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:

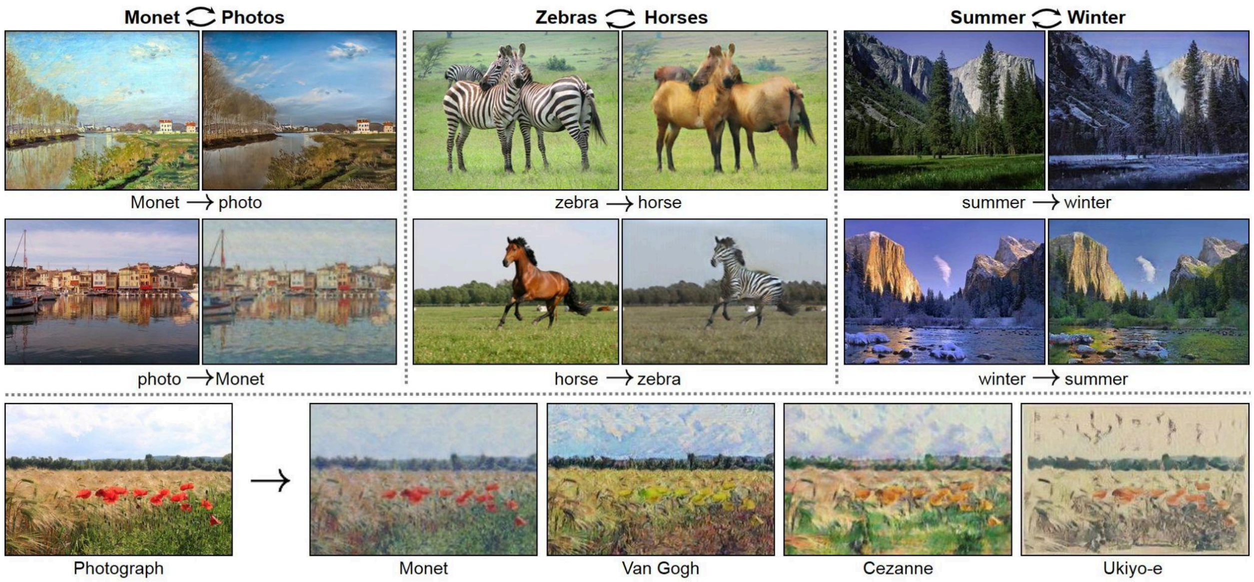
Ensuring safety and reliability in autonomous driving under adverse weather remains a major challenge. Studies by Zhang et al. (2023), Xu and Sankar (2024), and Wang et al. (2024) highlight that poor weather conditions hinder object detection and navigation, and that current solutions are still limited.

To address the lack of weather-affected data, we explored two strategies: dataset modification and data synthesis. Image augmentation techniques, as reviewed by Xu et al. (2023) and Shorten & Khoshgoftaar (2019), can enhance model performance, though not all methods are universally effective. Alternatively, Jo, Na, & Song (2017) showed that synthesized images can be a viable substitute for real data.

In our project, we applied CycleGAN—a generative model introduced by Zhu et al. (2017)—to simulate weather effects (rain, fog, snow) on traffic sign images. CycleGAN's ability to perform unpaired image-to-image translation makes it ideal for generating realistic weather-obscured images without manual data collection, providing an efficient solution for augmenting datasets in challenging visual environments.

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. As of Check-in #3, we've completed the image modification, and have begun testing the model.

Current Work:

Since Check-in #2, we have completed the generation of all obscured image datasets using both CycleGAN and custom weather-like distortions (rain, snow, and fog). With the datasets fully prepared, we proceeded to apply transfer learning using the pre-trained ResNet50 model. We trained and evaluated the model on both 25% and 50% obscured datasets to analyze its robustness under varying degrees of visual interference. Based on earlier results, we confirmed that Approach A (transfer learning) was effective and continued with it as our primary method for experimentation.

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.

CycleGan Modifications				
Weather / Method	**Accuracy**	**Precision**	**Recall**	**F1-Score**
Original (Baseline)	99.13%	98.76%	98.76%	98.74%
Rain - 25%	93.29%	94.22%	93.29%	93.50%
Rain - 50%	88.59%	91.03%	88.59%	89.09%
Fog - 25%	75.21%	77.41%	75.21%	75.75%
Fog - 50%	51.39%	56.47%	51.39%	52.67%
Snow - 25%	92.83%	93.73%	92.93%	92.96%

Snow - 50%	87.76%	89.94%	87.76%	88.01%

Weather-Like Distortions				
Weather / Method	**Accuracy**	**Precision**	**Recall**	**F1-Score**
Original (Baseline)	99.13%	98.76%	98.76%	98.74%
Rain - 25%	83.10%	90.12%	83.10%	85.06%
Rain - 50%	65.95%	83.48%	65.95%	69.97%
Fog - 25%	97.69%	97.69%	97.69%	97.69%
Fog - 50%	96.42%	96.61%	96.42%	96.42%
Snow - 25%	81.86%	91.78%	81.86%	85.02%
Snow - 50%	63.75%	86.85%	63.75%	70.25%

We modified 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 also developed simpler image obscurations using custom functions (Figure 3). For changes that we have made to the project, we are currently testing the effectiveness of the model at classifying the augmented images.

We evaluated the performance of a pretrained ResNet50 model fine-tuned on obscured images using two different methods: CycleGAN and custom weather-like distortions.

- The model maintained high performance on mildly obscured data (25% obscured images), with accuracies above 90% for CycleGAN cases.
- Severe distortions (50% obscured images) led to noticeable drops in accuracy and F1-score, especially with the custom distortions (63.75% accuracy for 50% snow)
- CycleGAN-obscured images generally resulted in better performance compared to the custom weather-like distortion method, particularly for moderate to high distortion levels.
- The model underperformed with CycleGAN fog, and weather-like rain and snow. The three of these sets have distortions that make the edges of shapes more difficult to discern. We think there might be some relationship between the two, but more testing will have to be done.
- Although the model's accuracy in the CycleGAN modification table does take a hit, it shows that we've successfully synthesized data with weather effects.
- There's a noticeable reduction in the performance of the model with the given modified datasets, mostly affecting the accuracy and recall.
- In the CycleGAN modification table, it appears that when rain obscuration is 50%, the model makes fewer false positives, with the price of missing some true positives (based on how precision is greater than the recall)

Figure 2

Images generated using CycleGan, rain, snow, and fog

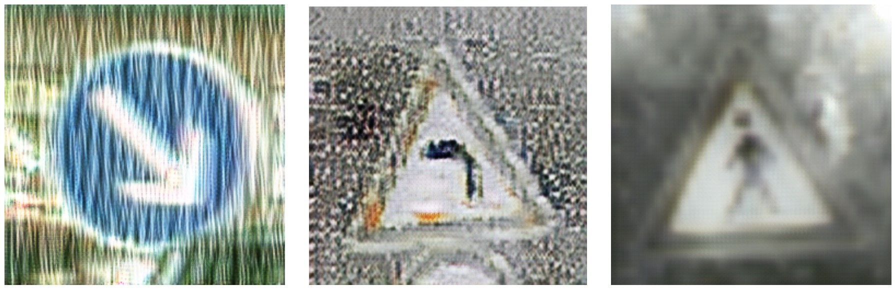


Figure 3

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

5. Conclusion:

As we run tests on our trained CNN models with our collected datasets, things seem quite positive. Our starting tests on the unaltered dataset with a pretrained model performed well enough that we proceeded with the Resnet50 Model. As we test the model, we're trying to identify how the accuracy fluctuates between different amounts of modified images within the dataset. We have two versions of the modified dataset, images modified with CycleGan and our own weather-like distortions, and introducing it to the model results in some interesting developments.

As we come to the conclusion of the testing of our Resnet50 model, we are going to spend some time analyzing how well the model performed and what we can do next. We've spent time working on transfer learning, investigating 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.

Since our last check-in, we completed generating all obscured datasets, including CycleGAN-based images for rain, fog, and snow. We also conducted transfer learning using both the CycleGAN and our custom weather-like distortion datasets. For CycleGAN, transfer learning was performed on rain and snow obscured images, while for the custom method, we ran training and evaluation across all distortion types and levels.

Our findings suggest that while transfer learning enables robust recognition of traffic signs under mild distortions, model performance significantly degrades under heavy visual interference; particularly with custom distortions. This highlights the importance of incorporating a diverse and realistic augmentation pipeline during training. Moving forward, we aim to analyze these results in more detail and explore potential improvements such as domain adaptation techniques or ensemble models to boost generalization under extreme visual conditions.

6. Contributions:

Max set up a pretrained model to enable transfer learning, introduced the idea to expand the project with this approach, and researched potential models. He modified the dataset using CycleGAN to generate foggy images for testing and provided documentation and updates related to CycleGAN and the overall project progress.

Saeah proposed the project idea of traffic sign image classification, prepared the training and test datasets, and identified class imbalance issues. She initiated the use of CycleGAN for style transfer, implemented weather simulation custom functions to create three condition-specific datasets, and evaluated a pretrained ResNet50 model on obscured GTSRB images using custom image processing, ensuring the robustness testing pipeline worked for all datasets.

Artem explored convolutional neural networks and methods for weather data simulation. He generated a rainy image dataset using CycleGAN and conducted experiments to evaluate model accuracy under these altered conditions. In addition to helping expand the dataset, he contributed research findings and played an active role in writing and reviewing project documentation.

Filipp researched applications of generative AI and contributed to enhancing the project's technical documentation. He created the snow-based CycleGAN dataset used for model testing and participated in team discussions on methodology. Filipp also supported the team by contributing background research and helping refine the project write-up.

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