Multimedia & Lab

Image-Denoising

Team 7

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INTRODUCTION

Digital images are normally prone to additive white Gaussian noise During image acquisition due to electronic circuits.



This noise increases over time and degrades image quality.

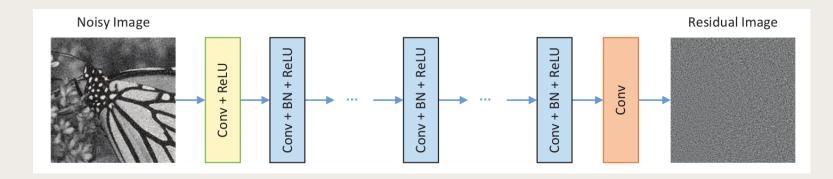
To maintain quality, it is important to reduce or eliminate noise.

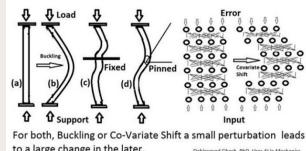
We have made various attempts to eliminate or minimize noise generated.

We tried to restore the image using Autoencoding. It's a simple way, but We tried to improve the results through various changes.

RELATED WORK

DnCNN





to a large change in the later. Dehinrasad Ghosh PhD Uses At in Mechanics

There are three types of layers in DnCNN.

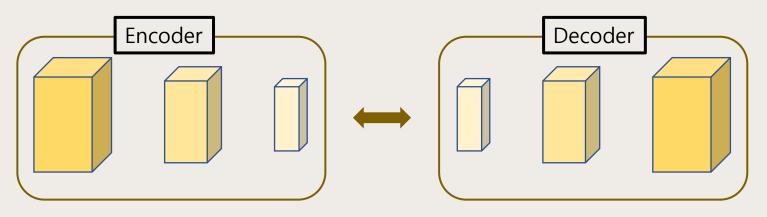
- Conv + ReLU
- Conv + BN + ReLU
- Conv

Predicting residential images instead of denied images. Residual learning and BN are combined to achieve better performance.

Similar to DnCNN, we used Conv, ReLU, and BN to construct the layer.

The difference is that DnCNN repeats the same hidden layer, but we don't.

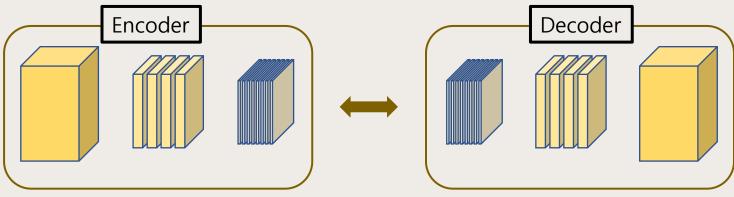
We started with the simplest Autoencoder structure.



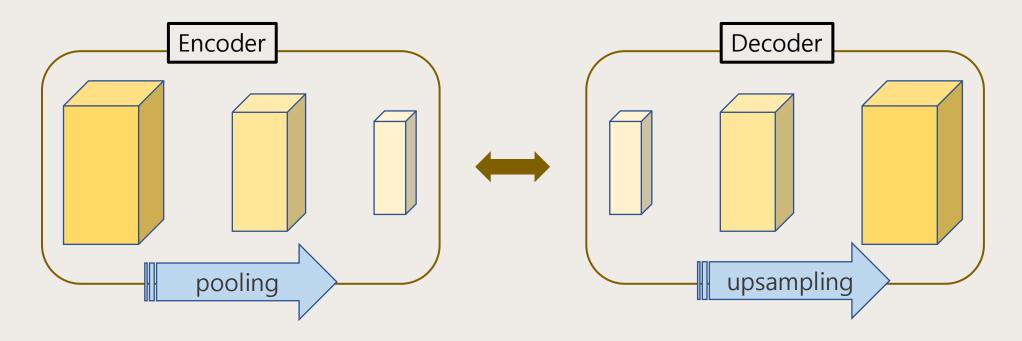
In the basic structure, encoding and decoding are carried out using pooling and upsampling.

Instead of using the basic method.

We use Conv that return various out channels

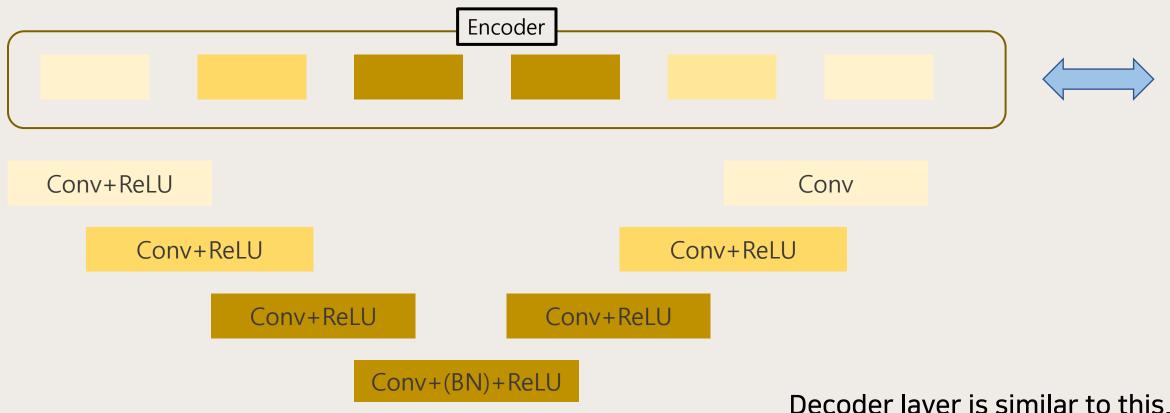


Of course, Pooling can reduce unnecessary parameters and extract features well. However, in order to return a denoised image, Upsampling is required during decoding.



Upsampling is not lossless.

So, we built a layer in the following way.



Decoder layer is similar to this.

Network Code

```
Reference code
[] import torch.nn as nn
     class autoencoder(nn.Module):
         def __init__(self):
             super(autoencoder, self).__init__()
             self.encoder = nn.Sequential(
                 nn.Linear(28 * 28, 256),
                 nn.ReLU(True),
                 nn.Linear(256, 64),
                 nn.ReLU(True))
             self.decoder = nn.Sequential(
                 nn.Linear(64, 256),
                 nn.ReLU(True),
                 nn.Linear(256, 64),
                 nn.Sigmoid())
         def forward(self, x):
             x = self.encoder(x)
             x = self.decoder(x)
             return x
```

Auto Encoder (Reference code)

```
AutoEncoder denoising network
import torch.nn as nn
    class Autoencoder(nn.Module):
         def __init__(self):
             super(Autoencoder, self).__init__()
             self.encoder = nn.Sequential(
                nn.Conv2d(3, 96, kernel_size=3, padding=1, bias=False),
                nn.Conv2d(96, 256, kernel_size=3, padding=1, bias=False),
                nn.ReLU(),
                nn.Conv2d(256, 384, kernel_size=3, padding=1, bias=False),
                nn.ReLU(),
                nn.Conv2d(384, 384, kernel_size=3, padding=1, bias=False),
                nn.BatchNorm2d(384),
                nn.Conv2d(384, 12, kernel_size=3, padding=1, bias=False),
                nn.Conv2d(12, 3, kernel_size=3, padding=1, bias=False),
             self.decoder = nn.Sequential(
                nn.Conv2d(3, 12, kernel_size=3, padding=1, bias=False),
                nn.Conv2d(12, 384, kernel_size=3, padding=1, bias=False),
                nn.Conv2d(384, 384, kernel_size=3, padding=1, bias=False),
                nn.BatchNorm2d(384),
                nn.ReLU().
                nn.Conv2d(384,256, kernel_size=3, padding=1, bias=False),
                nn.ReLU(),
                nn.Conv2d(256,96, kernel_size=3, padding=1, bias=False),
                nn.Conv2d(96,3, kernel_size=3, padding=1, bias=False),
         def forward(self, x):
            encoded = self.encoder(x)
             decoded = self.decoder(encoded)
             return encoded, decoded
```

Auto Encoder Network structure for Image Denoising

```
batch normalization 추가
import torch.nn as nn
    class Autoencoder(nn.Module):
        def __init__(self):
             super(Autoencoder, self).__init__()
             self.encoder = nn.Sequential(
                nn.Conv2d(3, 96, kernel_size=3, padding=1, bias=False),
                nn.BatchNorm2d(96),
                 nn.Conv2d(96, 256, kernel_size=3, padding=1, bias=False).
                nn.BatchNorm2d(256),
                nn.ReLU().
                 nn.Conv2d(256, 256, kernel_size=3, padding=1, bias=False),
                nn.ReLU(),
                nn.Conv2d(384, 384, kernel_size=3, padding=1, bias=False);
                nn.BatchNorm2d(384).
                nn.Conv2d(384, 12, kernel_size=3, padding=1, bias=False),
                nn.BatchNorm2d(12),
                nn.ReLU()
                 nn.Conv2d(12, 3, kernel_size=3, padding=1, bias=False),
             self.decoder = nn.Sequential(
                nn.Conv2d(3, 12, kernel_size=3, padding=1, bias=False),
                 nn.Conv2d(12, 384, kernel_size=3, padding=1, bias=False),
                nn.ReLU().
                nn.Conv2d(384, 384, kernel_size=3, padding=1, bias=False),
                nn.BatchNorm2d(384),
                nn.ReLU().
                nn.Conv2d(384,256, kernel_size=3, padding=1, bias=False),
                nn.Conv2d(256,96, kernel_size=3, padding=1, bias=False)
                 nn.Conv2d(96,3, kernel_size=3, padding=1, bias=False),
         def forward(self, x):
             encoded = self.encoder(x)
            decoded = self.decoder(encoded)
             return encoded, decoded
```

Auto Encoder Network structure for Image Denoising with batch normalization

We doubled the size of the test set by randomly flipping the test image horizontally or vertically.











OR



```
import zipfile
     import tqdm
    file_name = "Multimedia_dataset.zip"
    zip_path = os.path.join('/content/drive/MyDrive/Multimedia_dataset.zip')
     !unzip -q "{file_name}
    !rm "{file_name}"
Data Augmentation
[] from PIL import Image
    import random
    arg_root_path = "/content/"
    arg_train_dir = os.path.join(arg_root_path, "train")
    arg_img_list = [os.path.join(arg_root_path, "train", dirs) for dirs in os.listdir(arg_train_dir)]
      print("start arg")
       for idx,file_name in enumerate(arg_img_list):
        rand_ = random.randrange(1, 3)
          flip_img = arg_image.transpose(Image.FLIP_LEFT_RIGHT)
          flip_img.save(arg_train_dir+"/fliped_X06d.png" %(idx+1))
          flip_ing = arg_image.transpose(Image.FLIP_TOP_BOTTOM)
          flip_img.save(arg_train_dir+"/fliped_%06d.png" %(idx+1))
          print("wrong rand num")
      print("done")
```

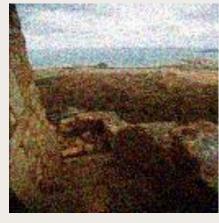
In addition,

We tested using Adam as optimizer while changing Ir and eps values.

We tested within limited resources while changing the batch size and epoch values.

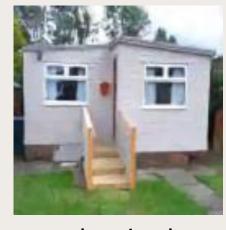
EXPERIMENTS

Result samples









noised

denoised

noised

denoised

score

52	Team7	kjh99723	AutoEncoder	2021-05-26 28.981156 0.918853	0.288882
				16:21:42.849414	

CONCLUSION

What's good about this project

- Building a network for image denoising in a simple structure using Auto encoder.
- Direct experience with various deep learning networks such as DnCNN, AlexNet, Auto Encoder, etc.

What's unfortunate about our project

- Google Colaboratory was used as a development environment, and limited resources allowed it to run up to its current parameters.
- We have yet to find any distinct ways to improve the performance of our network.

The potential for this network to evolve

- Increase the number of epochs and add more layers.
- Increase the train data further using more different augmentation methods.
- It can be applied in other fields besides image Denoising by using another layer instead of convolution.

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Thank you@