Enhancing Autonomous Vehicle Perception in Adverse Weather

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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, 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:

Although 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.

Many of the previous articles mentioned a lack of data for adverse weather in training these models, so to improve our results, we tried finding ways for us to acquire more data with adverse weather conditions. While we could collect this data ourselves, this process would be very time consuming because we would have to collect thousands of photos, properly format them, and then label each one. So we've decided to research the benefits of modifying datasets instead. The articles by Xu et al (2023) and Shorten and Khoshgoftaar (2019) did a survey on image augmentation to find benefits for deep learning, and found that these modifications do help improve the performance of the models. The only issue the articles had found was that not all techniques work for all models, which is reasonable because not all models are alike.

A second method we could potentially employ, if we don't decide to modify the original dataset, is to make more images. In the article written by Jo, Na, & Song (2017), they had found that synthesized images were a great alternative, showing that the overall performance of the datasets were very similar. This means we could use synthesized data to help increase the number of images we have if we lack images with adverse weather effects.

Another thing to take into consideration when doing this project is should we integrate some sort of GenAI for images or for creating filters for images. An article by Mo et al (2025), explores how to enhance images using AI to restore the distorted images for in-vehicle vision systems. What they have found is that their program worked well when it came to discerning and enhancing their images that they have made using synthetic images, but when it came to real world images it wasn't as great. What this can mean for us is that we may need to have more real world images compared to images that we have altered ourselves if we actually wish for this project to be used in real world applications.

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.

Dataset Preparation:

We decided to work further with the ideas proposed from Professor Ingle, and we decided to look into the potential ways to expand our image obfuscation. We need some way to modify the data, as simply training a model on regular traffic data doesn't get us to our goals of identifying under difficult conditions. We are looking into multiple ways we could accomplish this, such as using generative artificial intelligence to create obfuscations themed around difficult weather, but that leads into the issue of having far too many images to obscure. We also want to look into python augmentation libraries, but as to which we still have yet to decide.

Modifications:

For changes that we have made to the project, we are currently working on setting up the data to pass into the models themselves, and design. For example, the data we planned to use had little to no weather distortion, so we've decided to introduce weather effects onto the dataset. We also are currently setting up for further testing with either approach A or B, with a possibility of swapping either methods.

4. Results:

Initial Model Performance (Using Original, Unobscured GTSRB Data)

Before applying any obscuration techniques, we successfully trained a ResNet50 model using the original GTSRB dataset. This model, saved as resnet50_model.path, will be used as a base for transfer learning when evaluating the performance on obscured data. The first row of the table below shows the performance metrics of the initial model.

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. An original baseline of our model was added to show our current progress in this project.

Weather / Method	Accuracy	Precision	Recall	F1-Score
Original (Baseline)	99.13%	98.76%	98.76%	98.74%
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.

6. Contributions:

Current Member Contributions:

All members of our group have been working on sections of the project, focusing on sections they feel the most comfortable working on. Saeah prepared and labeled the train and test data, verifying its integrity and caching it for efficient use. She analyzed class label distribution, suggested oversampling to address imbalances, and documented the data structure for the team. Artem has been researching topics related to this project, such as finding methods of introducing weather effects onto the data set. Currently, he’s working on advancing his understanding of convolutional neural networks. Max has worked on setting up a pretrained model for the process of performing transfer learning on the existing Neural Nets. However, further testing needs to be done to ensure that the data will work effectively with existing models. Filipp has been researching topics related to GenAI and has added more to the documentation of this project.

Future Contributions/Plans:

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.

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