

## 1. 隊名及隊員

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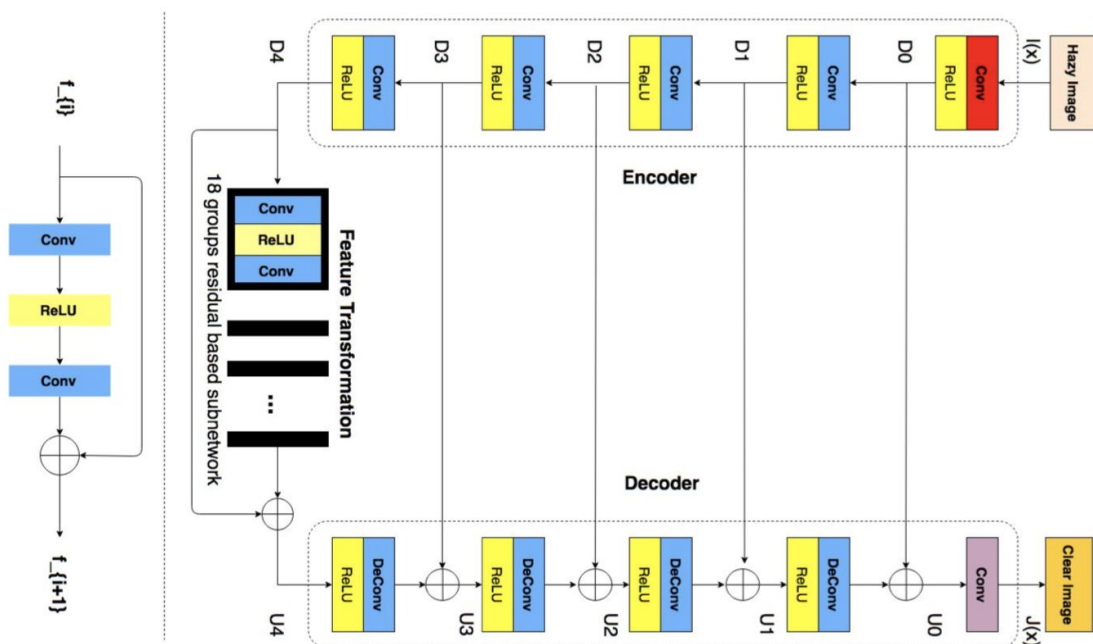
## 2. 所選擇的題目: Image Dehazing

3. Problem study: 與此次作業相關的 paper 閱讀，並寫出 paper 所提出的方法。（model架構、資料處理或是 training tips.....相關的 paper 皆可）最後面請務必附上 reference。

主要參考Paper: Progressive Feature Fusion Network for Realistic Image Dehazing (PFFNet)

特點：Performs feature fusion on spatial pyramid mappings between encoder and decoder, which enables maximally preserved structural details from inputs for deconvolution layers, and further makes the dehazing network more input-adaptive.

模型架構：



references:

- (1) Image Dehazing by Joint Estimation of Transmittance and Airlight using Bi-Directional Consistency Loss Minimized FCN
- (2) Progressive Feature Fusion Network for Realistic Image Dehazing (PFFNet)
- (3) Cycle-Dehaze: Enhanced CycleGAN for Single Image Dehazing
- (4) Multi-scale Single Image Dehazing using Perceptual Pyramid Deep Network

4. Proposed method: 簡要的寫出現在的模型架構及訓練方法，再提出之後預計使用的改進方法。

(1) 目前做法：

(a) 模型架構

使用 *Progressive Feature Fusion Network for Realistic Image Dehazing* 提出的 PFFNet，架構如上題所示。

詳細架構如下：

[Encoder]

```
(sub_mean): MeanShift(3, 3, kernel_size=(1, 1), stride=(1, 1))
(add_mean): MeanShift(3, 3, kernel_size=(1, 1), stride=(1, 1))
(conv_input): ConvLayer(
  (reflection_pad): ReflectionPad2d((5, 5, 5, 5))
  (conv2d): Conv2d(3, 16, kernel_size=(11, 11), stride=(1, 1))
)
(conv2x): ConvLayer(
  (reflection_pad): ReflectionPad2d((1, 1, 1, 1))
  (conv2d): Conv2d(16, 32, kernel_size=(3, 3), stride=(2, 2))
)
(conv4x): ConvLayer(
  (reflection_pad): ReflectionPad2d((1, 1, 1, 1))
  (conv2d): Conv2d(32, 64, kernel_size=(3, 3), stride=(2, 2))
)
(conv8x): ConvLayer(
  (reflection_pad): ReflectionPad2d((1, 1, 1, 1))
  (conv2d): Conv2d(64, 128, kernel_size=(3, 3), stride=(2, 2))
)
(conv16x): ConvLayer(
  (reflection_pad): ReflectionPad2d((1, 1, 1, 1))
  (conv2d): Conv2d(128, 256, kernel_size=(3, 3), stride=(2, 2))
)
```

[Residual Block] (共疊18個)

```
(res1): ResidualBlock(
  (conv1): ConvLayer(
    (reflection_pad): ReflectionPad2d((1, 1, 1, 1))
    (conv2d): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1))
  )
  (conv2): ConvLayer(
    (reflection_pad): ReflectionPad2d((1, 1, 1, 1))
    (conv2d): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1))
  )
  (relu): PReLU(num_parameters=1)
)
```

[Decoder]

```

(convd16x): UpsampleConvLayer(
  (reflection_pad): ReflectionPad2d((1, 1, 1, 1))
  (conv2d): ConvTranspose2d(256, 128, kernel_size=(3, 3), stride=(2, 2))
)
(convd8x): UpsampleConvLayer(
  (reflection_pad): ReflectionPad2d((1, 1, 1, 1))
  (conv2d): ConvTranspose2d(128, 64, kernel_size=(3, 3), stride=(2, 2))
)
(convd4x): UpsampleConvLayer(
  (reflection_pad): ReflectionPad2d((1, 1, 1, 1))
  (conv2d): ConvTranspose2d(64, 32, kernel_size=(3, 3), stride=(2, 2))
)
(convd2x): UpsampleConvLayer(
  (reflection_pad): ReflectionPad2d((1, 1, 1, 1))
  (conv2d): ConvTranspose2d(32, 16, kernel_size=(3, 3), stride=(2, 2))
)
(conv_output): ConvLayer(
  (reflection_pad): ReflectionPad2d((1, 1, 1, 1))
  (conv2d): Conv2d(16, 3, kernel_size=(3, 3), stride=(1, 1))
)
(rel): LeakyReLU(negative_slope=0.2)

```

#### (b) Data augmentation

對Indoor/Outdoor的Hazy/GT圖片做相同的数据 augmentation，將每張圖片crop出多張512\*512的圖片。從左上方開始，由左至右，由上而下，每次平移256，一張圖片約可以crop出170張圖片。Indoor的training data（不含validation）原本只有25張，經過data augmentation後，約有4200張；Outdoor的training data（不含validation）原本只有35張，經過data augmentation後，約有4900張。

#### (c) 訓練方法

Indoor和Outdoor的圖片分開訓練，使用相同的模型架構和訓練方法。訓練參數為batch size = 16, number of epochs = 300, optimizer為Adam(lr = 1e-4), loss function為生成的圖片和ground truth之間的mean square error。

#### (d) 目前結果

目前一共有三個模型，分別是依照上述模型架構和訓練方法得到的indoor和outdoor model，以及github上的pretrained model。我們訓練的model和pretrained model的差別是，我們疊了18個Residual Blocks，pretrained model則是疊13個。嘗試不同組合得到的結果如下：

	使用模型		PSNR x SSIM
	Indoor	Outdoor	
1	pretrained model	pretrained model	16.802760
2	our indoor model	our outdoor model	16.764459
3	our indoor model	pretrained model	16.737262
4	pretrained model	our outdoor model	16.830134

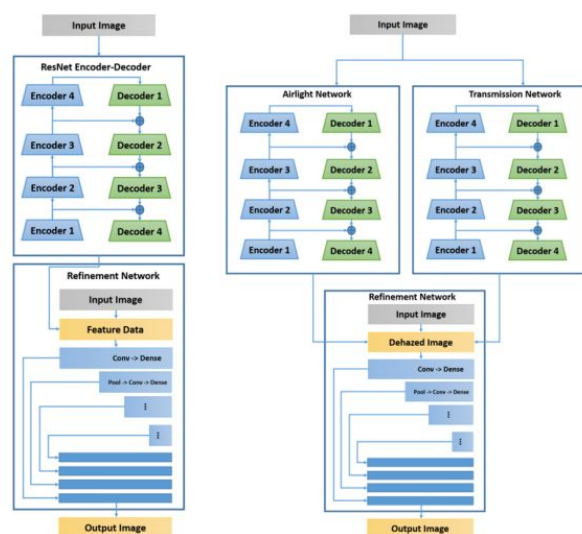
(2)後續改良作法：

希望再試試看不同論文所提出的方法，

例如：*Feature Forwarding for Efficient Single Image Dehazing*

<https://arxiv.org/pdf/1904.09059.pdf>

所提出的改良LinkNet的架構，將pretrained Resnet18 model所提出來的features，直接接到pyramid pooling network中去做refinement



以及Multi-scale Single Image Dehazing using Perceptual Pyramid Deep Network

[http://openaccess.thecvf.com/content\\_cvpr\\_2018\\_workshops/papers/w13/Zhang\\_Multi-Scale\\_Single\\_Image\\_Deconvolutional\\_Network\\_CVPR\\_2018\\_paper.pdf](http://openaccess.thecvf.com/content_cvpr_2018_workshops/papers/w13/Zhang_Multi-Scale_Single_Image_Deconvolutional_Network_CVPR_2018_paper.pdf)

所提出的encoder-decoder模型：利用dense block+residual block所建構的encoder，加上dense-residual block(two-layer dense block + an upsampling transition block)+pyramid pooling module所建構的decoder，得到最後的dehazed image。

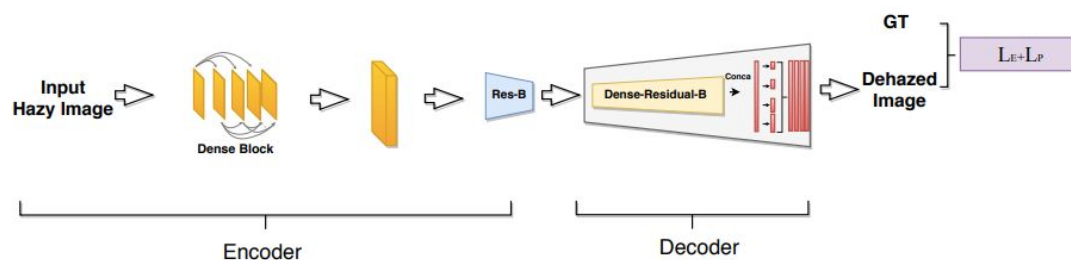


Figure 2. Overview of the proposed Multi-scale Single Image Dehazing using Perceptual Pyramid Deep Network.

之後我們會想辦法利用pretrained model所得到的features，加上例如Densely Connected Pyramid Dehazing Network的方法，得到更好的結果。