

Restoration of degraded images captured during adverse weather conditions with Generative Adversarial Networks

Deep Learning, Application of Engineering

Advisors:

Dr. Rahul Rai

Shengli Xu

Group 4 presenters:

Prasanna Gupta

Shailendran Poyyamozhi

Hesameddin Khosravi



Autonomous vehicle's development history

- The concept of self-driving cars equipped with a superior level of safety came into practice in the 20th century.
- In 2009, when Google announced to start their research in self-driving, the concept became majorly popular.



- In 2015, Tesla began to commercialize 'Autopilot' features in its cars and soon became one of the top autonomous vehicle companies in the world.
- Several automobile giants have announced their plans to launch fully autonomous cars during the last three years by 2020.



Introduction: Autonomous Vehicle Perception

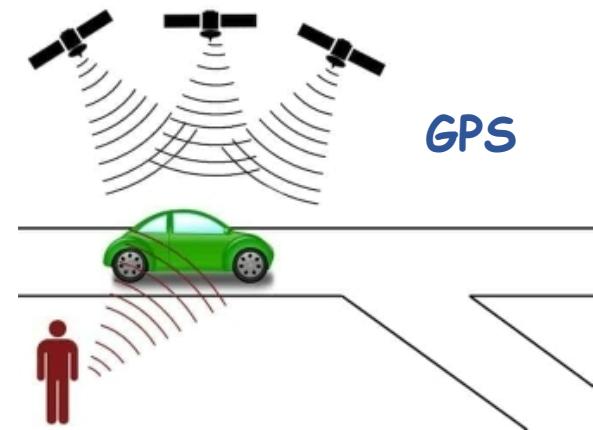
- Perception operation in autonomous Vehicles enables sensing environments around the vehicle.
- Perception is crucial to making decisions, planning, and operating in real-world environments through numerous functionalities and operations from **occupancy maps** to **object detection**.
- Autonomous Vehicles use a variety of sensors, namely RADAR, LiDAR, GPS, and Camera.

Each sensor has its functionality such as

GPS: path planning

RADAR/Lidar: distance tracking/object detection

Camera: lane-keeping/ object detection



Problem: perception accuracy in adverse weather conditions

- Out of these sensors, **LiDAR** and **Camera** play a key role in sensing the environment around the system.
- **LiDAR** generates the point cloud of the surrounding environment providing the depth/distance of the objects from the vehicle.
- All perceptual-related tasks such as traffic sign and signal detection, lanes detection, etc., are handled by the **Camera**.

It is also possible to extract the depth information, like **LiDAR**, with the help of a **stereo Camera** through correspondence.

- During adverse weather conditions such as **rain**, **fog**, and **snow**, **LiDAR** performance degrades drastically.
- The quality of images captured by the **Camera** also degrades during such situations.

Is there any way to improve the **perception accuracy** of autonomous vehicles during adverse weather conditions for safe navigation?



Autonomous vehicle's background of perception

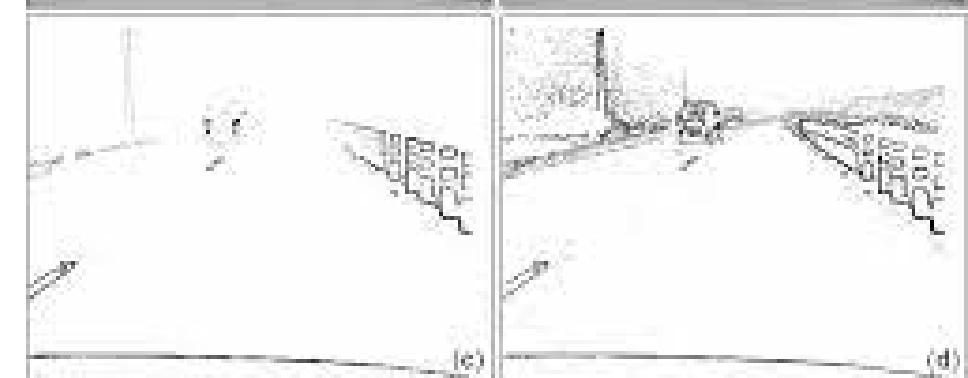
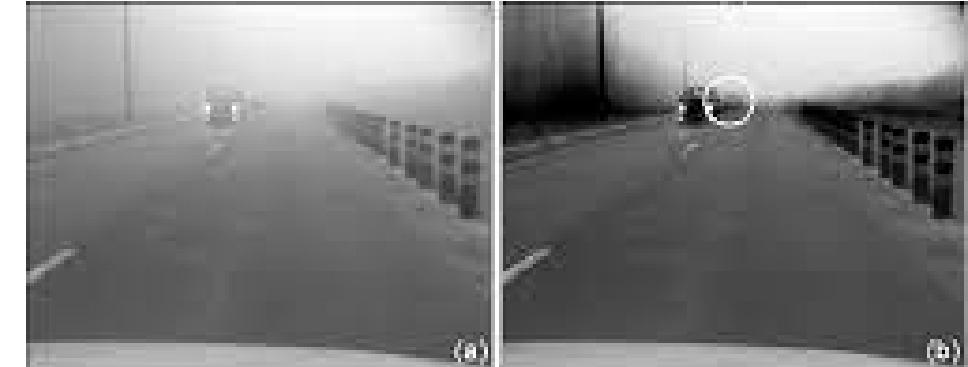
- The main objective of present autonomous companies is to use as **few sensors** as possible to perform perception operations without compromising safety.
- **Tesla**, relies only on cameras to see around the environment apart from Ultrasonic transducers and **RADAR**.
- Alphabet Inc.'s **Waymo** and GM's **Cruise** also use LiDAR along with a Camera for this purpose.
- John Dheere generates higher resolution data using **Cameras** (stereo) and **RADAR** alone, these systems are cost-efficient compared to other self-driving companies that use **LiDAR**, which is expensive

During adverse weather conditions such as **foggy**, **snowy**, and **rainy** conditions, the performance of **LiDAR** and Camera degrades. But unlike **LiDAR**, it is possible to restore the degraded images captured by the **Camera** with the help of low-level image processing techniques such as image enhancement and restoration.



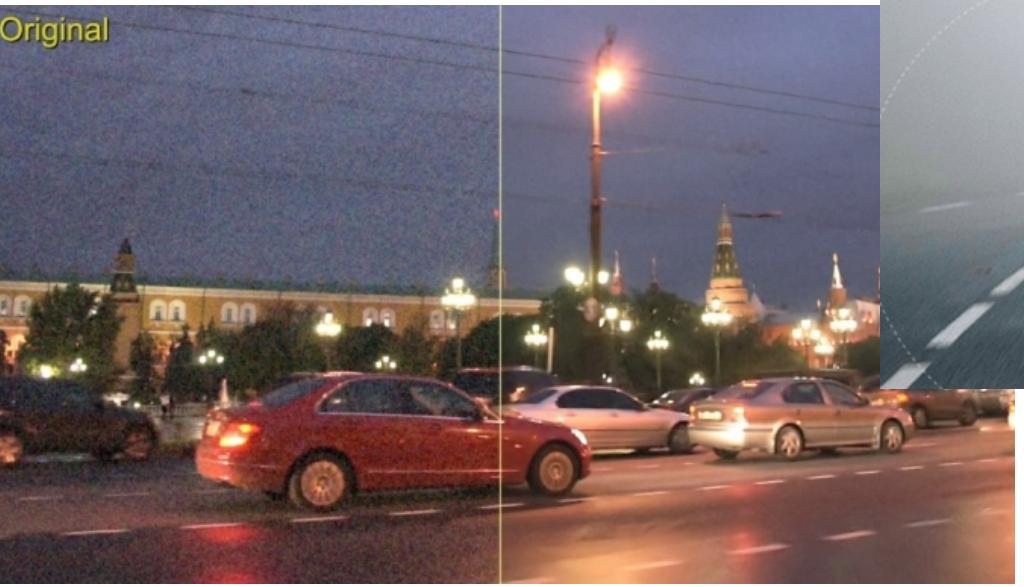
Factors affecting the perception using Camera

- Rain and snow conditions introduce sharp intensity fluctuations in images. This condition changes the image intensity and blurs the edges of various objects in an image. Usually, rain reduces the image intensity, and heavy snow increases the image intensity.
- Fog condition reduces the image's contrast and increases the difficulty of edge pattern recognition.
- In the case of an observed fog scene, the frequency components are concentrated at zero frequency, whereas in the absence of fog, the spectrum is widely spread. Sharp edges are defined by low and high frequencies, whereas smooth edges are determined solely by low frequencies



significant factors of degraded images

- **Salt and Pepper Noise:** Salt-and-pepper noise is a type of noise that can be seen in images. It is also referred to as impulse noise. Sharp and sudden disturbances in the image signal can cause this noise. It appears as sparsely distributed white and black pixels.
- **Bilateral Image:** These are images that contain huge noise and are non-linear. This image also shows the edges between various objects of the image. But the edge also includes the noise.
- **Saturated Image:** The intensity of a color is described by its saturation. A grayscale or black-and-white image has no color saturation, whereas a full-color image of a field of bright wildflowers may be highly saturated.



Existing methods for image restoration; Non-AI

a) Non-AI based image restoration:

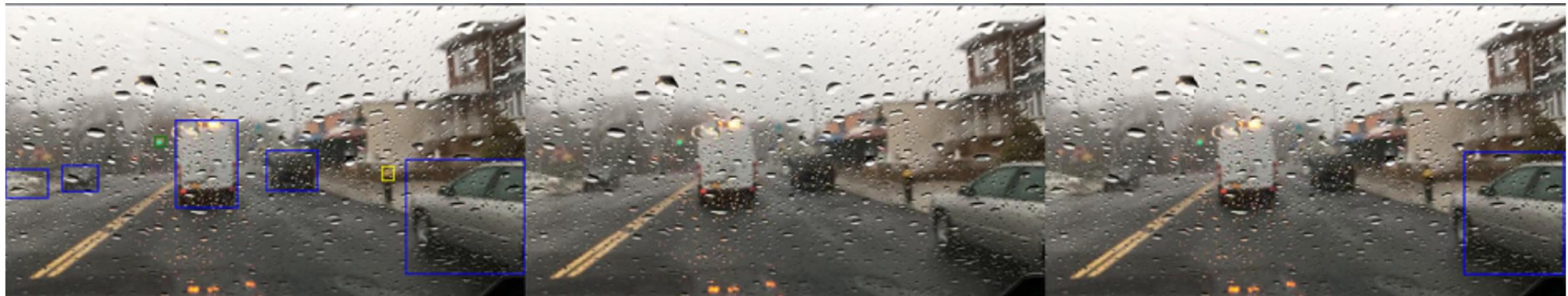
- Traditionally, three types of non-AI based image restoration methods have been in use for this purpose, which work based on algebraic methods through the application of filters such as
 - Inverse filter** - This type of restoration method is used when we have complete knowledge about the kind of blurring function/ filter leading to the degraded image.
 - Weiner filter** - This method is used if we only have partial knowledge about the blurring function/ filter leading to the degraded image.
 - Blind restoration filter** - This method is used if we do not have any prior knowledge about the blurring function/ filter causing image degradation etc.



Existing methods for image restoration; AI-based

a) AI-based image restoration:

- AI-based image restoration methods, such as the usage of Convolutional Neural Networks (CNNs), have resulted in better results in terms of quality and accuracy of the restored images in comparison with image restoration using algebraic methods. There are many types of neural networks that are based on CNN's which have been developed over time for restoring images, such as
 - i. [CNNs](#) - Plain convolutional neural networks for dirt or rain removal
 - ii. [DehazeNet](#) - Deep network for rain removal
 - iii. [SPANet](#) - Spatial attentive network for rain removal



DesnowNet

Input image

Plain CNN



Dataset consideration

- The data is divided into two parts:
 1. **Ground truth data:** This data is basically self-driving data with no adverse conditions and noise. This data is considered with high accuracy and proper features.
 2. **Adverse data:** This data is appropriate data with adverse and noise features for self-driving conditions.



Adverse
weather
Data



Ground
truth clear
weather
Data



Dataset Selection criteria



- Dawn Dataset.
 - Cityscapes
 - ADUULM Dataset



- Radiate Dataset.



GAN Selection

Paired Dataset with label



GAN or Conditional-GAN

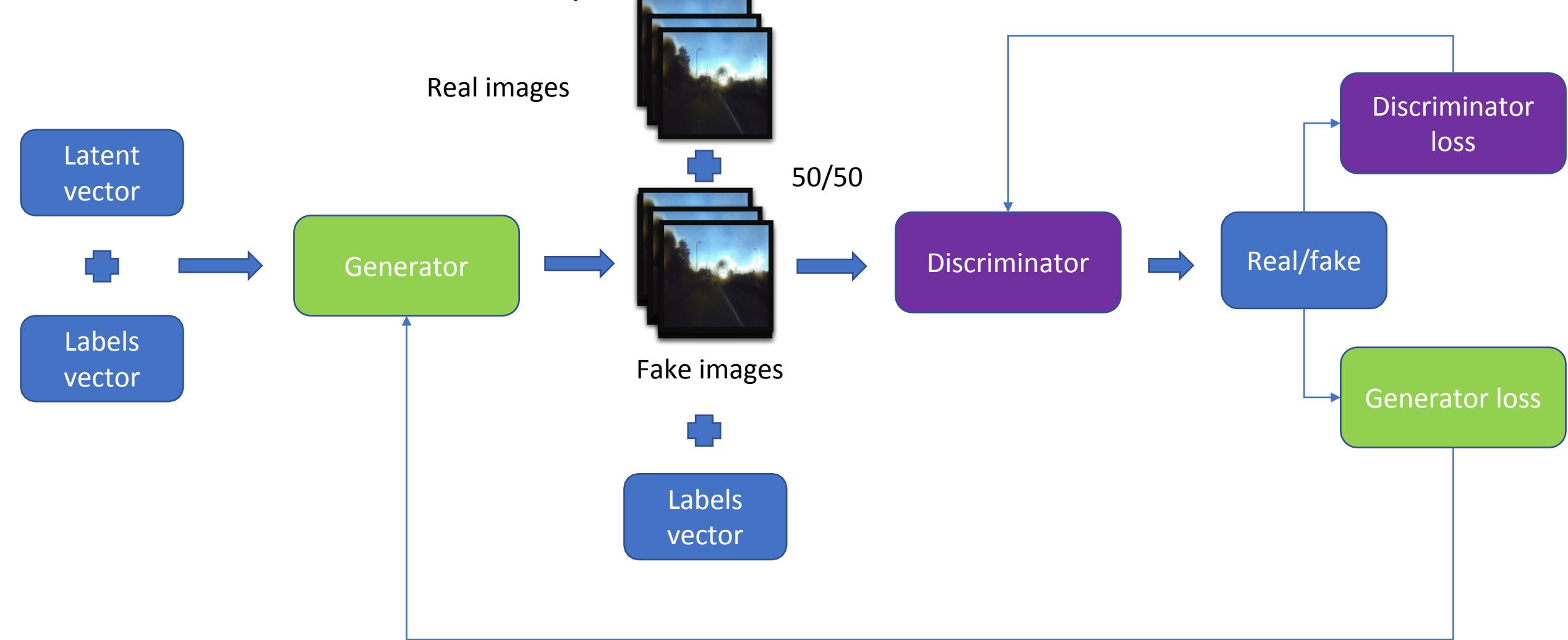
Unpaired Dataset



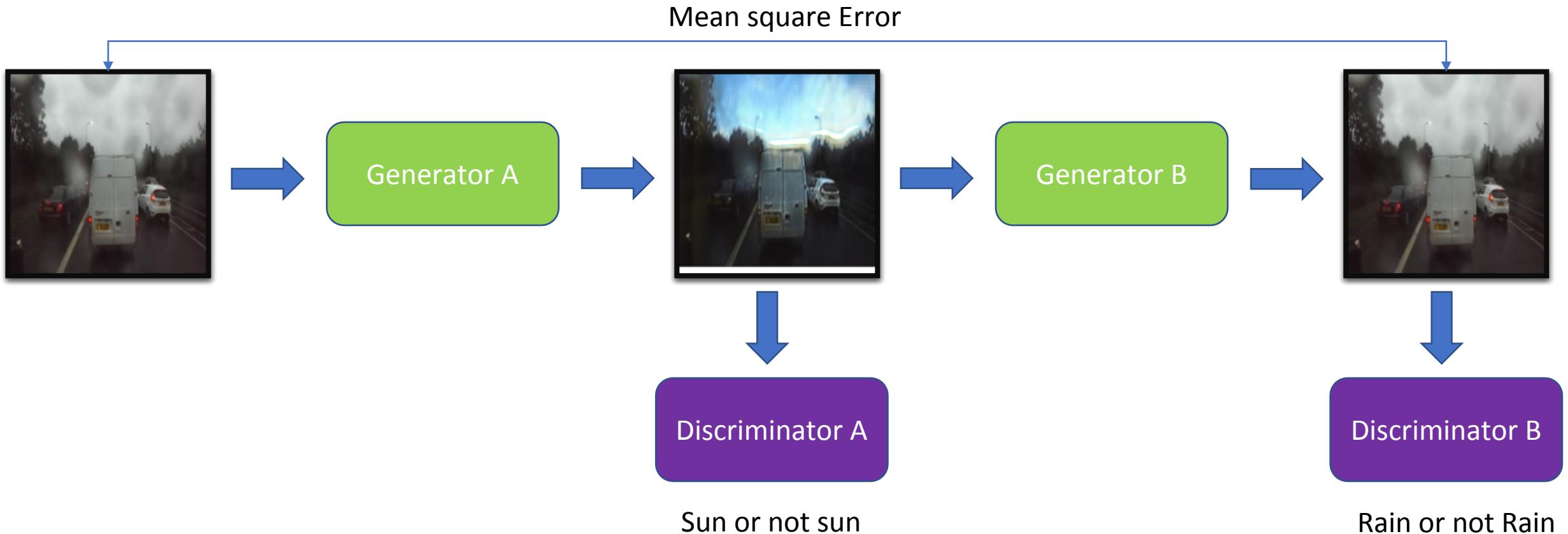
Cycle GAN



Conditional-GAN vs Cycle-GAN



Cycle-GAN



Errors are not mentionable in the flow chart
because of complexity.



Forward and backward cycle consistency

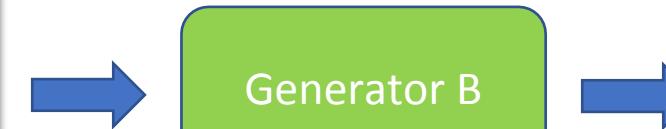
Forward Consistency



Rain



Clear weather



Rain

Backward Consistency



Clear weather



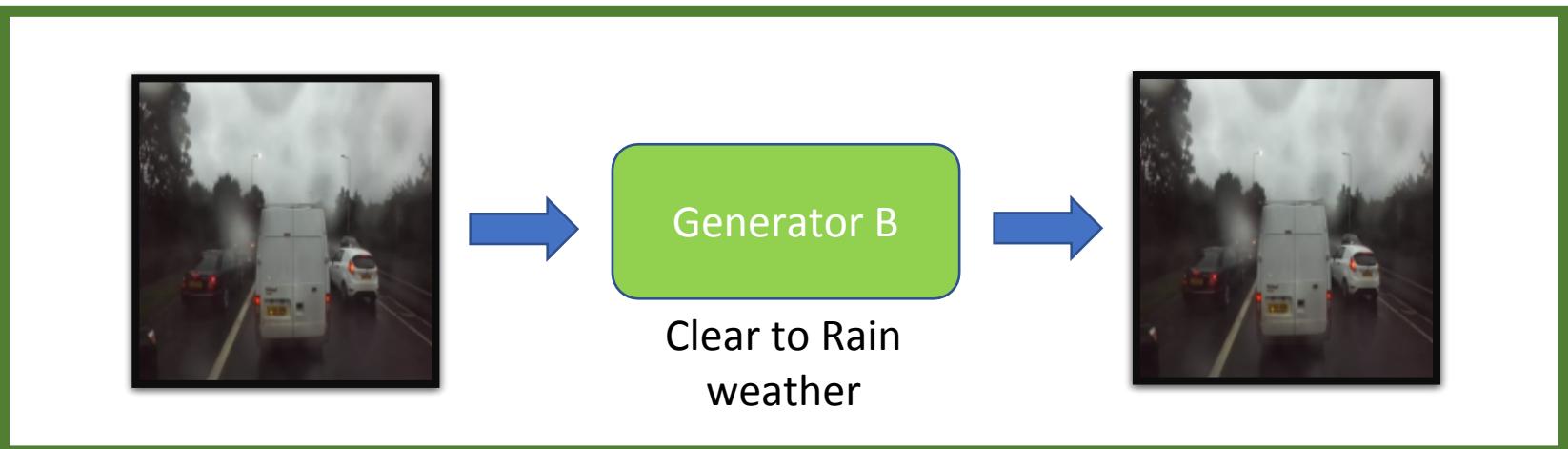
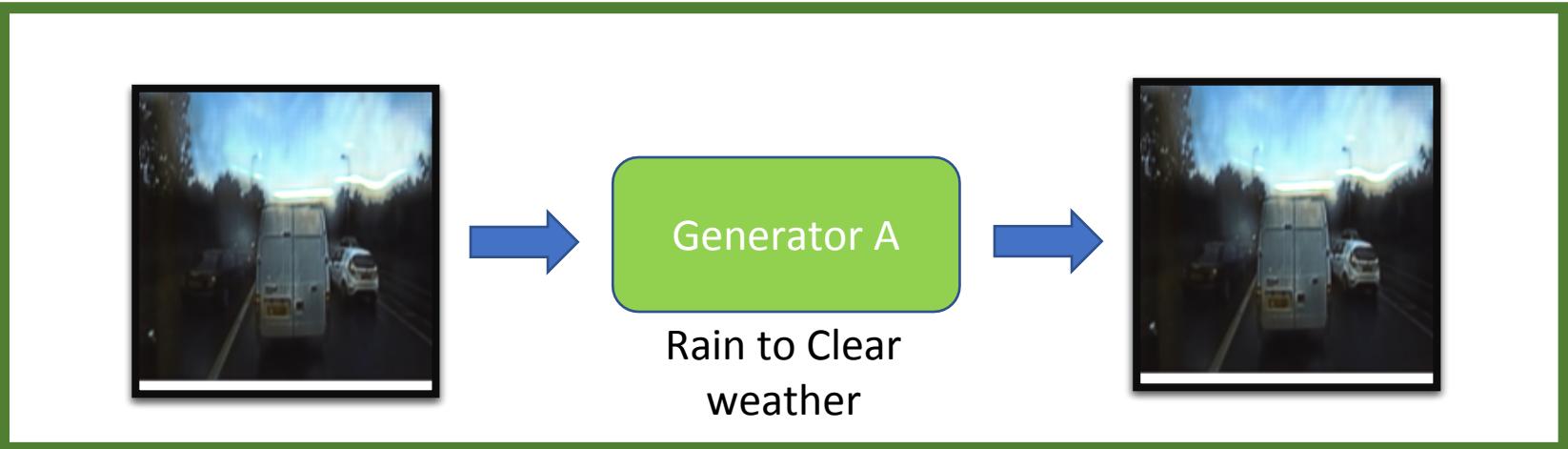
Rain



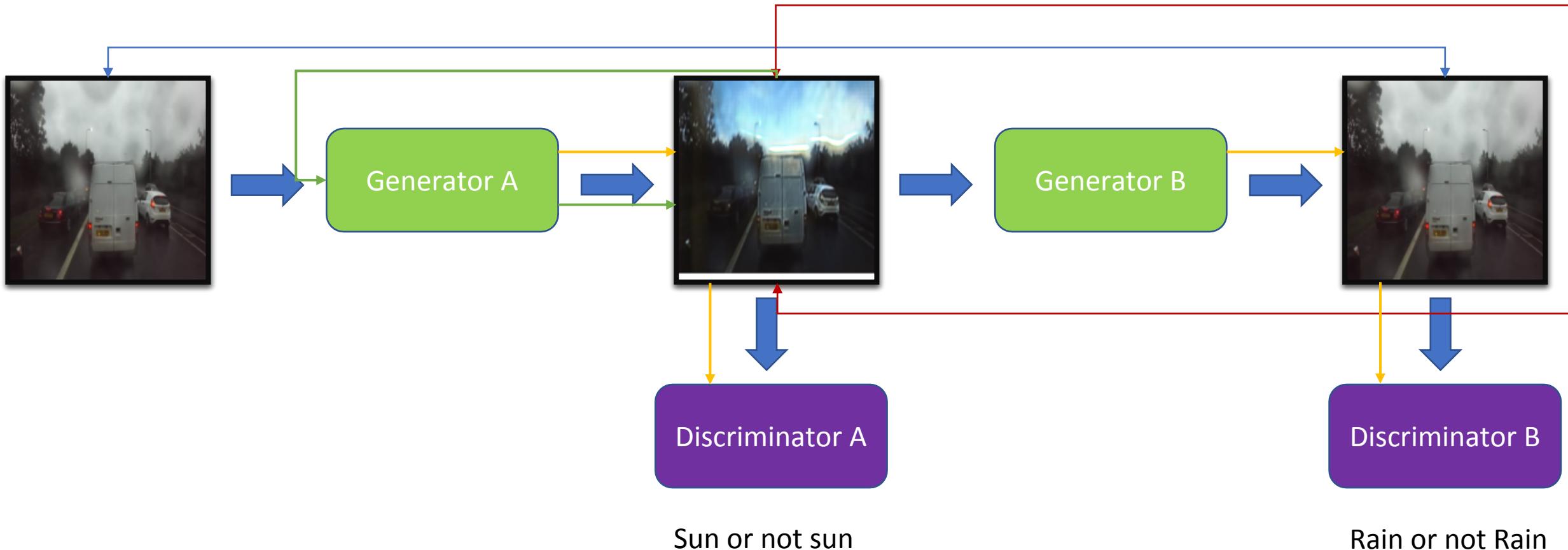
Clear weather



Identity Mapping



Cycle-GAN training

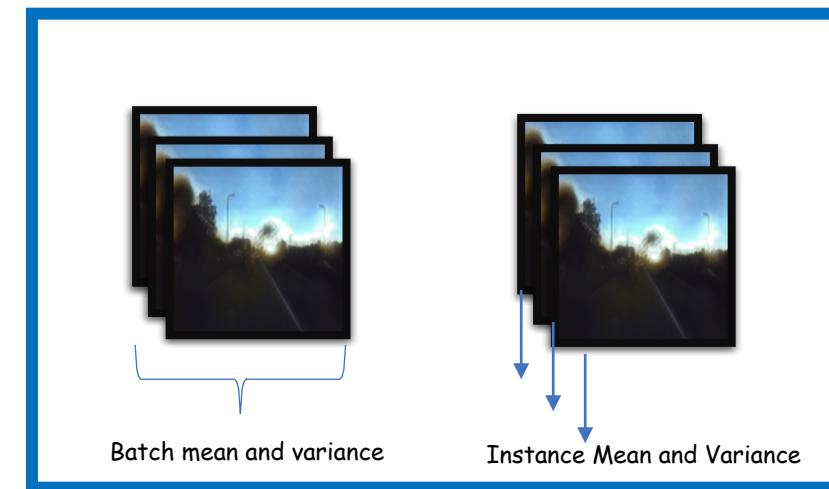
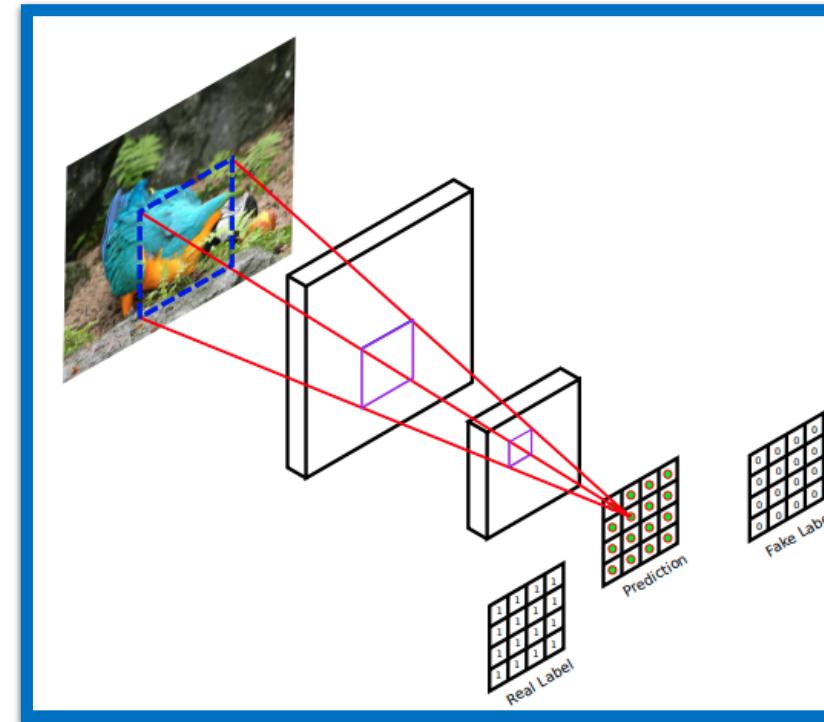
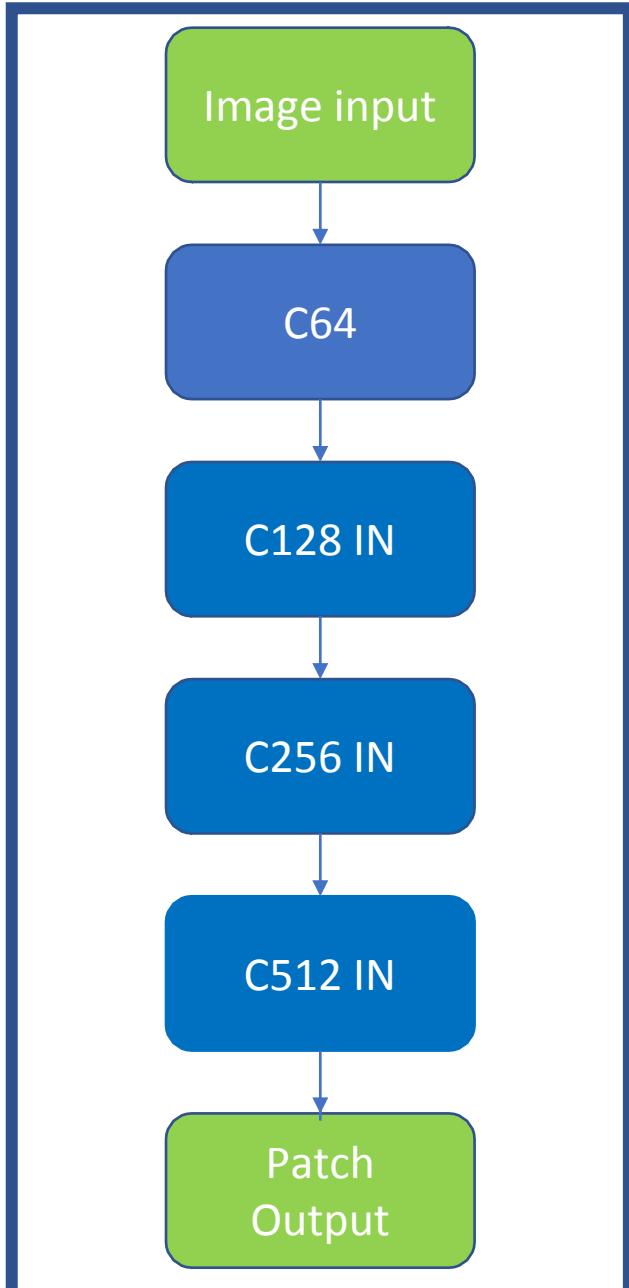


For Every Composite model we compute:

- Forward Consistency Loss
- Backward Consistency Loss
- Identity mapping loss
- Adversarial Loss



Discriminator Model

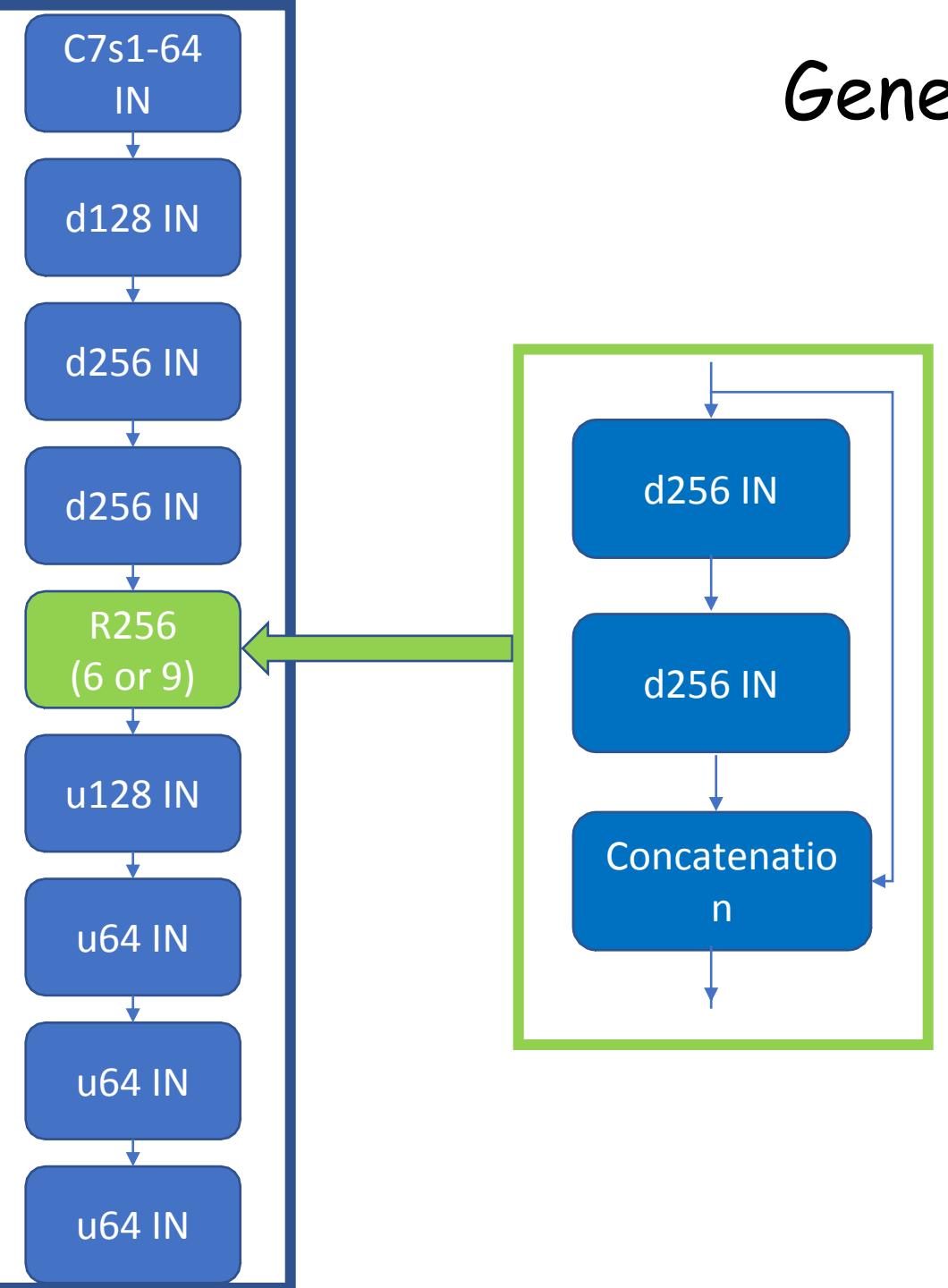


Patch GAN

**Instance
Normalization VS
Batch
normalization**



Generator Model

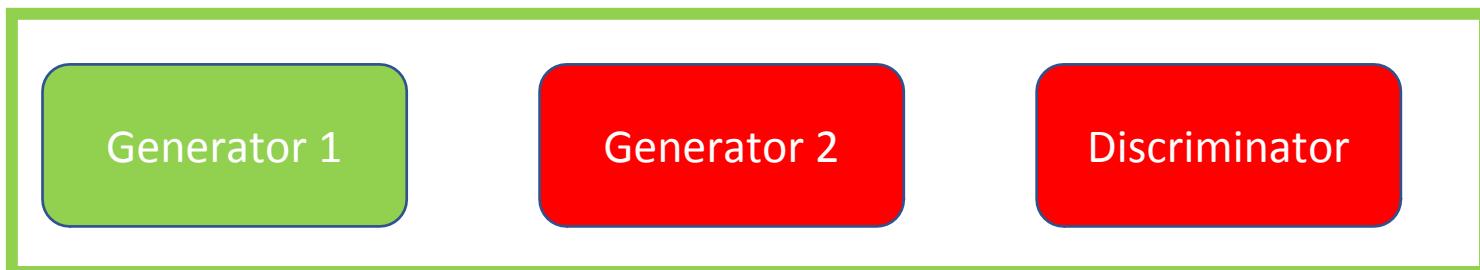
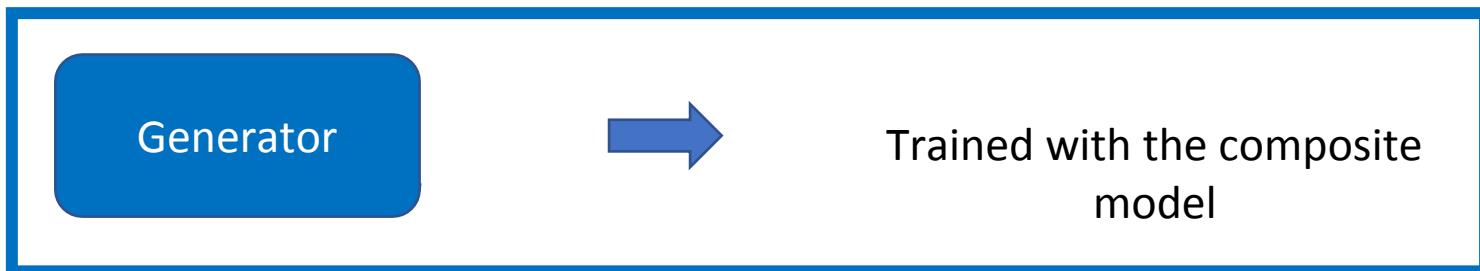
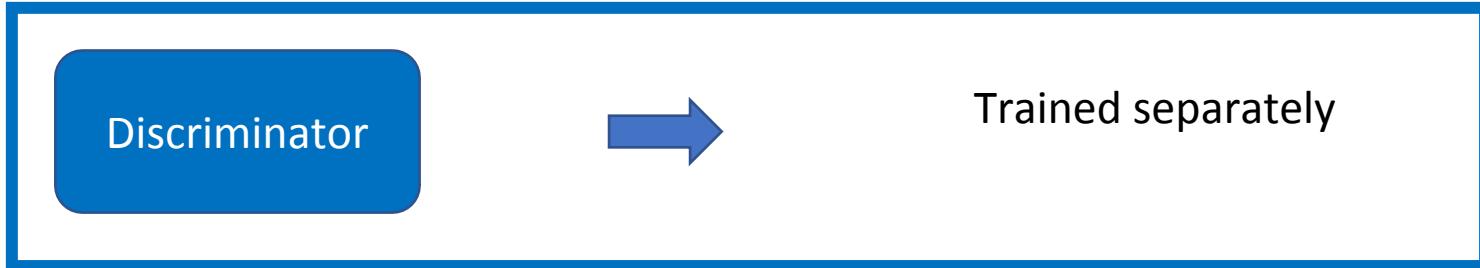


Generator Model:

- $dN \rightarrow 3 \times 3 \text{ Conv2D with } N \text{ filters and ReLU activation.}$
- $R256 \rightarrow \text{Residual Network}$
- $uN \rightarrow 3 \times 3 \text{ Conv2D transpose with } N \text{ filters and ReLU activation}$
- $C7s1 \text{ N} \rightarrow 7 \times 7 \text{ Conv2D with } N \text{ filters and stride 1}$



Composite Model training



Implementation

- Data preprocessing -
 - Data normalization – Images normalized to [-1, 1]
- Metrics -
 - Discriminator loss – Discriminator weights are updated based on MSE.
 - Composite model loss – Generator weights are updated based on the weighted average of the following errors
 - Discriminator loss – MSE
 - Identity loss – MAE
 - Forward loss – MAE
 - Backward loss – MAE
- Hardware -
 - # CPU cores - 12
 - RAM – 300 gb
 - GPU – V100
 - Simulation time – 48:00:00



Iteration 1 – image shape

- Image shapes
 1. 256x256
 2. 512x512
- Similar results with both image shapes.
- Fast results with image shape 512x512.

Rainy Image



Restored Image



Rainy Image



Restored Image



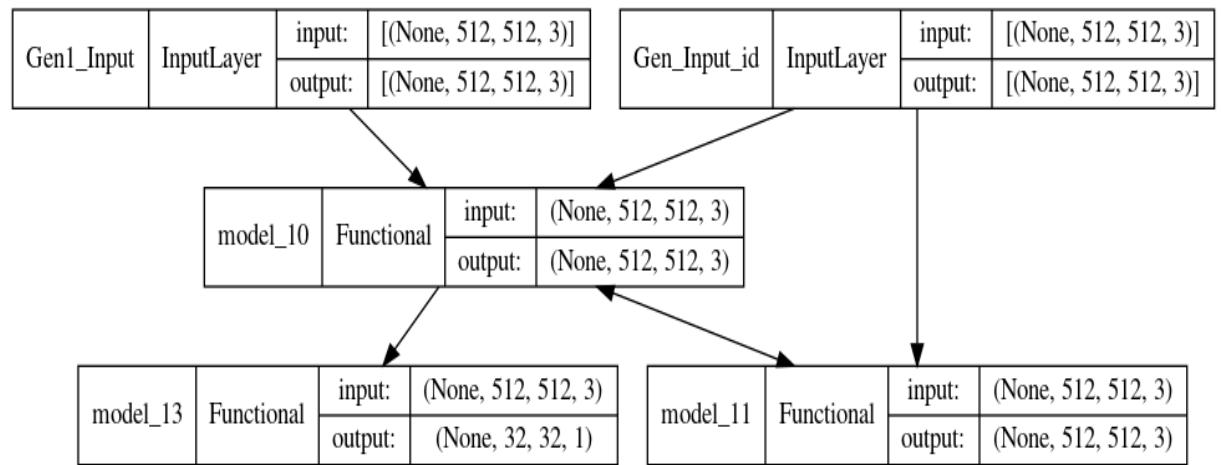
Iteration 1 – Issue

- The network is masking the vehicles as well along with the droplets.
- Also started overfitting, with fake realistic scenarios.



Composite model architecture

- Generator A
- Discriminator A/B
- Generator B
- MSE - discriminator loss
- MAE - identity, forward and backward losses.
- Loss weights



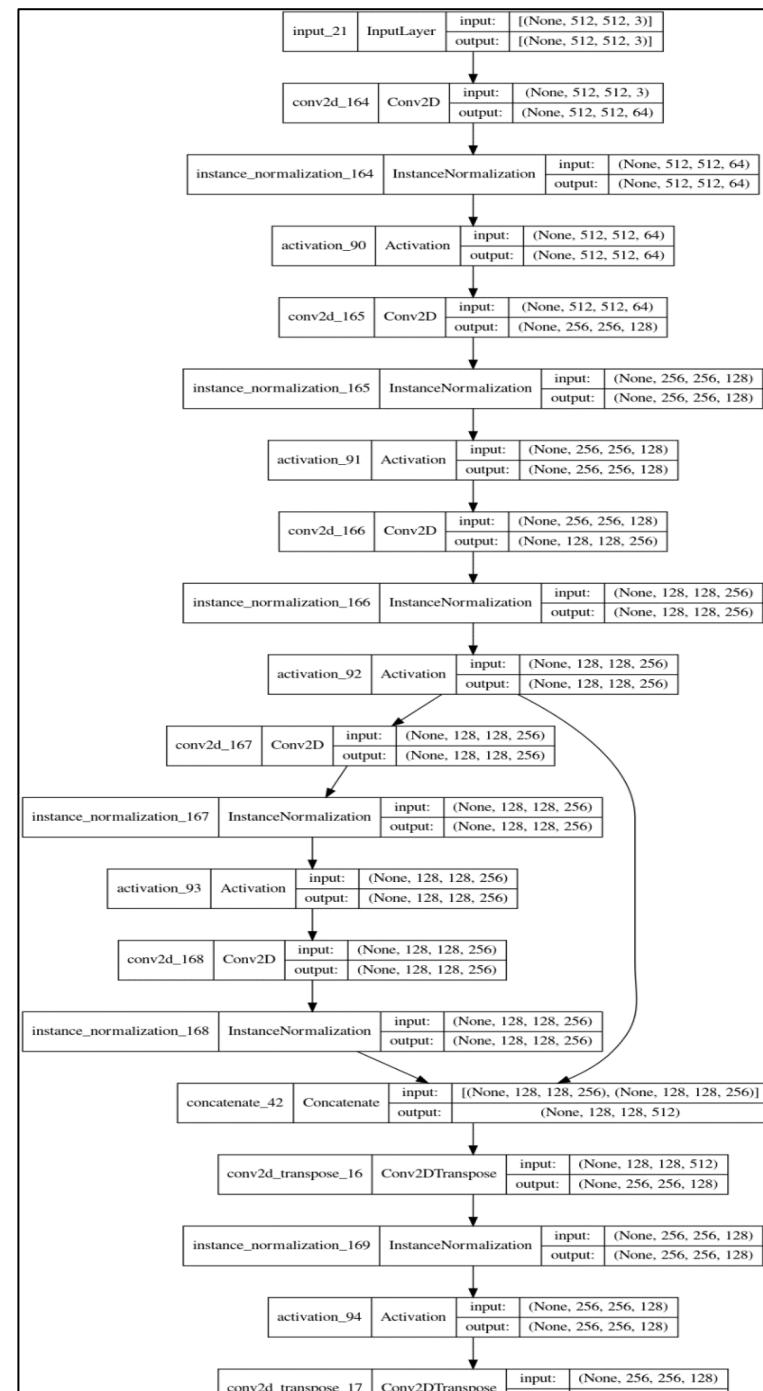
Iteration 2 – Composite model weights

- Weights
 - 1. 1, 1, 1, 1
 - 2. 1, 3, 3, 3
- Poor performance of the network.
- Unable to filter noise even from the images without vehicles.



Generator architecture

- Convolution layer
- Instance normalization
- Leaky ReLU
- Residual network layer
- Deconvolution layer



Iteration 3 – Generator

- Filter sizes
 1. 5x5
 2. 7x7
- Similar results with both filter sizes.
- Stopped masking vehicles if only 1 or 2 vehicles present in the image.
- Masking vehicles as well if many of them are present.



Rainy Image



Restored Image



Rainy Image

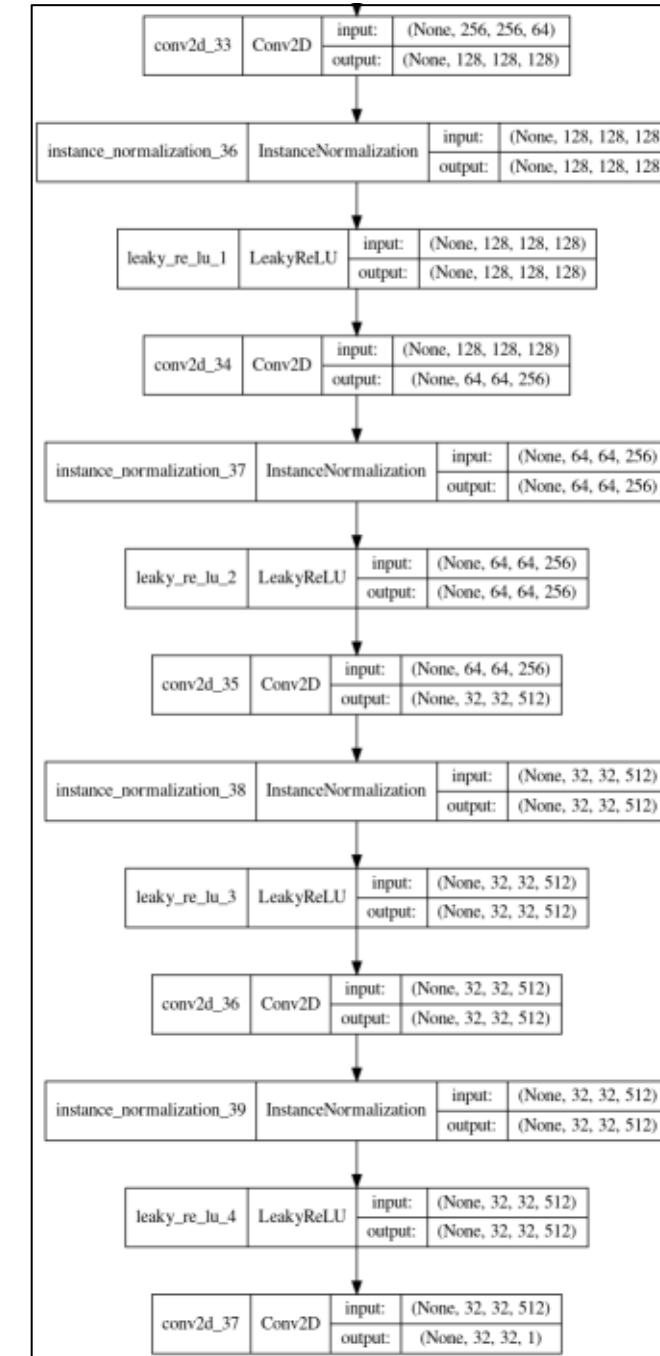


Restored Image



Discriminator architecture

- Convolution layer
- Instance normalization
- Leaky ReLU
- Patch output
- MSE loss



Iteration 4 - Discriminator

- Number of layers
 - 1. 5
- Now, the discriminator started to discriminate between droplets and vehicles.
- Stopped masking vehicles along with droplets.

Rainy Image



Restored Image



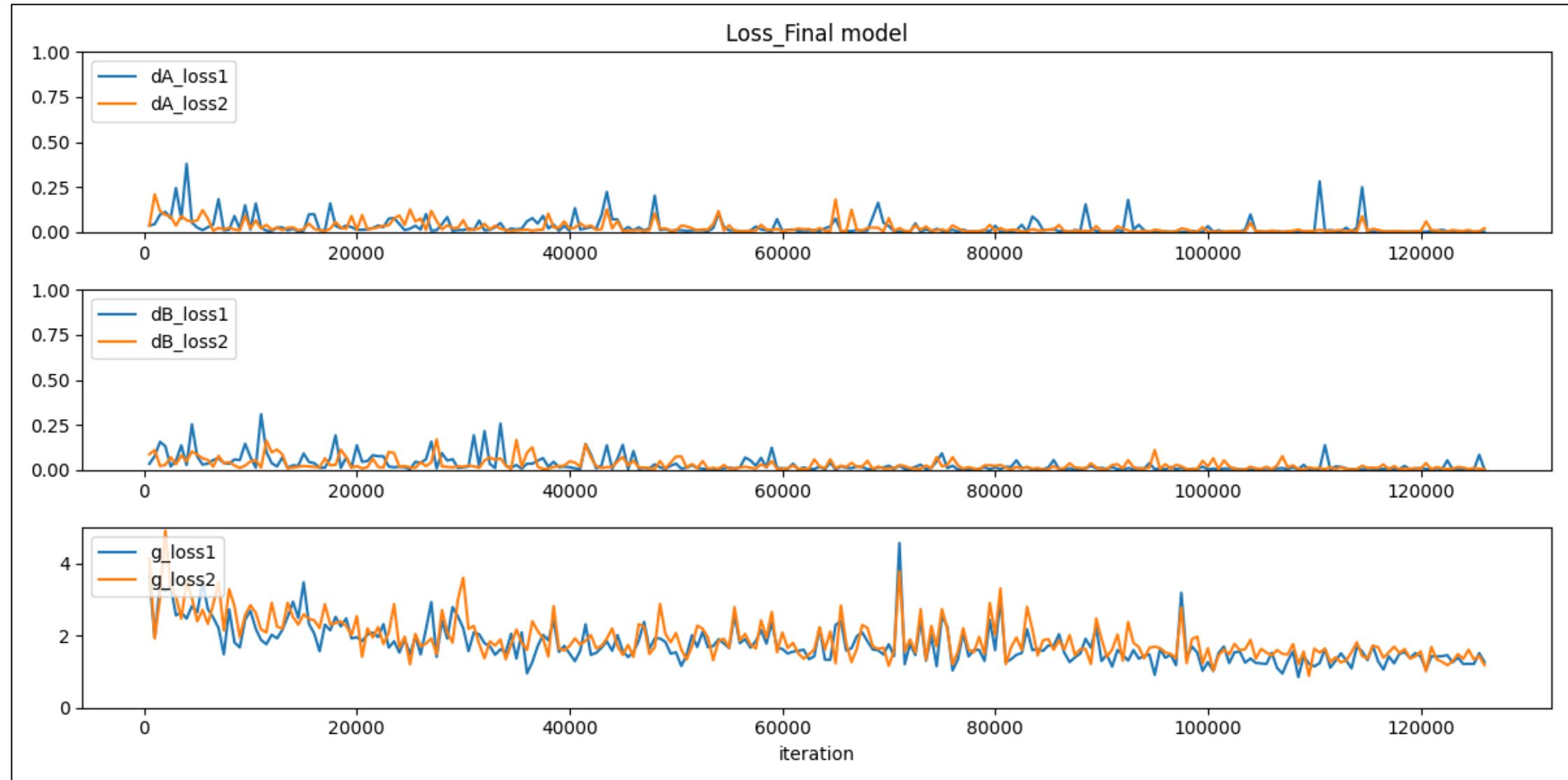
Rainy Image



Restored Image



Results



Conclusions

- In all the rainy images, the dark clouds have been replaced with the clear sky.
- Overtraining of the network is leading to the generation of fake trees in the image.
- More diverse dataset may give better results by better reconstructing of the vehicles.

Rainy Image



Restored Image



Future Work

- More improved dataset with good features needs to be collected.
- The resolution of the image needs to be improved in order to apply further perception operations.
- Geometric limitation issues.

Rainy Image



Restored Image

