



SINGLE IMAGE SUPER RESOLUTION USING SRCNN

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Roll no. : 25MA60R06**

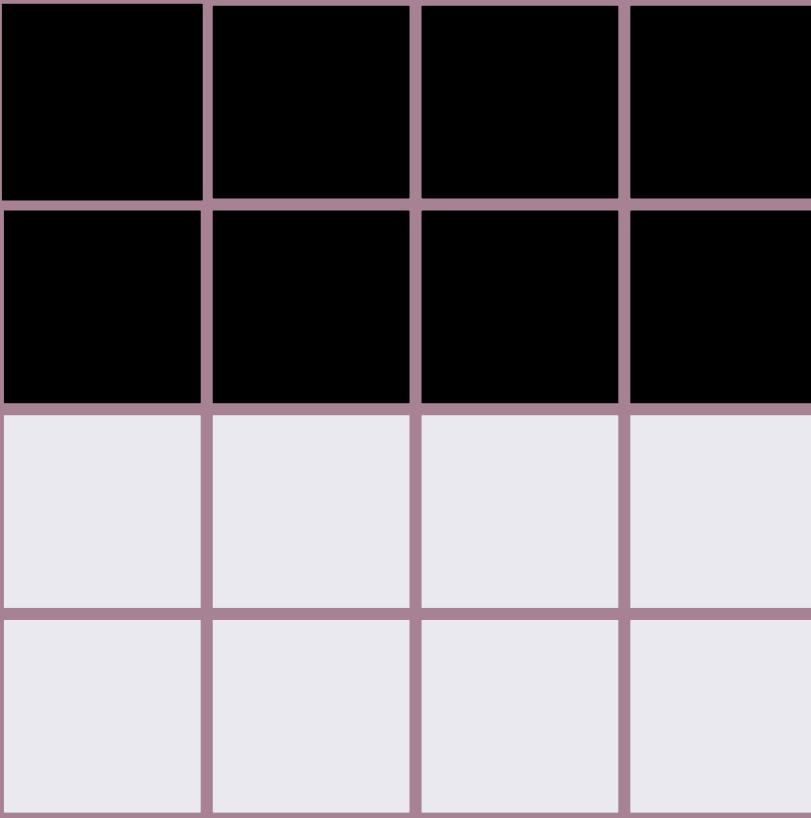
IIT Kharagpur | 2025

OVERVIEW

- What is Image?
- Super Resolution
- SRCNN Overview
- Convolution Operation
- Padding
- SRCNN Architecture
- Image Processing
- Evaluation Metric
- Results
- Conclusion

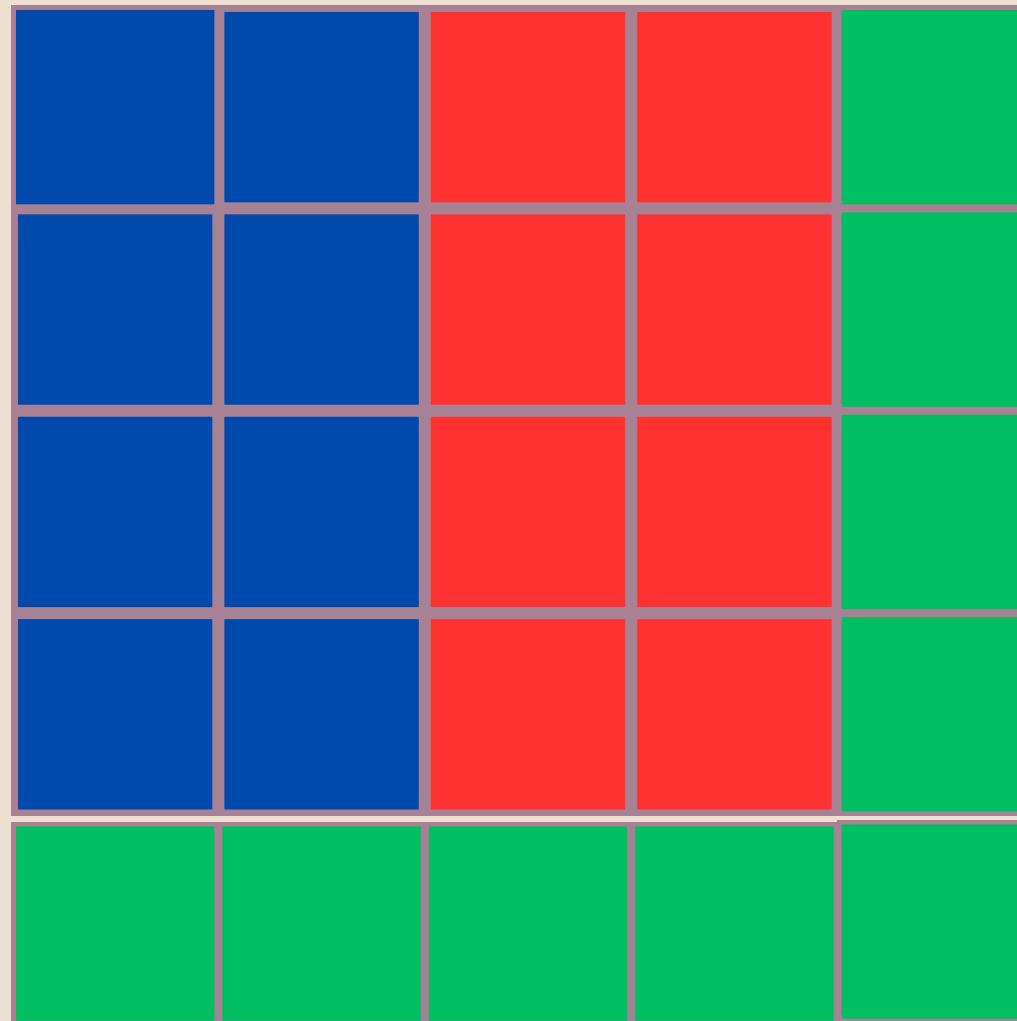
What is Image ?

- An image is a 2D representation of visual information.
- It is made up of tiny square elements called pixels.
- Each pixel stores a value representing brightness or color.



0.0	0.0	0.0	0.0
0.0	0.0	0.0	0.0
255	255	255	255
255	255	255	255

What is Image ?



5x5



RGB Channel

0.0	0.0	255	255	0.0
0.0	0.0	255	255	0.0
0.0	0.0	255	255	0.0
0.0	0.0	255	255	0.0
0.0	0.0	0.0	0.0	0.0

5x5x3

0.0	0.0	0.0	0.0	255
0.0	0.0	0.0	0.0	255
0.0	0.0	0.0	0.0	255
0.0	0.0	0.0	0.0	255
255	255	255	255	255

255	255	0.0	0.0	0.0
255	255	0.0	0.0	0.0
255	255	0.0	0.0	0.0
255	255	0.0	0.0	0.0
0.0	0.0	0.0	0.0	0.0

What is Super Resolution ?

- Enhancing the Resolution of an Imaging System



a measure of amount of details in an image



LR



HR

Application

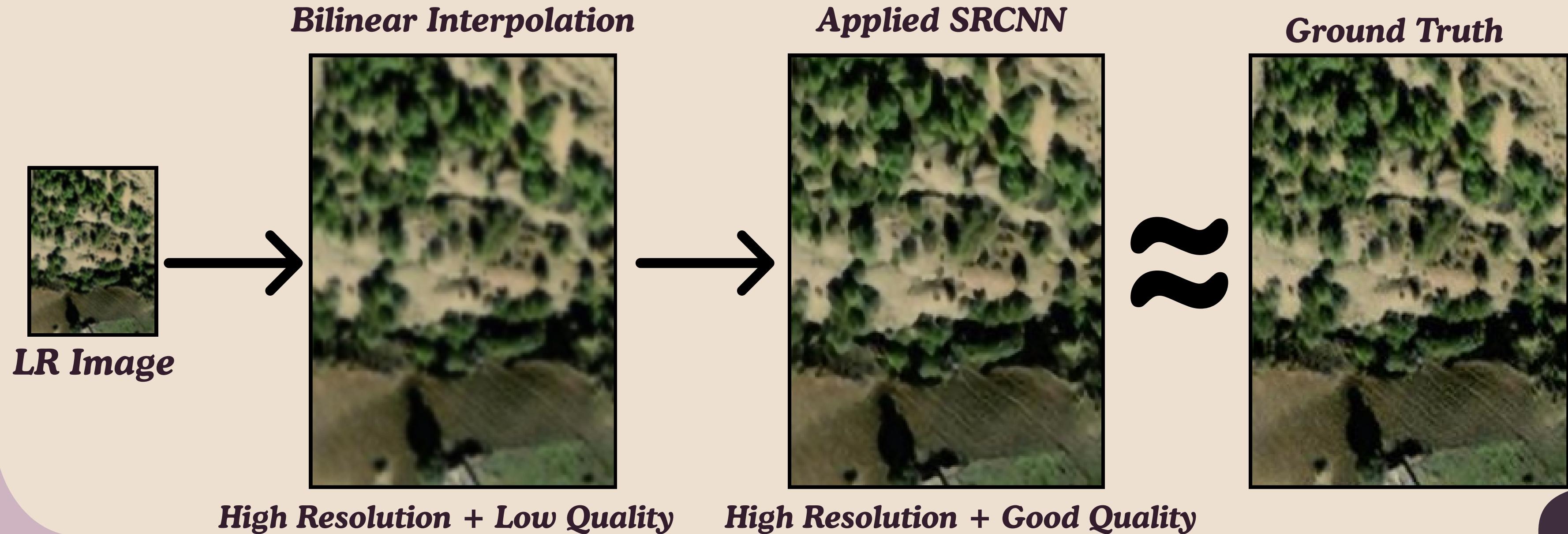
- Satellite Imaging
- Medical imaging
- Surveillance
- Old Image Restoration

Some Mathematical Methods for Super Resolution ?



- *Nearest Neighbor*
- *Bilinear Interpolation*
- *Bicubic Interpolation*

Super Resolution Convolutional Neural Network (SRCNN)



Convolution Operation

0.0	0.0	0.0	0.0	0.0	0.0
0.0	0.0	0.0	0.0	0.0	0.0
0.0	0.0	0.0	0.0	0.0	0.0
255	255	255	255	255	255
255	255	255	255	255	255
255	255	255	255	255	255

6 X 6

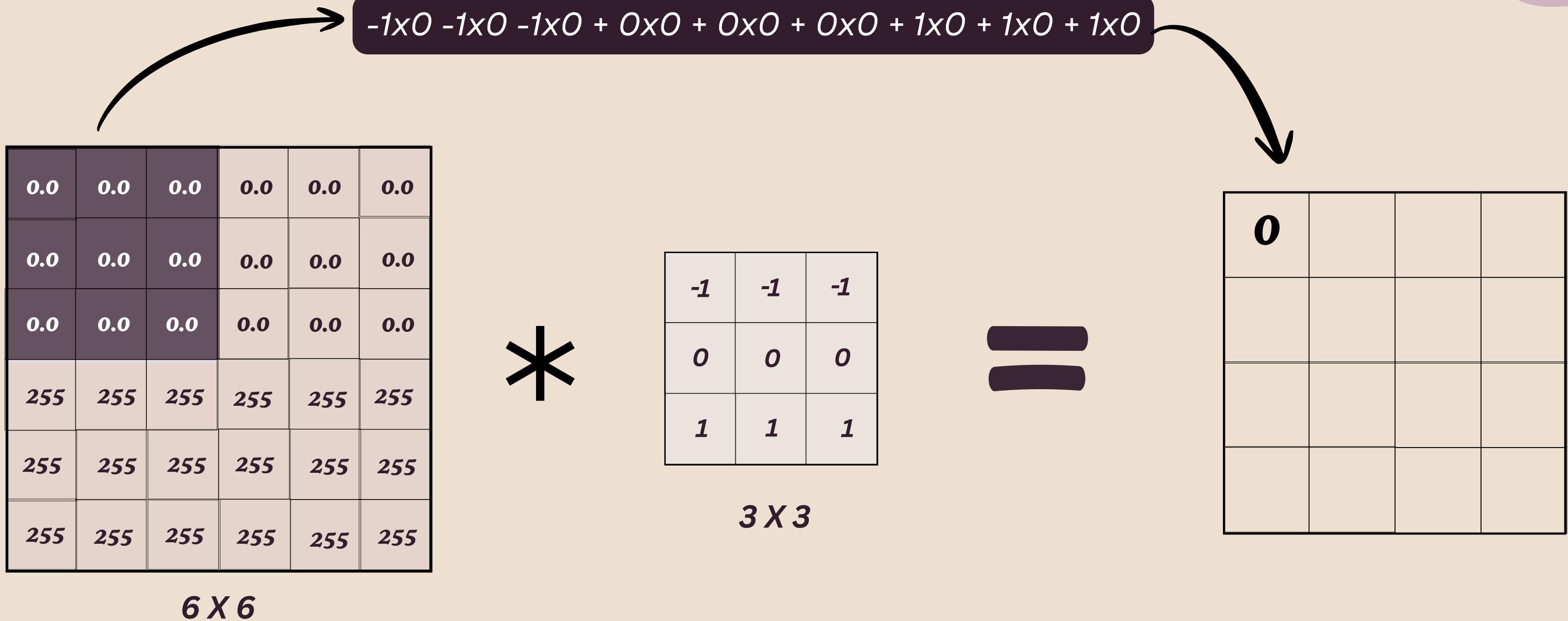


-1	-1	-1
0	0	0
1	1	1

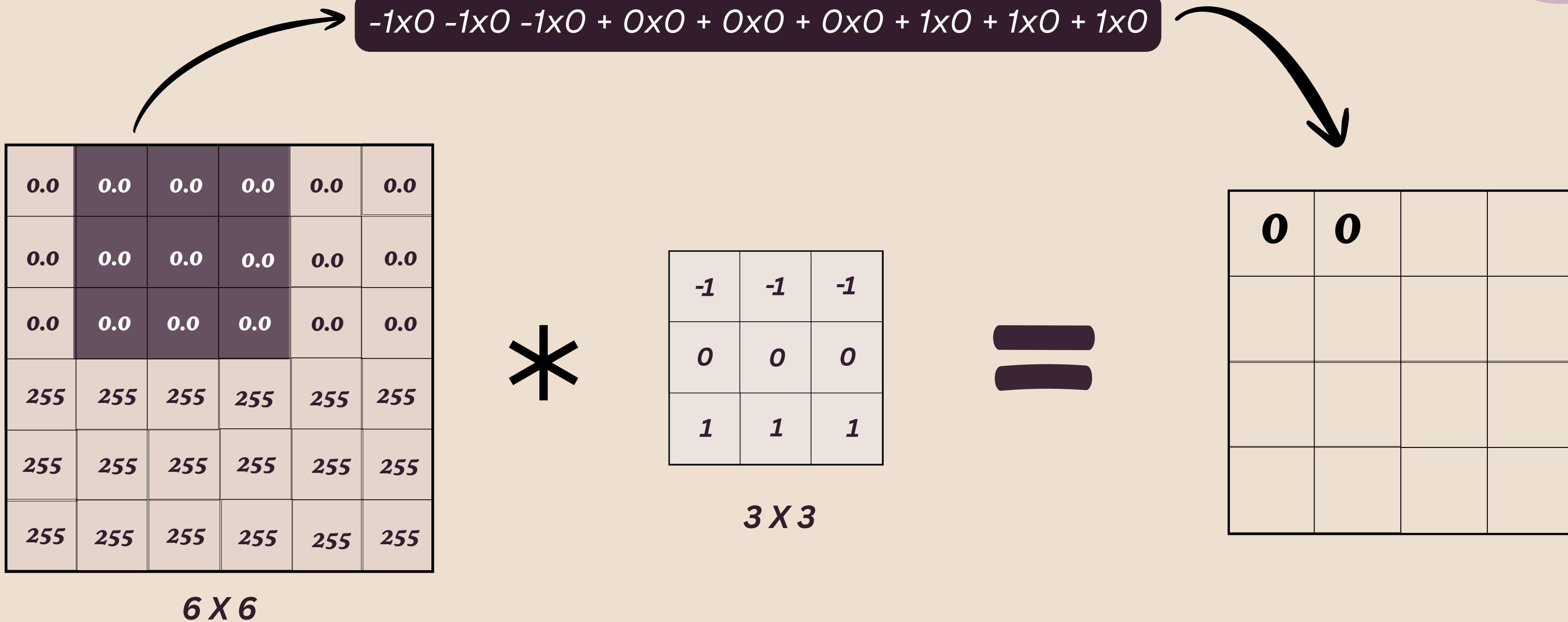
3 X 3



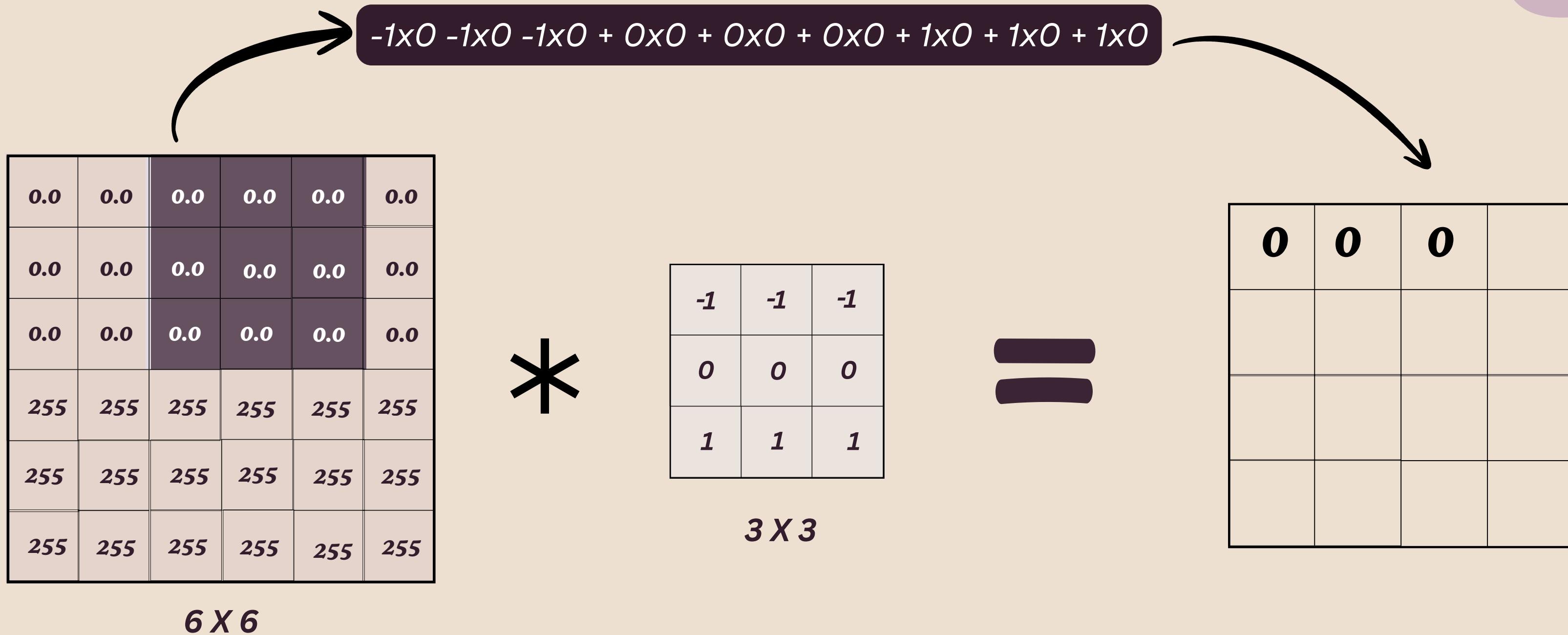
Convolution Operation



Convolution Operation



Convolution Operation



Convolution Operation

0.0	0.0	0.0	0.0	0.0	0.0
0.0	0.0	0.0	0.0	0.0	0.0
0.0	0.0	0.0	0.0	0.0	0.0
255	255	255	255	255	255
255	255	255	255	255	255
255	255	255	255	255	255

6 X 6

-1x0 -1x0 -1x0 + 0x0 + 0x0 + 0x0 + 1x0 + 1x0 + 1x0

*

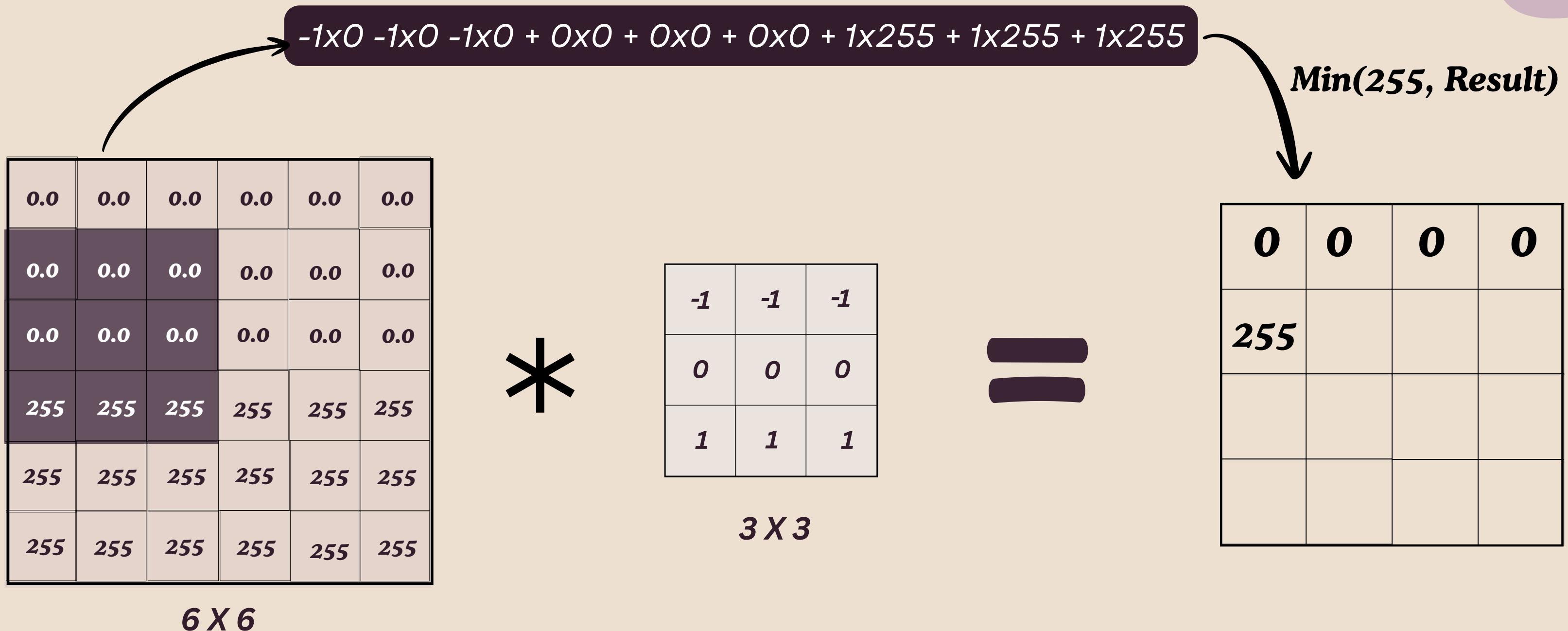
-1	-1	-1
0	0	0
1	1	1

3 X 3

=

0	0	0	0

Convolution Operation



Convolution Operation

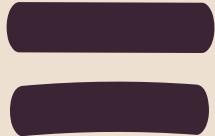
0.0	0.0	0.0	0.0	0.0	0.0
0.0	0.0	0.0	0.0	0.0	0.0
0.0	0.0	0.0	0.0	0.0	0.0
255	255	255	255	255	255
255	255	255	255	255	255
255	255	255	255	255	255

6 X 6



-1	-1	-1
0	0	0
1	1	1

3 X 3



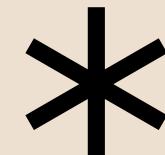
0	0	0	0
255	255	255	255
255	255	255	255
0	0	0	0

Convolution Operation

Image

0.0	0.0	0.0	0.0	0.0	0.0
0.0	0.0	0.0	0.0	0.0	0.0
0.0	0.0	0.0	0.0	0.0	0.0
255	255	255	255	255	255
255	255	255	255	255	255
255	255	255	255	255	255

6 X 6



Filter

-1	-1	-1
0	0	0
1	1	1

3 X 3



Feature Map

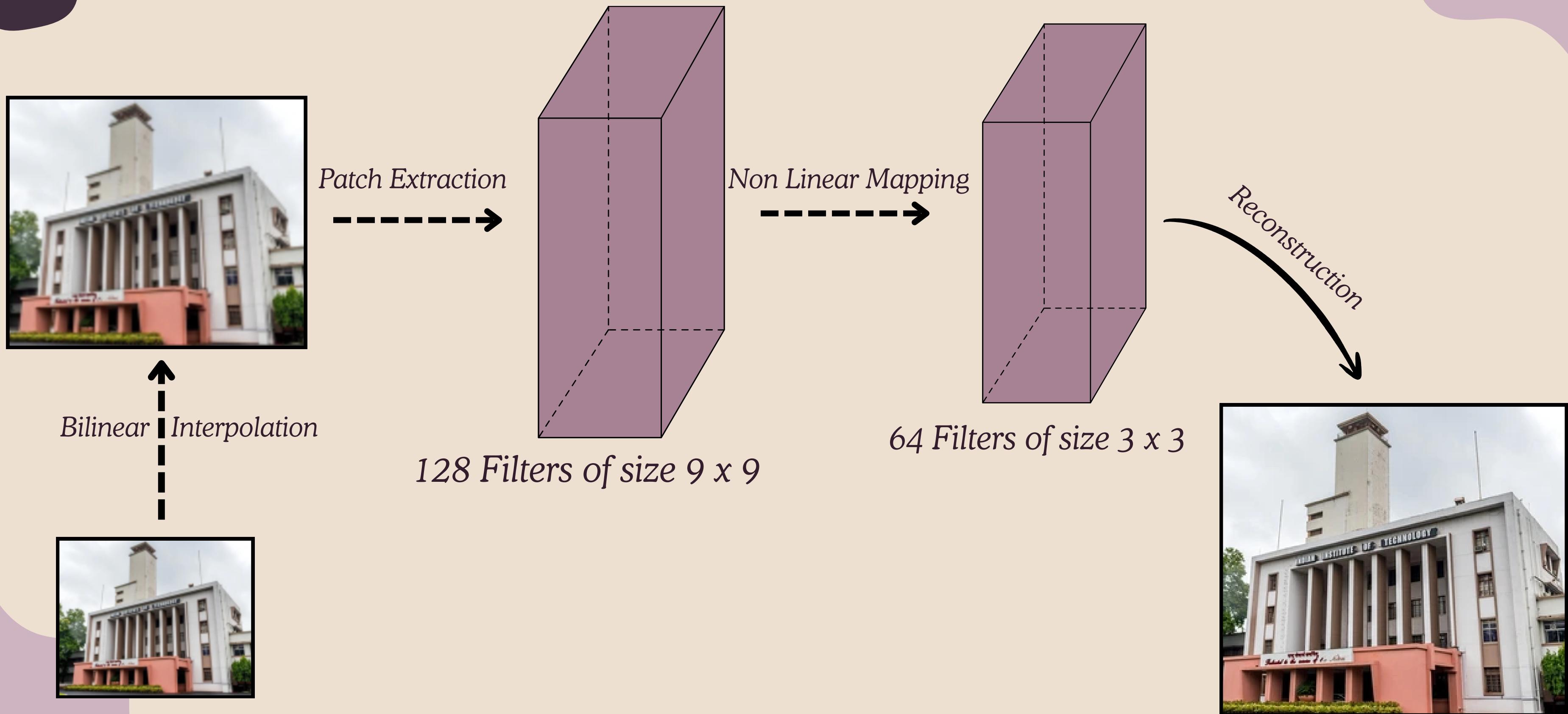
0	0	0	0
255	255	255	255
255	255	255	255
0	0	0	0

4 X 4

*Image Size : n x n,
Filter Size : m x m,
Then Output size : (n-m+1) x (n-m+1)*

Padding

Architecture of SRCNN



```
def model():

    # define model type
    SRCNN = Sequential()
    # SRCNN.add(Input(shape=(None, None, 3)))
    # add model layers
    SRCNN.add(Conv2D(filters=128, kernel_size = (9, 9), kernel_initializer='glorot_uniform',
                    activation='relu', padding='valid', use_bias=True, input_shape=(None, None, 1)))
    SRCNN.add(Conv2D(filters=64, kernel_size = (3, 3), kernel_initializer='glorot_uniform',
                    activation='relu', padding='same', use_bias=True))
    SRCNN.add(Conv2D(filters=1, kernel_size = (5, 5), kernel_initializer='glorot_uniform',
                    activation='linear', padding='valid', use_bias=True))

    # define optimizer
    adam = Adam(learning_rate=0.0003)

    # compile model
    SRCNN.compile(optimizer=adam, loss='mean_squared_error', metrics=['mean_squared_error'])

    return SRCNN
```

- SRCNN is trained on Y channel only

About YCrCb Channel

- **Y Channel** : Black-and-white information of the image is stored here.
- **Cr Channel** : Measures how much red is in the pixel compared to brightness.
- **Cb Channel** : Measures how much blue is in the pixel compared to brightness.

RGB to YCrCb Conversion Formula

$$Y = 0.299R + 0.587G + 0.114B$$

$$Cb = 128 - 0.168736R - 0.331264G + 0.5B$$

$$Cr = 128 + 0.5R - 0.418688G - 0.081312B$$

Data Preparation

```
def prepare_images(path, factor):

    # loop through the files in the directory
    for file in os.listdir(path):
        try:
            # open the file
            img = cv2.imread(path + '/' + file)

            # find old and new image dimensions
            h, w, _ = img.shape
            new_height = int(h / factor)
            new_width = int(w / factor)

            # resize the image - down
            img = cv2.resize(img, (new_width, new_height), interpolation = cv2.INTER_LINEAR)

            # resize the image - up
            img = cv2.resize(img, (w, h), interpolation = cv2.INTER_LINEAR)

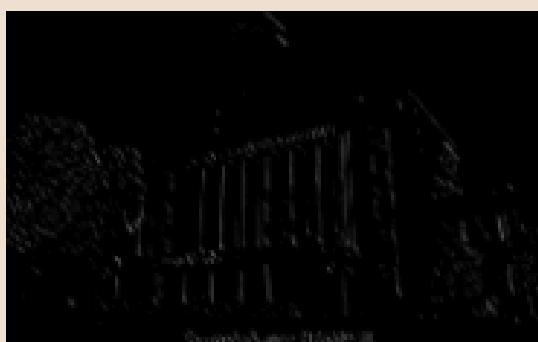
            # save the image
            print('Saving {}'.format(file))
            cv2.imwrite('images/{}'.format(file), img)
        except:
            print('ERROR for file-', file, '!')
            pass

prepare_images('source/', 2)
```

Layer by Layer Output



Input : Y channel of the degraded image



Outputs of Layer 1 Showing 3 images



Outputs of Layer 2 Showing 3 images

***Third Layer :
Reconstruction***



Converting Back to RGB
-----→



Evaluation Metric Used

Peak Signal to Noise Ratio (PSNR)

$$PSNR = 10 \cdot \log_{10}(255^2 / MSE)$$

- Represents the ratio between the maximum possible signal (image) power and the error introduced by the model.
- Higher PSNR → better image quality
- $PSNR > 30$ implies Good image

```
def psnr(target, ref):  
  
    target_data = target.astype(float)  
    ref_data = ref.astype(float)  
  
    diff = ref_data - target_data  
    diff = diff.flatten('C')  
  
    rmse = math.sqrt(np.mean(diff ** 2.))  
  
    return 20 * math.log10(255. / rmse)
```

Results

Original



Bilinear Interpolation



PSNR : 24.74
MSE : 654

SRCNN



PSNR : 26.64
MSE : 420.5



PSNR : 26.87
MSE : 400.15



PSNR : 27.68
MSE : 332.24

Results

Original



Bilinear Interpolation



PSNR : 33.01

MSE : 97.32

SRCCNN



PSNR : 36.67

MSE : 41.98



PSNR : 30.93

MSE : 157.46



PSNR : 34.88

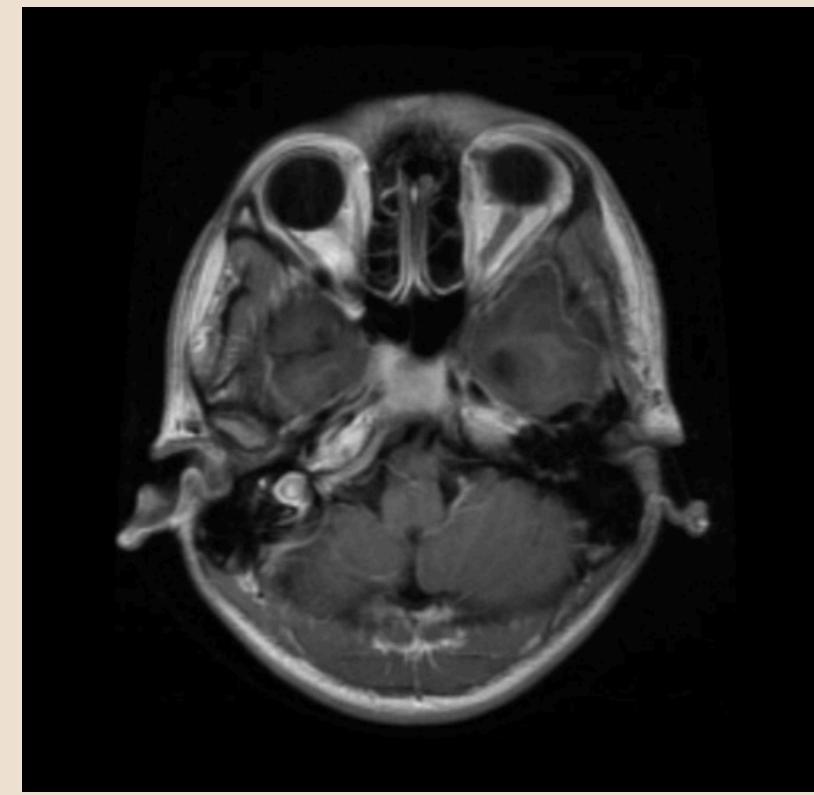
MSE : 63.28

Results

Original



Bilinear Interpolation



PSNR : 36.72

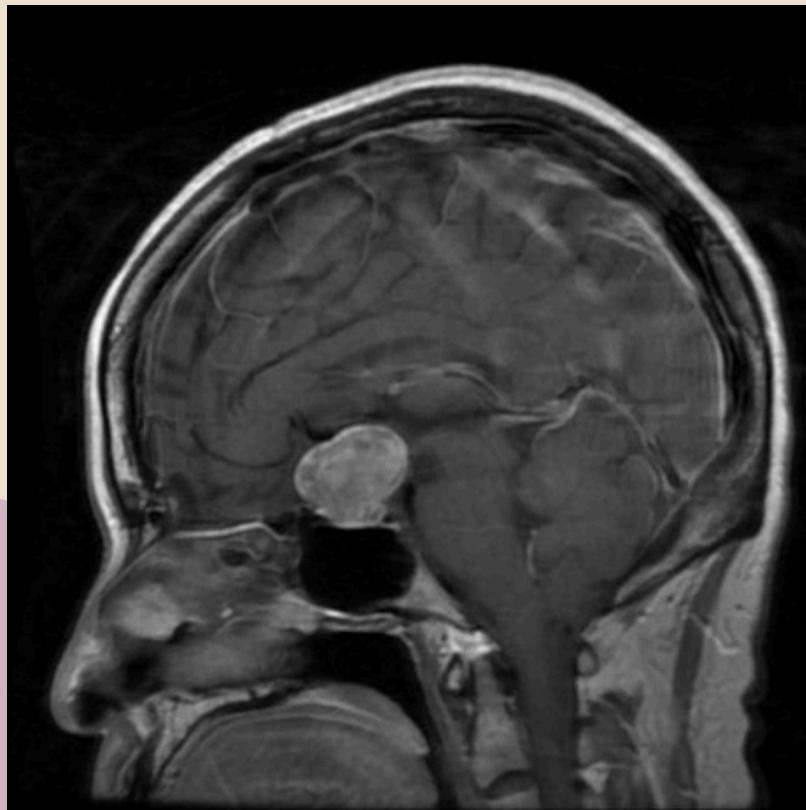
MSE : 41.47

SRCCN



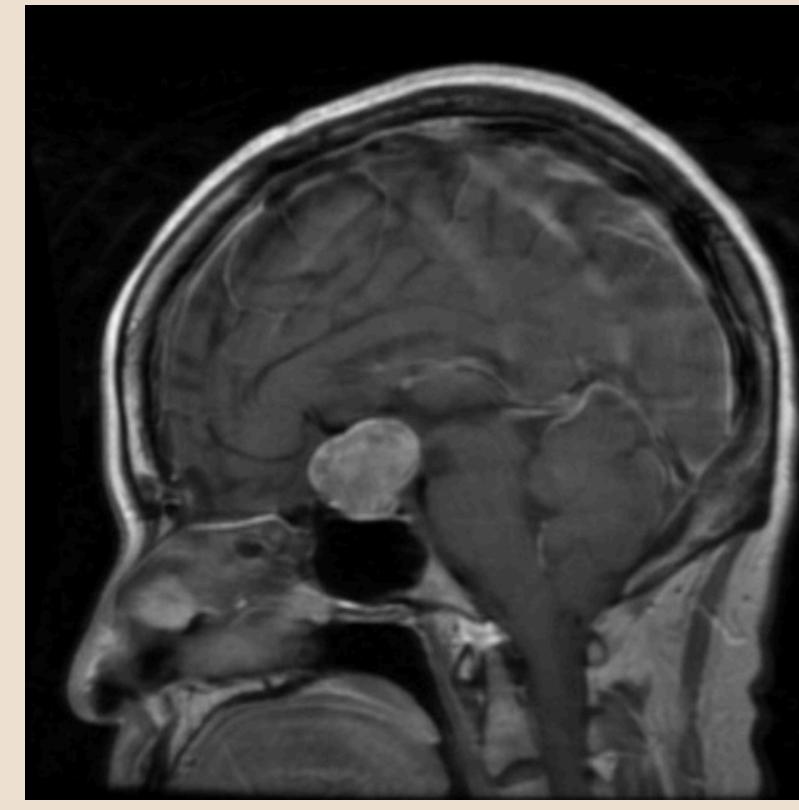
PSNR : 40.44

MSE : 17.61



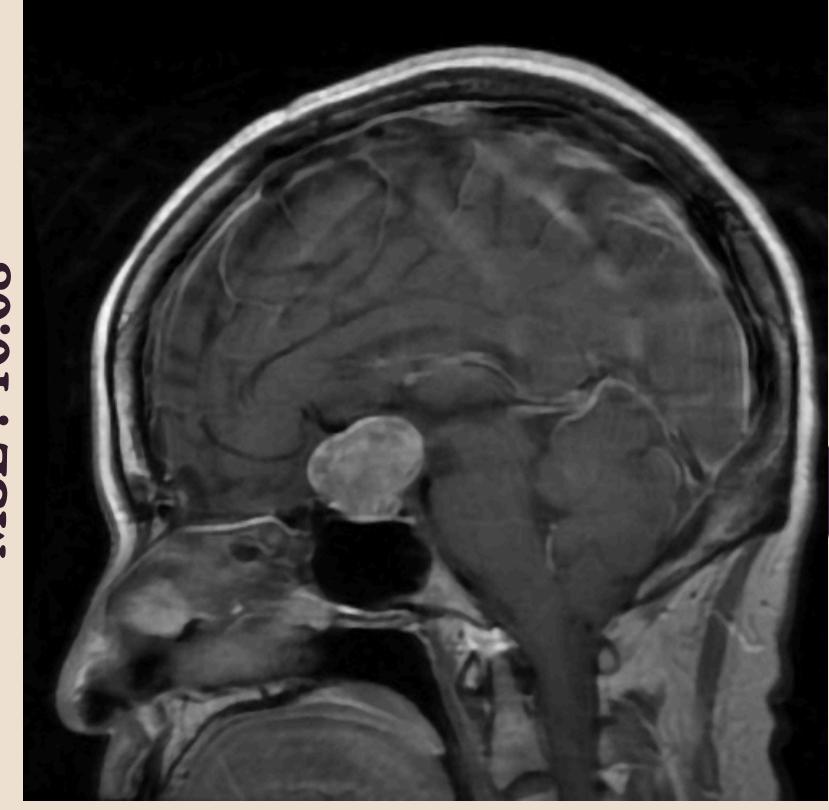
PSNR : 38.88

MSE : 25.22



PSNR : 42.86

MSE : 10.08



Conclusion

- Super-Resolution is crucial for enhancing image details in fields like medical imaging, satellite imaging, and photography.
- SRCNN, proposed by Dong et al., is the first CNN-based model for image super-resolution and laid the foundation for many advanced deep learning methods.
- SRCNN outperforms traditional interpolation methods, producing sharper and more accurate reconstructions.

References

- Dong, Chao, et al. "Image super-resolution using deep convolutional networks." *IEEE transactions on pattern analysis and machine intelligence* 38.2 (2015): 295-307..
- Super Resolution Benchmark Dataset :
<https://www.kaggle.com/datasets/jesucristo/super-resolution-benchmarks>
- Brain Tumor MRI Dataset :
<https://www.kaggle.com/datasets/masoudnickparvar/brain-tumor-mri-dataset>

THANK YOU