Grading Rubric/Requirements

**1. Introduction:**

Autonomous vehicles have made significant advancements in recent years, yet their performance remains limited to ideal conditions—clear, dry roads with good visibility. In reality, environments like Portland often experience rain, fog, and occasional snow, all of which can degrade the reliability and safety of these systems. Current models struggle when exposed to visual obstructions caused by adverse weather, making robust perception a critical challenge in the development of truly reliable autonomous driving.

This project aims to address this limitation by experimenting with obscured visual data, simulating real-world conditions that autonomous vehicles are likely to encounter. Using the [GTSRB dataset](https://www.kaggle.com/datasets/meowmeowmeowmeowmeow/gtsrb-german-traffic-sign), we will apply various obscuration techniques to traffic sign images to mimic the visual challenges posed by environmental factors. Our goal is to identify methods and model improvements that can maintain high accuracy despite visual degradation, contributing to safer and more adaptable autonomous vehicle systems.

# **2. Literature Review:**

While these automated driving systems have been rapidly evolving for the past decade, a significant challenge still remains in ensuring safety and reliability during non-ideal weather conditions. The articles we’ve found have assessed the challenges that autonomous vehicles face in adverse weather while also reviewing various solutions. Zhang et al. (2023), Xu and Sankar (2024), and Wang et al. (2024) each describe how adverse weather conditions hinder the vehicle’s ability to detect objects, recognize road features, and navigate safely. They also indicated that while current advancements are capable of solving some of the significant issues, they still haven’t been able to solve all of them.

We can also look into crash reports relating to autonomous vehicles to better understand the current issues related to this topic. In the articles written by Fu et al. (2024) and Chougule et al. (2023), they analyzed crash reports and found that weather conditions had a noticeable effect on autonomous vehicles. Also, many of the listed articles have stated that there’s a lack of training for adverse weather conditions in these autonomous vehicles.

# **3. Methods:**

*Approach A: Transfer Learning on Existing Convolutional Neural Networks*  
 We plan to start by taking a pre-trained CNN model, such as ResNet, and use it to identify our data. We hope to use Transfer Learning, the process of using an existing trained model to solve a new problem, to get us started. We will experiment with a few existing models, with multiple experiments of varying obscuration, by obscuring 5% of the images per obscuration and by 25% per obscuration. This would give us 25% of the images obscured and the other with 50% of the images obscured. This could give insight into how the models handle difficult data.

*Approach B: Construction of a New Convolution Neural Network*

Alternatively, we could try to construct our own simple Convolution Neural Network, if the pre-trained models are not as accurate as we hope. We would use the previously mentioned obscuration experiments, as well as modifying the convolution, pooling, and fully-connected layers to find a sweet spot in analyzing the images.

*Approach C: Analysis of Difficulties*

If we are unable to achieve desired accuracy using either methods with Convolution Neural Networks, we plan to look into the difficulties with this particular data. We will look into what challenges appeared when trying to engineer these systems, and document our possible shortcomings. We can also look into challenges that others in the field have run into when designing their own systems, and what can be done or overcome to fix them.

# **4. Results:**

The results that will determine how well the method has worked is based on the accuracy, precision, recall, and the f1-score of the weather/method of distortion.

| **Weather / Method** | **Accuracy** | **Precision** | **Recall** | **F1-Score** |
| --- | --- | --- | --- | --- |
| **Overcast/Low Light** |  |  |  |  |
| **Fog** |  |  |  |  |
| **Blurring** |  |  |  |  |
| **Occlusion** |  |  |  |  |
| **Weather-like-distortions** |  |  |  |  |

# **5. Conclusion:**

For a prediction on how our project will turn out, it is difficult for us to see until we get started on the project itself. We all expressed difficulties in identifying how things would potentially turn out. Reviewing the problem from others specializing in the field has shown it to still remain a challenge, with advancements still being made. As a group, we’ve decided that one goal for us is to look into these difficulties in the field to try and understand why things are challenging and where the challenges come from. We hope that even if our work doesn’t come out with decent results, that we can still hope to learn and have something to say in the process of getting there.

We expect the transfer learning model will outperform the CNN model trained from scratch. The transfer learning model will likely perform better due to its ability to leverage pre-trained features. As we test both models under increasing levels of obscuration, we anticipate a decrease in performance, with the 50% obscured dataset compared to the 25% obscured one.

# **7. Contributions:**

Each group member will contribute to the project based on their assigned focus areas. Max will handle data obscuration related to overcast/low light conditions as well as weather-like distortions. Filipp will focus on implementing data obscuration caused by fog and will also be responsible for developing Model 1 using transfer learning. Artem will contribute by simulating blurring as a form of data obscuration and by building Model 2 using a convolutional neural network. Saeah will work on data obscuration caused by occlusion, as well as data cleaning and experiment setup. All team members (Max, Filipp, Artem, and Saeah) will collaborate on creating the final report and presentation slides to summarize the project outcomes.

**Works Cited**

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