees that the model learns from reliable, correctly labeled data.
- **Dataset Diversity:** We will ensure at least **90%** representation of different object categories across various environmental conditions (e.g., day, night, rain, fog) to build a robust model capable of handling real-world scenarios.

2. Model Performance

➢ These metrics directly measure the effectiveness and efficiency of our object detection model.

- **Model Accuracy (mAP):** Our target is a **mean Average Precision (mAP) of 85-95%** on the validation dataset. This metric provides a comprehensive measure of the model's ability to accurately detect and classify objects.
- **Model Prediction Speed (Latency):** The model must achieve a latency of **less than 200 milliseconds** per frame, enabling real-time operation crucial for autonomous vehicles.
- **Error Rate (False Positive/False Negative):** We aim to maintain a low error rate, specifically a **False Positive/False Negative rate of less than 5%**, to ensure the system reliably identifies critical objects while minimizing incorrect detections.

3. Deployment & Scalability

➢ These KPIs focus on the system's operational reliability and real-world performance.

- **API Uptime:** The final deployed system will be designed for a guaranteed API uptime of **99.9%**, ensuring continuous and reliable service.
- **Response Time per Request:** We will target an average response time of **less than 500 milliseconds** per inference request to support quick decision-making.
- **Real-time Processing Speed:** The system will process data at an average speed of **more than 20 frames per second (FPS)** to ensure smooth and responsive real-time operation.

4. Business Impact & Practical Use

➢ These metrics evaluate the project's real-world value and effectiveness.

- **Reduction in Manual Effort:** The system will automate the visual perception task for autonomous vehicles, leading to a projected **reduction in manual effort of over 75%** for on-road object identification.
- **Expected Cost Savings:** By improving the efficiency and safety of autonomous systems, the project is expected to contribute to a projected **reduction in operational costs of over 10%**.
- **User Satisfaction:** The primary "user" is the autonomous vehicle system. We will measure success by improved navigation, a reduction in near-miss incidents, and enhanced overall safety ratings.

➢ Project KPIs are **approximate** and may be adjusted based on the actual progress and results of the model development process.