

The background of the slide features a dark, vertical wood-grain texture. Scattered across this background are numerous water droplets of various sizes. Some droplets are large and prominent, showing clear highlights and reflections, while others are small and subtle. The droplets are distributed across the frame, with a higher concentration in the upper and lower portions, leaving the central area where the text is located relatively clear.

# Image De-raining for autonomous vehicle

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**Rain impact our computer vision model performance a lot**



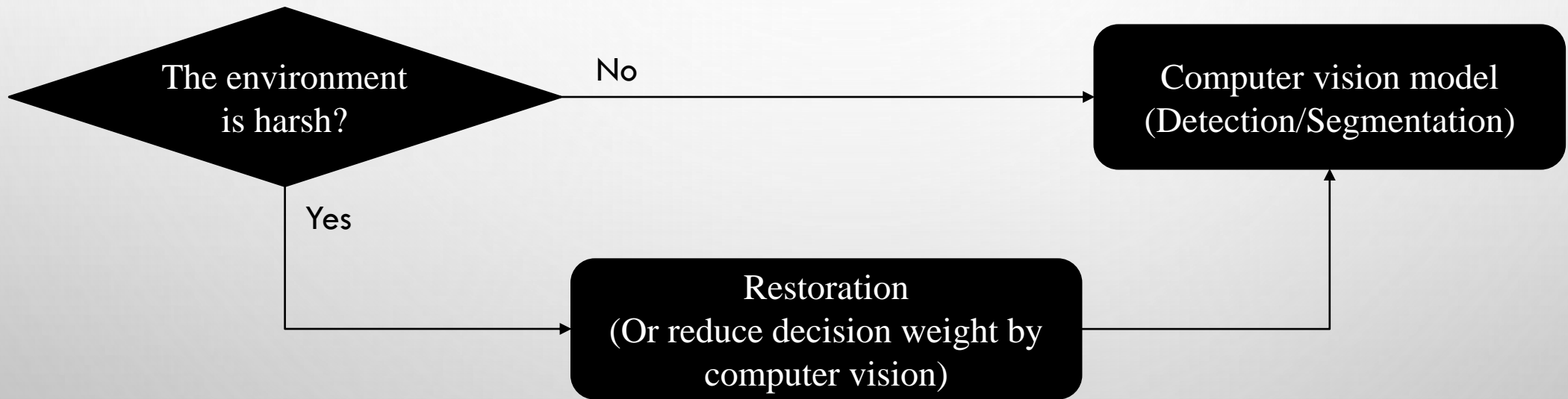
Synthetic rain image



Raw Image

**To solve the rain image problem or another harsh environment**

We take a two-stage strategy



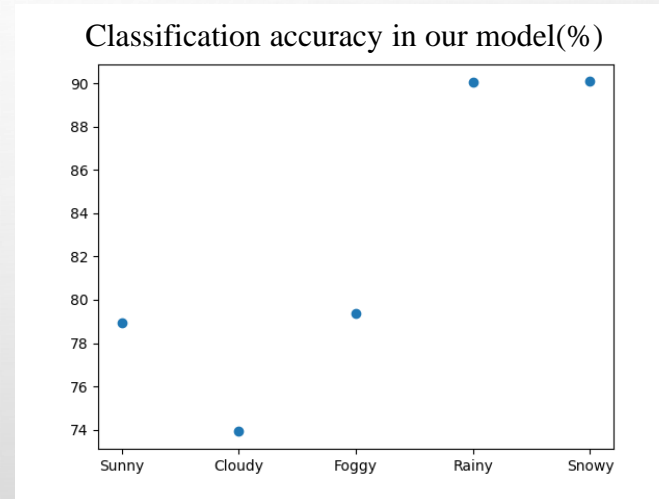
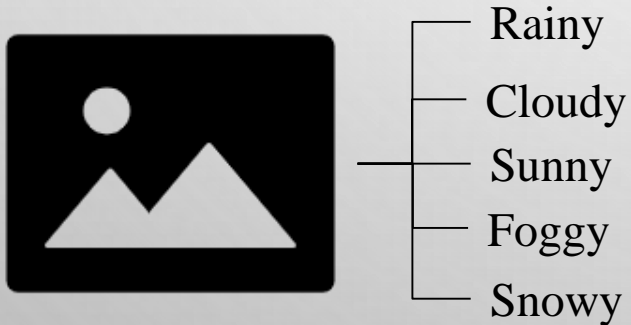
## The environment is harsh?

Action:

1. Use classification model
2. Periodically trigger classification model

We use EfficientNet (B3) as our network architecture

Collect image dataset from Flickr  
(About 5000 image data with different weathers)



In rainy and snowy weather conditions can get about 90% accuracy

Inference time about 0.02(s) we also can use the faster network to classify our weather



## Rain image restoration

We select Rain-free and Residue Hand-in-Hand: A Progressive Coupled Network for Real-Time Image Deraining (PCNet)

Traditional restore noise image: the degraded input (ID) is separated as degradation (D) and the ground truth (IB)

This Paper: Use progressive structure to separate rain and background image use coupled representation module (CRM) structure.

R  
(rain image)

B  
(background image)

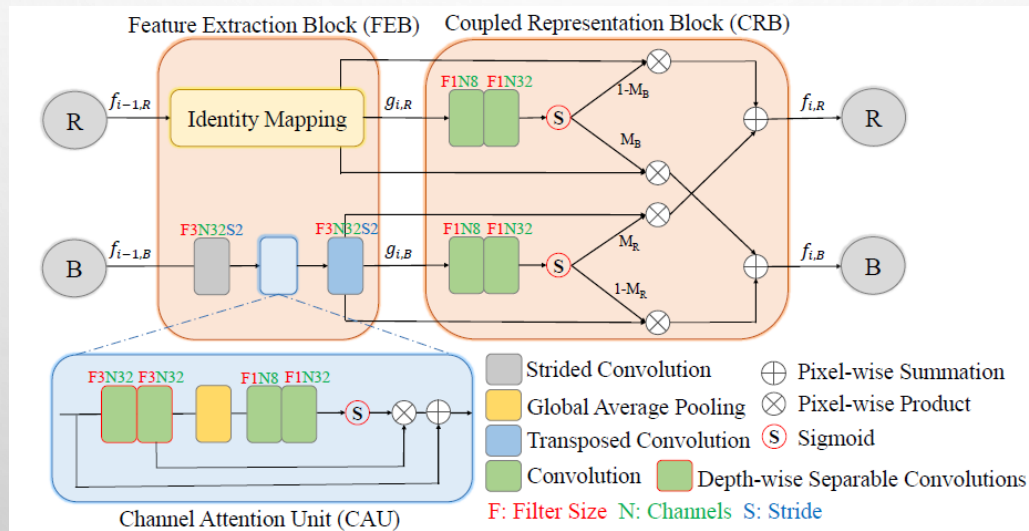


Fig. 3. Architecture of our proposed coupled representation module (CRM).

Use depth-wise separable convolutions (MobileNet) to reduce calculate loading

# Rain image restoration

## PCNet architecture

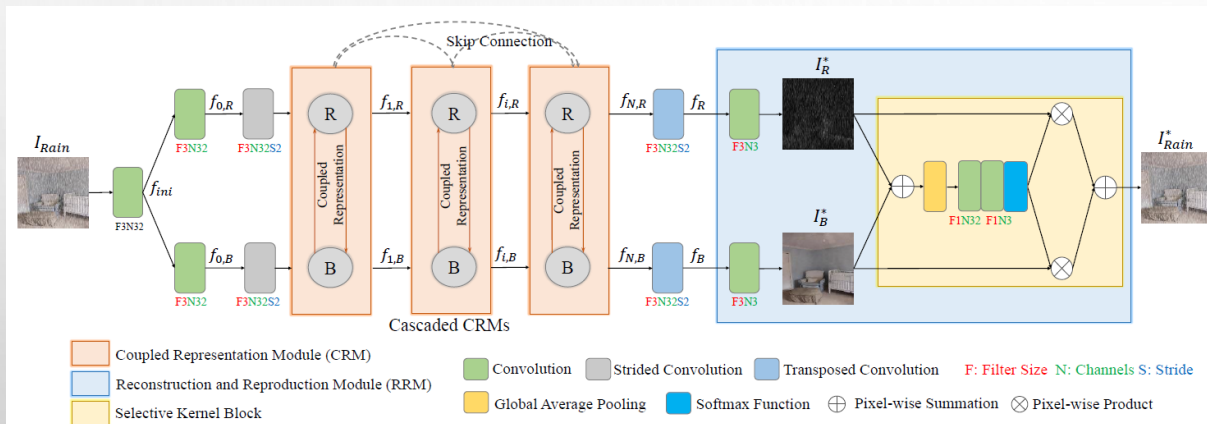


Fig. 2. Framework of our proposed progressive coupled network (PCNet). PCNet contains several cascaded CRMs as the backbone for feature extraction and one RRM to generate the predicted rain-free image  $I_B^*$ , rain streaks  $I_R^*$  and the reproduced rainy image  $I_{Rain}^*$ .

Use cascaded CRMs to separate rain and background information

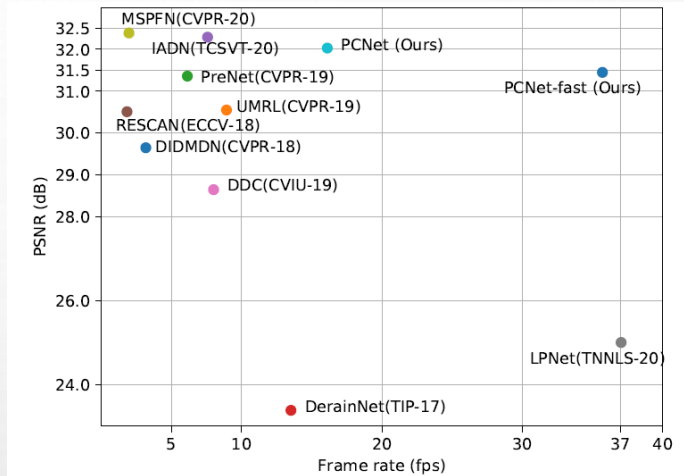


Fig. 1. Comparison of state-of-the-art detrainning methods in terms of efficiency (processing speed (fps)) vs. performance (PSNR). The results are reported on the *TEST1200* dataset with image size of  $512 \times 512$ . Compared with the top-performing method MSPFN [1], our proposed PCNet achieves comparable deraining performance (32.03dB vs. 32.39dB) with about 8× faster inference speed (16.1 fps vs. 1.97 fps). Our light-weight model PCNet-fast not only achieves real-time throughput (35.7fps) but also outperforms the representative high-accuracy method PreNet [2].

Inference speed



## Rain image restoration

Use PCNet to restore our rainy image from Flickr (real)



## Rain video restoration

Use PCNet to restore the NTURain dataset

(In this 3-second image were detected to a rainy image by our classification model)



Raw video



Restore video



## Some problems have to solve

Weather classification dataset

Image label error from Flickr creator misleading our classification network



Label: Cloudy Predict: Foggy



Label: Rainy Predict: Snowy

## Some problems have to solve

Raining dataset

Difficult to get ground truth data



Use synthetic dataset



But...

## Some problems have to solve

Rain video restoration



The raindrop blur problem  
(Related video sampling rate or  
moving motion blur)