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 apply two different methods to obscure traffic sign images in order to mimic the visual challenges posed by environmental factors. The first method uses custom image transformation functions to simulate effects such as rain, snow, and fog. The second method leverages a generative AI technique—CycleGAN—for style transfer, transforming the original images using weather-specific domain datasets (Snow100K, Rain100, and Foggy Cityscapes) to produce realistic weather effects. By comparing the performance of models trained with each type of obscured data, we aim to identify effective strategies for maintaining 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.

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.

For potential GenAI models we could implement, we've decided to work and explore the implementation of CycleGan, a generative adversarial network architecture introduced by Zhu et al. (2017) and researchers at UC Berkeley. CycleGAN was designed to perform image-to-image translation without requiring paired training examples, a significant innovation in the field of generative models. Traditional image translation models often rely on having a dataset with matching input-output image pairs (e.g., a photo and its corresponding stylized version). However, CycleGAN overcomes this constraint by using unpaired datasets, making it a highly flexible and scalable approach for real-world tasks where paired data is unavailable or difficult to collect.

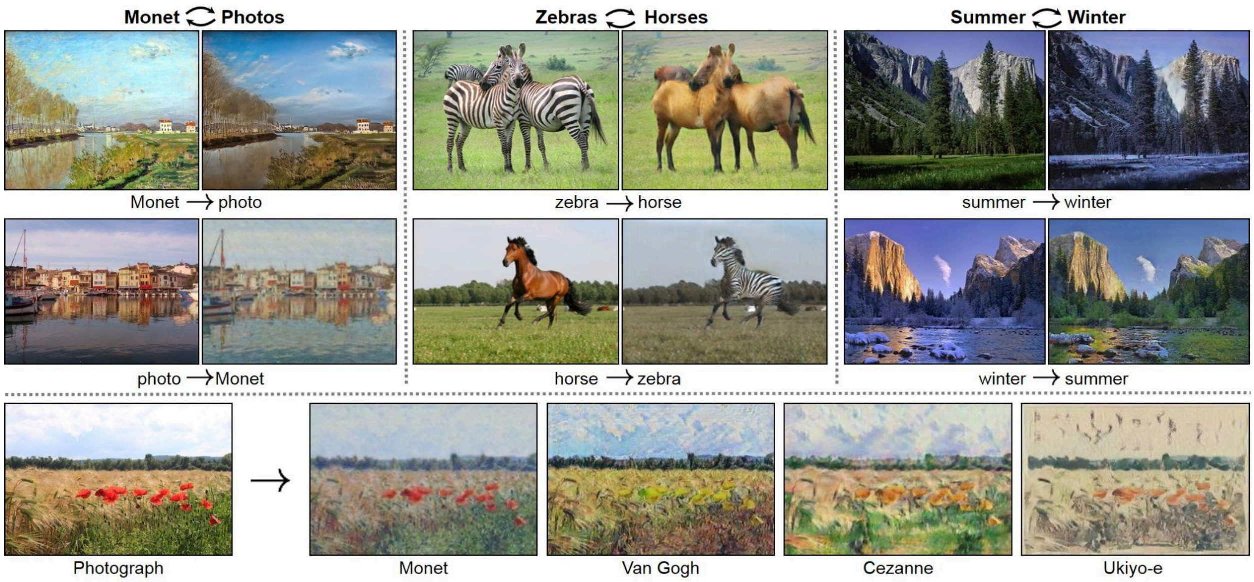
The architecture of CycleGAN consists of two generator networks and two discriminator networks. The generators learn to map images from one domain (e.g., photos) to another (e.g., Monet paintings), and vice versa. The discriminators evaluate how realistic the generated images are in their respective domains. A key innovation in CycleGAN is the cycle-consistency loss, which ensures that if an image is translated to another domain and then translated back, it should closely resemble the original input. This constraint enforces consistency and helps the model preserve structural content during style transfer.

One of the well-known demonstrations of CycleGAN's capabilities includes translating real-world photographs into Monet-style paintings and converting those paintings back into photorealistic images (Zhu et al., 2017). Such examples illustrate the model's ability to capture the stylistic and textural characteristics of one domain and convincingly apply them to another, while retaining the spatial and semantic structure of the original image (see Figure 1, top left).

In the context of our project, we leverage CycleGAN for simulating adverse weather conditions such as snow, rain, and fog. By training the model with our original traffic sign dataset (GTSRB) as the source domain and using weather-specific image datasets (e.g., Snow100K for snow, Rain100 for rain, and Foggy Cityscapes for fog) as the target domain, CycleGAN can learn to generate realistic weather-obscured images. This enables us to simulate real-world driving conditions without needing to manually collect and label thousands of weather-affected images. As such, CycleGAN provides an efficient and scalable solution for data augmentation in environments where traditional image alteration methods may fall short in realism or diversity.

Figure 1

CycleGan Example Image



Zhu, J.-Y., Park, T., & Wang, T. (2017). junyanz/pytorch-CycleGAN-and-pix2pix. GitHub. https://github.com/junyanz/pytorch-CycleGAN-and-pix2pix?tab=readme-ov-file

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:

To experiment a little further, we decided to work with the ideas proposed from Professor Ingle, and to also work on the original idea we planned. Professor Ingle suggested looking into generative AI. For which to use, we decided to use CycleGan, a model that works to apply effects over existing images. Our dataset now includes, our original dataset, three datasets with modified images simulating weather effects, and a dataset with simulated weather distorsions.

Another method we implemented is making custom functions to simulate weather. Originally planned to leverage albumentations, but it didn't work as our image size is too small (32x32). Instead, we obscured images using custom image transformation functions. For Check-in #2, we focused on creating obscured image data for both methods to apply the obscured data later into the pre-trained ResNet50 model.

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 were considering either starting with approach A or B, but since the pre-trained Resnet50 model showed promising results, we decided to stick with approach A, and observe.

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. For the final version, we plan to have two tables for both CycleGan obscuration, and customized distortion methods.

Data Set Template				
Weather / Method	**Accuracy**	**Precision**	**Recall**	**F1-Score**
Original (Baseline)	99.13%	98.76%	98.76%	98.74%
Rain - 25%				
Rain - 50%				
Fog - 25%				
Fog - 50%				

Snow - 25%				
Snow - 50%				

For changes that we have made to the project, currently we are attempting to modify our data with CycleGan (Figure 2), as it seems to provide a way to batch modify our existing image set, based on a passed-in trained weather type. We are still testing the effectiveness of the model, and developed simpler image obscurations using custom functions (Example results available in Figure 3). We intend to test the pre-trained Resnet50 model on our collection of image sets, and record the statistics soon.

Figure 2

Images generated using CycleGan, heavy rainfall

Figure 3

Obscured images generated using custom functions to simulate rain, snow, and fog effects

5. Conclusion:

As we get closer to the actual process of running tests on CNN models with our collected datasets, things seem quite positive. Tests on the unaltered dataset with a pretrained model performed well enough that we want to proceed with the Resnet50 Model. Currently, we are preparing our modified data with both CycleGan and with our own weather like distortions, and we hope that introducing it to the model results in some interesting developments.

Moving forward, we plan to apply transfer learning using the original ResNet50 model to evaluate its performance on these obscured datasets. This will allow us to investigate how robust pre-trained models are under increasingly degraded visual input, comparing performance between datasets with 25% and 50% obscuration levels.

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.

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 was responsible for implementing the first methodology, making custom functions to simulate weathers. She created three dataset for each weather condition. Max, Artem, and Filipp spent their time researching CycleGan's ability to modify the dataset and have been working on some coding for it. Artem specifically focused on generating images with rainfall, Filipp focused on snow, and Max focused on fog. Max and Saeah also did more documentations.

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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