FORMATTING INSTRUCTIONS FOR APS360 PROJECT BASED ON ICLR CONFERENCE FORMAT

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ABSTRACT

This template should be used for all your project related reports in APS360 course. – Write an abstract for your project here. Please review the **First Course Tutorial** for a quick start —-Total Pages: 6

1 PROJECT DOCUMENT SUBMISSION FOR APS360 COURSE

The format for the submissions is a variant of the ICLR 2022 format. Please read carefully the instructions below, and follow them faithfully. There is a **9 page** limit for the main text. References do not have any limitation. This is also ICLR's standard length for a paper submission. If your main text goes to page 10, a -20% penalty would be applied. If your main text goes to page 11, you will not receive any grade for your submission.

1.1 STYLE

Papers to be submitted to APS360 must be prepared according to the instructions presented here.

Authors are required to use the APS360 LaTeX style files obtainable at the APS360 website on Quercus. Tweaking the style is not permitted.

1.2 RETRIEVAL OF STYLE FILES

The file `APS360_Project.pdf` contains these instructions and illustrates the various formatting requirements your APS360 paper must satisfy. Submissions must be made using LaTeX and the style files `iclr2022_conference.sty` and `iclr2022_conference.bst` (to be used with LaTeX2e). The file `APS360_Project.tex` may be used as a "shell" for writing your paper. All you have to do is replace the author, title, abstract, and text of the paper with your own.

The formatting instructions contained in these style files are summarized in sections 2, 4, and **??** below.

2 GENERAL FORMATTING INSTRUCTIONS

The text must be confined within a rectangle 5.5 inches (33 picas) wide and 9 inches (54 picas) long. The left margin is 1.5 inch (9 picas). Use 10 point type with a vertical spacing of 11 points. Times New Roman is the preferred typeface throughout. Paragraphs are separated by 1/2 line space, with no indentation.

Paper title is 17 point, in small caps and left-aligned. All pages should start at 1 inch (6 picas) from the top of the page.

Authors' names are set in boldface, and each name is placed above its corresponding address. The lead author's name is to be listed first, and the co-authors' names are set to follow. Authors sharing the same address can be on the same line.

Please pay special attention to the instructions in section **??** regarding figures, tables, acknowledgments, and references.

There will be a strict upper limit of 9 pages for the main text of the initial submission, with unlimited additional pages for citations.

3 Background and Related Works

3.1 Autonomous RC Car Related Projects

Through the use of deep learning, many autonomous car projects have been developed and tested, showing the potential of this technology in real-world applications. The following is an overview of five works related to autonomous vehicles using deep learning.

3.1.1 Deep CNN End-to-End Learning for Autonomous RC Cars (Bhutta, 2023)

In this study, end-to-end learning using deep convolutional neural networks (CNNs) was used to autonomously control an RC car around a race track. A front-facing camera is used to collect images of the car's view, which is fed to the model. The CNN extracts features through convolutional and poling layers, then applies the nonlinear ReLU activation function, which is then passed through 3 fully connected layers to generate the output of necessary steering angles and speed the car needs to travel (Bhutta, 2023).

3.1.2 Autonomous RC Car Using Neural Networks (Mallik, 2023)

This project explores autonomous driving through a small RC car using a Raspberry Pi and a CNN based end-to-end steering angle prediction system. To train the model, the car was manually driven around a track and the Raspberry Pi was used to track the analog steering inputs along with recording video frames taken at 10-20 fps. The project highlights limited computing resources from the Pi's onboard chips which may constrain CNN complexity along with data diversity being an issue where overfitting to a single environment leads to issues in other environments. Additionally, the project highlights the feasibility of deep learning for autonomous navigation and that it can be scaled up to larger robotic systems.

3.1.3 Development of Single-board Computer-based Self-Driving Car Model (Hamzah et al., 2022)

In this paper, an RC car based on the DonkeyCar project, powered by a Nvidia Jetson Nano and controlled by a CNN was used to drive autonomously around a track. The CNN uses live photos of the car's front view to predict the steering angle and speed required. The authors created varied training set sizes of 3000, 6000, 12000 and 24000 along with variations of network depth of between two and five layers of convolutional layers to find the best model (Hamzah et al., 2022). Their results showed that the model with 24000 images with three convolution layers performed the best with an absolute error at 0.18257 (Hamzah et al., 2022). Additionally, the results showed that having more data consistently reduced error, while adding layers above three had diminishing returns.

3.1.4 CNN based End to End Learning Steering Angle Prediction for Autonomous Electric Vehicles (Mygapula et al., 2021)

This paper explores CNN based end-to-end learning for steering angle prediction in autonomous vehicles using images captured of the front view of the car which is passed through to the model in a Jetson TX1. The team trained 3 different models based on different CNN architectures with different numbers of layers and the results showed that the CNN model with 4 CNN layers and 4 connected layers performed the best with 0.0354 test loss (Mygapula et al., 2021). These results highlight the viability of CNNs in learning steering behaviours compared to typical approaches in which systems are broken into multiple stages (such as road and object detection, and path planning)as it has fewer potential failure points.

3.1.5 End to End Learning for Self-Driving Cars (Bojarski et al., 2016)

In this paper, the team trained a CNN to map raw pixels from a front-facing camera directly to steering commands for a car. The network made up of nine layers, with one normalization layer, five convolutional layers and three fully connected layers was trained to minimize the mean squared error between steering commands and the human driver's inputs. Using only 72 hours of driving data, the team was able to successfully train the car to operate in diverse conditions showing how a CNN can perform the entire task without manual decomposition into smaller systems.

4 Data Processing

The Data Processing pipeline for the self-driving car project has three critical phases: Data Collection, Data Cleaning and Preprocessing, and Dataset Splitting. These phases are needed to ensure a proper and high quality training, validation, and testing of our model.

4.1 Data Collection

4.1.1 Public Datasets

- Udacity Self-Driving Car Dataset
- Berkeley DeepDrive (BDD100K)

4.1.2 Custom Data Collection

- Simulated Data: Using CARLA Simulator to generate high-resolution images with corresponding control commands.
- Real-World Data: Dash-mounted Camera on RC Cars.

4.2 Data Cleaning and Preprocessing

This phase involves preparing the image data and labels to reduce maximize model accuracy. This includes image normalization, label consistency checks.

4.2.1 Remove Corrupted or Blurry Frames

Removal of incomplete metadata, heavy blur, overexposure, and distorted images using automated filters. These filters include: Laplacian Variance for blur detection, Histogram Analysis for overexposure, and Pixel Clipping Detection.

4.2.2 Image Resizing and Normalization

All images are resized to uniform size of 320x240 pixels to match input expectation for deep CNNs. Additionally, pixel values are normalizedto seed up convergence during training.

4.2.3 Label Alignment and Verification

Control labels are synchronized with their corresponding images using timestamps. Outliers and inconsistent data are flagged and removed.

4.3 Dataset Splitting

The dataset is split into:

- 80% Training
- 10% Validation

- 10% Testing

Since we are using data that comes from continuous streams, randomly shuffling data could have it so very similar frames of the stream can land in training, validation, and testing leading to memorization of the data. Thus, we will split the data chronologically, first 80% goes to training, the next 10% goes to validation, and the last 10% goes to testing.

5 Architecture

6 Baseline Model

A hand-coded rule-based controller serves as a reasonable baseline for evaluating the performance of the autonomous RC car. This baseline model simulates traditional line-following logic, where decisions are made using simple heuristics based off of pixel color thresholds and pre-defined turning logic (Likmeta et al., 2020). The rule-based controller follows a deterministic flow, first, the incoming video frame is converted to grayscale or HSV color space, and then a threshold is applied to detect the track line (usually a black line on a white surface or vice versa) (Likmeta et al., 2020). The centroid of the detected line is computed, and based on its position relative to the image center, turning decisions are made. For example, steering left if the line is on the left half of the image, right if on the right half, and forward if centered (Bojarski et al., 2016). This model does not involve learning or generalization; it is purely reactive and works well in constrained, consistent environments with high-contrast tracks. While simplistic, this approach is widely used as a baseline in autonomous driving projects due to its reproducibility and interpretability.

7 Ethical Considerations

7.1 Model Usage

Since this project involves physical hardware operating in real-time, safety is a primary concern. The model may make poor decisions in edge cases (obstacles, unfamiliar lighting conditions), which could lead to hardware damage or unintended collisions (”davidad” Dalrymple et al., 2024). If used as part of a demonstration involving human interaction, ensuring safety measures (kill switches, limited speed) is essential. Another ethical concern is over-reliance on the model’s predictions. If used in future deployments (real vehicles or educational kits), assuming the trained model can handle all situations without proper validation may mislead users and cause harm or accidents (Laskey et al., 2017).

7.2 Data Collection

The data used for imitation learning is sourced from human demonstrations. A bias may arise if only a single driving style or track layout is captured. For instance, if the human driver consistently takes tight turns or drives aggressively, the model may learn to imitate that behavior, limiting generalization to new tracks or drivers. Additionally, reinforcement learning episodes are generated in a simulated or controlled environment (Laskey et al., 2017). This might restrict the model’s robustness in diverse real-world settings. Ethical considerations also include ensuring no unnecessary wear is inflicted on hardware during data collection or that any modifications to the car setup are clearly documented and standardized.

8 Project Plan

To ensure the seamless progression of the project and collaboration among team members, we have devised guidelines and a timeline as seen below.

8.1 TEAM GUIDELINES

Meeting Guidelines	**Details**
In-person meeting	Location and time decided by the team
Online meetings	Tuesdays (3-5 pm) and Saturdays (1-3 pm)
Absence Notification	Must notify team 24 hours before meeting if absence will occur

Table 1: Meeting Specifications

Communication Guidelines

- Group chat is active on weekdays and weekends (24/7)
- Group chat is active on weekdays and weekends (24/7)
- Members are required to frequently check discord messages (less than 2 hour response time)

Collaboration Guidelines

- The team will be working together in a Github repository
- Each member is required to give a daily update message on their progress
- If conflicts arise, the team must discuss them together and decide on a solution that makes everyone happy
- Ensure code has informational comments that help the team understand it

8.2 PROJECT TIMELINE

9 RISK REGISTER

The risk register contains some scenarios that could negatively impact our project. These potential risks negatively affect deadlines, quality of work, and more. Our team has discussed these scenarios and came up with solutions for each project risk.

Project Risk	**Likelihood**	**Solution**
A teammate drops the course	Unlikely	The team has to approach splitting up tasks differently as teammates will now have more responsibilities. We have to start tasks earlier and move internal deadlines to an earlier date because each member has more tasks to complete
Model training takes longer than expected	Likely	It's common to procrastinate on less important or easier tasks, so this would be the time to complete them. The team should start working on tasks earlier, so if this does occur it doesn't affect project deadlines
Experience hardware problems during testing	Likely	The team should keep extra hardware components in case they fail during testing stages. Also, try not to overuse the physical components, and use simulation software to test
Model works in simulation but not on physical RC car	Likely	We shouldn't fully rely on simulations, and should test the model on the physical RC car frequently. The earlier the team faces these issues, the longer we have to fix them. Compare the results from simulation and physical RC car and that might help solve problems
A teammate misses an internal deadline	Likely	The team should hold everyone accountable as each member is responsible for their assigned tasks. The teammate should finish tasks as soon as possible after the missed deadline because this will hold back the team

Table 2: Project Risks

10 Final instructions

Do not change any aspects of the formatting parameters in the style files. In particular, do not modify the width or length of the rectangle the text should fit into, and do not change font sizes (except perhaps in the References section; see below). Please note that pages should be numbered.

Author Contributions

If you'd like to, you may include a section for author contributions as is done in many journals. This is optional and at the discretion of the authors.

Acknowledgments

Use unnumbered third level headings for the acknowledgments. All acknowledgments, including those to funding agencies, go at the end of the paper.

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