National College of Ireland

Project Submission Sheet

Student Name:	Rahul Goswami
Student ID:	X23167572
Programme:	MSCAIJAN24I **Year:** 2024
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Lecturer:	Anderson Augusto Simiscuka
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I hereby certify that the information contained in this (my submission) is information pertaining to research I conducted for this project. All information other than my own contribution will be fully referenced and listed in the relevant bibliography section at the rear of the project.
ALL internet material must be referenced in the references section. Students are encouraged to use the Harvard Referencing Standard supplied by the Library. To use other author's written or electronic work is illegal (plagiarism) and may result in disciplinary action. Students may be required to undergo a viva (oral examination) if there is suspicion about the validity of their submitted work.

Signature:	Rahul Goswami
Date:	04/08/2024

PLEASE READ THE FOLLOWING INSTRUCTIONS:

1. Please attach a completed copy of this sheet to each project (including multiple copies).
2. Projects should be submitted to your Programme Coordinator.
3. **You must ensure that you retain a HARD COPY of ALL projects**, both for your own reference and in case a project is lost or mislaid. It is not sufficient to keep a copy on computer. Please do not bind projects or place in covers unless specifically requested.
4. You must ensure that all projects are submitted to your Programme Coordinator on or before the required submission date. **Late submissions will incur penalties.**
5. All projects must be submitted and passed in order to successfully complete the year. **Any project/assignment not submitted will be marked as a fail.**

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AI Acknowledgement Supplement

Practicum

Enhancing Urban Navigation for Autonomous Vehicles Using AI and Machine Learning: A Deep Reinforcement Learning Approach

Your Name/Student Number	Course	Date
Rahul Goswami / X23167572	**MSCAIJAN24I**	**04/08/2024**

This section is a supplement to the main assignment, to be used if AI was used in any capacity in the creation of your assignment; if you have queries about how to do this, please contact your lecturer. For an example of how to fill these sections out, please click here.

AI Acknowledgment

This section acknowledges the AI tools that were utilized in the process of completing this assignment.

Tool Name	Brief Description	Link to tool
ChatGPT	To know information on setting up simulator	https://chatgpt.com/c/d4e49bb8-62cb-4dfa-a05e-9463c6cac1ae
ChatGPT	CARLA, DQN and PPO algorithms	https://chatgpt.com/c/d4e49bb8-62cb-4dfa-a05e-9463c6cac1ae

Description of AI Usage

This section provides a more detailed description of how the AI tools were used in the assignment. It includes information about the prompts given to the AI tool, the responses received, and how these responses were utilized or modified in the assignment. **One table should be used for each tool used**.

ChatGPT	
As I have never used CARLA simulator and my project on autonomous vehicles requires it, I have used chatgpt to understand the system requirements, installation and how CARLA is linked with algorithms like DQN and PPO.	
1) **CARLA and how to set up CARLA environment at local laptop along with system requirements**	Setting up Carla on a local laptop involves several steps, including ensuring your system meets the requirements, installing the necessary dependencies, and configuring the environment.
2) **CARLA, DQN and PPO algorithm**	Integrating CARLA with reinforcement learning algorithms like Deep Q-Network (DQN) and Proximal Policy Optimization (PPO) involves setting up the environment in CARLA, implementing the algorithms, and then training the agents using these algorithms.

Evidence of AI Usage

This section includes evidence of significant prompts and responses used or generated through the AI tool. It should provide a clear understanding of the extent to which the AI tool was used in the assignment. Evidence may be attached via screenshots or text.

carla and how to set up carla environment at local laptop along with system requirements

Carla (Car Learning to Act) is an open-source autonomous driving simulator designed for research and development in autonomous driving. Setting up Carla on a local laptop involves several steps, including ensuring your system meets the requirements, installing the necessary dependencies, and configuring the environment. Here's a guide to get you started:

System Requirements

To run Carla smoothly, your system should meet the following requirements:

1. **Operating System**: Ubuntu 18.04 or 20.04 (Recommended). Carla also supports Windows but is primarily developed and tested on Ubuntu.
2. **Processor**: Multi-core CPU, preferably Intel i5 or higher.
3. **Memory**: At least 16 GB of RAM.
4. **Graphics**: NVIDIA GPU with at least 4 GB VRAM and CUDA support (NVIDIA GTX 1060 or higher recommended).
5. **Disk Space**: At least 50 GB of free disk space.

Step-by-Step Setup

Additional Evidence:

carla and dqn and ppo algorithm

Integrating CARLA with reinforcement learning algorithms like Deep Q-Network (DQN) and Proximal Policy Optimization (PPO) involves setting up the environment in CARLA, implementing the algorithms, and then training the agents using these algorithms. Below, I'll guide you through the basics of setting this up.

1. Setting Up the CARLA Environment

Ensure that you have CARLA running and the Python API installed as described in the previous steps.

2. Setting Up the Python Environment

Ensure you have the necessary libraries installed. You'll need `torch` (PyTorch) for the DQN and PPO implementations, as well as `gym`, `numpy`, and `stable-baselines3` for easy integration and handling of the reinforcement learning algorithms.

bash Copy code

Enhancing Urban Navigation for Autonomous Vehicles Using AI and Machine Learning: A Deep Reinforcement Learning Approach

Rahul GOSWAMI
x23167572
MSCAIJAN24I
National College of Ireland

Abstract

In this research paper I will how autonomous vehicles can navigate urban environment by using AI and machine learning, specifically focussing on Deep Reinforcement Learning (DRL). Navigating in an urban environment has its own problems related to dynamic traffic, pedestrians and some or the other obstacles. In this paper I aim to use DRL algorithms to improve the decision making capabilities of autonomous vehicles in such a dynamic and complex condition. For training and testing of the model I would be using CARLA simulator, which can provide realistic urban environment. To assess the performance, evaluation metrics such as speed, success rate, and collision rate are used. These metrics are widely used by any automotive industry. By doing so, the outcome of this paper shows how significantly DRL can improve the efficiency and safety of the autonomous vehicles and can contribute to the challenges faced in real-world urban environments.

Keywords: Autonomous Vehicles, Deep Reinforcement Learning, AI and Machine Learning, CARLA Simulation Environment.

1. Introduction [1] [2] [3] [4]

Autonomous vehicles were introduced in the transport industry to revolutionize the transportation sector and to improve convenience, efficiency, and safety. But, the major challenge with AVs is navigating through the urban environment due to its complex and dynamic traffic, pedestrians, and various unknown and unpredicted objects. Using the power of Artificial Intelligence and Machine Learning, specifically through Deep Reinforcement Learning (DRL), this research paper tries to address this situation.

Avs require complex decision making so that they can navigate through the urban areas which are densely populated and has unpredicted road condition, this ensure that the AV's can provide not only safe but efficient transport. Supervised learning and traditional rule based systems have shown some limitations. These models often face difficulties in real time decision making and do not handle unexpected situations very well. Hence in this research I aim to overcome these limitations by using DRL which can handle high dimensional data using deep learning along with reinforcement learning in decision making based on interaction with environment.

Using DRL algorithms, this research study focuses on the primary problem with AVs which is enhancing their decision making capabilities especially in urban areas including the reliability, safety and efficiency of the AV navigation systems in these areas where we have traffic lights, pedestrians and other vehicles.

The importance of this research on AV navigation in urban areas is its potential benefits. We can reduce traffic accidents if we can improve navigation system in autonomous vehicles and thereby improving urban mobility and traffic flow. With such advancements we can contribute to the development of efficient, safer and sustainable cities. Recent studies [19] shows that there is a lot of interest for autonomous vehicles using deep reinforcement learning and the results are very promising in a simulation environment.

"How can self-driving cars enhance their decision-making skills for successful and safe navigation in city environments through Deep Reinforcement Learning (DRL)?" is our first research question from CA1. This paper will further dig deeper into the DRL algorithms, the CARLA simulation environment, and the evaluation metrics for measuring performance. The proposed solution in this study will utilize the DRL algorithms such as Deep Q-Networks (DQN) and Proximal Policy Optimization (PPO) to train AVs in a simulated urban environment. Evaluating these models on basis of collision rate, success rate, and average speed will help to find the effectiveness of the model in urban scenarios.

This research has multiple contributions. Firstly, by using AI technology like DRL in self driving car navigation it offers a method for training and testing in urban environment. Secondly, by utilizing state-of-the-art CARLA simulation environment, our research provides a strong testing ground that is similar to the real world urban environment. Therefore, by utilizing CARLA we are bridging the gap between the simulated and the real world. The results are expected to add to the knowledge that we have currently for AI and AVs and to lead to a safer and better autonomous vehicle systems. The advantages also include improved safety for both AV passengers and pedestrians, an enhanced urban mobility and a step towards using the AV technology in our everyday life.

The document will be structured into several key points:

1) *Introduction:* It mentions the background, research problem, importance, research questions, contributions, and structure of the document.
2) *Literature Review:* This section will summarize the existing research on DRL applications in AVs along with highlighting the gaps and opportunities.
3) *Methodology:* We will describe the DRL algorithms used, the simulation environment setup and the training process.
4) *Setup and Results:* It will provide the experimental setup, evaluation metrics, and results obtained from testing the DRL models.
5) *Implications:* Here, I will analyze the results, discusses its implications, and compare them with existing studies.
6) *Conclusion and Future Work:* This section will summarize the findings, outline the contributions, and suggest directions for future research.

2. Literature Review

In the literature review of this paper, we will deep dive into the advancement of autonomous vehicles navigation system using deep reinforcement learning. Here we will be giving emphasis on the latest contribution from reputed journals and conferences. In this section I will identify gaps and potential improvements in this field by examining references, their findings and methodologies. Here our final goal is to create a foundation on the current research question “How can self-driving cars enhance their decision-making skills for successful and safe navigation in city environments through Deep Reinforcement Learning (DRL)?”

2.1 Deep Reinforcement Learning in Autonomous Vehicles

Grigorescu et al. (2020) In this paper “A Survey of Deep Learning Techniques for Autonomous Driving,” on Intelligent Transportation Systems (JCR Impact Factor: 7.4), the authors provide an in and out review of deep learning applications in autonomous driving.The authors mentions a combination of convolutional neural networks (CNNs) and DRL for the AV driving. The discusses various architectures and their performance in a controlled environment. [5]

Sallab et al. (2017) In their paper “Deep Reinforcement Learning framework for Autonomous Driving,” published in the Journal of Advanced Transportation (JCR Impact Factor: 2.6), they propose a hierarchical DRL method that involves high-level policy learning with low-level control. Their study shows how effective hierarchical DRL is in managing complex driving tasks by breaking them into simpler sub tasks. [6]

Contrast and Relevance:
Sallab et al. concentrate on the use of a hierarchical deep reinforcement learning (DRL) model in their AV navigation work. Grigorescu et al discuses a wider concept of deep learning techniques in autonomous driving, Although, both the studies highlight the importance of DRL in AV’s navigation, they also discuss the need for more advanced models to handle the complexities of the urban environment.

Conclusion and Transition:
Both the authors made an important contribution in the field of AV by using deep learning and DRL. However, in urban areas we require more advanced and sophisticated simulation environment to handle its complex nature. In the next subsection I will explore how recent advancements have addressed these challenges by integrating more complex sensory inputs and environments.

2.2 Integration of Complex Sensory Inputs

In the 2020 paper "Learning by Cheating," Chen and the fellow authors presents a method that uses simulation and real-world data to improve the performance of AVs. The authors first uses the strengths of each training method. Once the model has undergone simulation-based training, they tune it with real-world data. [7]

CARLA simulator was developed by Dosovitskiy et al. (2017). This simulator is an open-source platform to research AV. The work provide a testing ground for AVs which allow the researchers to create complex urban environment using pedestrians, traffic lights and other dynamic situations. [8]

Contrast and Relevance:
Author Chen et al method provides a solution to the limitations of simulated training environments by combining simulation and real-world data. The CARLA simulator by Dosovitskiy et al provides necessary grounds for initial training and testing. This research uses both - CARLA for DRL training and also calibrating with real world data.

Conclusion and Transition:
Using simulation environment like CARLA and incorporating sensory inputs, the studies have made huge advancements in improving AV navigation. In the next subsection I will look into the DRL algorithms that's been proposed to improve the decision making of AVs.

2.3 DRL Algorithms for Urban Navigation

In the paper entitled "Learning to Drive in a Day" which was published during the IEEE International Conference on Robotics and Automation in 2018, by Kendall and his team. They are going to let us export their method and enable an AV to learn how to navigate through a particular geography in one day rather than spending several weeks or months 'preconditioning' it to recognize the place. Also described as a 'bottom-up' teaching technique, the method employs deep reinforcement learning to teach AVs in an elaborate task-specific manner and applies the DDPG algorithm for enhanced learning. [9]

Zhu et al. (2017) The authors uses DRL to navigate indoor environments using visual inputs, as researched in their paper "Target-driven Visual Navigation in Indoor Scenes Using Deep Reinforcement Learning," Although their research was made in indoor environment, but it provided valuable insights of using visuals for decision making. [10]

Contrast and Relevance:
An aspect in Kendall et al's approach is the AVs need to learn and adapt to the environment quickly which is very important for real world environment. Zhu et al's work on visual navigation highlights the importance of visual inputs in dynamic navigation tasks.

Conclusion and Transition:
The above discussed DRL algorithms have shown promising results in various navigation tasks. How- ever, their application to the AV navigation system is still under explored. In the next subsection I will look at the evaluation metrics that were utilized to access the performance of these algorithms.

2.4 Evaluation Metrics and Performance Assessment

The year 2016's article "Safe, Multi-Agent, Reinforcement Learning for Autonomous Driving" by the authors Shalev-Shwartz et al. shows the importance of safety metrics such as collision rate and time-to- collision in evaluating AV systems.In their work they have given importance on multi-agent scenario which means multiple AVs interacting with each other as well as with other elements such as other cars, pedestrians, and various obstacles, along with safe learning. [11]

The paper "Deep Reinforcement Learning for Autonomous Driving: A Survey," published in the IEEE Transactions on Intelligent Transportation Systems, by Kiran et al in the year 2020 provided a review of DRL algorithms which was implemented to autonomous vehicles. The survey records important metrics such as success rate, path efficiency and average speed. These metrics provides us with ground for performance assessment. [12]

Contrast and Relevance:
While the authors Shalev-Shwartz et al highlights safety metrics with urban navigation challenges like pedestrian and other vehicles, the survey by Kiran et al provides a view on evaluating DRL-based AV systems ensuring performance assessment.

Conclusion and Transition:
The evaluation metrics provides a robust framework to assess the performance of DRL-based AV systems. In the final subsection I will discuss the research niche identified and the expected contributions of the research.

2.5 Research Niche

The above literature review has shown a great advancement by using DRL for AV navigation, however there is still a gap in its practical application in the urban environment. Our aim in this paper is to fill the niche by integrating advanced DRL algorithms with high fidelity simulations like CARLA to enhance urban AV navigation system by:

1. *Improved Decision-Making*: By developing DRL models that can enhance AV decision making in urban environments.

2. *Robust Evaluation Framework:* By establishing a evaluation framework using CARLA and relevant metrics to assess AV performance.

3. *Knowledge Contribution:* By providing knowledge in the applicability of DRL in urban navigation and to contribute in the field of AI and AVs.

3. Research Methods and Specifications

I will go over the suggested approach to improve AV navigation in an urban setting using deep reinforcement learning (DRL) in this section of the study. I'll outline the procedures and exercises we'll employ to finish the research assignment here. Additionally, I'll go over the test data and tools that need to be employed, how to analyze them, and the ethical issues that come with them.

3.1 Proposed Solution:

The solution I propose in developing the decision making capabilities of the AVs in urban environment is to use DRL and specifically Deep Q-Networks and Proximal Policy Optimization. Also, to train and test the model I will also utilize CARLA simulator environment to create a realistic urban environment. [3] [13] [14]

3.2 Steps and Activities Planned:

The research will involve several steps and activities planned for the Capstone project semester which will focus on development, training, testing, and evaluation.

1. *Literature Review:*
   I'll undertake a thorough literature analysis in this section of the study to pinpoint DRL approaches and how they are used in autonomous driving. Together with creating the study framework I will also develop the research questions and hypotheses.

2. *Setting up a Simulation Environment:*
   In this step, I will setup and configure CARLA simulator to create realistic urban scenarios. We'll also integrate various sensory inputs (cameras, LiDAR) into the simulation.

3. *Model Development:*
   In our model development step, we'll implement DQN and PPO algorithms.
   The second step in model development will be to develop the hierarchical DRL framework combining high-level policy learning with low-level control.

4. *Training and Testing:*
   In this step I will train the model using the CARLA simulation environment which we have configured in the above step.
   Later we'll conduct testing in simulated urban scenarios to evaluate the model's performance.

5. *Evaluation and Analysis:*
   Metrics like collision rate, success rate, average speed, path efficiency, and time to destination to be used to access the model.
   The next step in this will be to analyze the results to identify strengths, weaknesses, and areas for improvement.

6. *Documentation and Reporting:*
   Here, I'll document the research process, findings, and the implications. Lastly, a final report and for the research will be prepared.

4. Research Resources - Tools and Test Data for Research and Validation

In this section I'll provide an overview of the tools and test data I'll be using which are useful for enhancing urban navigation for autonomous vehicles using Deep Reinforcement Learning (DRL).

4.1 Tools

1. CARLA Simulator: [3]
   - Car Learning to Act or CARLA is an open source simulator which is designed for autonomous vehicle research. It can mimic real world conditions of an urban environment like pedestrians, other vehicles and even weather.
   - CARLA simulator will be used to generate realistic driving environment and collect sensor data like camera, LiDAR and GPS.

2. Deep Reinforcement Learning Libraries:
   - I will be using TensorFlow and PyTorch which are deep learning libraries.
   - I will use these libraries for development and training DRL algorithms such as Deep Q-Networks (DQN) and Proximal Policy Optimization (PPO).

4.2 Test Data: [3]

a) Data from CARLA Simulator:
   - CARLA simulator will generate artificial data which will mimic real world driving conditions. The data will have data from cameras, LiDAR, and GPS. Along with this data we will also get important information like vehicle speed, its position, and events of collisions.
   - Data Collection: In order to collect the data, we must first set up an urban driving condition in CARLA that includes variables for road kinds, traffic density, pedestrian behavior, and weather. Next, during simulation runs, we will generate data from LiDAR, record GPS coordinates at regular intervals, and take pictures from various camera angles using the CARLA Python API to gather sensor data.

b) Publicly available Datasets: [15] [16] [17]
  - To validate the DRL models, we will use real world sensor data from publicly available datasets like KITTI, NuScenes and Waymo.
  - Once we have the datasets we'll preprocess and standardize it for formats, resolutions, and coordinate systems to ensure consistency.

5. Evaluation Plan

To evaluate the effectiveness of the model, we will use the below steps:

1. *Model Training*
   - We will train the DQN and PPO models using the combined data from CARLA and data from public datasets.
   - This will ensure that our models can learn effective decision-making and urban navigation scenarios.
2. *Performance Metrics*
   - Collision Rate: Frequency of collisions over a period of time.
   - Success Rate: Percentage of events in which the AV had a successful run without collisions.
   - Average Speed: Average speed of the vehicle during navigation.
   - Path Efficiency: How straight the vehicle's route is as compared to the best possible path.
   - Time to Destination: Time taken by the AV to reach destination.
   - Evaluation Plan: Write functions that can calculate how often collisions happen in the simulation using the CARLA Python API. Then test these functions to make sure they correctly show how the vehicle is performing.
3. *Robustness Testing:*
   - We will be testing models in unpredictable scenarios in the CARLA simulator to ensure their robustness and reliability. Doing this we can verify if the models fits well to different urban environments and can also handle unexpected scenarios effectively.

4. *Real-world Validation:*

   Here we will then validate the simulation results with real world data from public datasets like KITTI, NuScenes and Waymo. This is to ensure that the models which were trained in the simulation environment can perform well in real world scenarios.

6. Ethical Considerations of the Research [18]

Below are the ethical consideration of this research:

1. *Safety:*
   - The priority of these models is safety so that it does not show any risk to pedestrians, other vehicles and any property..
   - Mitigation Plan: Before beginning any experiments in the actual world, we must carry out extensive testing in simulated settings. In addition, we must put in place emergency protocols, fail-safe features like auto shutdown, alerts, and warnings, and emergency protocols that guarantee that, in the case of a malfunction or failure, the system either stays safe or returns to a safe condition.

2. *Privacy:*
    - Ensuring compliance with data protection requirements by safeguarding any real-world data utilized in the research.
    - Mitigation Plan: By securely storing and anonymizing any sensitive data used.

3. *Bias:*
    - By making sure there is no bias in the models toward particular circumstances or environments.
    - Mitigation Plan: Use various datasets for training and testing and by regularly evaluating the models for potential biasness.

4. *Documentation:*
    - Documenting all research activities and by sharing data and code when possible this will allow transparency in the research process and methodologies.

7. Conclusion and Future Work

By utilizing Deep Reinforcement Learning (DRL) techniques like Proximal Policy Optimization (PPO) and Deep Q-Networks (DQN), this research aims to improve autonomous vehicle navigation in metropolitan areas. Using the CARLA simulator, which enables us to generate real-world situations for model training and testing, we want to address the intricacies and issues associated with driving in urban environments.

The robustness of the DRL models is improved by combining publically accessible data from Waymo, NuScenes, and KITTI with data from CARLA. The goal of the research is to increase the safety, effectiveness, and dependability of autonomous urban navigation through a methodical review of performance indicators such as collision rate, success rate, average speed, path efficiency, and time to destination. Also, by prioritizing safety, ensuring privacy, minimizing bias, and maintaining transparency throughout the research also maintains ethical values throughout the study.

Below is the future work for this research: [1] [3] [15] [16] [17]

- *Multi-Agent Coordination:* To enhance traffic flow and lessen congestion, research how various autonomous vehicles can cooperate in complex metropolitan settings.
- *Dynamic Environment Adaptation:* Create models that can adjust dynamically to shifting urban environments, including shifting weather patterns, construction on roads, and unforeseen obstructions.
- *Integration with Smart City Infrastructure:* Integrating autonomous cars with smart city infrastructure, such traffic lights and sensor networks, may provide several advantages that might enhance urban mobility as a whole.
- *Ethical and Social Implications:* Make sure that technology improvements are in line with society values and public acceptability by looking more closely at the ethical and social consequences of deploying autonomous cars in urban environments.
- *Real-World Testing:* Extensive real-world testing should be done to verify simulation results and pinpoint areas that require development for DRL-based autonomous navigation systems.
- *Human-AI Interaction:* Research ways to enhance the interaction between autonomous vehicles and human drivers or pedestrians, ensuring a harmonious and safe coexistence.
- *Scalability and Deployment:* Create plans for extending DRL-based autonomous navigation systems to a variety of urban settings in various cities and areas.

8. Project Plan:

The project is proposed to start at the beginning of September 2024 and end by the end of December 2024. A week wise description is provided in the below Gantt chart.

Task	Duration	Start Date	End Date	Dependencies
Literature Review	4 Weeks	01-09-2024	29-09-2024	
Setting up Simulation Environment	3 Weeks	30-09-2024	20/10/2024	Literature Review
Model Development	6 Weeks	21/10/2024	30/11/2024	Setting up a Simulation Environment
Training & Testing	2 Weeks	01/12/2024	15/12/2024	Model Development
Evaluation and Analysis	1 Week	16/12/2024	22-12-2024	Model Development
Documentation and Reporting	1 Week	23-12-2024	31-12-2024	Evaluation and Analysis

Figure 1. Gantt Chart for Project Plan

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