# Image denoising using deep learning

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(C) Oge Marques, PhD - 2020-2021
```

**Goal:** Build and evaluate image denoising solutions using deep learning architectures.

**Learning objectives:**

- Learn how to implement an Image Processing **workflow** in MATLAB
- Learn how to implement and evaluate **contemporary** (deep-learning-based) image denoising techniques in MATLAB
- Get acquainted with representative **datasets** and problems in image denoising

**Table of Contents**



## Part 1: Noise types and image quality metrics

### Effects of different noise types

`imnoise()` allows you to add noise to an image. You can choose from different noise types: Gaussian, Poisson, salt-and-pepper.

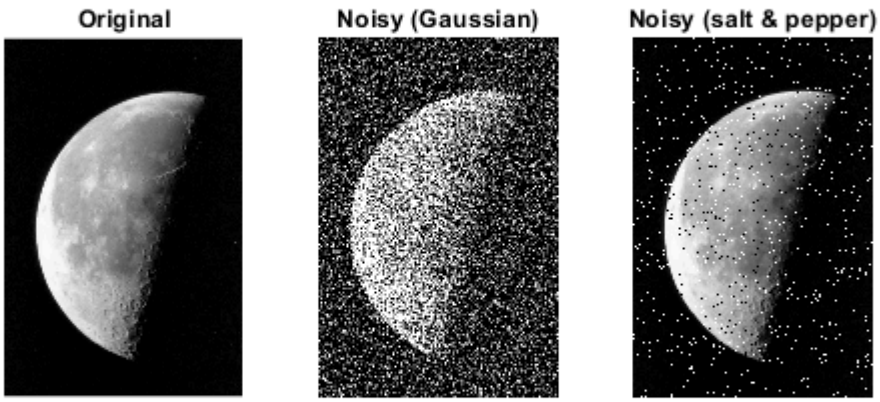
**Suggested steps:**

1. Load test image and add noise.
2. Try out a few noise types, and play with associated parameters.
3. Visualize the image before and after adding noise.

**Example code:**

```
I = imread('moon.tif');
Jg = imnoise(I, 'gaussian', 0, 0.2);    % Add gaussian noise with zero mean and variance=0.2
Jsp = imnoise(I,'salt & pepper');       % Add salt-and-pepper noise
```

```
% Display images
figure('Name','Adding noise to an image');
subplot(1,3,1), imshow(I), title('Original')
subplot(1,3,2), imshow(Jg), title ('Noisy (Gaussian)')
subplot(1,3,3), imshow(Jsp), title ('Noisy (salt & pepper)')
```




## Assess different image quality metrics

*"Image quality can degrade due to distortions during image acquisition and processing. Examples of distortion include noise, blurring, ringing, and compression artifacts.*

*Efforts have been made to create objective measures of quality. For many applications, a valuable quality metric correlates well with the subjective perception of quality by a human observer. Quality metrics can also track unperceived errors as they propagate through an image processing pipeline, and can be used to compare image processing algorithms."*

Check Image Quality Metrics for more details.

**Suggested steps:**

1. Load test image and add noise.
2. Measure the quality of the resulting (noisy) image (and compare with the original, when appropriate).
3. Visualize the image before and after adding noise.

**Example code:**

Mean-squared error (immse)

```
I = imread('moon.tif');
Jg = imnoise(I, 'gaussian');        % Add gaussian noise
Jsp = imnoise(I,'salt & pepper');   % Add salt-and-pepper noise

err1 = immse(Jg, I);
fprintf('\n The mean-squared error between the noisy image and the original image is %0.4f\n',
```

```
 The mean-squared error between the noisy image and the original image is 425.0537
```

Peak Signal-to-noise ratio (psnr)

```
[peaksnr, snr] = psnr(Jg, I);
fprintf('\n The Peak-SNR value is %0.4f', peaksnr);
```

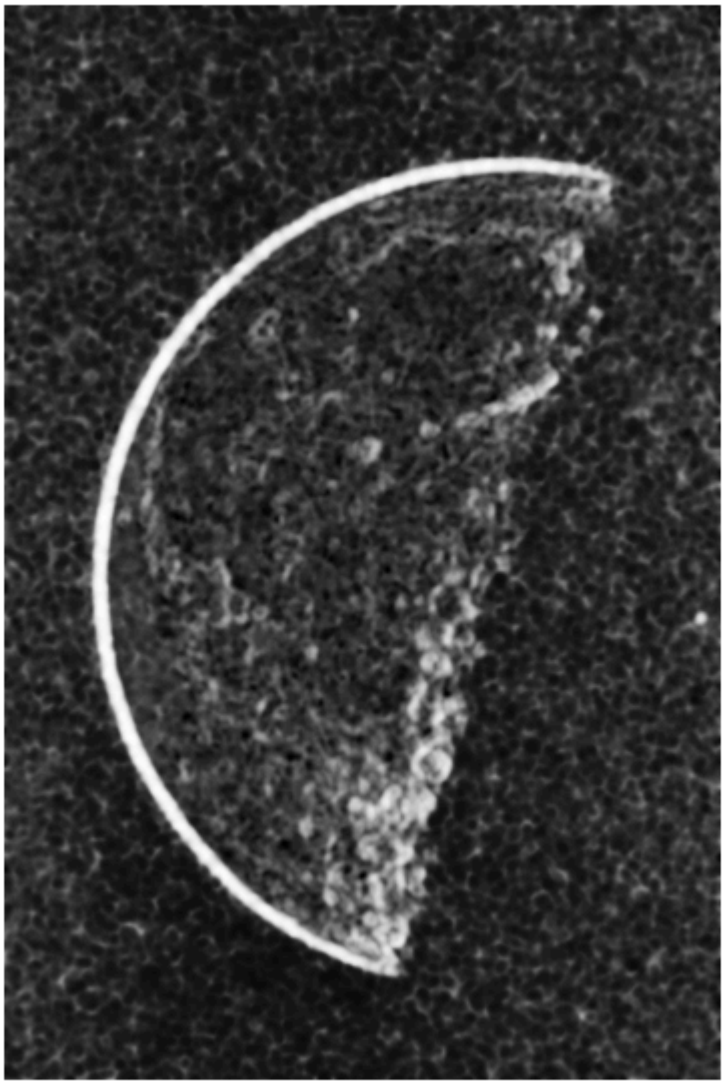
```
 The Peak-SNR value is 21.8464
```

```
fprintf('\n The SNR value is %0.4f \n', snr);
```

```
 The SNR value is 13.2019
```

Structural similarity index (ssim)

```
[ssimval,ssimmap] = ssim(Jg,I);
% figure('Name','Local SSIM Map');
figure
imshow(ssimmap,[])
```



```
% title(['Local SSIM Map with Global SSIM Value: ',num2str(ssimval)])  % Commented out due to f
fprintf('\n The Global SSIM Value is %0.6f \n', ssimval);
```

```
The Global SSIM Value is 0.177362
```

Blind/Referenceless Image Spatial Quality Evaluator (brisque), no-reference image quality score

```
brisqueI = brisque(I);
fprintf('\nBRISQUE score for original image is %0.4f.\n',brisqueI)
```

```
BRISQUE score for original image is 14.0315.
```

```
brisqueJg = brisque(Jg);
fprintf('BRISQUE score for noisy (Gaussian) image is %0.4f.\n',brisqueJg)
```

```
BRISQUE score for noisy (Gaussian) image is 44.3370.
```

```
brisqueJsp = brisque(Jsp);
fprintf('BRISQUE score for noisy (Salt & Pepper) image is %0.4f.\n',brisqueJsp)
```

```
BRISQUE score for noisy (Salt & Pepper) image is 47.5104.
```

Naturalness Image Quality Evaluator (`niqe`), no-reference image quality score

```
niqeI = niqe(I);
fprintf('\nNIQE score for original image is %0.4f.\n',niqeI)
```

```
NIQE score for original image is 2.8985.
```

```
niqeJg = niqe(Jg);
fprintf('NIQE score for noisy (Gaussian) image is %0.4f.\n',niqeJg)
```

```
NIQE score for noisy (Gaussian) image is 17.1320.
```

```
niqeJsp = niqe(Jsp);
fprintf('NIQE score for noisy (Salt & Pepper) image is %0.4f.\n',niqeJsp)
```

```
NIQE score for noisy (Salt & Pepper) image is 20.0177.
```

Perception based Image Quality Evaluator (`piqe`), no-reference image quality score

```
piqeI = piqe(I);
fprintf('\nPIQE score for original image is %0.4f.\n',piqeI)
```

```
PIQE score for original image is 23.1441.
```

```
piqeJg = piqe(Jg);
fprintf('PIQE score for noisy (Gaussian) image is %0.4f.\n',piqeJg)
```

```
PIQE score for noisy (Gaussian) image is 74.9761.
```

```
piqeJsp = piqe(Jsp);
fprintf('PIQE score for noisy (Salt & Pepper) image is %0.4f.\n',piqeJsp)
```

```
PIQE score for noisy (Salt & Pepper) image is 74.3908.
```

**Your turn (step 3 of the guidelines):**

(OPTIONAL) Expand "Part 1" of the starter code to include other test images, noise types (and their parameters) and image quality metrics.

```
% ENTER YOUR CODE HERE
% ...
% ...
```

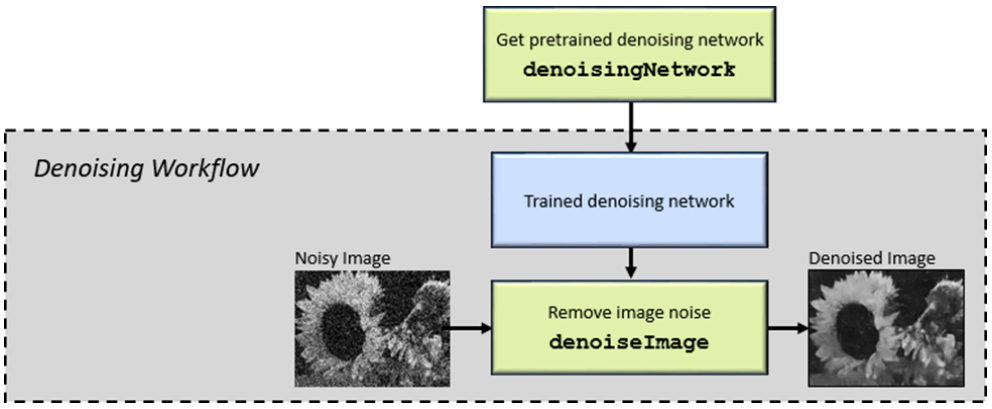
```
% ...
```

Go back to top

## Part 2: Denoising using pretrained deep neural network

There are many ways to remove noise from images. The simplest workflow for removing image noise from an individual image using deep learning is to use a pretrained denoising neural network (`DnCNN`), and is illustrated in the figure below.

Please refer to MATLAB documentation for more details.




**Suggested steps:**

1. Load test image, covert it to appropriate class (if needed) and split it into R, G, and B channels.
2. Load the pretrained DnCNN network.
3. Use the DnCNN network to remove noise from each color channel.
4. Recombine the denoised color channels to form the denoised RGB image.
5. Display the original, noisy, and denoised color image.
6. (OPTIONAL) Explore the details of the denoising convolutional neural network (DnCNN).

**Example code:**

Run this section of the starter code and ensure it works as intended.

```
% Load RGB image
pristineRGB = imread('lighthouse.png');
% Convert to double
pristineRGB = im2double(pristineRGB);
% Add Gaussian noise
noisyRGB = imnoise(pristineRGB,'gaussian',0,0.01);

% Split the noisy RGB image into its individual color channels.
[noisyR,noisyG,noisyB] = imsplit(noisyRGB);

% Load the pretrained DnCNN network
preTrainedDnCNN = denoisingNetwork('dncnn');
```

```
% Use the DnCNN network to remove noise from each color channel
denoisedR = denoiseImage(noisyR,preTrainedDnCNN);
denoisedG = denoiseImage(noisyG,preTrainedDnCNN);
denoisedB = denoiseImage(noisyB,preTrainedDnCNN);

% Recombine the denoised color channels to form the denoised RGB image
denoisedRGB = cat(3,denoisedR,denoisedG,denoisedB);

% Display the original, noisy, and denoised color image
figure('Name','Denoising with pretrained DnCNN');
subplot(1,3,1), imshow(pristineRGB), title('Pristine Image')
subplot(1,3,2), imshow(noisyRGB), title('Noisy Image')
subplot(1,3,3), imshow(denoisedRGB), title('Denoised Image')
```


**Your turn (step 5 of the guidelines):**

Write code to apply the DnCNN-based denoising technique of "Part 2" to at least 2 (two) different test images of your choice, using both Gaussian and salt-and-pepper noise, and compare their results using at least 2 (two) image quality metrics.

Summarize your results in a table (see *Guidelines* for additional information).

```
% Load RGB image
pristineRGB = imread('butterfly.jpg');

pristineRGB1 = imread('image3.jpg');
```

```
% Convert to double
pristineRGB = im2double(pristineRGB);
pristineRGB1 = im2double(pristineRGB1);

% Add Gaussian noise
noisyRGB = imnoise(pristineRGB,'gaussian',0,0.01);
noisyRGB2 = imnoise(pristineRGB1,'gaussian',0,0.01);

% Add Salt and Pepper Noise
noisyRGB1 = imnoise(pristineRGB,'salt & pepper');
noisyRGB3 = imnoise(pristineRGB1,'salt & pepper');

% Split the noisy RGB image into its individual color channels.
[noisyR,noisyG,noisyB] = imsplit(noisyRGB);
[noisyR1,noisyG1,noisyB1] = imsplit(noisyRGB1);
[noisyR2,noisyG2,noisyB2] = imsplit(noisyRGB2);
[noisyR3,noisyG3,noisyB3] = imsplit(noisyRGB3);

% Load the pretrained DnCNN network
preTrainedDnCNN = denoisingNetwork('dncnn');

% Use the DnCNN network to remove noise from each color channel
denoisedR = denoiseImage(noisyR,preTrainedDnCNN);
denoisedG = denoiseImage(noisyG,preTrainedDnCNN);
denoisedB = denoiseImage(noisyB,preTrainedDnCNN);

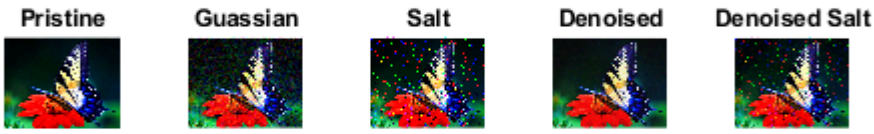
denoisedR1 = denoiseImage(noisyR1,preTrainedDnCNN);
denoisedG1 = denoiseImage(noisyG1,preTrainedDnCNN);
denoisedB1 = denoiseImage(noisyB1,preTrainedDnCNN);

denoisedR2 = denoiseImage(noisyR2,preTrainedDnCNN);
denoisedG2 = denoiseImage(noisyG2,preTrainedDnCNN);
denoisedB2 = denoiseImage(noisyB2,preTrainedDnCNN);

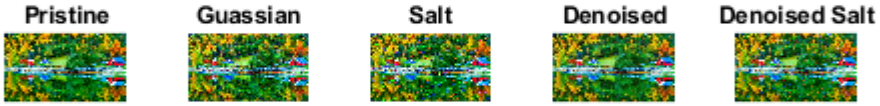
denoisedR3 = denoiseImage(noisyR3,preTrainedDnCNN);
denoisedG3 = denoiseImage(noisyG3,preTrainedDnCNN);
denoisedB3 = denoiseImage(noisyB3,preTrainedDnCNN);

% Recombine the denoised color channels to form the denoised RGB image
denoisedRGB = cat(3,denoisedR,denoisedG,denoisedB);
denoisedRGB1 = cat(3,denoisedR1,denoisedG1,denoisedB1);
denoisedRGB2 = cat(3,denoisedR2,denoisedG2,denoisedB2);
denoisedRGB3 = cat(3,denoisedR3,denoisedG3,denoisedB3);

% Display the original, noisy, and denoised color image
figure('Name','Denoising with pretrained DnCNN');
subplot(1,5,1), imshow(pristineRGB), title('Pristine')
subplot(1,5,2), imshow(noisyRGB), title('Guassian')
subplot(1,5,3), imshow(noisyRGB1), title('Salt')
subplot(1,5,4), imshow(denoisedRGB), title('Denoised')
subplot(1,5,5), imshow(denoisedRGB1), title('Denoised Salt')
```




```
figure('Name','Denoising with pretrained DnCNN');
subplot(1,5,1), imshow(pristineRGB1), title('Pristine')
subplot(1,5,2), imshow(noisyRGB2), title('Guassian')
subplot(1,5,3), imshow(noisyRGB3), title('Salt')
subplot(1,5,4), imshow(denoisedRGB2), title('Denoised')
subplot(1,5,5), imshow(denoisedRGB3), title('Denoised Salt')
```




Naturalness Image Quality Evaluator (niqe), no-reference image quality score

Perception based Image Quality Evaluator (piqe), no-reference image quality score

```
niqepristineRGB = niqe(pristineRGB);
fprintf('\nNIQE score for butterfly image is %0.4f.\n',niqepristineRGB)
```

```
NIQE score for butterfly image is 3.5445.
```

```
niqepristineRGB1 = niqe(pristineRGB1);
fprintf('\nNIQE score for image2 is %0.4f.\n',niqepristineRGB1)
```

```
NIQE score for image2 is 3.3652.
```

```
niqeNoisy = niqe(noisyRGB);
fprintf('NIQE score for noisy (Gaussian) image is %0.4f.\n',niqeNoisy)
```

```
NIQE score for noisy (Gaussian) image is 11.7428.
```

```
niqeDenoise = niqe(denoisedRGB);
fprintf('\nNIQE score for denoise (Gaussian) image is %0.4f.\n',niqeDenoise)
```

```
NIQE score for denoise (Gaussian) image is 2.6999.
```

```
niqeNoisy1 = niqe(noisyRGB2);
fprintf('NIQE score for noisy (Gaussian) image2 is %0.4f.\n',niqeNoisy1)
```

```
NIQE score for noisy (Gaussian) image2 is 8.6800.
```

```
niqeDenoise1 = niqe(denoisedRGB2);
fprintf('\nNIQE score for denoise (Gaussian) image2 is %0.4f.\n',niqeDenoise1)
```

```
NIQE score for denoise (Gaussian) image2 is 2.8166.
```

```
niqeNoisySalt = niqe(noisyRGB1);
fprintf('NIQE score for noisy (Salt & Pepper) image is %0.4f.\n',niqeNoisySalt)
```

```
NIQE score for noisy (Salt & Pepper) image is 15.5197.
```

```
niqeDenoise2 = niqe(denoisedRGB1);
fprintf('\nNIQE score for denoise (Salt & Pepper) image is %0.4f.\n',niqeDenoise2)
```

```
NIQE score for denoise (Salt & Pepper) image is 14.3426.
```

```
niqeNoisySalt1 = niqe(noisyRGB3);
fprintf('NIQE score for noisy (Salt & Pepper) image2 is %0.4f.\n',niqeNoisySalt1)
```

```
NIQE score for noisy (Salt & Pepper) image2 is 13.0992.
```

```
niqeDenoise3 = niqe(denoisedRGB3);
fprintf('\nNIQE score for denoise (Salt & Pepper) image2 is %0.4f.\n',niqeDenoise3)
```

```
NIQE score for denoise (Salt & Pepper) image2 is 8.5554.
```

```
piqepristineRGB = piqe(pristineRGB);
fprintf('\nPIQE score for butterfly image is %0.4f.\n',piqepristineRGB)
```

```
PIQE score for butterfly image is 57.0828.
```

```
piqepristineRGB1 = piqe(pristineRGB1);
fprintf('\nPIQE score for image2 is %0.4f.\n',piqepristineRGB1)
```

```
PIQE score for image2 is 31.0903.
```

```
piqeNoisy = piqe(noisyRGB);
fprintf('PIQE score for noisy (Gaussian) image is %0.4f.\n',piqeNoisy)
```

```
PIQE score for noisy (Gaussian) image is 62.8424.
```

```
piqeDenoise = piqe(denoisedRGB);
fprintf('PIQE score for denoise (Gaussian) image is %0.4f.\n',piqeDenoise)
```

```
PIQE score for denoise (Gaussian) image is 23.7481.
```

```
piqeNoisy1 = piqe(noisyRGB2);
fprintf('PIQE score for noisy (Gaussian) image2 is %0.4f.\n',piqeNoisy1)
```

```
PIQE score for noisy (Gaussian) image2 is 56.5658.
```

```
piqeDenoise1 = piqe(denoisedRGB2);
```

```
fprintf('PIQE score for denoise (Gaussian) image2 is %0.4f.\n',piqeDenoise1)
```

```
PIQE score for denoise (Gaussian) image2 is 25.3076.
```

```
piqeSalt = piqe(noisyRGB1);
fprintf('PIQE score for noisy (Salt & Pepper) image is %0.4f.\n',piqeSalt)
```

```
PIQE score for noisy (Salt & Pepper) image is 72.5612.
```

```
piqeDenoise2 = piqe(denoisedRGB1);
fprintf('PIQE score for denoise (Salt & Pepper) image is %0.4f.\n',piqeDenoise2)
```

```
PIQE score for denoise (Salt & Pepper) image is 57.6712.
```

```
piqeSalt1 = piqe(noisyRGB3);
fprintf('PIQE score for noisy (Salt & Pepper) image2 is %0.4f.\n',piqeSalt1)
```

```
PIQE score for noisy (Salt & Pepper) image2 is 54.9405.
```

```
piqeDenoise3 = piqe(denoisedRGB3);
fprintf('PIQE score for denoise (Salt & Pepper) image2 is %0.4f.\n',piqeDenoise3)
```

```
PIQE score for denoise (Salt & Pepper) image2 is 40.8884.
```

**Question 6 Table:**

| Image | PIQE (original) | PIQE (Gaussian) | PIQE (Salt) | PIQE (Denoised Gaussian) | PIQE (Denoised Salt) | NIQE (original) | NIQE (Gaussian) | NIQE (Salt) | NIQE (Denoised Gaussian) | NIQE (Denoise Salt) |
|---|---|---|---|---|---|---|---|---|---|---|
| Butterfly.jpg | 57.08 | 62.84 | 72.56 | 23.74 | 57.67 | 3.54 | 11.74 | 15.52 | 2.69 | 14.34 |
| Image2.jpg | 31.09 | 56.57 | 54.94 | 25.30 | 40.89 | 3.37 | 8.68 | 13.09 | 2.82 | 8.55 |

**Your turn (step 7 of the guidelines):**

(OPTIONAL) Add code to inspect/analyze the selected pretrained neural network in more detail.

```
% ENTER YOUR CODE HERE
% ...
```

Go back to top

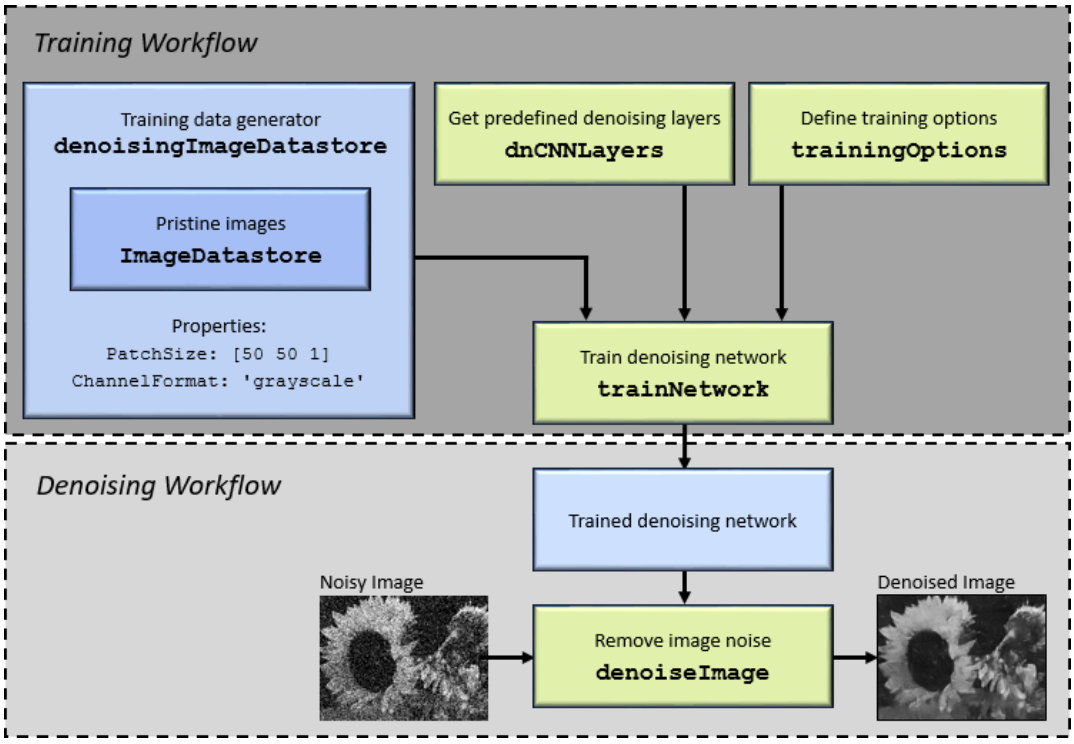
**Question 8:**

1. The deep learning based noise reduction technique performed okay according to the image quality metrics. The unusual thing I noticed was: for the salt and pepper noise reduction, some of the noise didn't go away.
2. I noticed the quality of the Guassian denoise is way better than the Salt denoise. With the salt noise, the image is still noisy, whereas there is less noise in the Guassian (making the image clearer). I think this is because the noise is larger in the salt and pepper noise and not in the Gaussian noise.
3. For someone who is new to this topic and wants to use deep learning to reduce noise in an image, I would tell them to go with the simpler and easier option. The reason for this is because sometimes simpler is better and it can be easy to spend hours on this code understanding it even for the simpler version. Going the harder route can take a really long time and be frustrating when there are already built in functions to reduce noise or add noise.

## Part 3 (OPTIONAL): Training your own denoising network

In this part, we will move to a more comprehensive workflow, where you will train your denoising network from scratch before using it, as illustrated in the figure below.

Please refer to MATLAB documentation for more details.




**Note: this is a very time-consuming operation that can only be successfully completed if you have powerful GPUs.**

**You can skip it entirely and it will not affect your grade.**

**If you decide to give it a try, you'll have to uncomment all code blocks within this part.**

**Suggested steps:**

1. Create an `imageDatastore` object that stores pristine images.
2. Create a `denoisingImageDatastore` object.
3. Get the predefined denoising layers using the `dnCNNLayers` function.
4. Define training options.
5. Train the network.
6. Test and compare with the network in Part 2.

**Step 1:** Create an `imageDatastore` object that stores pristine images. We will use 984 color images of flowers (tulips), of size `224x224` pixels.

```
% imds2 = imageDatastore(fullfile('tulip'),...
% 'IncludeSubfolders',true,'FileExtensions','.jpg','LabelSource','foldernames');
```

**Step 2**: Create a `denoisingImageDatastore` object

`denoisingImageDatastore(imds)` creates a denoising image datastore, `dnimds` using images from image datastore `imds`. To generate noisy image patches, the denoising image datastore randomly crops pristine images from `imds` then adds zero-mean Gaussian white noise with a standard deviation of `0.1` to the image patches.

```
% dnimds2 = denoisingImageDatastore(imds2,'PatchSize', 50, 'ChannelFormat', 'grayscale');
```

**Step 3:** Get the predefined denoising layers using the `dnCNNLayers` function

```
% layers2 = dnCNNLayers;
```

**Step 4:** Define training options

```
% options = trainingOptions('adam', ...
%     'InitialLearnRate',0.1, ...
%     'LearnRateSchedule',"none", ...
%     'MiniBatchSize',256, ...
%     'MaxEpochs',2, ...
%     'Plots','training-progress', ...
%     'Verbose',false);
```

**Step 5:** Train the network

```
% dnCNN2 = trainNetwork(dnimds2,layers2,options);
```

**Step 6**: Test and compare with the network in Part 2.

```
% % Load RGB image
% pristineRGB = imread('lighthouse.png');
% % Convert to double
% pristineRGB = im2double(pristineRGB);
% % Add Gaussian noise
% noisyRGB = imnoise(pristineRGB,'gaussian',0,0.01);
%
% % Split the noisy RGB image into its individual color channels.
% [noisyR,noisyG,noisyB] = imsplit(noisyRGB);
%
% % Use the DnCNN2 network to remove noise from each color channel
% denoisedR2 = denoiseImage(noisyR,dnCNN2);
% denoisedG2 = denoiseImage(noisyG,dnCNN2);
% denoisedB2 = denoiseImage(noisyB,dnCNN2);
%
% % Recombine the denoised color channels to form the denoised RGB image
% denoisedRGB2 = cat(3,denoisedR2,denoisedG2,denoisedB2);
%
% % Display the original, noisy, and denoised color image
% figure('Name','Denoising with DnCNN trained from scratch');
% subplot(1,3,1), imshow(pristineRGB), title('Pristine Image')
% subplot(1,3,2), imshow(noisyRGB), title('Noisy Image')
% subplot(1,3,3), imshow(denoisedRGB2), title('Denoised Image')
```

**Your turn (step 10 of the guidelines):**

Write code to apply the DnCNN-based denoising technique of "Part 3" to at least 2 (two) different test images of your choice, using both Gaussian and salt-and-pepper noise, and compare their results using at least 2 (two) image quality metrics.

Summarize your results in a table (see *Guidelines* for additional information).

```
% ENTER YOUR CODE HERE
% ...
% ...
% ...
```

Go back to top

## Part 4: Denoising using autoencoders

In this part, we will use a convolutional autoencoder architecture for denoising and apply it to images from a built-in dataset containing handwritten digits (similar to MNIST).

Please refer to MATLAB documentation for more details.

**Suggested steps:**

1. Load test images and add noise.

2. Prepare the data for network training, validation, and testing.
3. Visualize the images before and after adding noise.
4. Define a convolutional autoencoder network.
5. Train the network.
6. (Visually) evaluate the results.
7. Measure the quality of the resulting (denoised) image (and compare with the original).

**Example code:**

Based on (and adapted from): https://www.mathworks.com/help/deeplearning/ug/image-to-image-regression-using-deep-learning.html

Notes:

- The datastore contains 10,000 synthetic images of digits from 0 to 9.
- The images are generated by applying random transformations to digit images created with different fonts.
- Each digit image is 28-by-28 pixels.
- The datastore contains an equal number of images per category.

**Build `imds`**

```
digitDatasetPath = fullfile(matlabroot,'toolbox','nnet', ...
    'nndemos','nndatasets','DigitDataset');
imds = imageDatastore(digitDatasetPath, ...
    'IncludeSubfolders',true, ...
    'LabelSource','foldernames');

imds.ReadSize = 500;
rng(0)
imds = shuffle(imds);
```

**Split `imds` into three image datastores containing pristine images for training, validation, and testing**

```
[imdsTrain,imdsVal,imdsTest] = splitEachLabel(imds,0.95,0.025);
```

**Create noisy versions of each input image** using the helper function `addNoise` (see https://www.mathworks.com/help/deeplearning/ug/image-to-image-regression-using-deep-learning.html)

```
dsTrainNoisy = transform(imdsTrain,@addNoise);
dsValNoisy = transform(imdsVal,@addNoise);
dsTestNoisy = transform(imdsTest,@addNoise);
```

**Combine the noisy images and pristine images into a single datastore that feeds data to `trainNetwork`**

This combined datastore reads batches of data into a two-column cell array as expected by `trainNetwork`.

```
dsTrain = combine(dsTrainNoisy,imdsTrain);
dsVal = combine(dsValNoisy,imdsVal);
dsTest = combine(dsTestNoisy,imdsTest);
```

### Perform additional preprocessing operations that are common to both the input and response datastores

The `commonPreprocessing` helper function (see https://www.mathworks.com/help/deeplearning/ug/image-to-image-regression-using-deep-learning.html) resizes input and response images to 32-by-32 pixels to match the input size of the network, and normalizes the data in each image to the range [0, 1].

```
dsTrain = transform(dsTrain,@commonPreprocessing);
dsVal = transform(dsVal,@commonPreprocessing);
dsTest = transform(dsTest,@commonPreprocessing);
```

### Perform image data augmentation

The `augmentImages` helper function (see https://www.mathworks.com/help/deeplearning/ug/image-to-image-regression-using-deep-learning.html) applies randomized 90 degree rotations to the data. Identical rotations are applied to the network input and corresponding expected responses.

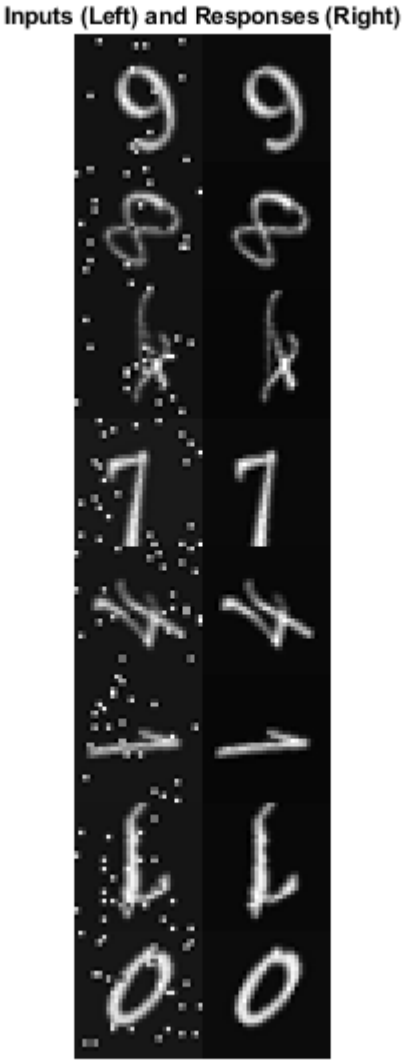
```
dsTrain = transform(dsTrain,@augmentImages);
```

### Preview preprocessed data

The code below shows examples of paired noisy and pristine images using the `montage` function.

The training data looks correct. Salt and pepper noise appears in the input images in the left column. Randomized 90 degree rotation is applied to both input and response images in the same way.

```
exampleData = preview(dsTrain);
inputs = exampleData(:,1);
responses = exampleData(:,2);
minibatch = cat(2,inputs,responses);
figure
montage(minibatch','Size',[8 2])
title('Inputs (Left) and Responses (Right)')
```




**Define convolutional autoencoder network**

See https://www.mathworks.com/help/deeplearning/ug/image-to-image-regression-using-deep-learning.html for details.

```
imageLayer = imageInputLayer([32,32,1]);

encodingLayers = [ ...
    convolution2dLayer(3,16,'Padding','same'), ...
    reluLayer, ...
    maxPooling2dLayer(2,'Padding','same','Stride',2), ...
    convolution2dLayer(3,8,'Padding','same'), ...
    reluLayer, ...
    maxPooling2dLayer(2,'Padding','same','Stride',2), ...
    convolution2dLayer(3,8,'Padding','same'), ...
    reluLayer, ...
```

```
    maxPooling2dLayer(2,'Padding','same','Stride',2)];

decodingLayers = [ ...
    createUpsampleTransponseConvLayer(2,8), ...
    reluLayer, ...
    createUpsampleTransponseConvLayer(2,8), ...
    reluLayer, ...
    createUpsampleTransponseConvLayer(2,16), ...
    reluLayer, ...
    convolution2dLayer(3,1,'Padding','same'), ...
    clippedReluLayer(1.0), ...
    regressionLayer];

layers = [imageLayer,encodingLayers,decodingLayers];
```

**Define training options**

```
options = trainingOptions('adam', ...
    'MaxEpochs',30, ...
    'MiniBatchSize',imds.ReadSize, ...
    'ValidationData',dsVal, ...
    'Shuffle','never', ...
    'Plots','training-progress', ...
    'Verbose',false);
```

**Train the network**

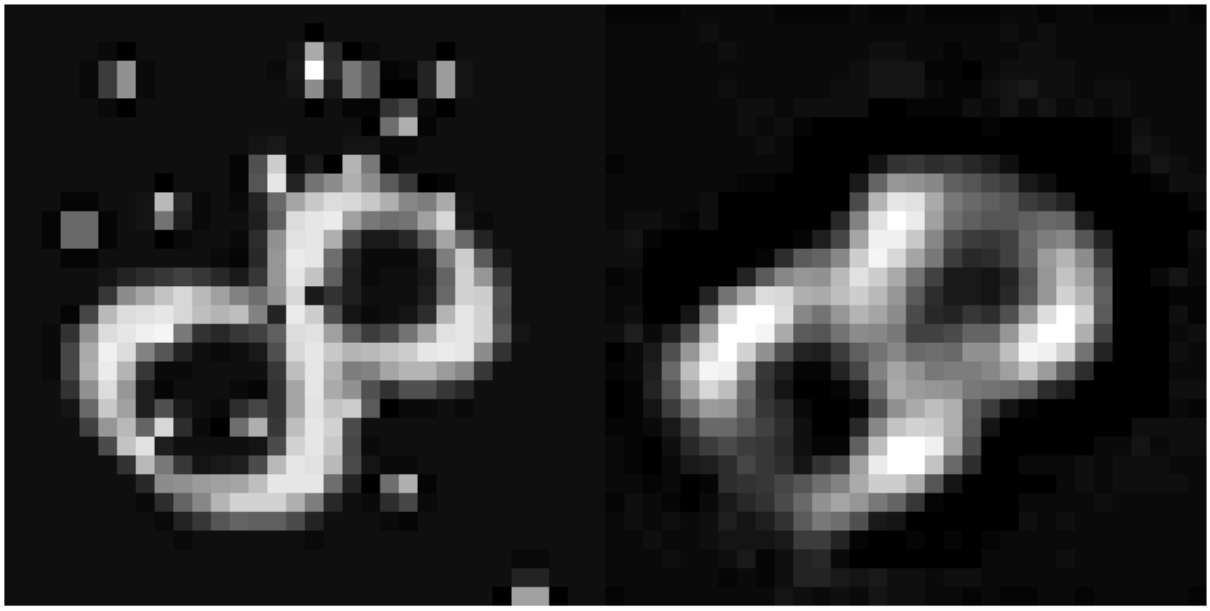
```
autoEncoder = trainNetwork(dsTrain,layers,options);
```

**Evaluate the performance of the network on the test set**

```
ypred = predict(autoEncoder,dsTest);
```

**Perform visual inspection of selected results**

```
inputImageExamples = preview(dsTest);
figure
montage({inputImageExamples{1},ypred(:,:,:,1)});
```



### Calculate PSNR

```
ref = inputImageExamples{1,2};
originalNoisyImage = inputImageExamples{1,1};
psnrNoisy = psnr(originalNoisyImage,ref);
psnrDenoised = psnr(ypred(:,:,:,1),ref);

fprintf('\nThe PSNR of the noisy image is %.4f', psnrNoisy);
```

```
The PSNR of the noisy image is 19.2094
```

```
fprintf('\nThe PSNR of the denoised image is %.4f\n', psnrDenoised);
```

```
The PSNR of the denoised image is 17.8918
```

### Calculate PIQE

```
piqeNoisy = piqe(originalNoisyImage);
piqeDenoised = piqe(ypred(:,:,:,1));

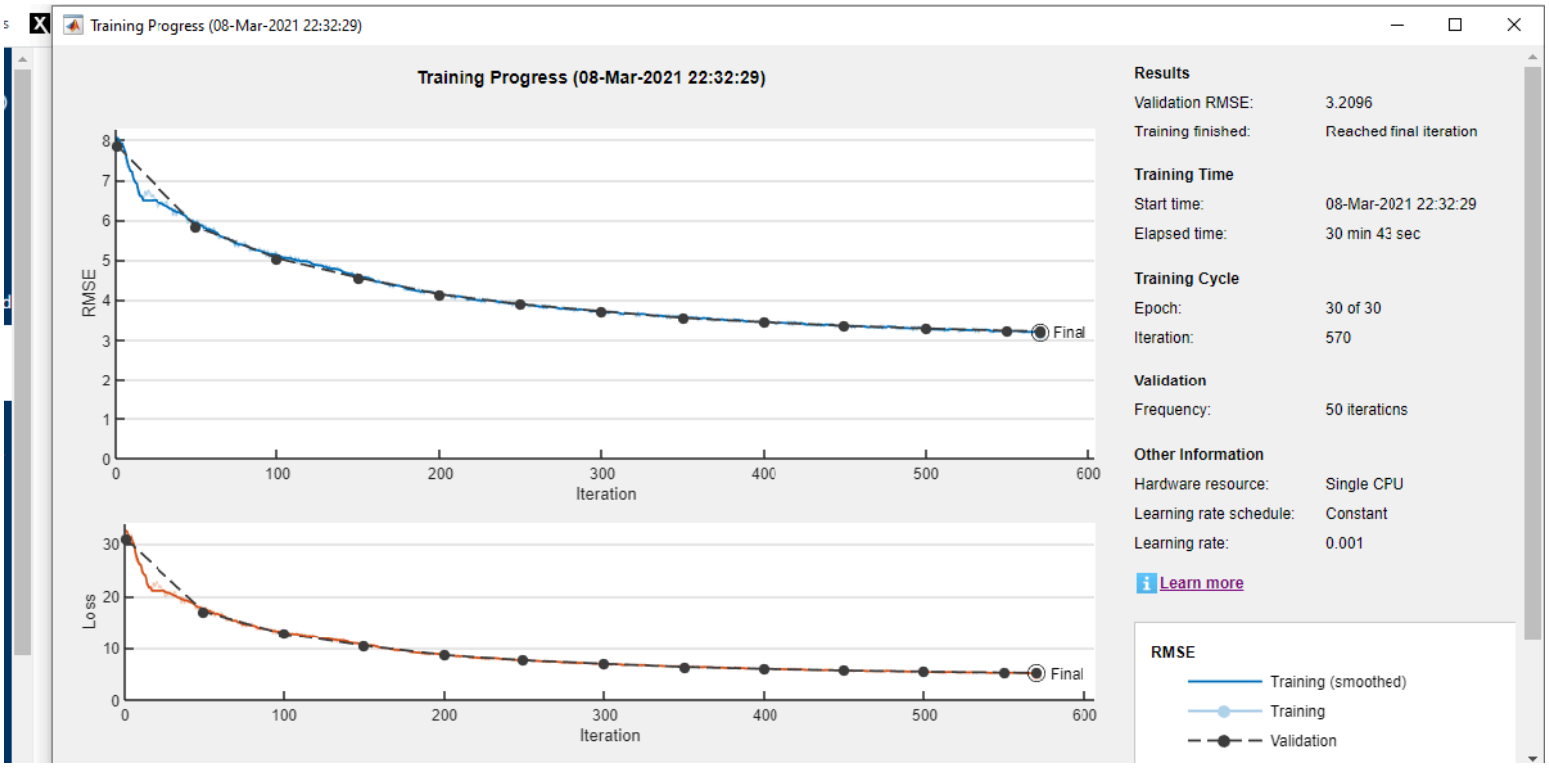
fprintf('\nThe PIQE of the noisy image is %.4f', piqeNoisy);
```

```
The PIQE of the noisy image is 82.1434
```

```
fprintf('\nThe PIQE of the denoised image is %.4f\n', piqeDenoised);
```

```
The PIQE of the denoised image is 20.0000
```

**GRAPH:**




**Question 4:**

I would say the choice of hyperparameters is appropriate. I think so because the number of epochs (30) is a good number as it is not too many to overwhelm the network but also not too little that the network won't learn. The learning rate was .001 so the network was able to learn at a slower rate which allows it to take its time to learn and not make as many mistakes.

**Question 5:**

The network is not overfitting because in an overfitted network, the line plots of the loss training will drop and the validation will drop at first and then begin to rise. This is not the case in this network as the validation line does not rise. The lines also match up very precisely.

**Question 6:**

I would say autoencoders work well for denoising because they copy their input to their output. The autoencoders encode the input by compressing the data and then decodes the output.

**Question 7:**

I noticed the quality of the Guassian denoise is way better than the Salt denoise. With the salt noise, the image is still noisy, whereas there is less noise in the Guassian (making the image clearer). I think this is because the noise is larger in the salt and pepper noise and not in the Gaussian noise.

**Your turn (step 16 of the guidelines):**

(OPTIONAL) Write code to compute other figures of merit for selected images.

```
% ENTER YOUR CODE HERE
% ...
% ...
```

Go back to top

```
% Helper functions
```

```
function dataOut = addNoise(data)
    dataOut = data;
    for idx = 1:size(data,1)
       dataOut{idx} = imnoise(data{idx},'salt & pepper');
    end
end

function dataOut = commonPreprocessing(data)
    dataOut = cell(size(data));
    for col = 1:size(data,2)
        for idx = 1:size(data,1)
            temp = single(data{idx,col});
            temp = imresize(temp,[32,32]);
            temp = rescale(temp);
            dataOut{idx,col} = temp;
        end
    end
end

function dataOut = augmentImages(data)
    dataOut = cell(size(data));
    for idx = 1:size(data,1)
        rot90Val = randi(4,1,1)-1;
        dataOut(idx,:) = {rot90(data{idx,1},rot90Val),rot90(data{idx,2},rot90Val)};
    end
end

function out = createUpsampleTransponseConvLayer(factor,numFilters)
    filterSize = 2*factor - mod(factor,2);
    cropping = (factor-mod(factor,2))/2;
    numChannels = 1;

    out = transposedConv2dLayer(filterSize,numFilters, ...
        'NumChannels',numChannels,'Stride',factor,'Cropping',cropping);
```

```
end
```