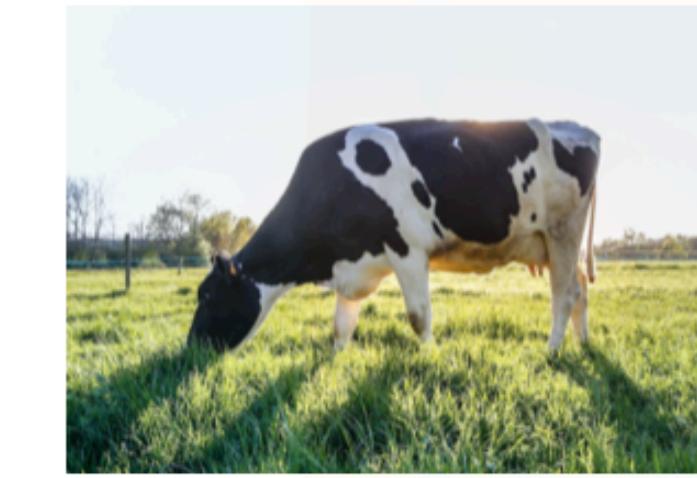


Original Image



Label: Cow

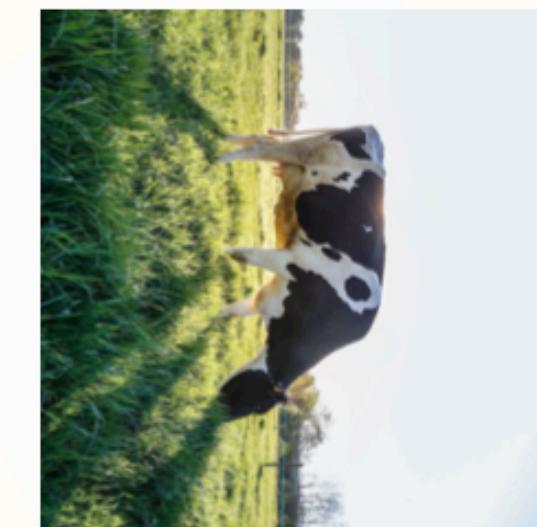
Augmented Images



Label: Cow



Label: Cow



Label: Cow

Lecture 11-1: Computer Vision

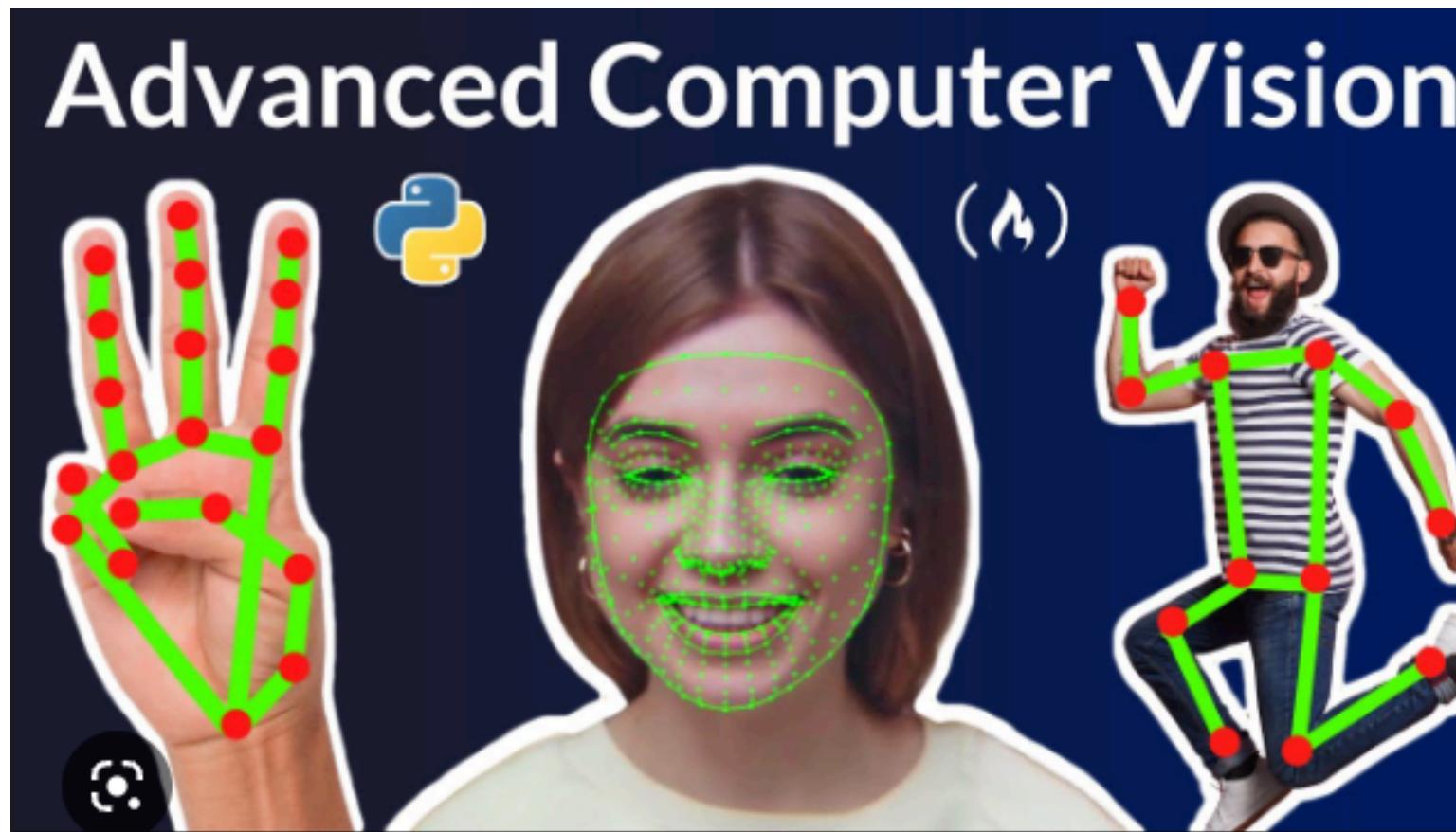
Dr. James Chen, Animal Data Scientist, School of Animal Sciences

2023 APSC-5984 SS: Agriculture Data Science



Overview - Computer Vision (CV)

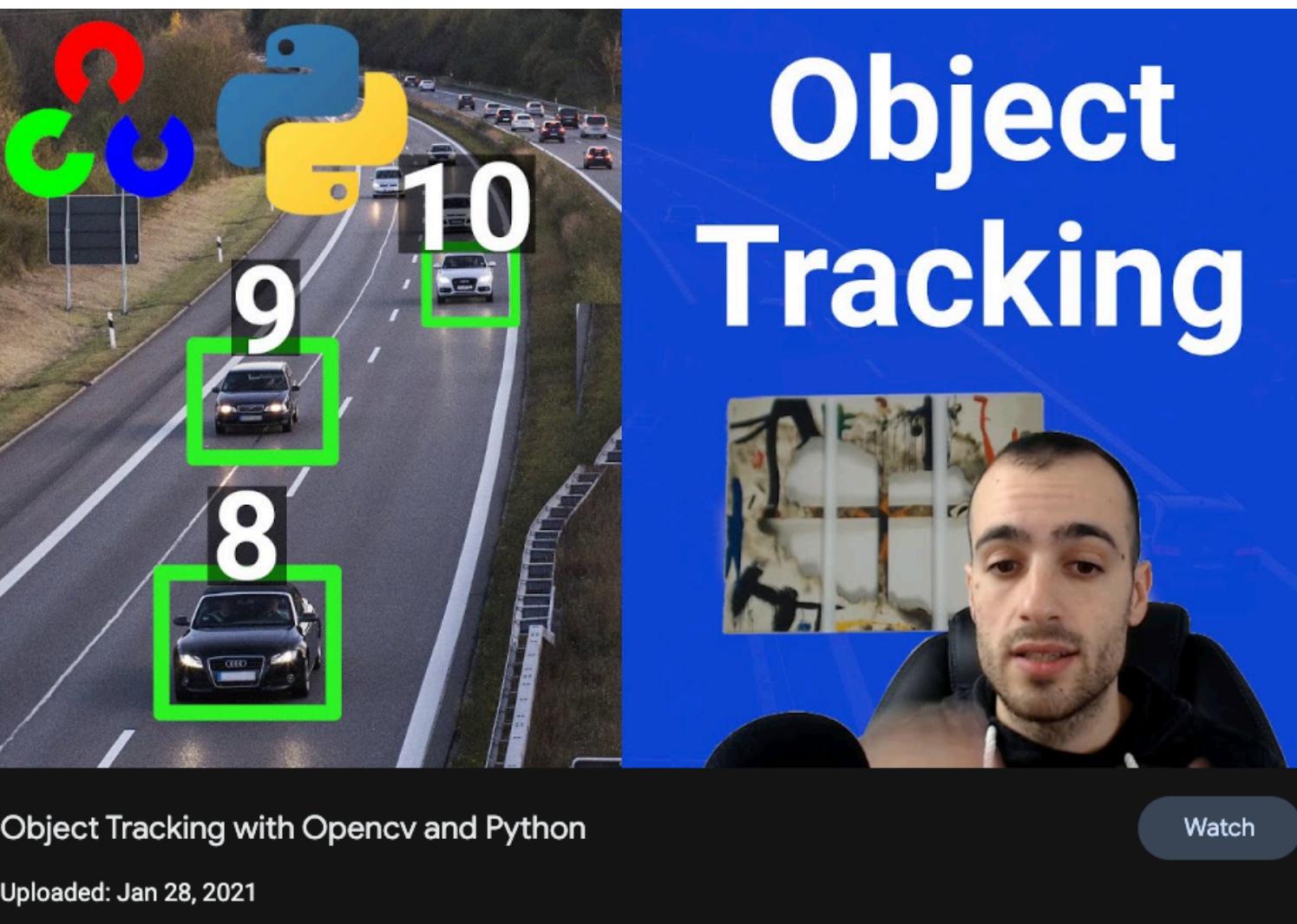
COMPUTER VISION 2



Advanced Computer Vision with Python -
Full Course

Uploaded: May 27, 2021

1.28M Views · 46K Likes



Object Tracking with OpenCV and Python

Uploaded: Jan 28, 2021

479K Views · 8.36K Likes

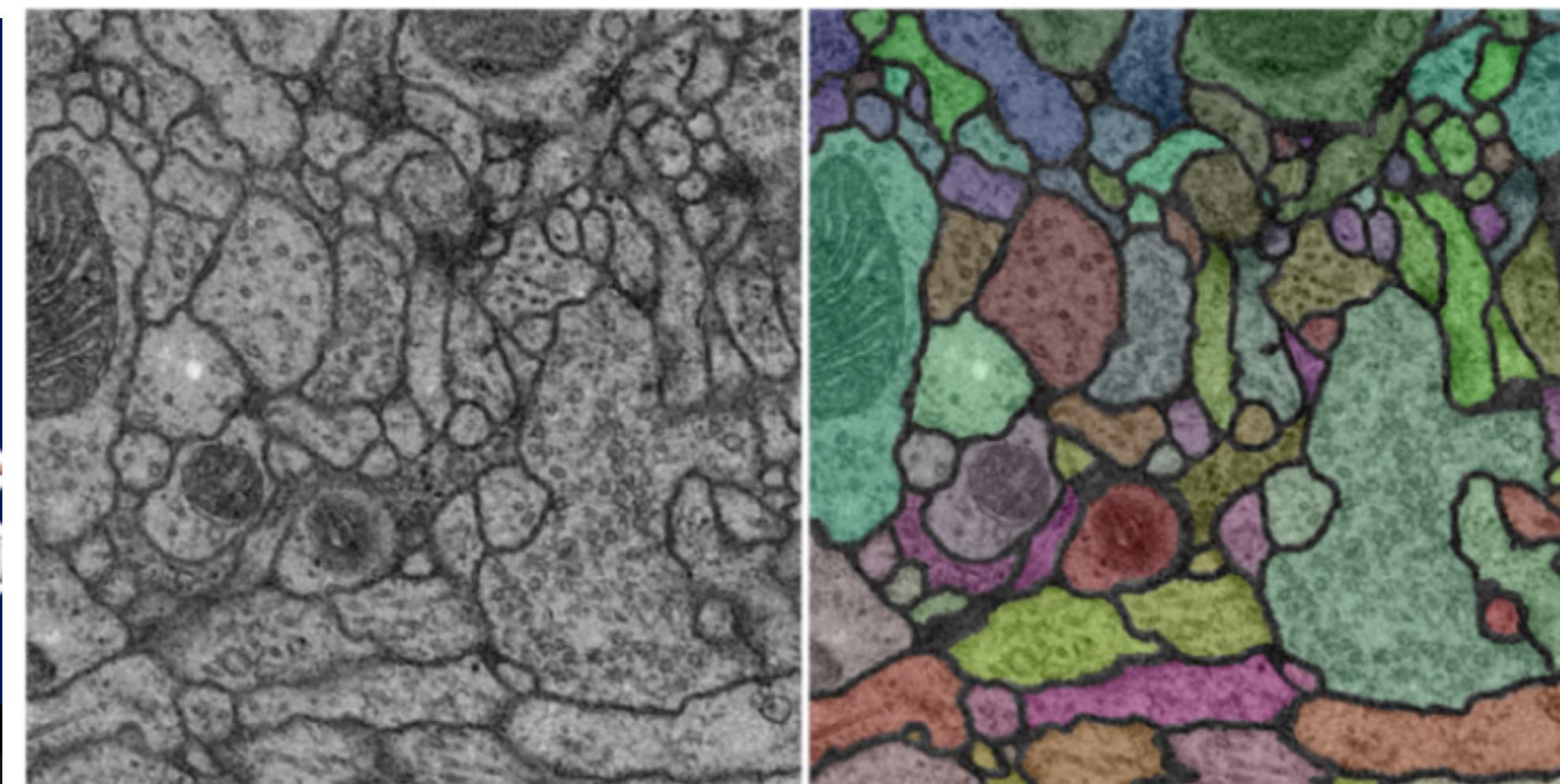
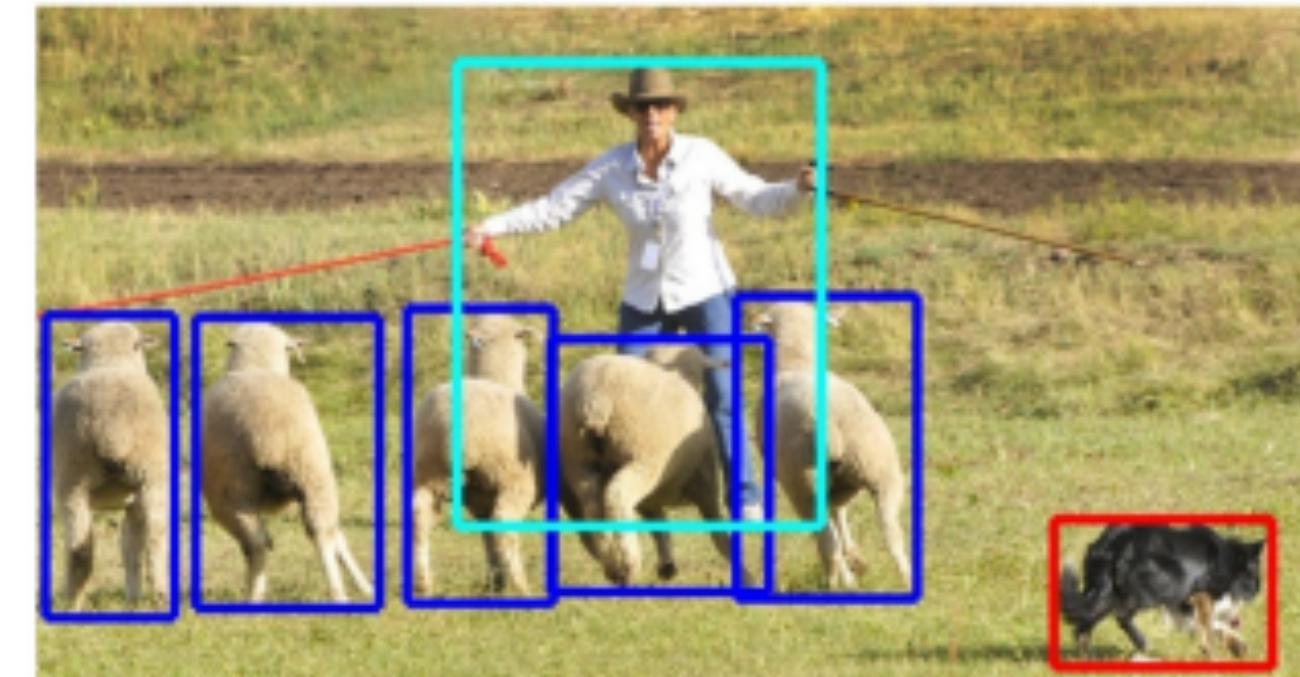
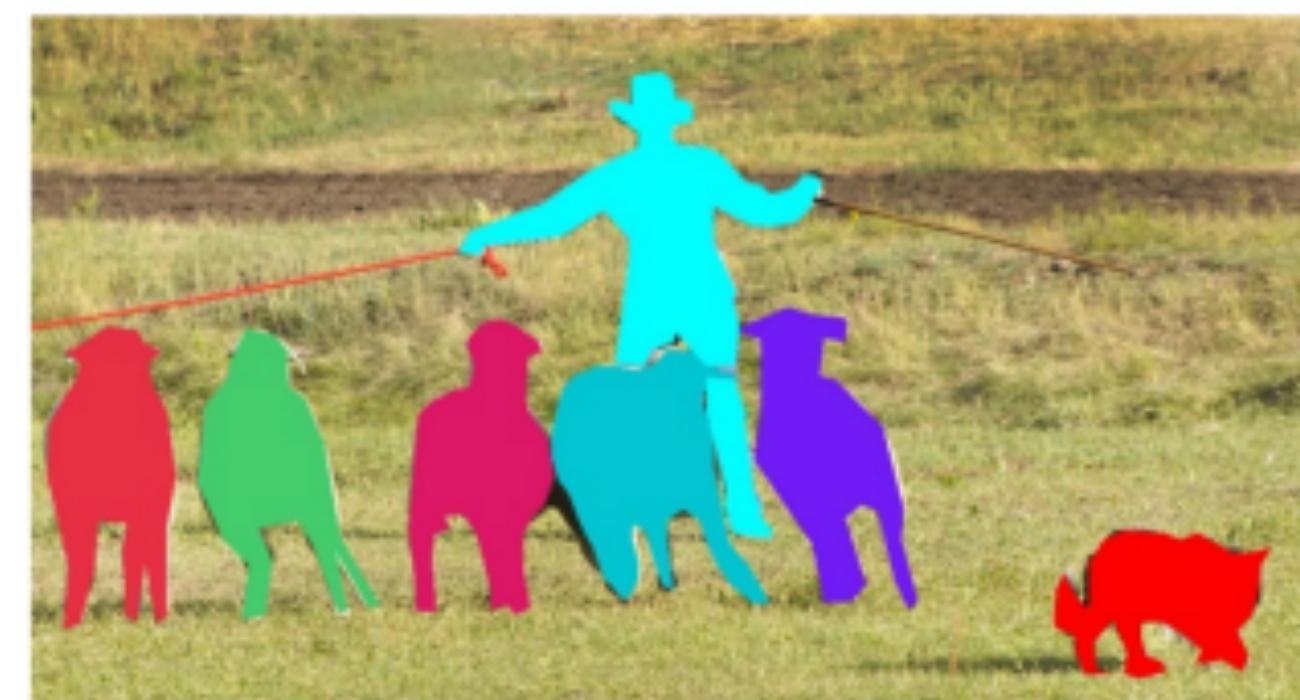


Figure 10: Ciresan - Neuronal membrane segmentation



(b) Object localization



(d) This work

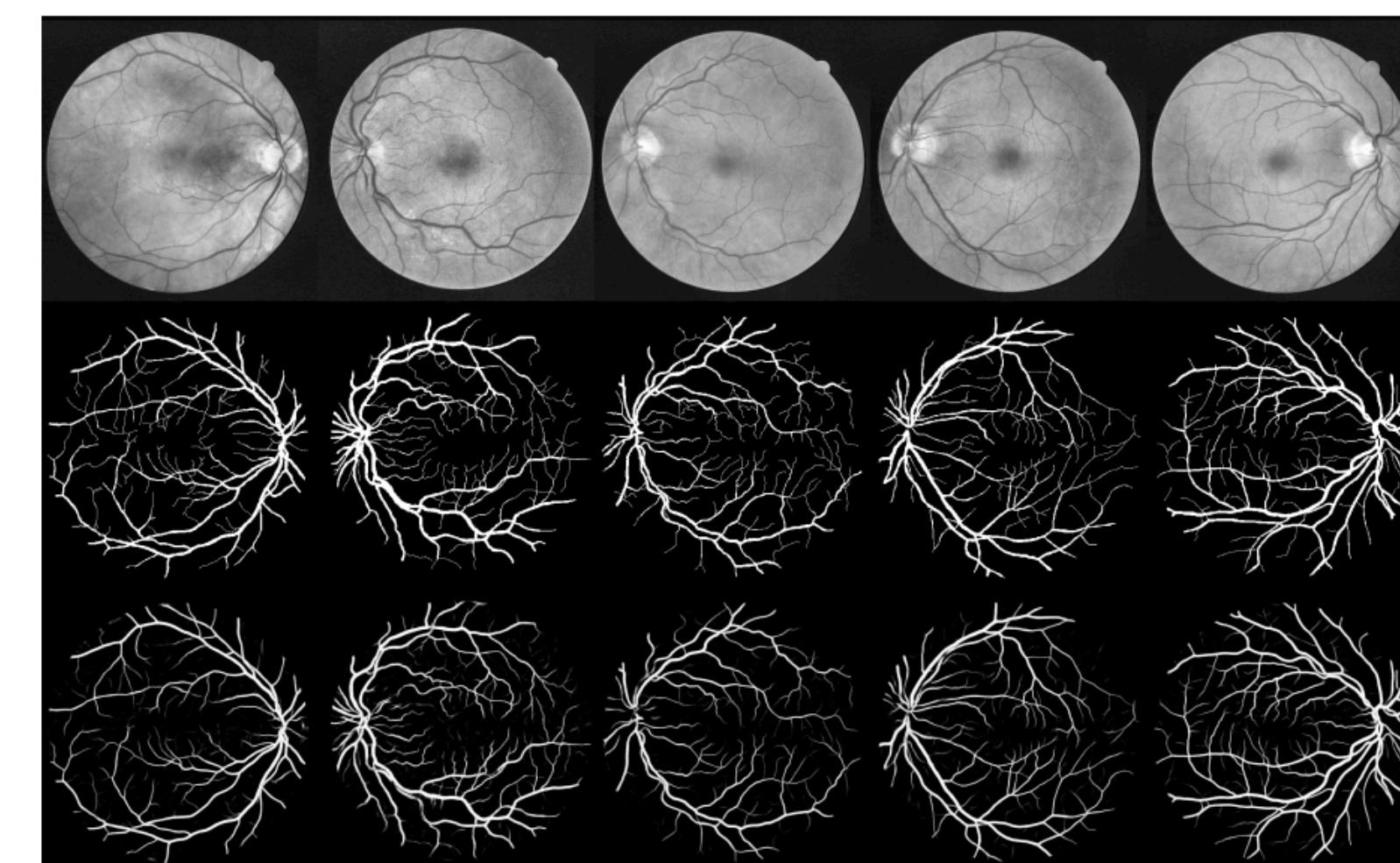


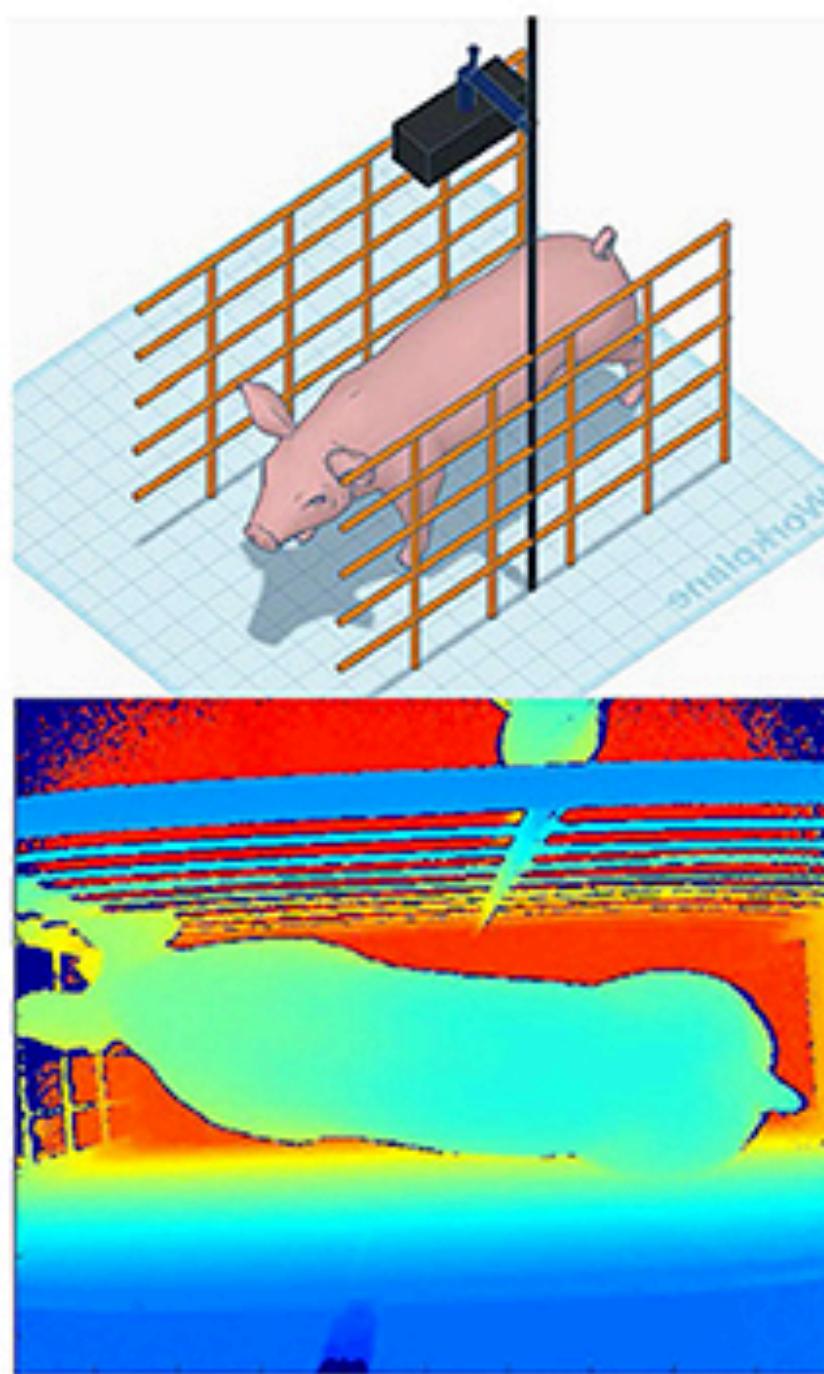
Figure 15: Ronneberger et al., U-Net: Biomedical Image Segmentation

Image Analysis and Computer Vision Applications in Animal Sciences: An Overview

Arthur Francisco Araújo Fernandes^{1*}, João Ricardo Rebouças Dórea¹ and Guilherme Jordão de Magalhães Rosa^{1,2}

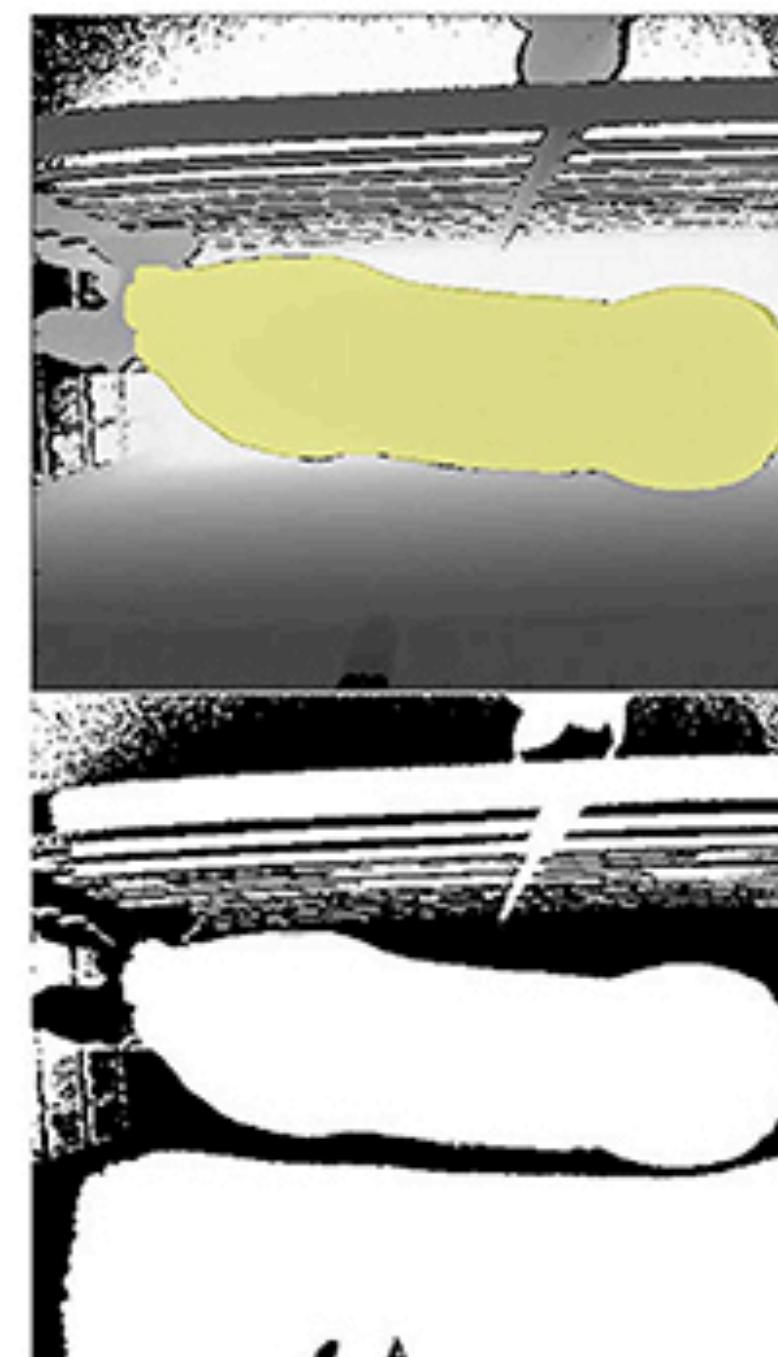
¹ Department of Animal and Dairy Sciences, University of Wisconsin-Madison, Madison, WI, United States, ² Department of Biostatistics and Medical Informatics, University of Wisconsin-Madison, Madison, WI, United States

A Image acquisition



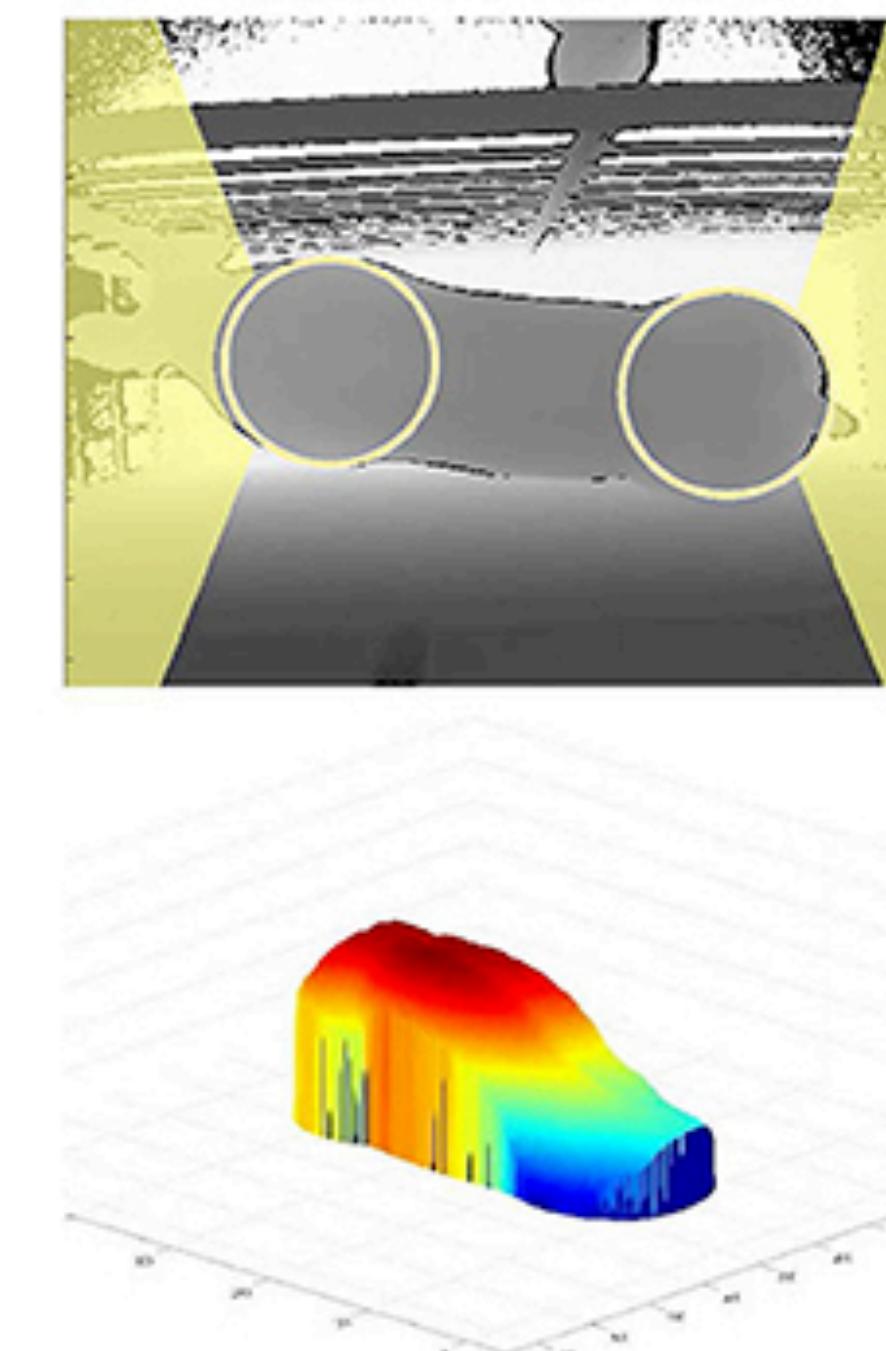
B Image Processing

- Thresholding
- Binarization



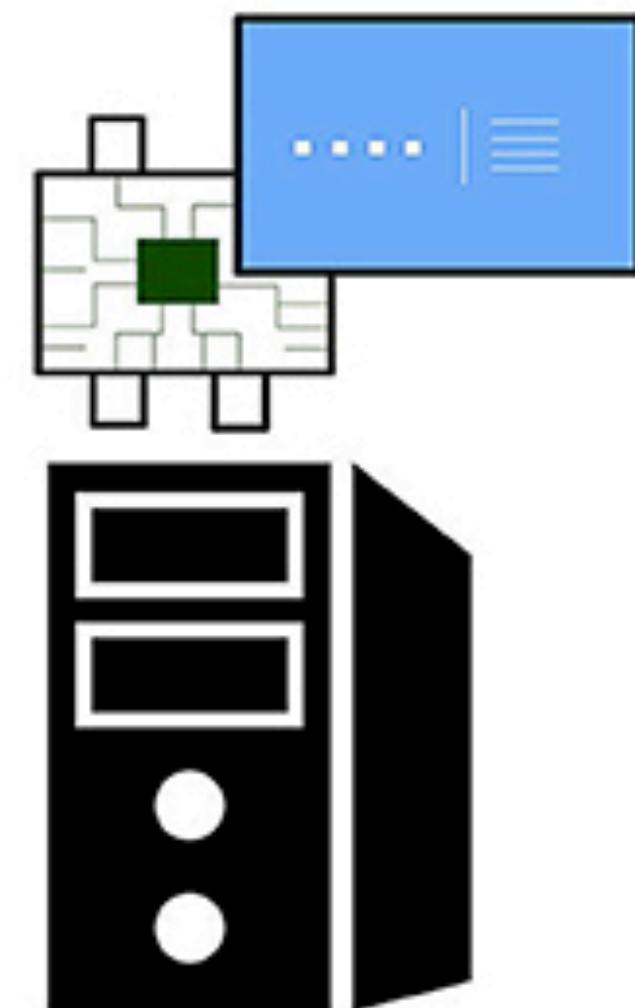
C Image Analysis

- Image Segmentation
- Feature extraction



D Data Analysis

- Data normalization
- Model fitting
- Validation and tuning
- Prediction

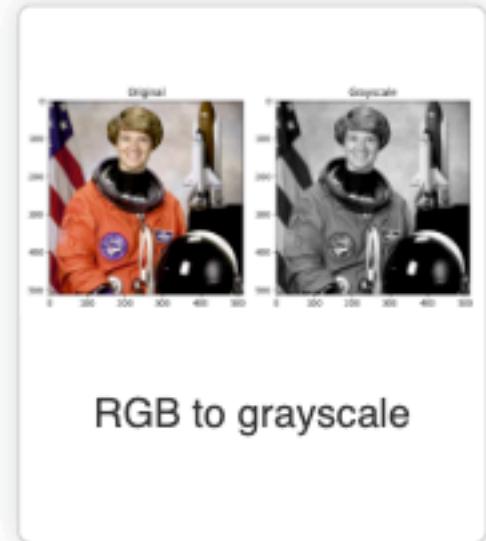


Depth camera



scikit-image
image processing in python

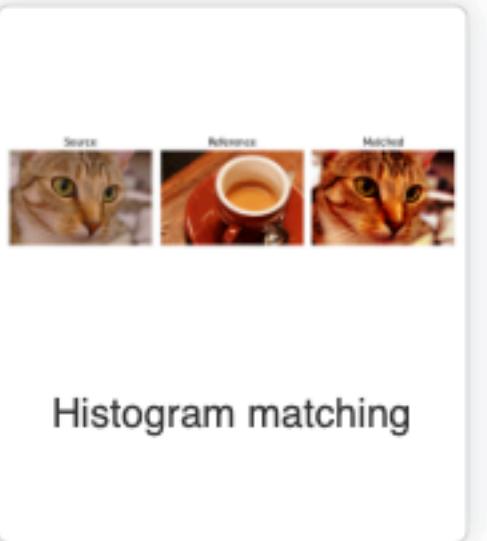
Manipulating exposure and color channels



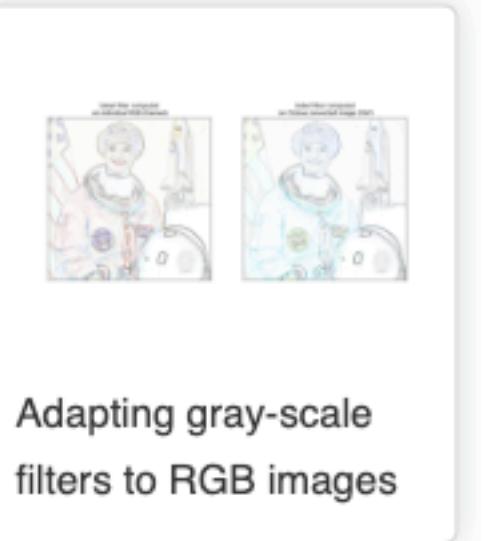
RGB to grayscale



RGB to HSV



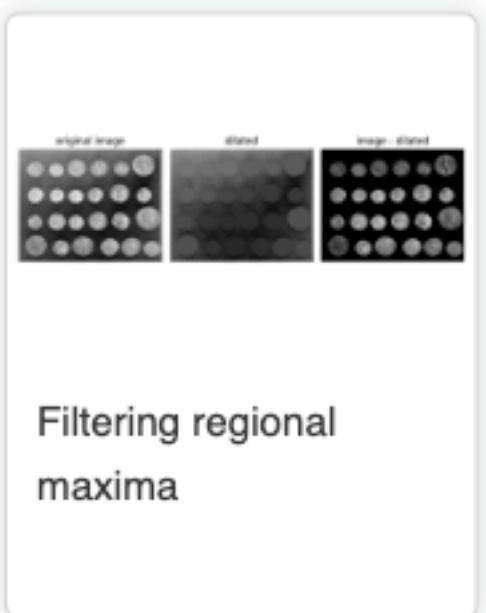
Histogram matching



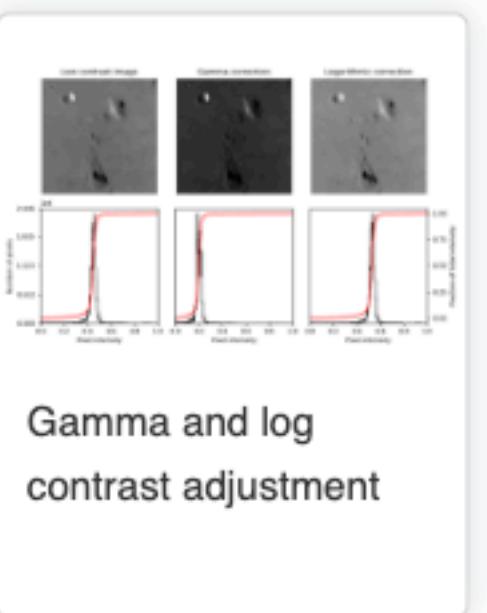
Adapting gray-scale filters to RGB images



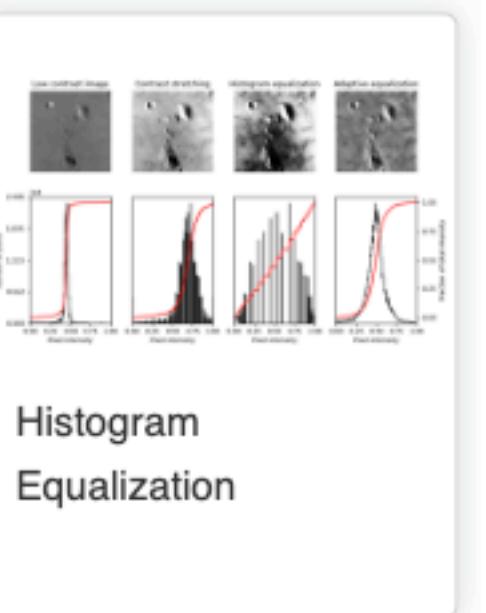
Separate colors in immunohistochemical staining



Filtering regional maxima

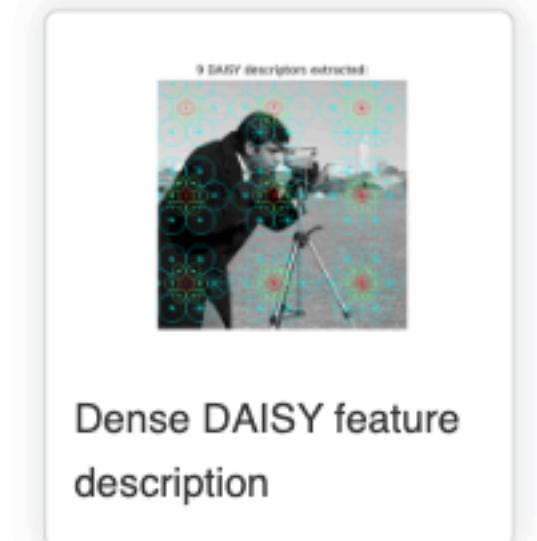


Gamma and log contrast adjustment

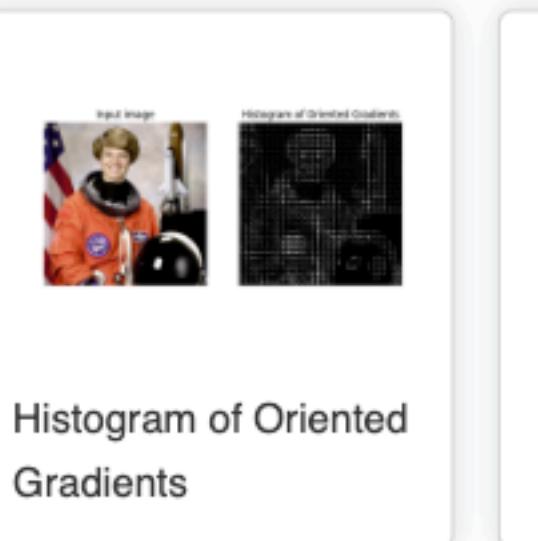


Histogram Equalization

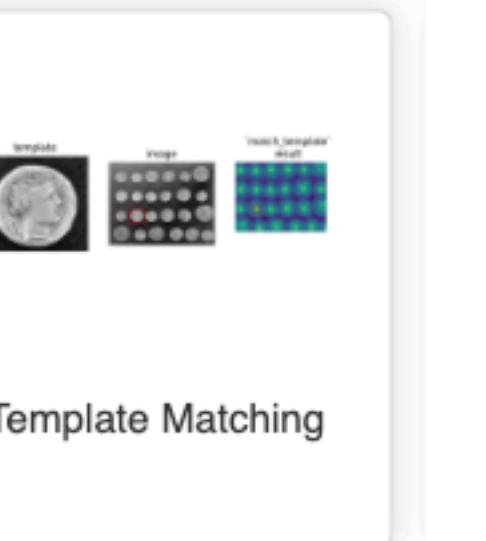
Detection of features and objects



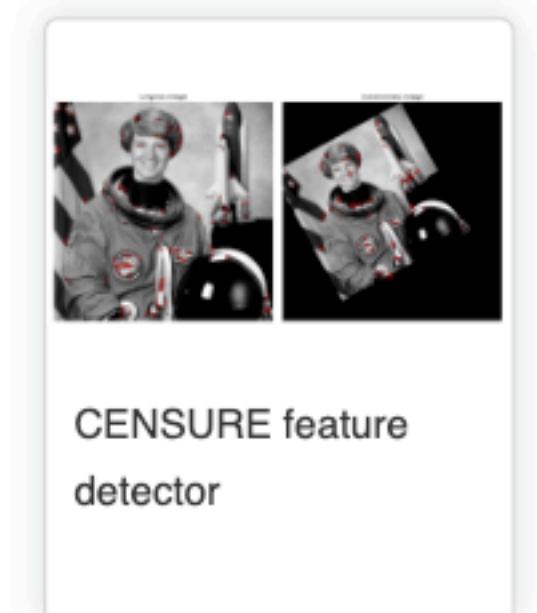
Dense DAISY feature description



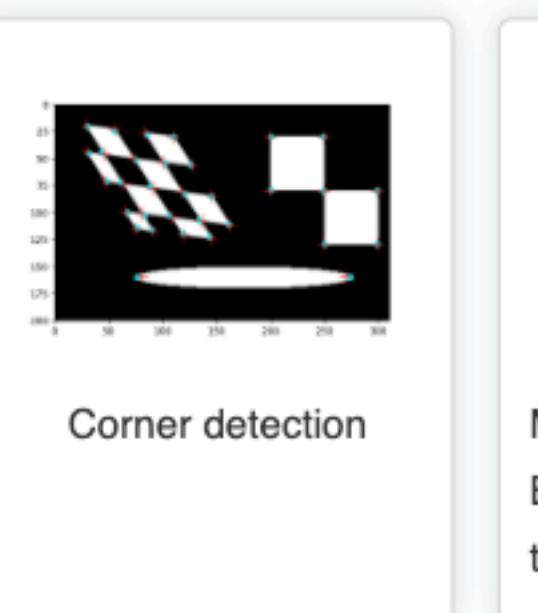
Histogram of Oriented Gradients



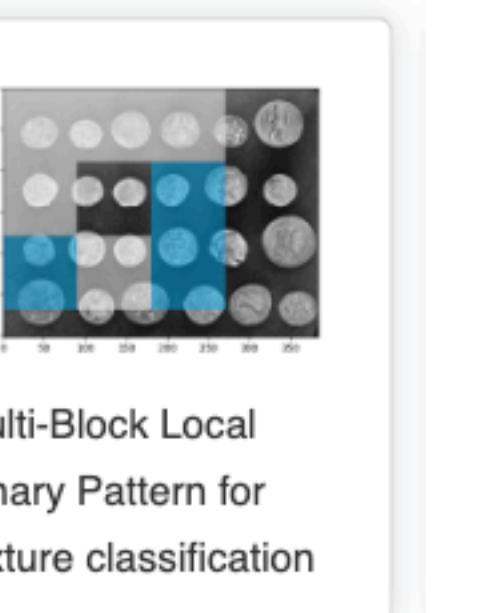
Template Matching



CENSURE feature detector

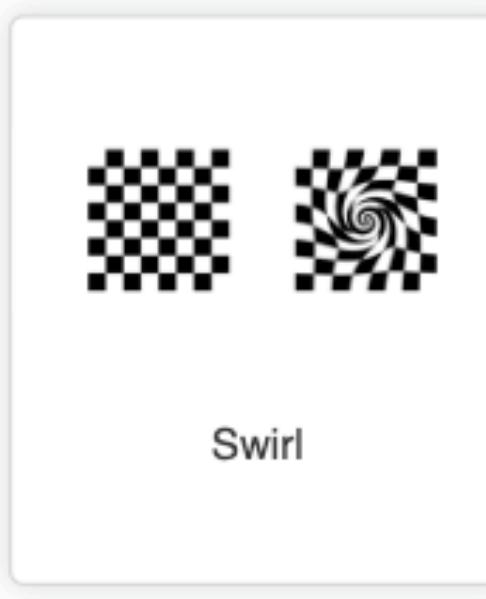


Corner detection

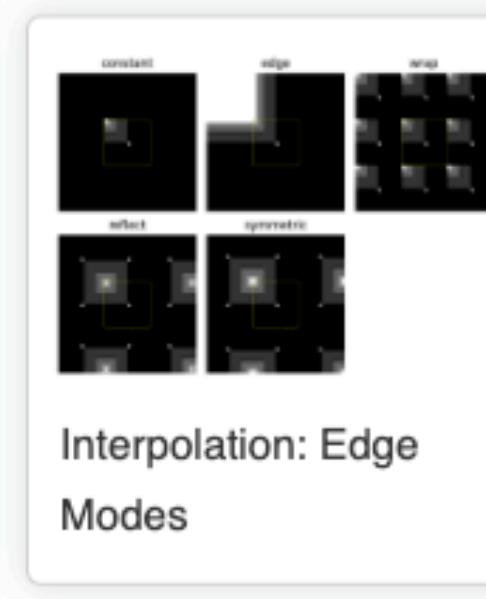


Multi-Block Local Binary Pattern for texture classification

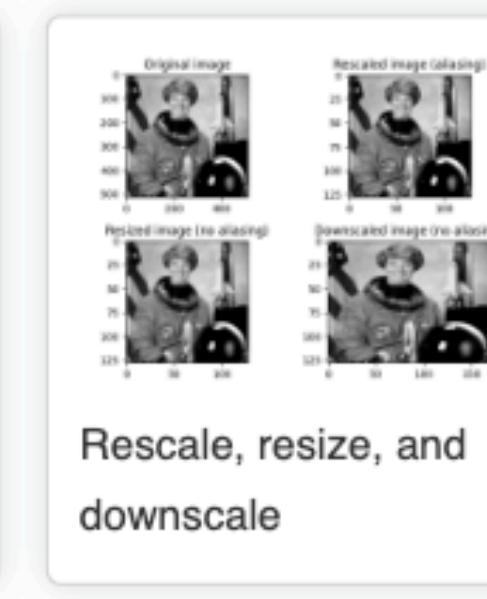
Geometrical transformations and registration



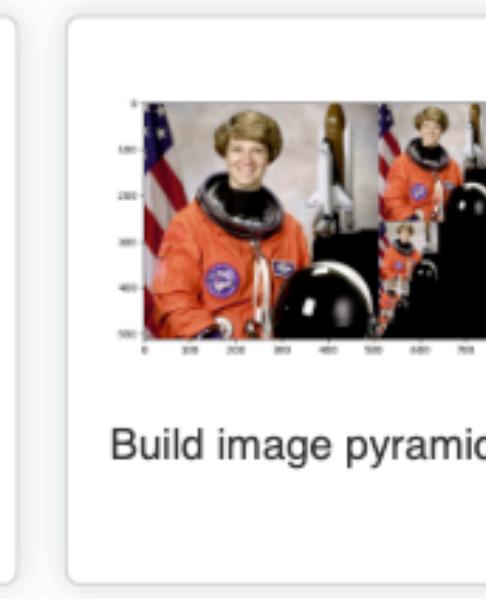
Swirl



Interpolation: Edge Modes

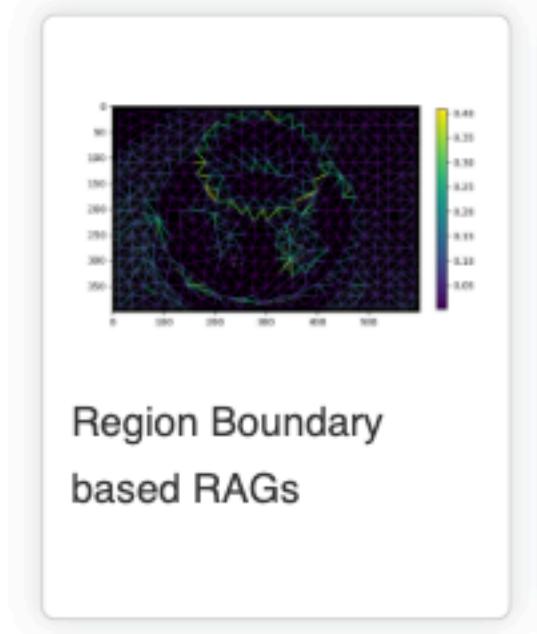


Rescale, resize, and downscale

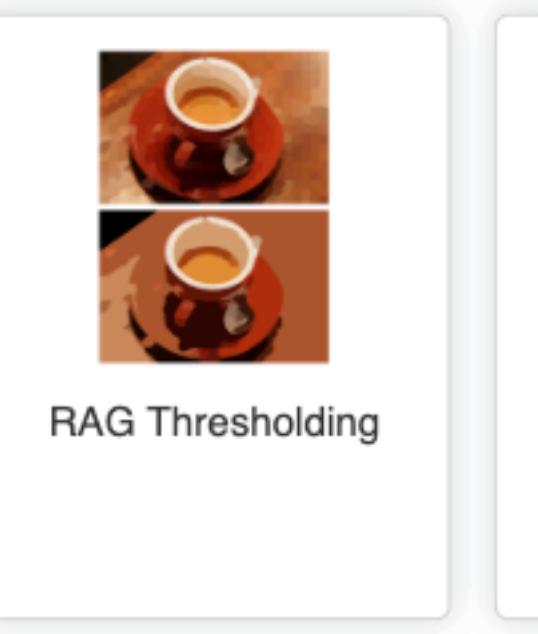


Build image pyramids

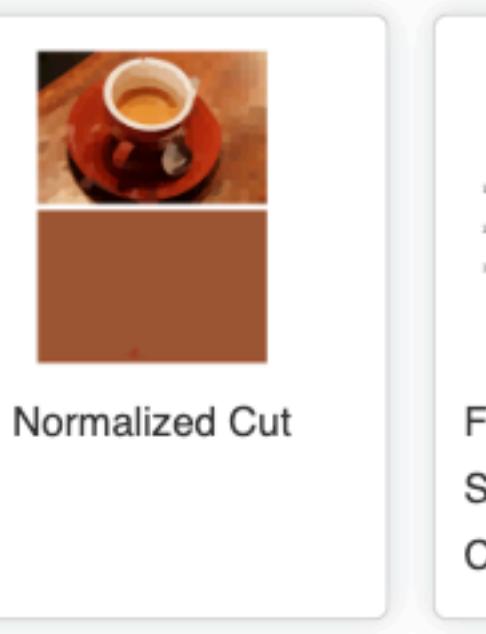
Segmentation of objects



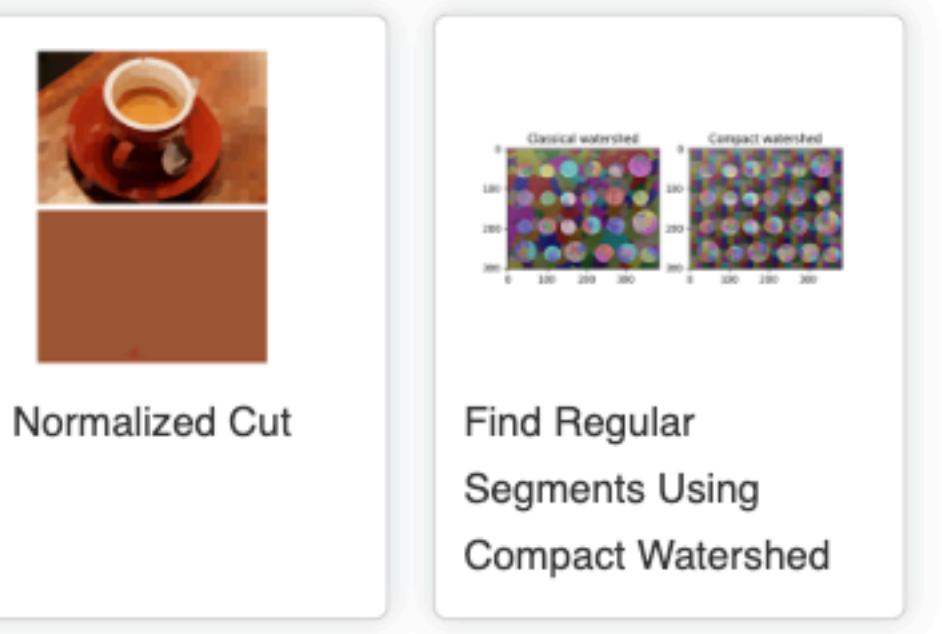
Region Boundary based RAGs



RAG Thresholding



Normalized Cut

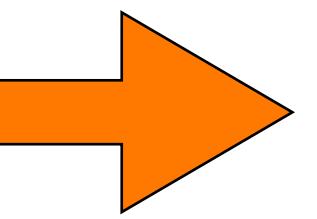


Find Regular Segments Using Compact Watershed

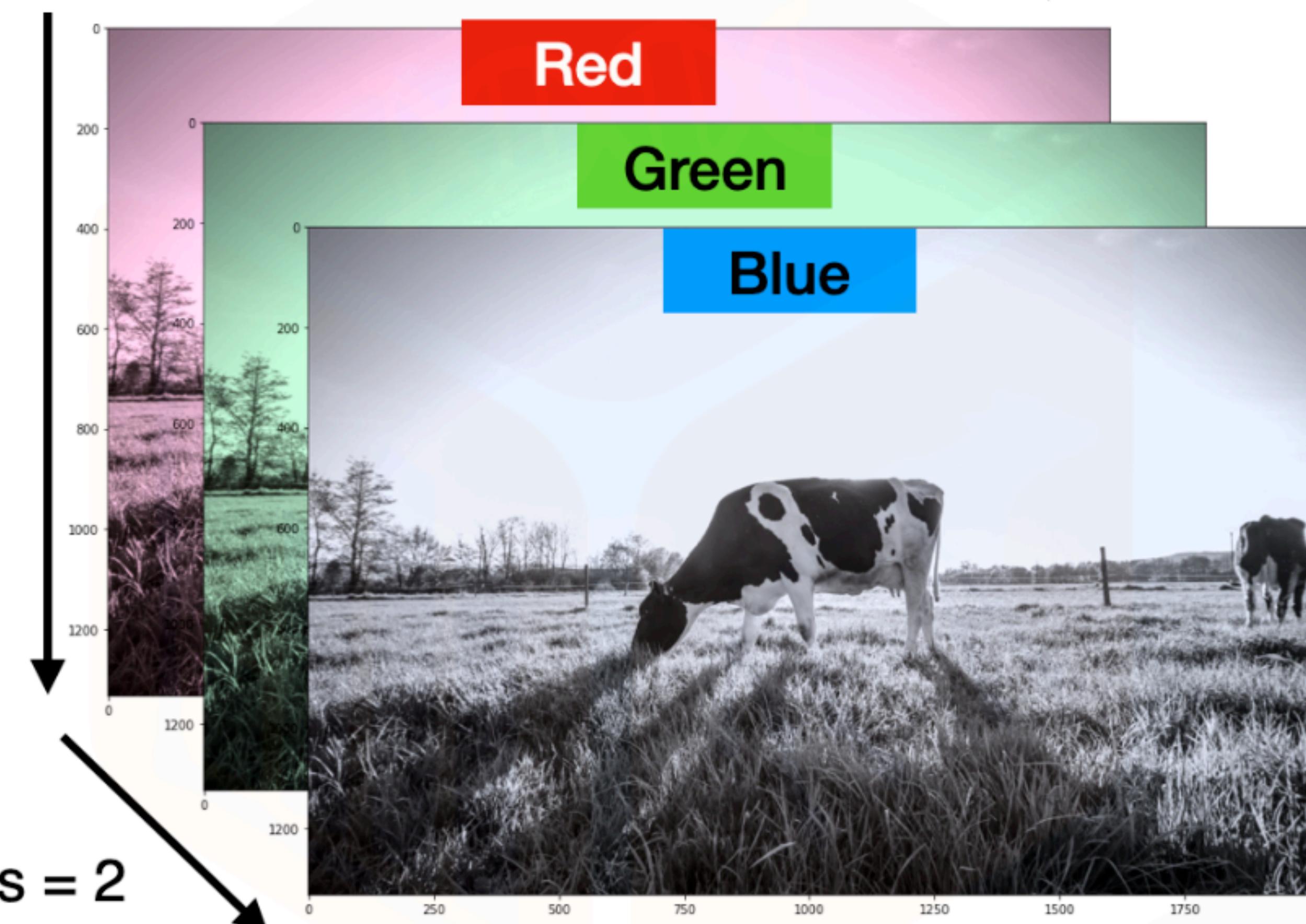
An Image Array Is Typically a Three-Dimensional Array



axis = 0



axis = 1



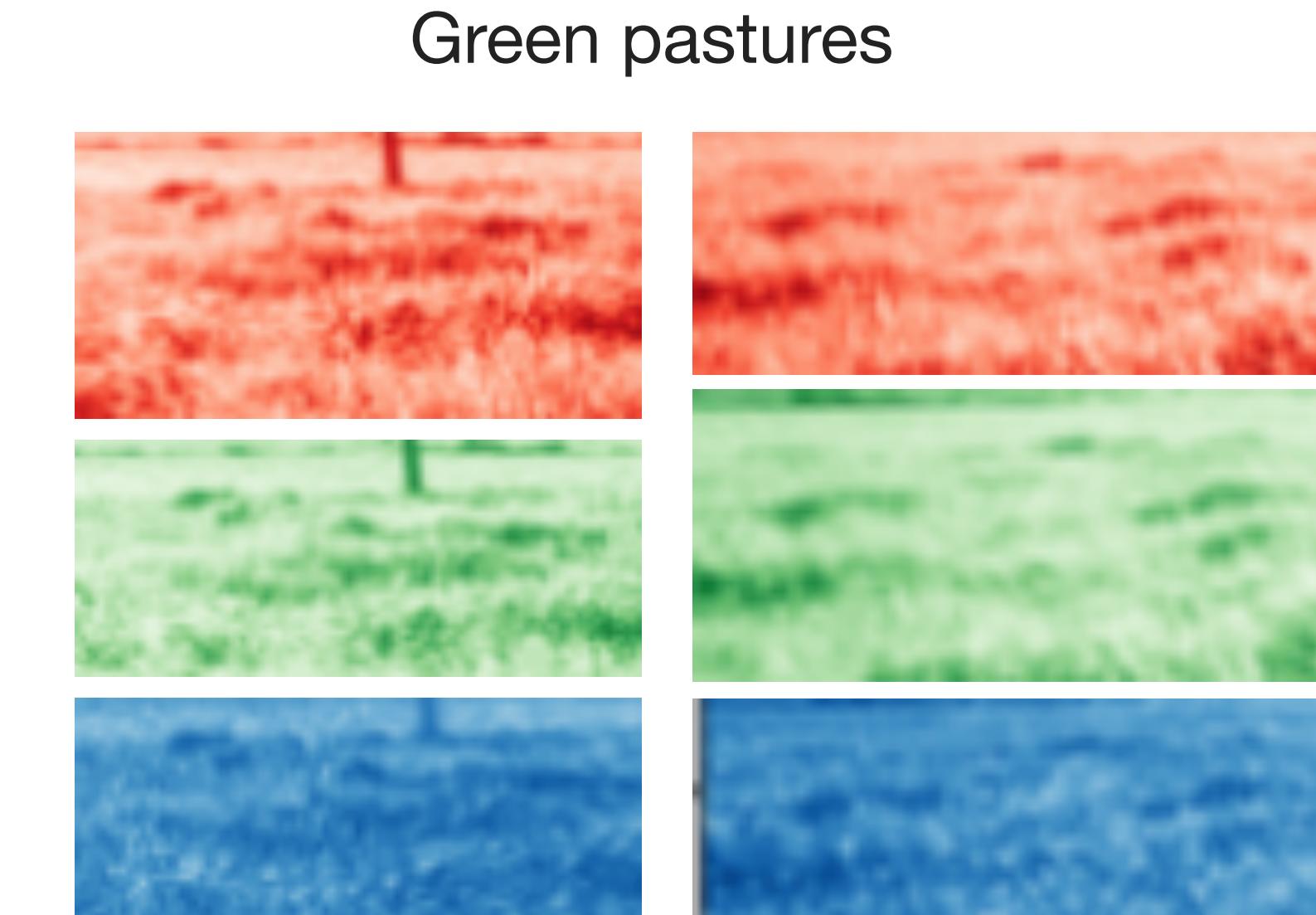
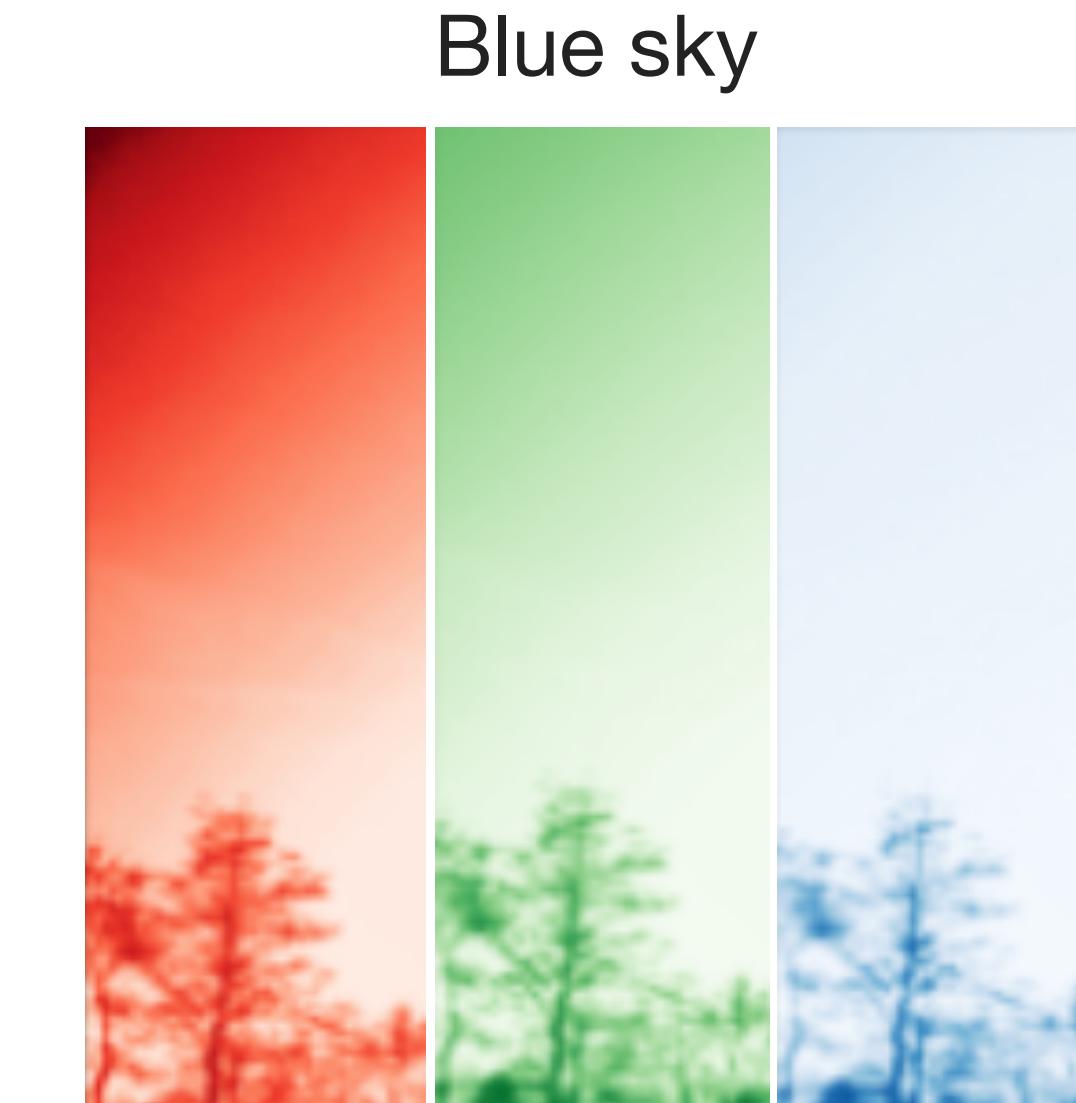
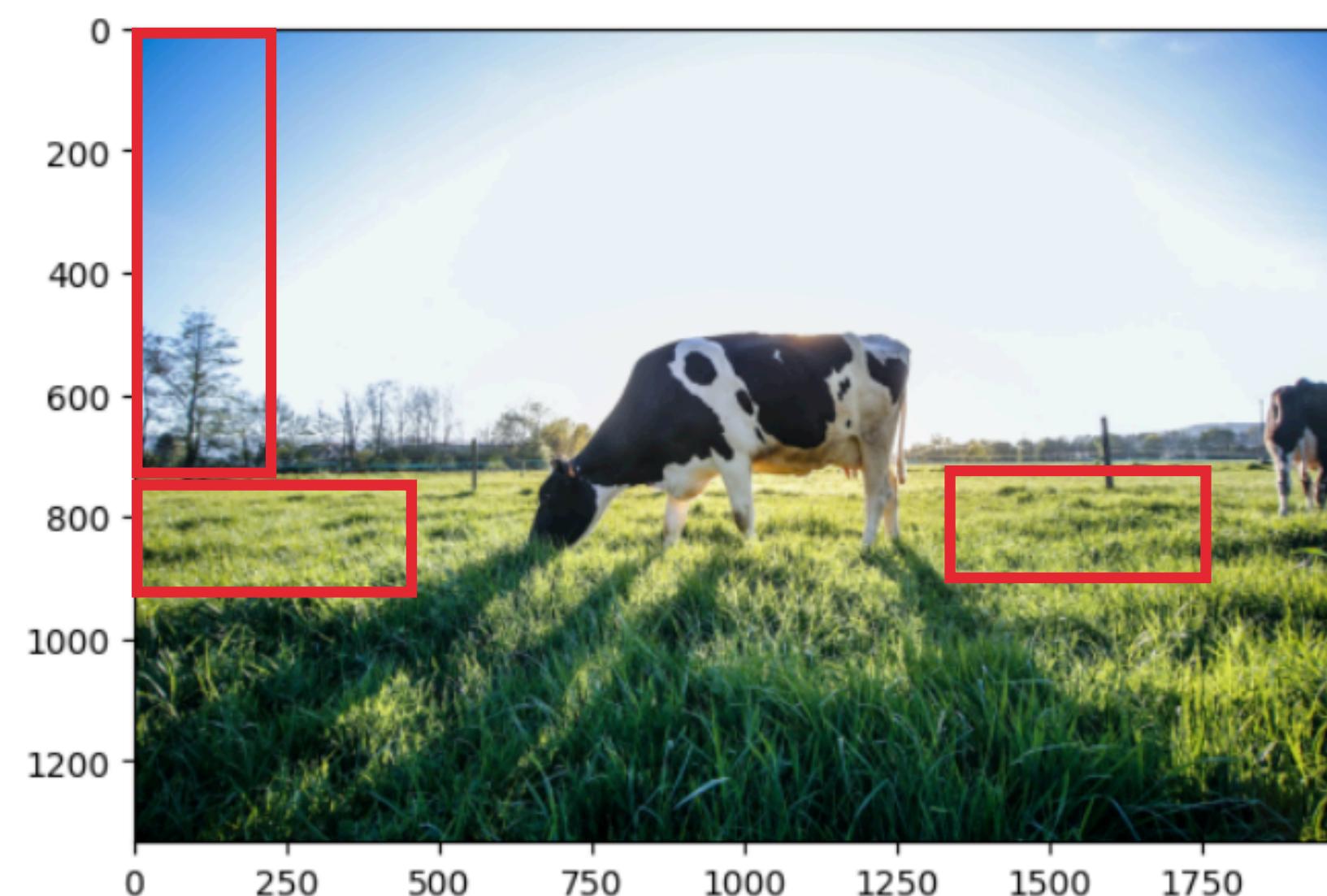
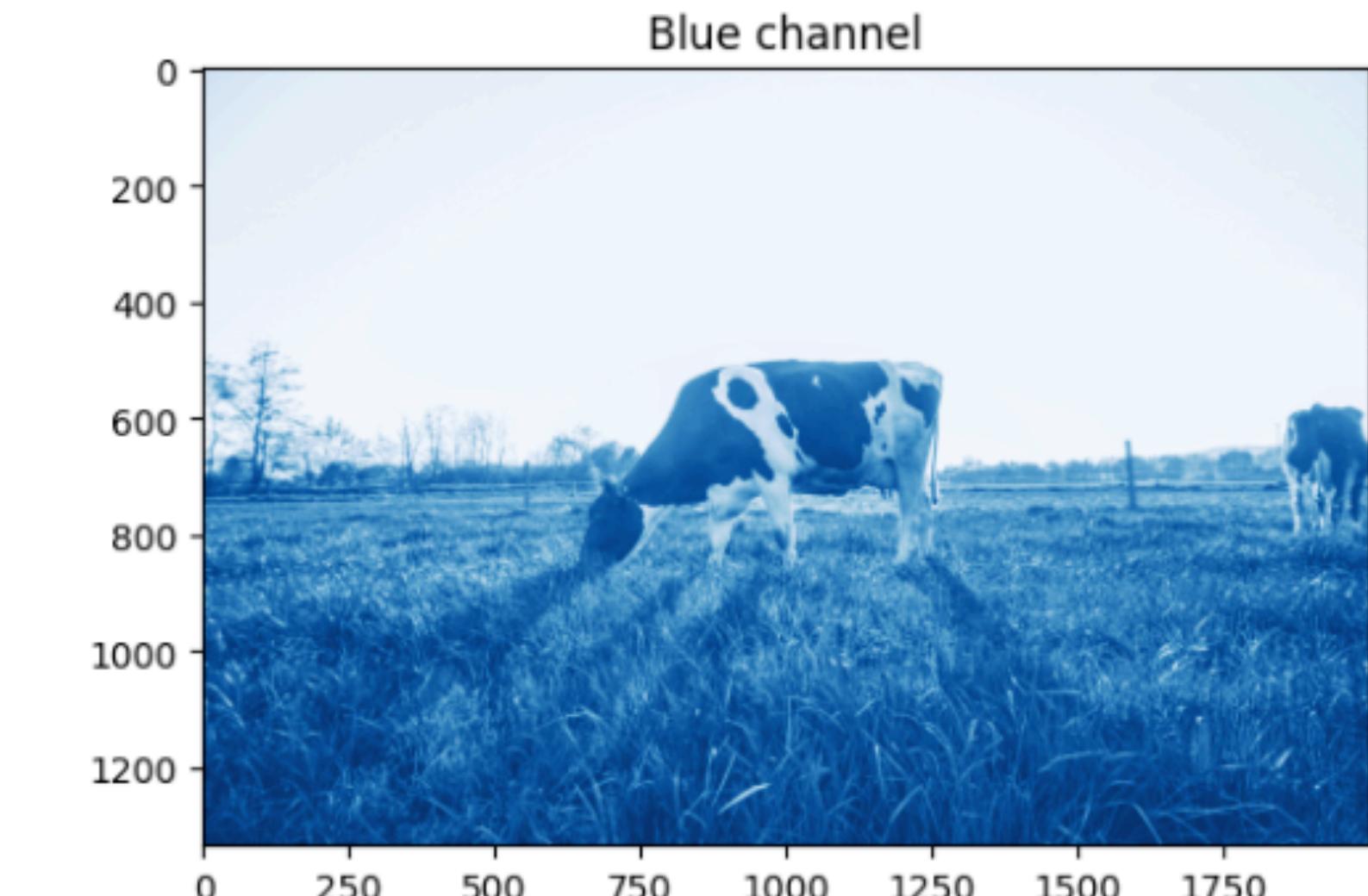
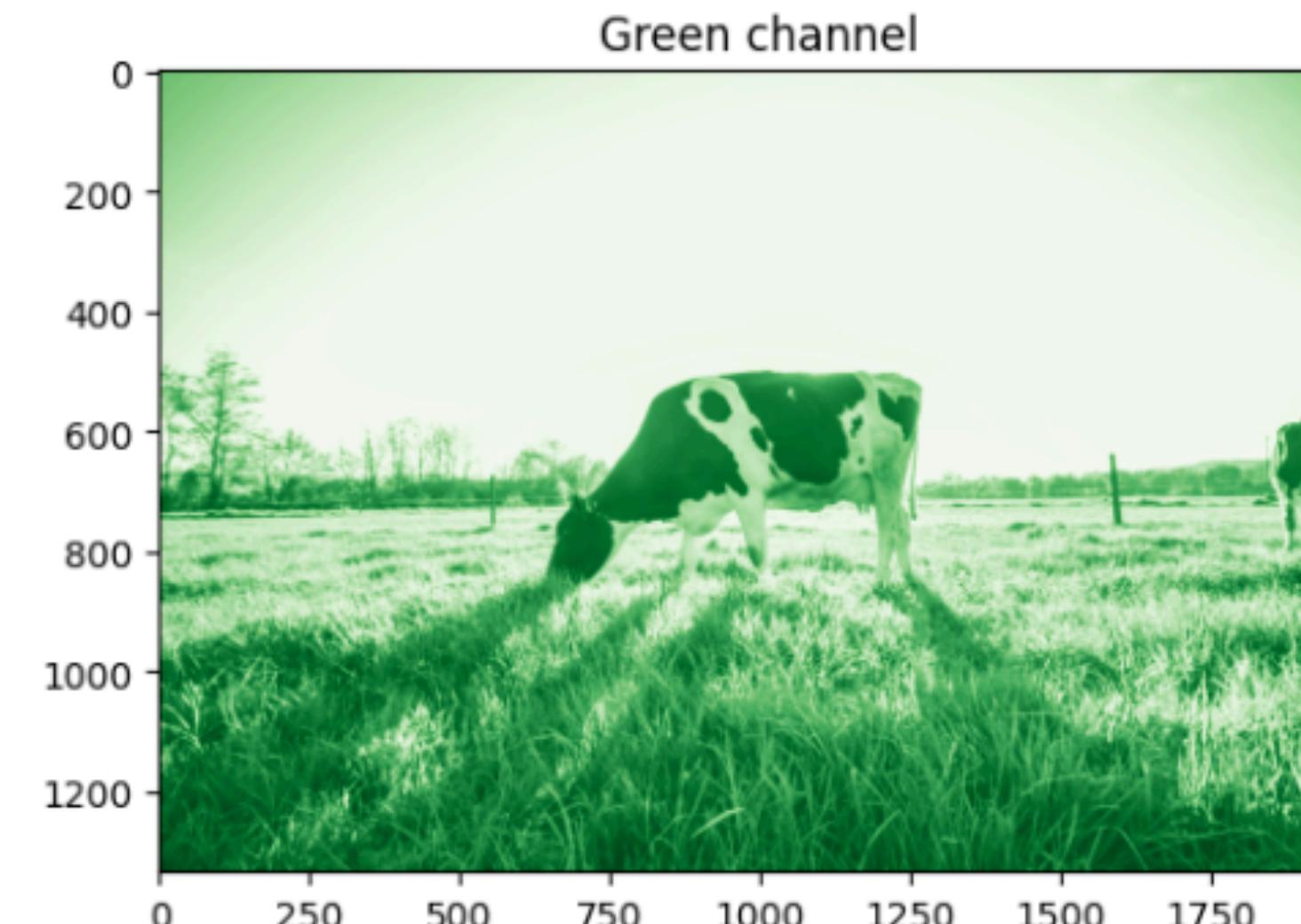
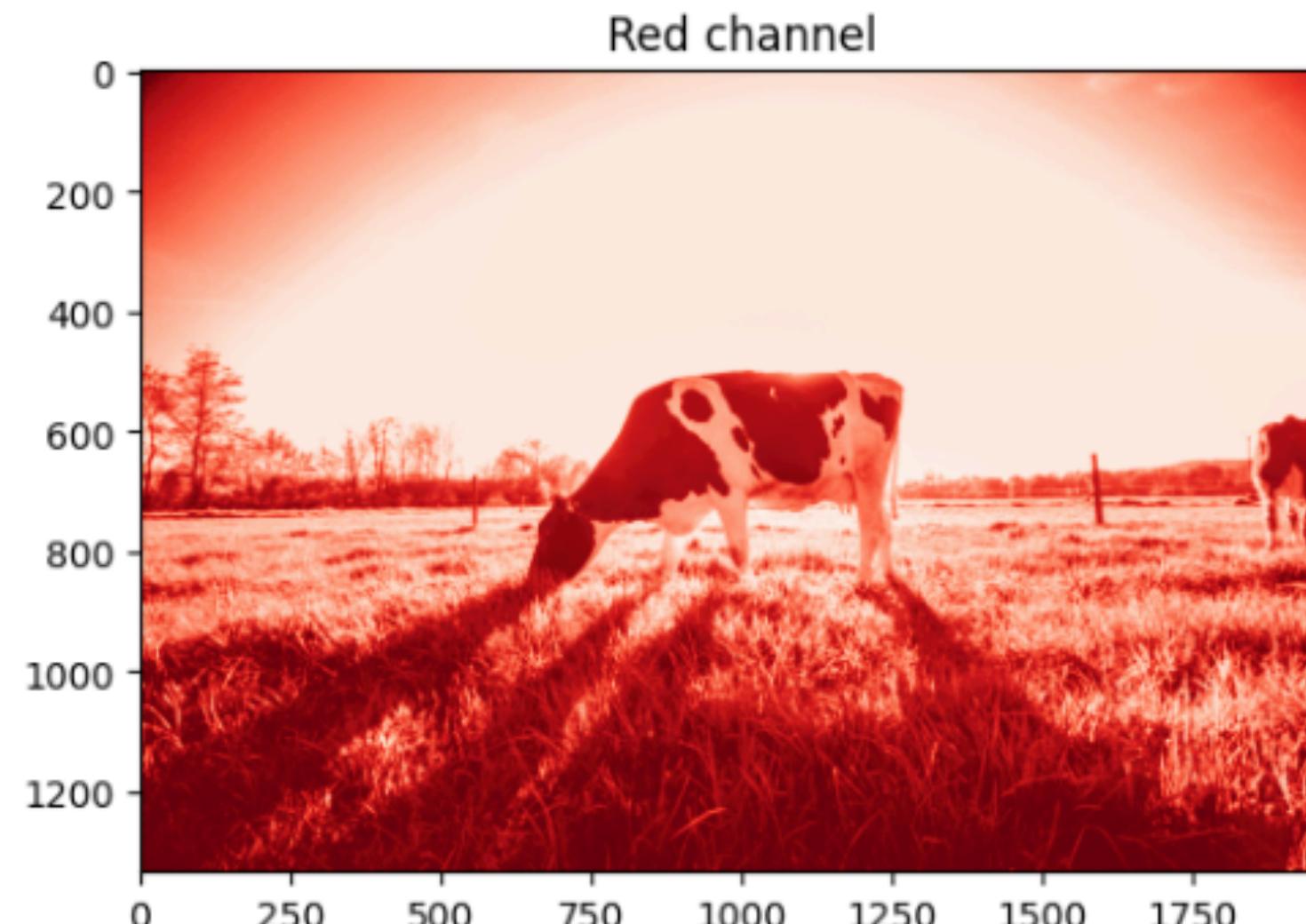
axis = 2

An Image Array Is Typically a Three-Dimensional Array

COMPUTER VISION

6

The brighter the color, the higher the value of the corresponding channel

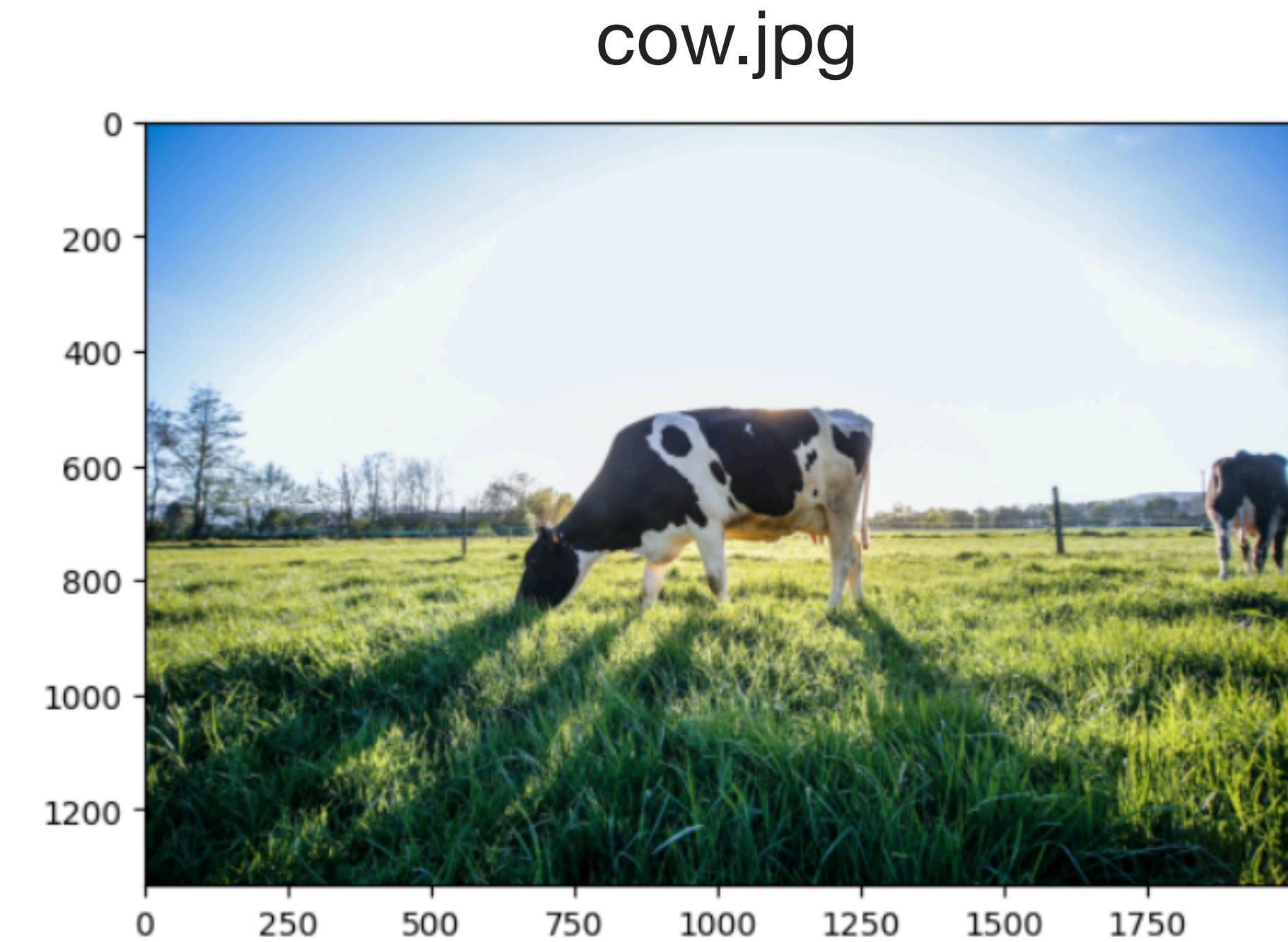


File loading

We can use the knowledge of matrix operations we learned earlier to conduct basic image processing.
Let's load an image and convert it to a matrix using the library PIL (Python Imaging Library).

```
# Option 1: Load the data (with statement)
with PIL.Image.open('cow.jpg') as image_file:
    image = np.array(image_file)

# Option 2: Equivalent to the above
image_file = PIL.Image.open('cow.jpg')
image = np.array(image_file)
image_file.close()
```



Inspect the Image Array

```
# check the dimensions of the image  
print("Shape of the image: ", image.shape)  
  
# check the data type of the image  
print("Data type of the image: ", image.dtype)  
  
# check the minimum and maximum values of the image  
print("Minimum value of the image: ", image.min())  
print("Maximum value of the image: ", image.max())
```

Shape of the image: (1333, 2000, 3)
Data type of the image: uint8
Minimum value of the image: 0
Maximum value of the image: 255

Use “.imshow” method to show an image

`plt.imshow(image)`

<matplotlib.image.AxesImage at 0x17ff53190>



Inspect the Image Array

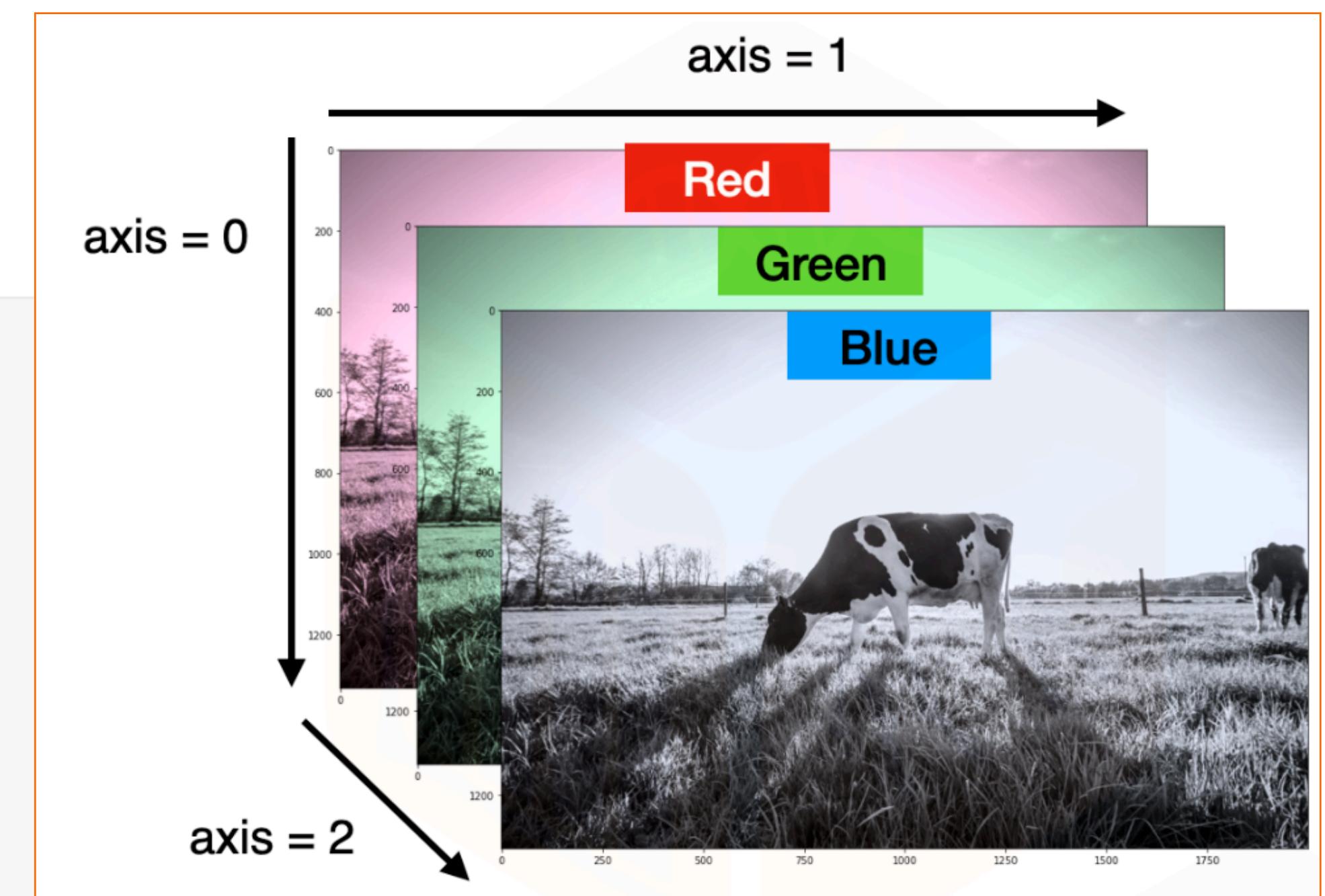
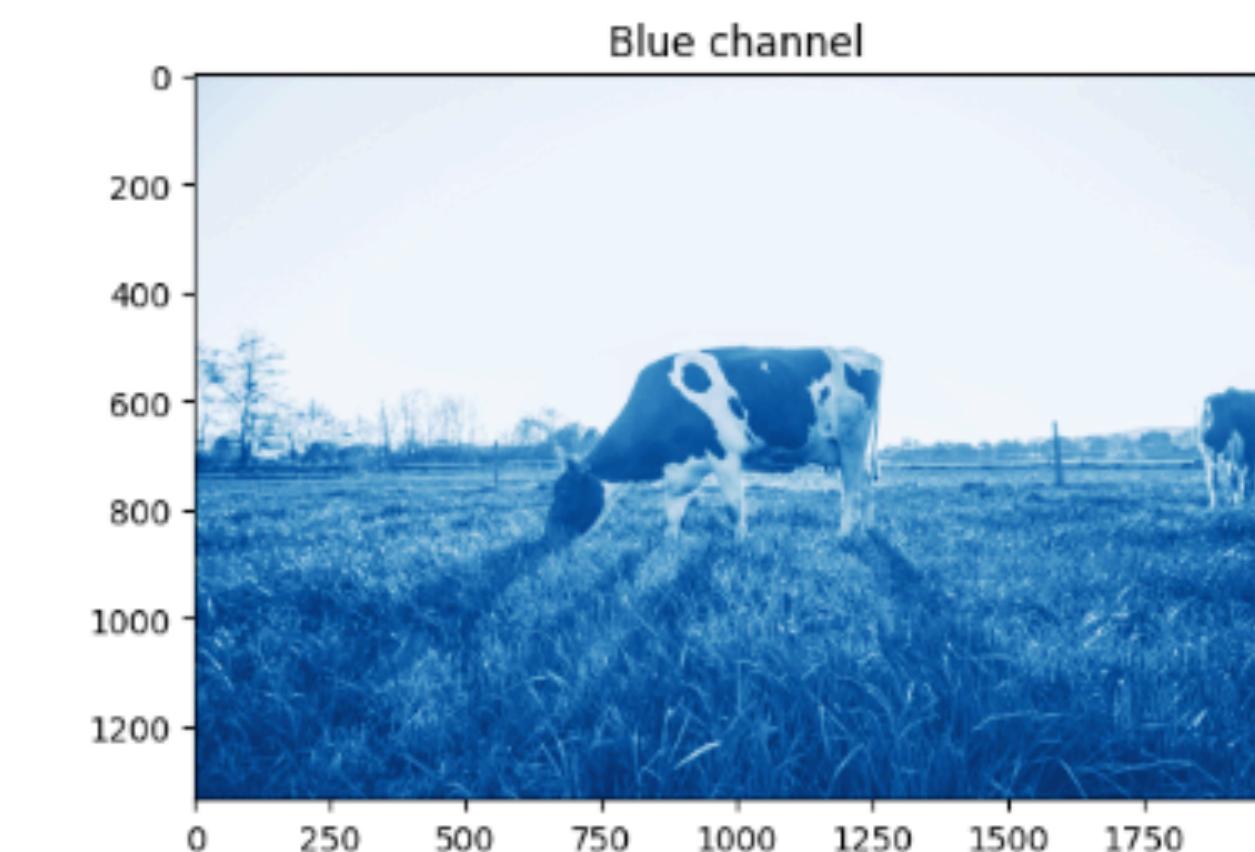
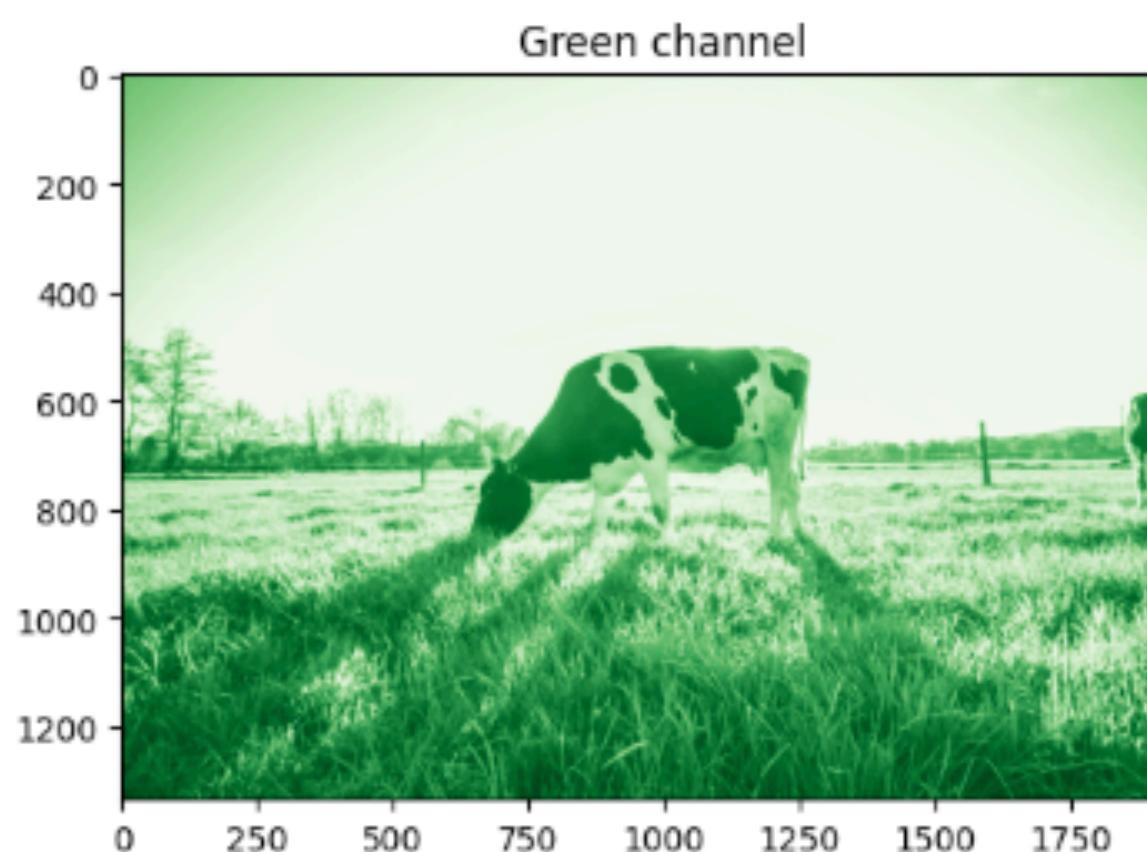
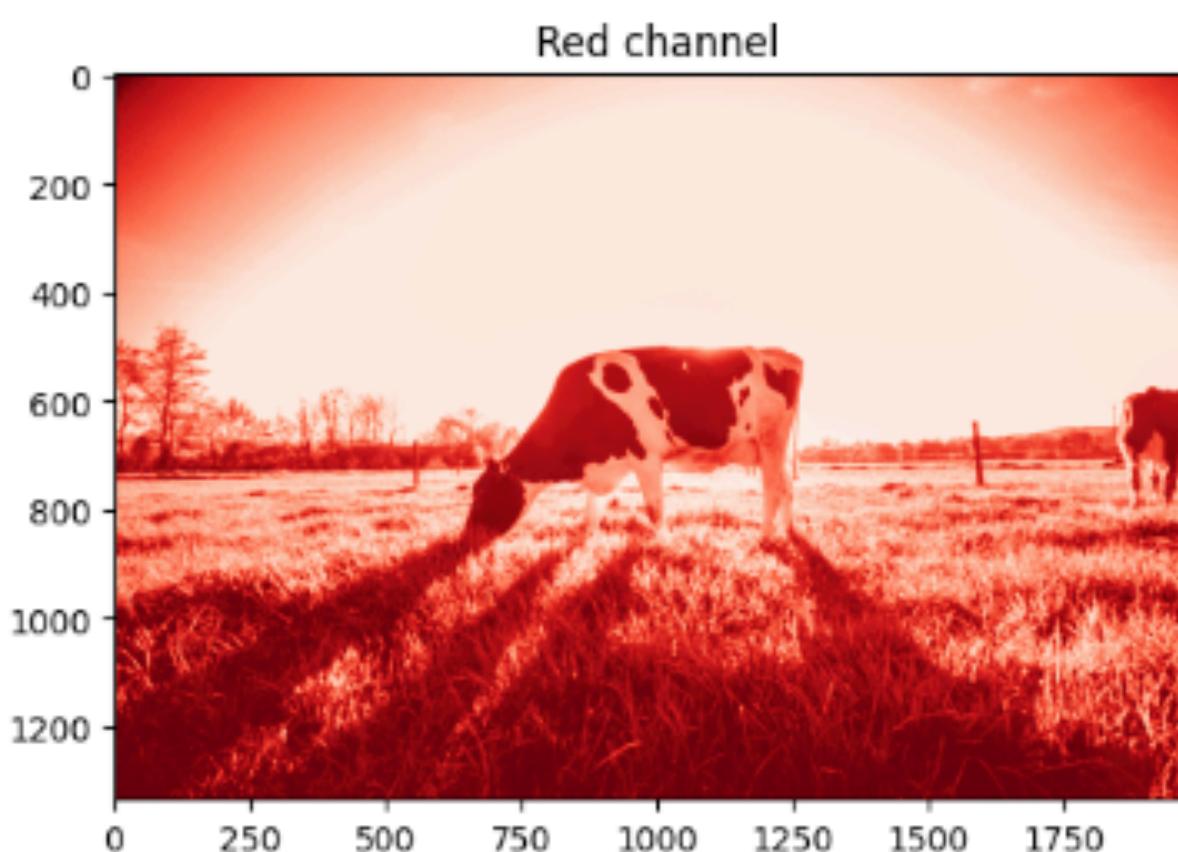
Check each color channel (axis = 2)

`image[:, :, 0]` Print out the first channel

```
fig, ax = plt.subplots(1, 3, figsize=(20, 15))
ax[0].imshow(image[:, :, 0], cmap='Reds_r')
ax[0].set_title('Red channel')
ax[1].imshow(image[:, :, 1], cmap='Greens_r')
ax[1].set_title('Green channel')
ax[2].imshow(image[:, :, 2], cmap='Blues_r')
ax[2].set_title('Blue channel')
```

✓ 0.6s

`Text(0.5, 1.0, 'Blue channel')`



Inspect the Image Array

Compute a pixel-wise variation

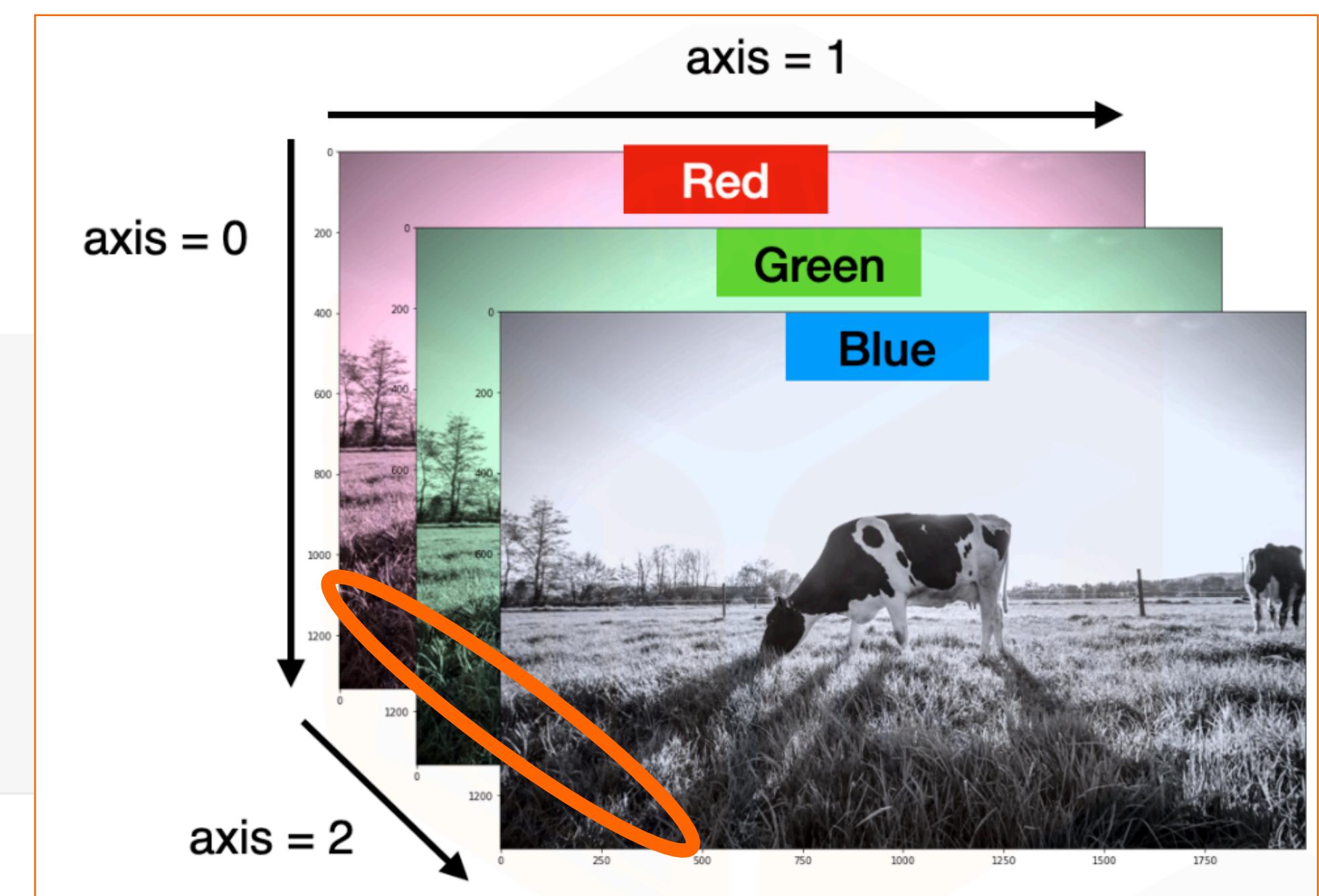
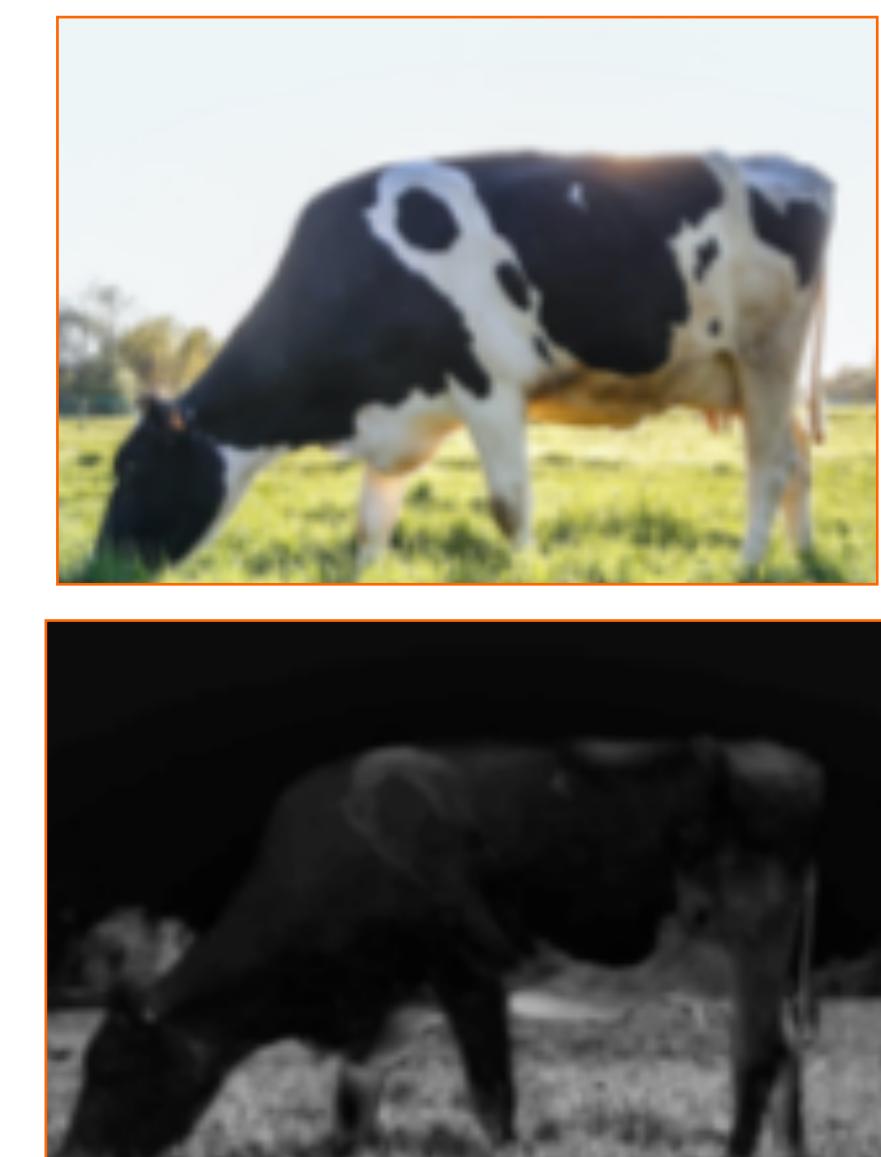
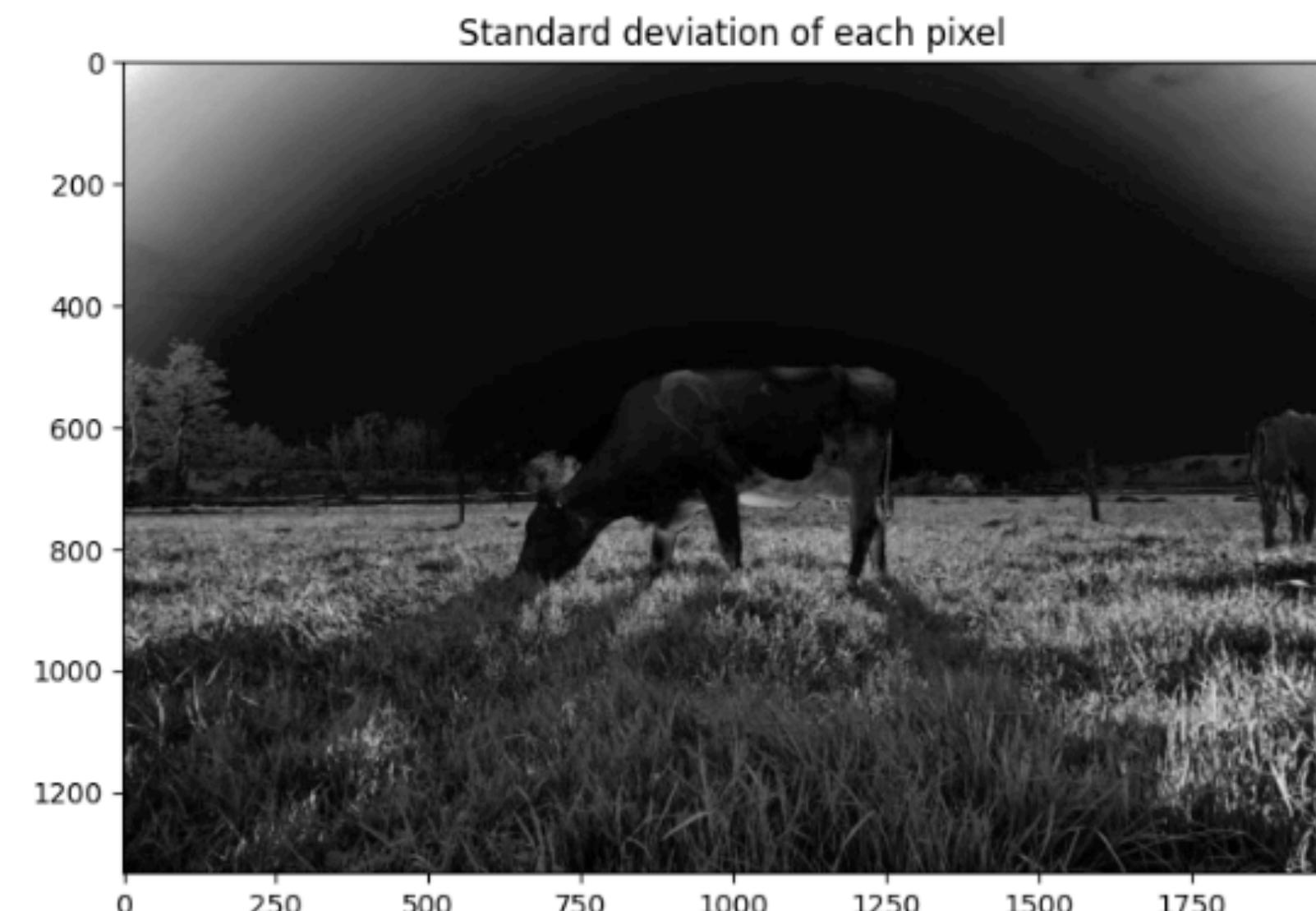
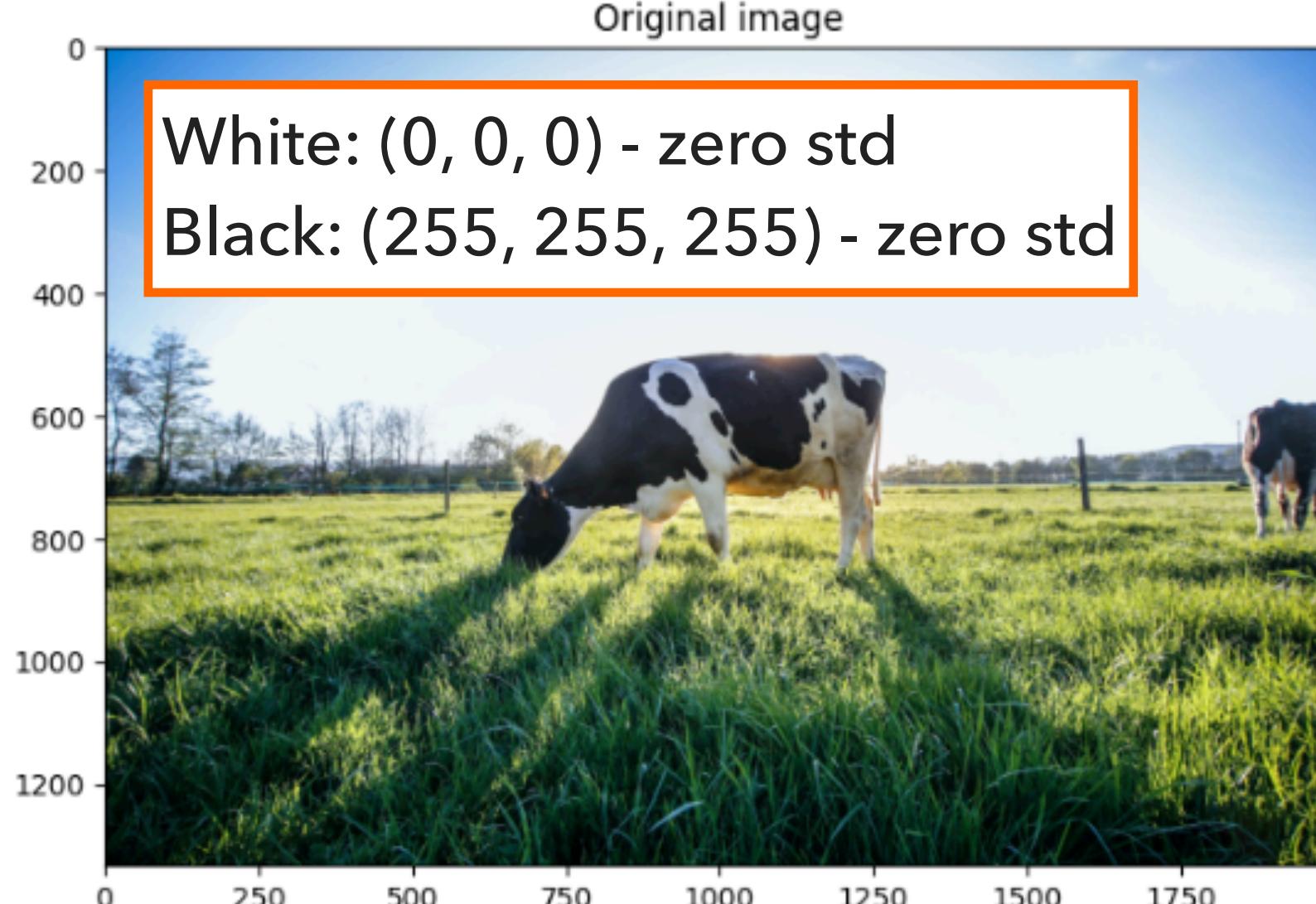
`image.std(axis=2)` channel axis

```
fig, axes = plt.subplots(nrows=1, ncols=2, figsize=(17, 10))
axes[0].imshow(image)
axes[0].set_title("Original image")
# std image (the brighter the higher)
axes[1].imshow(image.std(axis=2), cmap="gray")
axes[1].set_title("Standard deviation of each pixel")

```

✓ 0.6s

Text(0.5, 1.0, 'Standard deviation of each pixel')



We can apply any matrix (NumPy) operation to an image matrix

We can crop the image by slicing the array.

```
image_crop = image[450:950, 500:1400]
plt.imshow(image_crop)
]
✓ 0.1s
<matplotlib.image.AxesImage at 0x292e77d60>
```

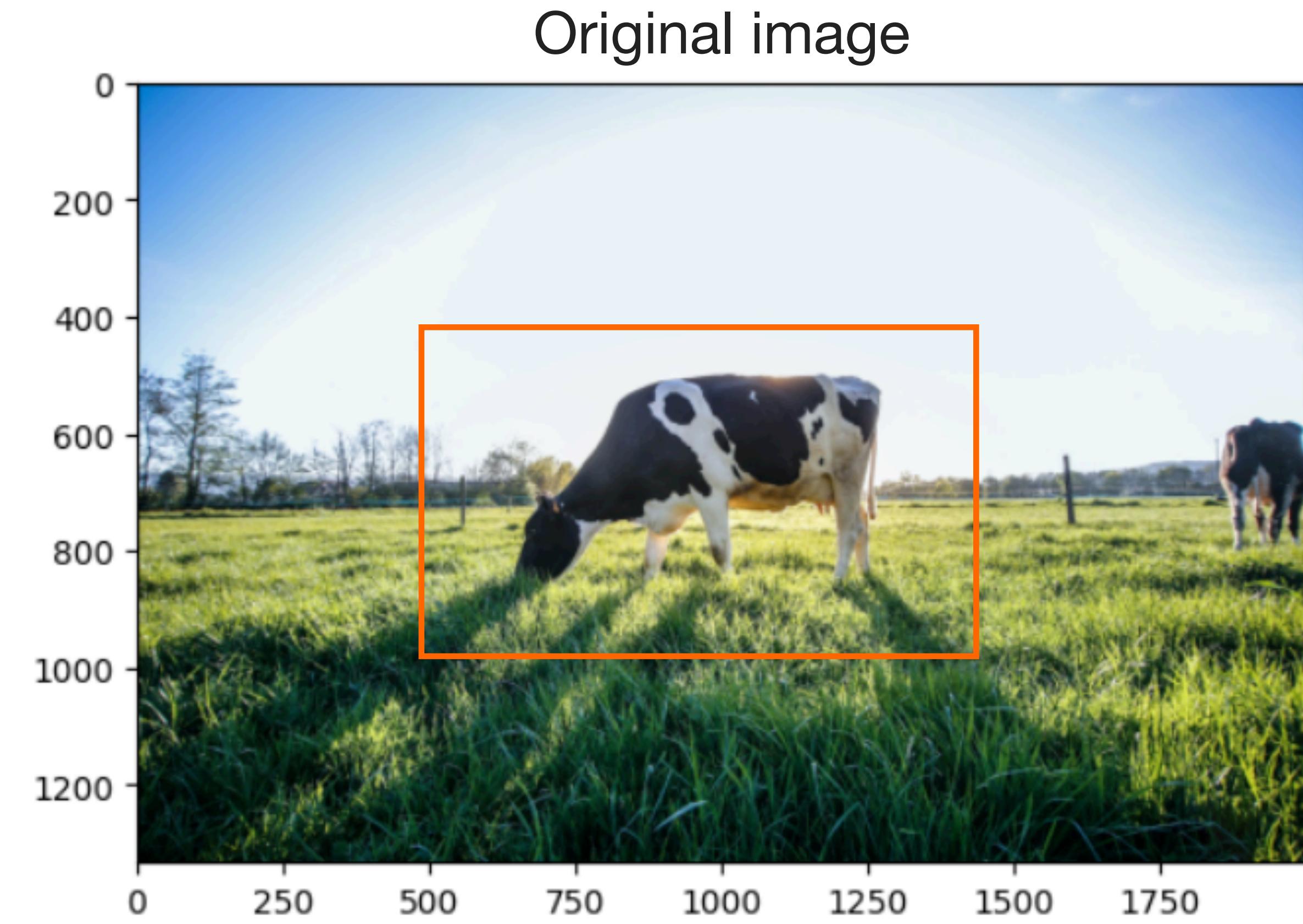
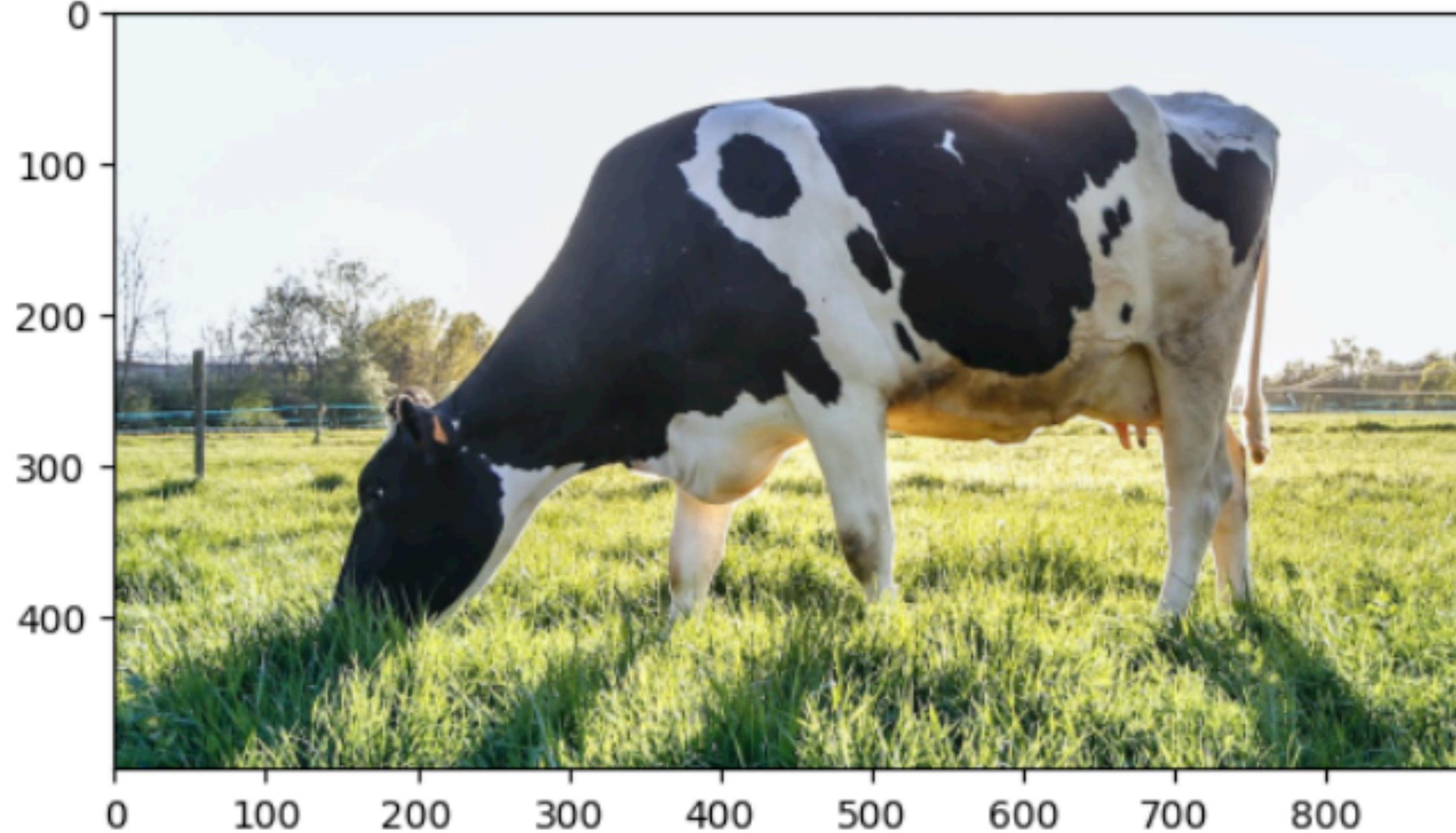


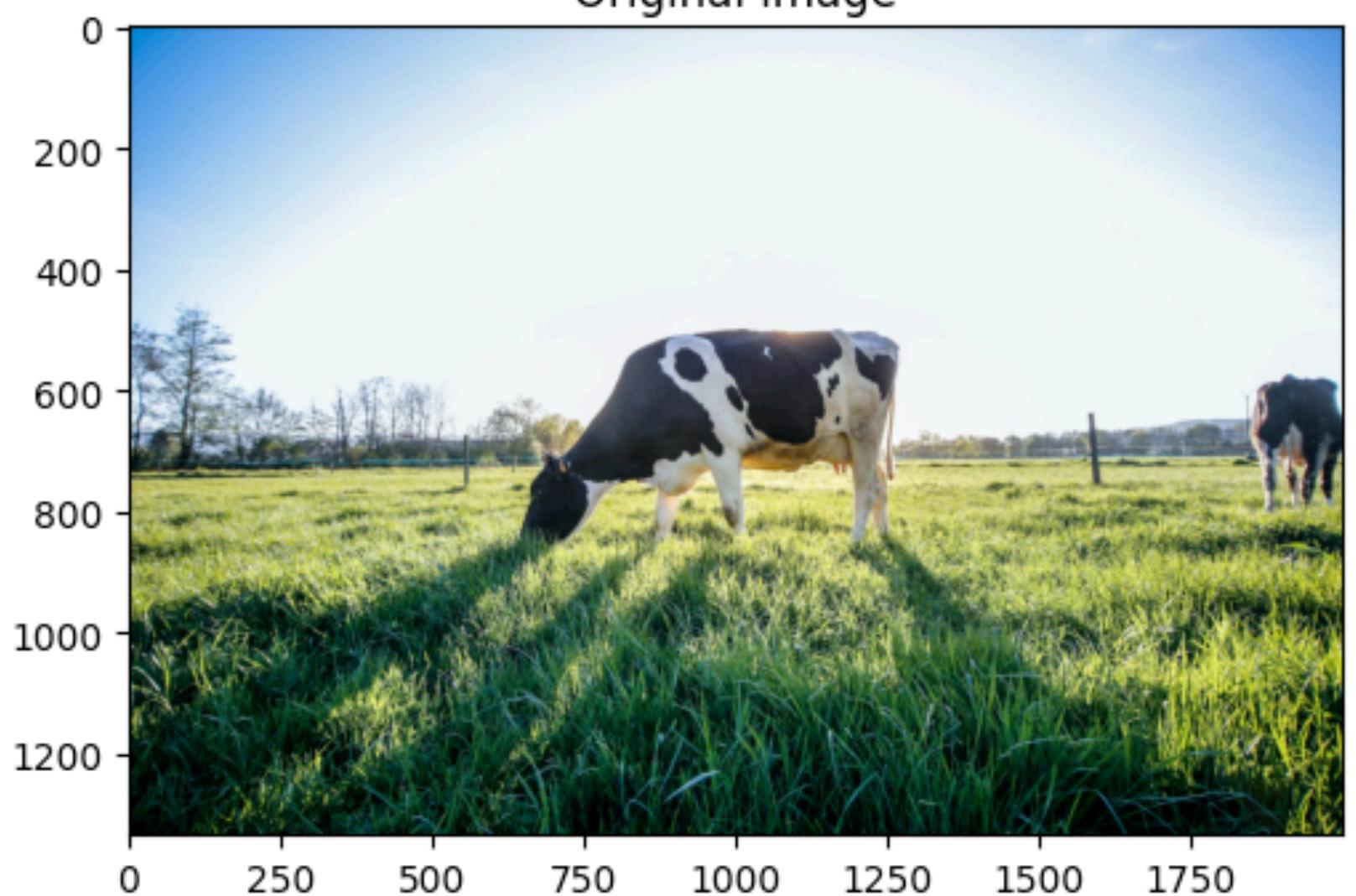
Image Flipping

Reversing the order of the sequence (matrix)

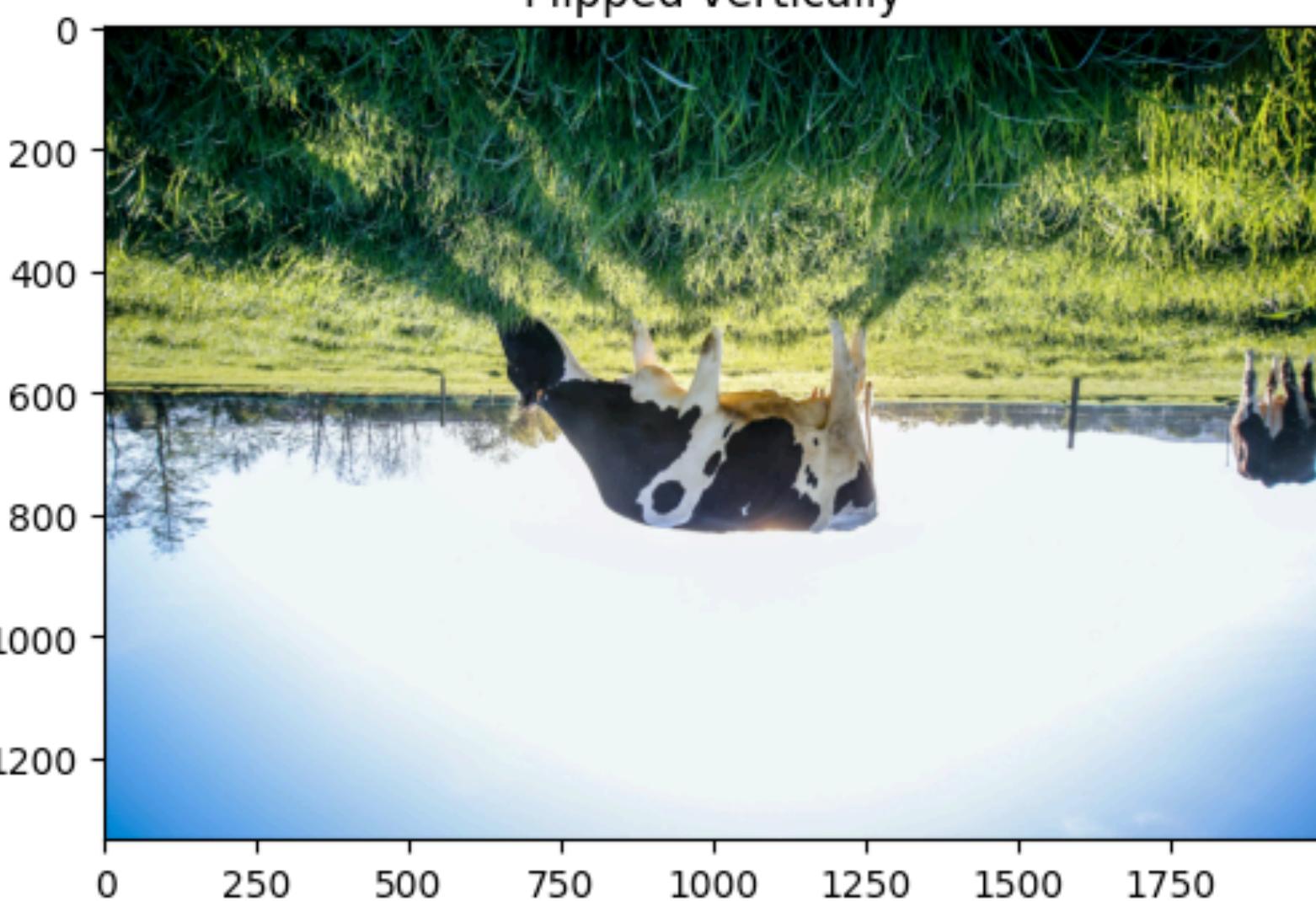
row col channel

`image[:: -1, :, :]`

Original image



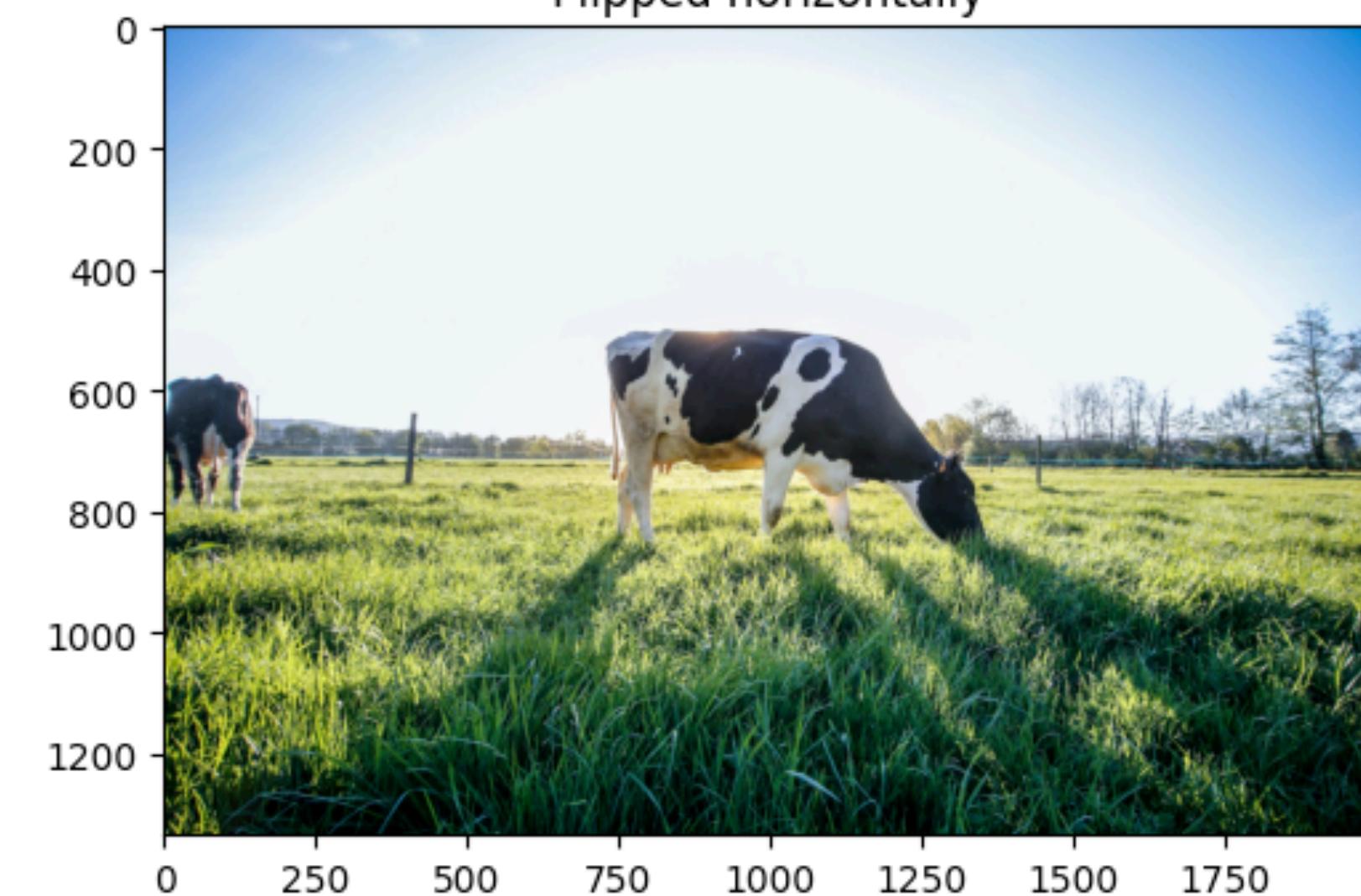
Flipped vertically



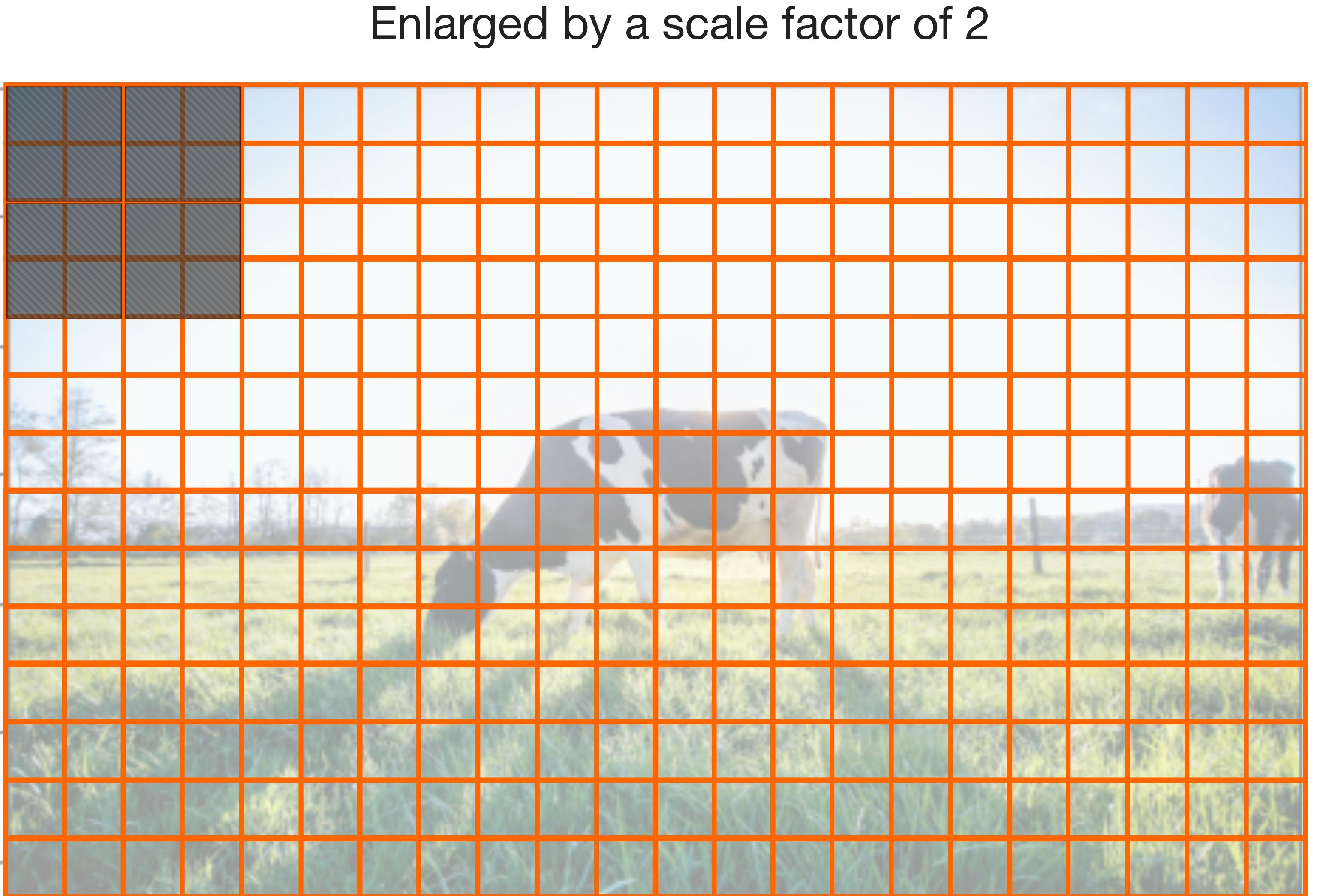
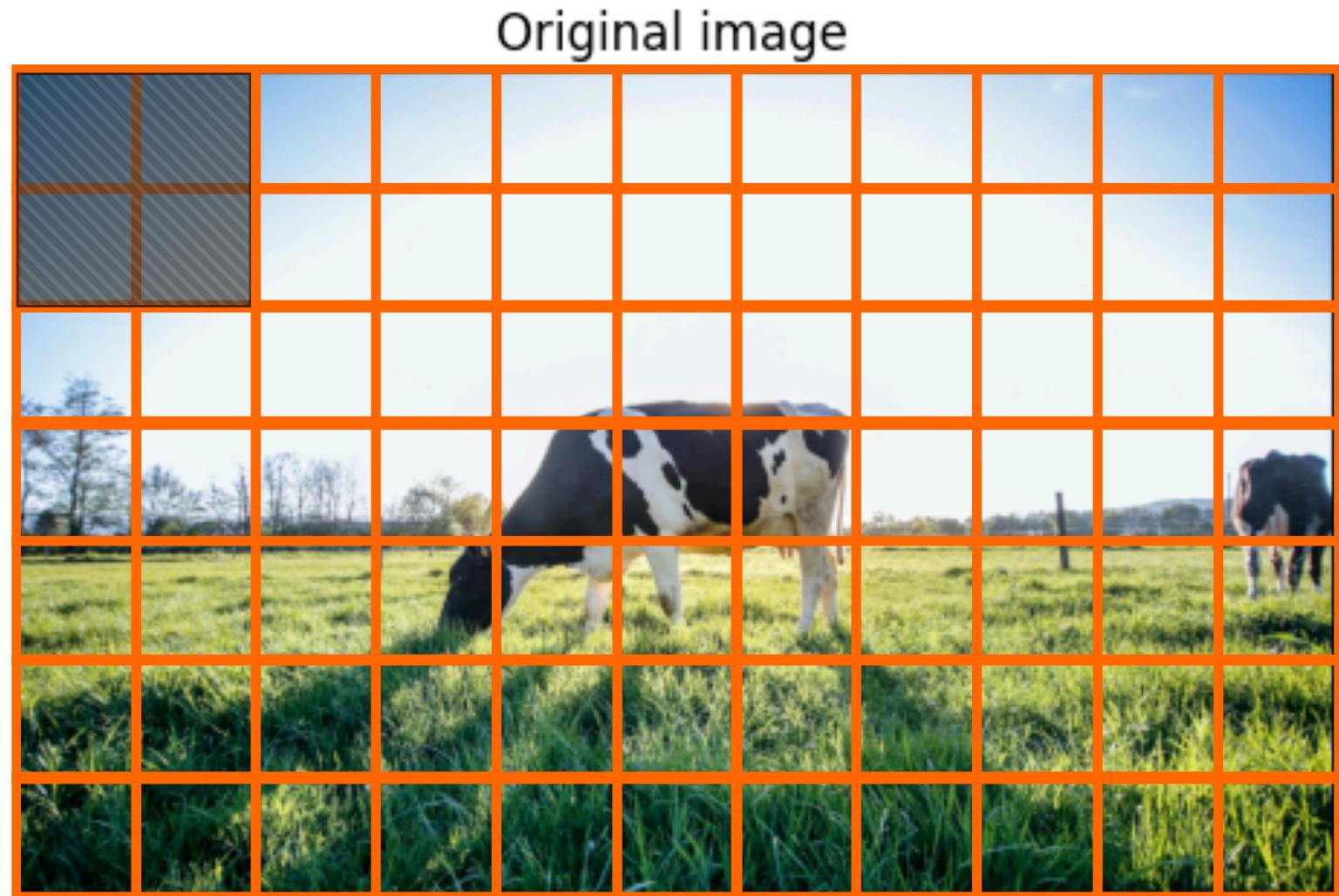
row col channel

`image[:, :: -1, :]`

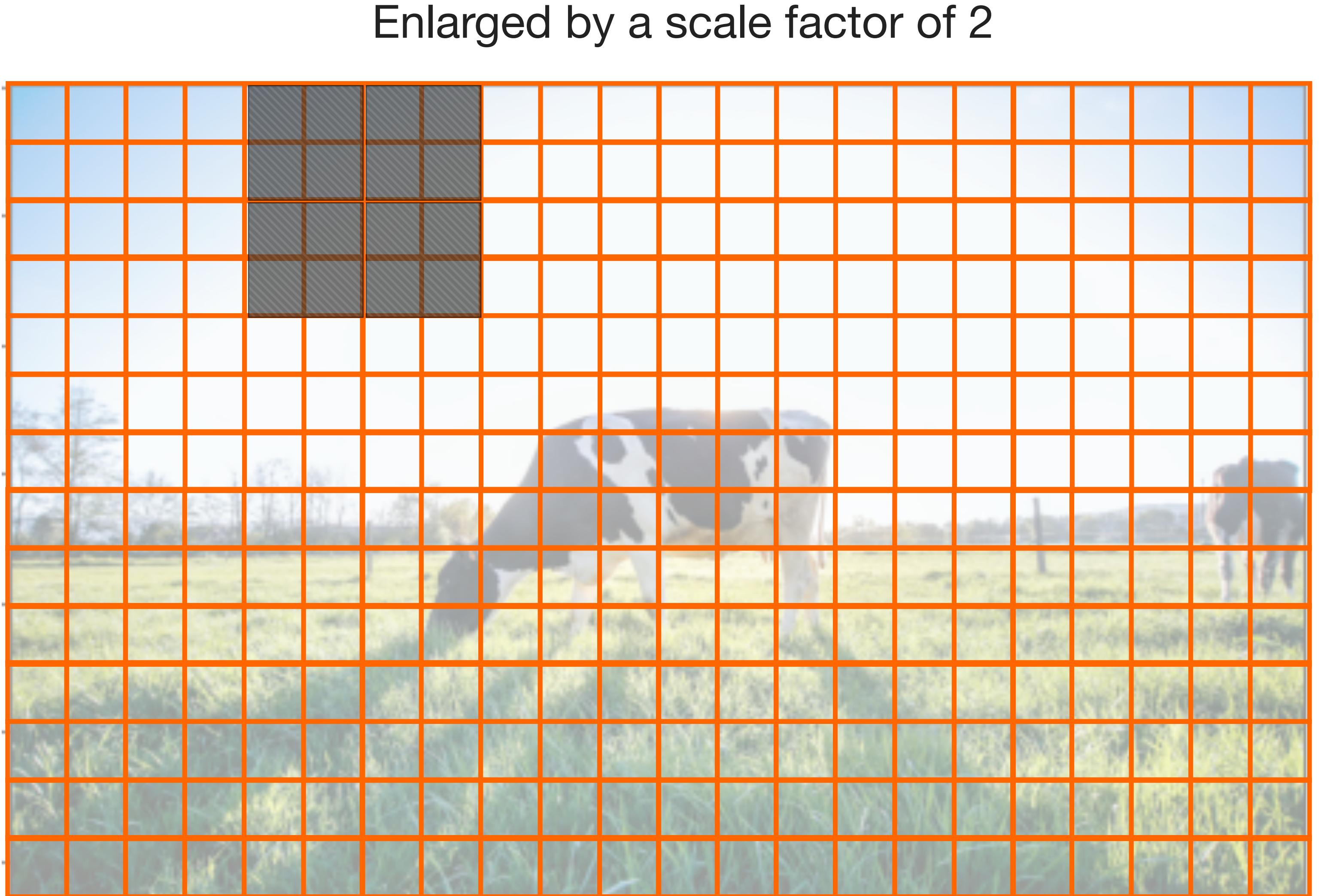
Flipped horizontally



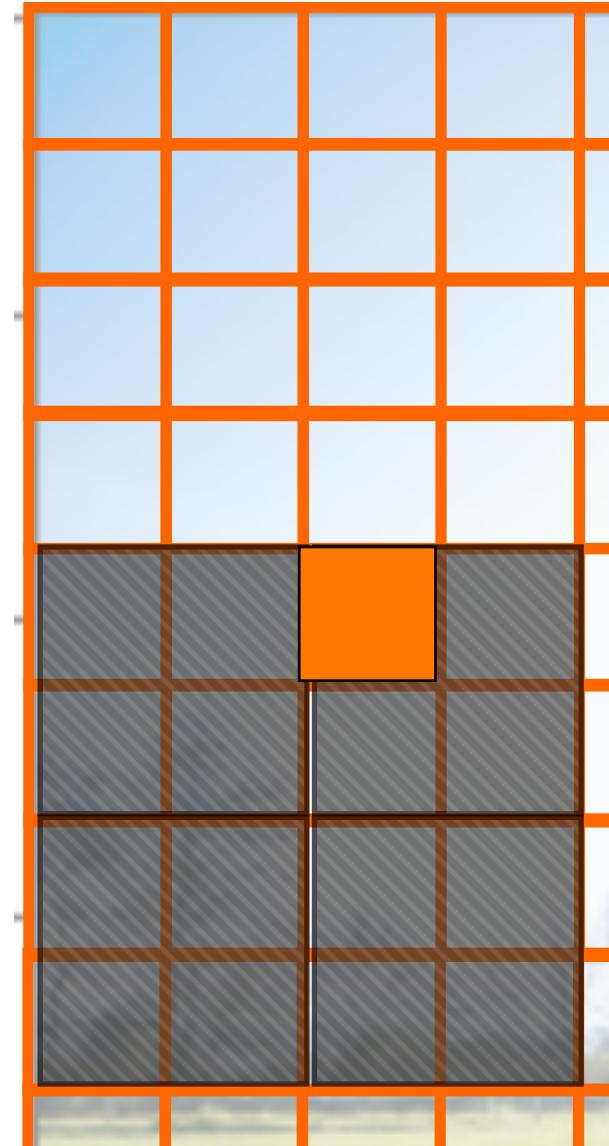
Resizing an image can be understood as mapping the original image to a new array with different size.



Resizing an image can be understood as mapping the original image to a new array with different size.



Resizing an image can be understood as mapping the original image to a new array with different size.



```
# resize an image in a larger canvas
H, W, C = image.shape
RESIZE_RATE = 2
nH, nW = H * RESIZE_RATE, W * RESIZE_RATE

# create a new image
img_new = np.zeros((nH, nW, C), dtype=np.uint8)
for h in range(nH):
    for w in range(nW):
        img_new[h, w, :] = image[int(h / RESIZE_RATE),
                                int(w / RESIZE_RATE),
                                :]
```

(2.5, 1.5) —————— (5, 3)

(3 , 2)

2x

Rounding to the
nearest integers



```
def resize_img(image, resize_rate):
    """
    """
    H, W, C = image.shape
    nH, nW = int(H * resize_rate), int(W * resize_rate)
    Create the output
    img_new = np.zeros((nH, nW, C), dtype=np.uint8)
    for h in range(nH):
        for w in range(nW):
            img_new[h, w, :] = image[int(h / resize_rate),
                                     int(w / resize_rate),
                                     :]
    print("original image shape: ", image.shape)
    Debug messages
    print("new image shape: ", img_new.shape)
    return img_new
```

Image Resizing - Function

```
img_large = resize_img(image, 2)
img_small = resize_img(image, 0.1)

fig, ax = plt.subplots(1, 3, figsize=(20, 15))
ax[0].imshow(image)
ax[0].set_title('Original image')
ax[1].imshow(img_large)
ax[1].set_title('Resized image (enlarged)')
ax[2].imshow(img_small)
ax[2].set_title('Resized image (shrinked)')
```

✓ 5.8s

original image shape: (1333, 2000, 3)

new image shape: (2666, 4000, 3)

original image shape: (1333, 2000, 3)

new image shape: (133, 200, 3)

Text(0.5, 1.0, 'Resized image (shrinked)')

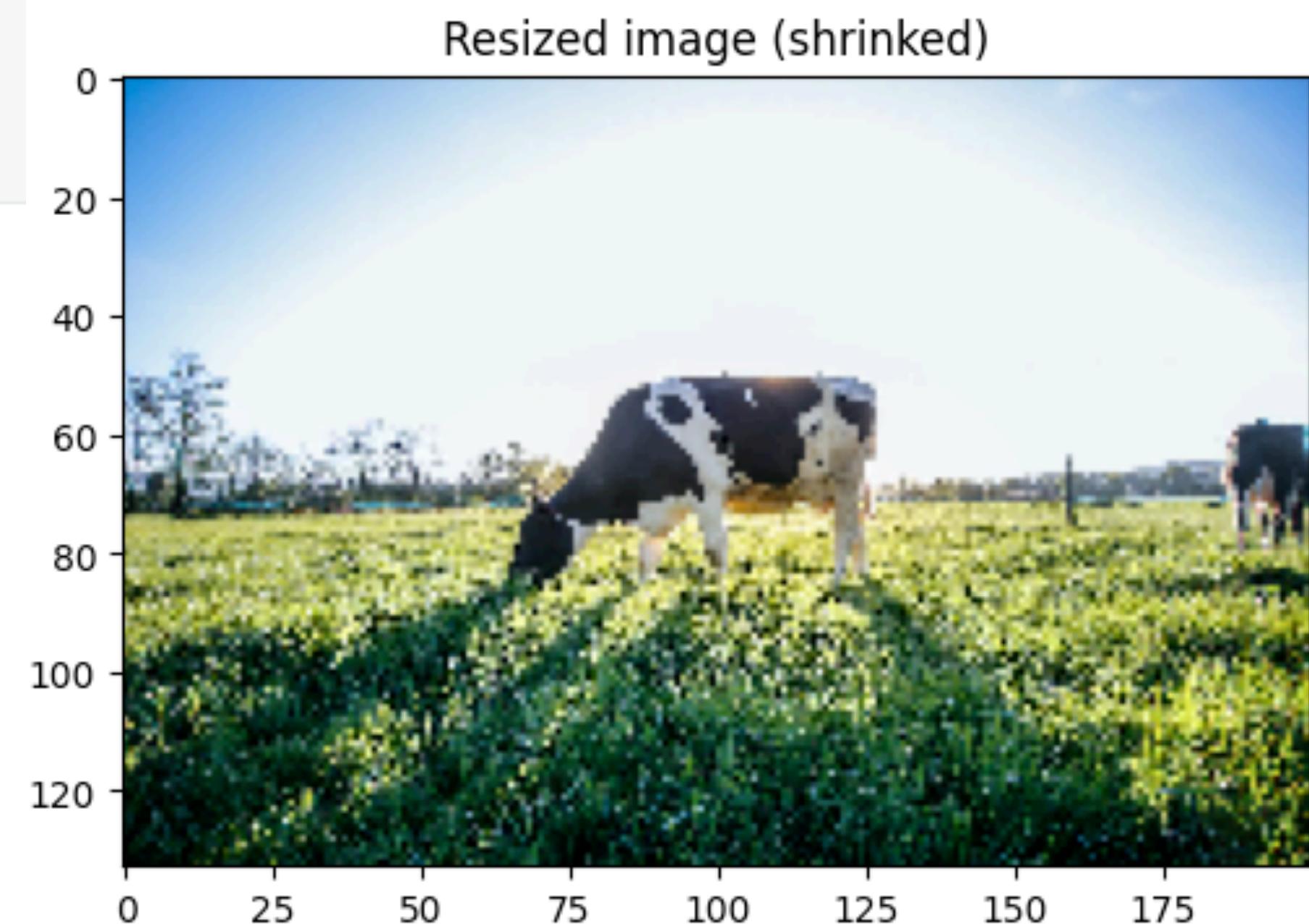


Image histogram is a histogram plot to visualize the distribution of pixel values in each channel. This plot allows us to visually inspect if the image is correctly exposed, or, for example, if any channel has significant higher signals than other channels.

Image

Underexposed



Regular exposure

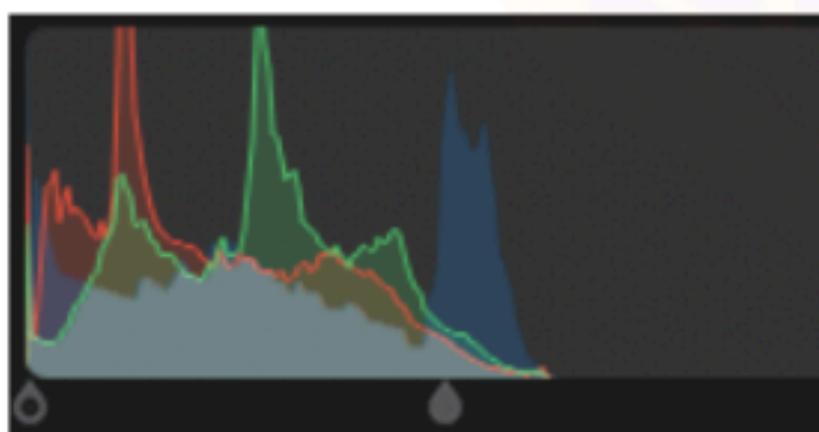


Overexposed

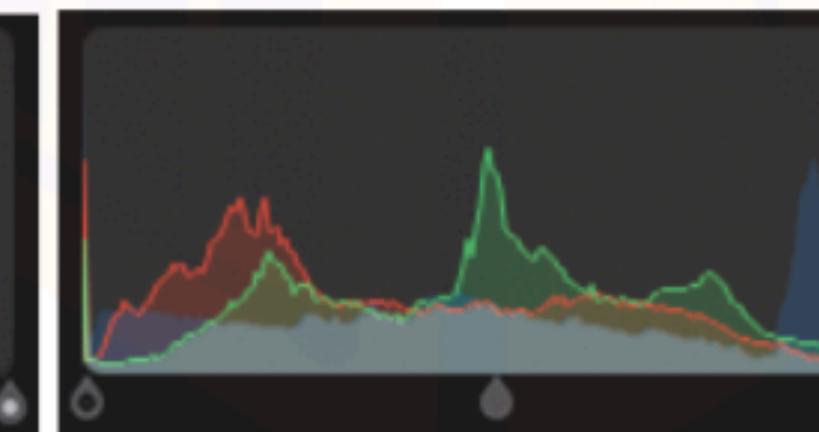


Histogram

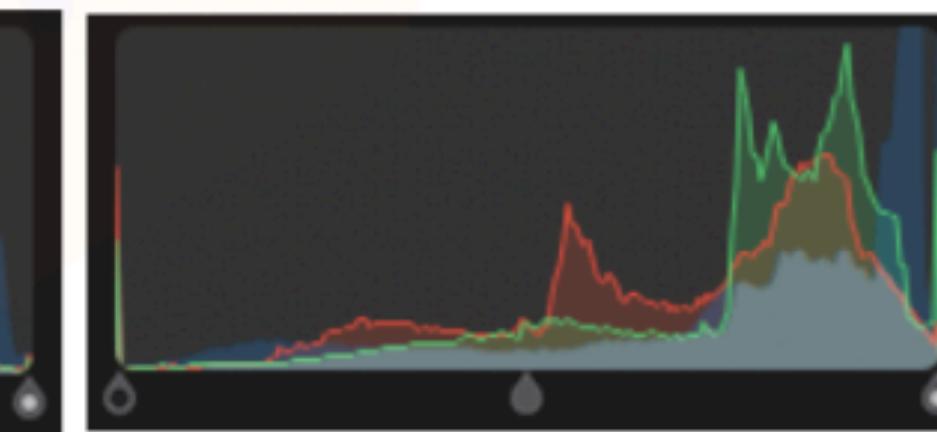
Pixel count



Channel values (0-255)



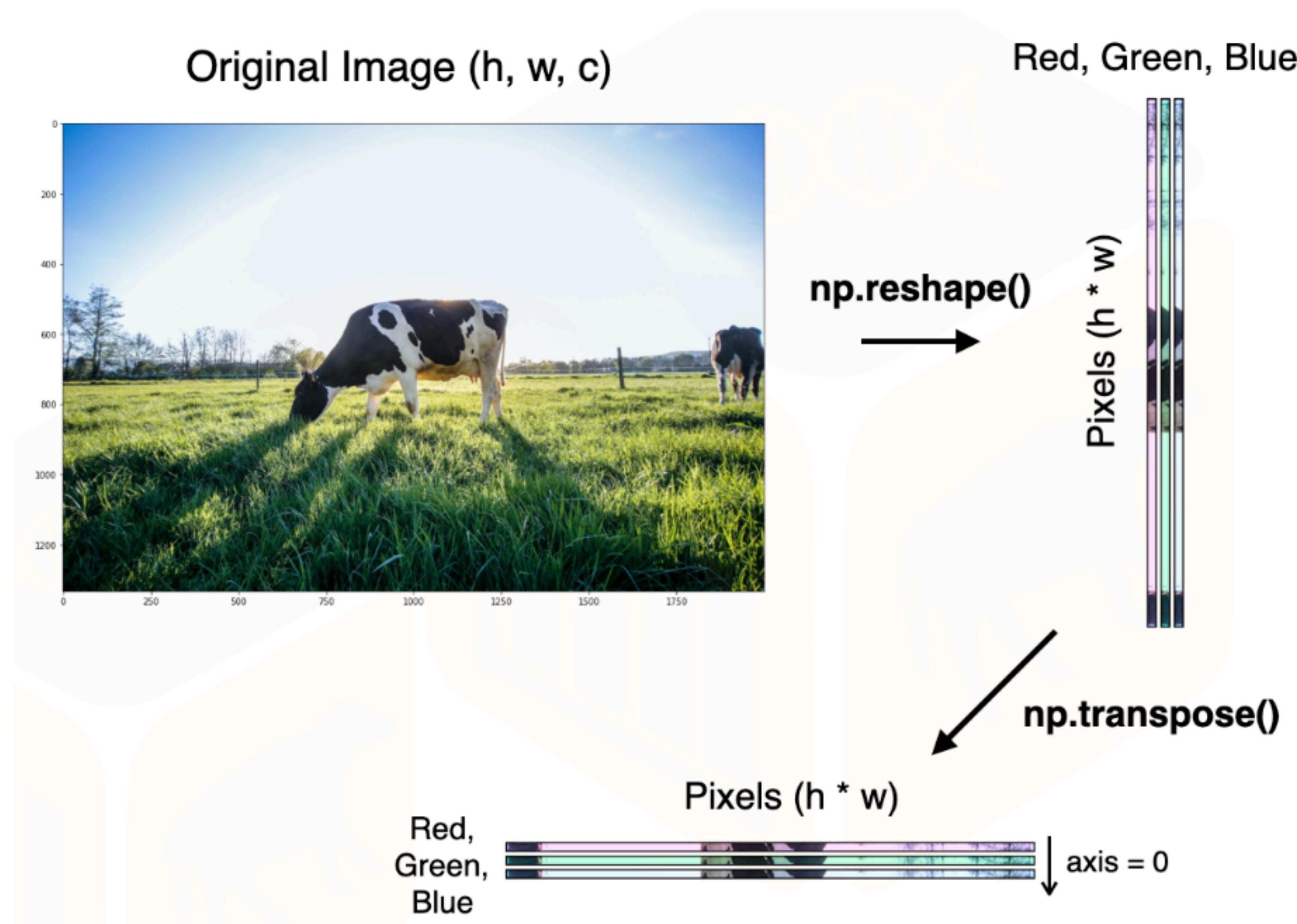
Channel values (0-255)



Channel values (0-255)

Image Histogram - Reshape the Matrix

We can change the image dimension (i.e., reshaping) from 3D to 2D for a better representation of the pixel distribution.



```
print("original dimension ", image_crop.shape)

# Use "-1" to let Python figure out the remaining dimension
# (pixels, channels)
channels = image_crop.reshape(-1, 3)
print("flattened dimension", channels.shape)

# Let the channel axis become the first axis
# (channels, pixels)
channels = channels.transpose()
print("final dimension    ", channels.shape)

✓ 0.0s

original dimension (500, 900, 3)
flattened dimension (450000, 3)
final dimension     (3, 450000)

# since (r, g, b) are now on the first axis.
red, green, blue = channels
print("red:   ", red.shape)
print("green: ", green.shape)
print("blue:  ", blue.shape)

✓ 0.0s

red:   (450000,)
green: (450000,)
blue:  (450000,)
```

Image Histogram - Visualization

```
# define parameters
params = dict(bins=30, alpha=.3, edgecolor="black")
colors = ["red", "green", "blue"]
# plotting
plt.figure(figsize=(10, 5))
plt.title("Histogram of RGB channels")
for i, bar in enumerate([red, green, blue]):
    # i is the iteration number starting from 0 (and 1, 2, ... )
    plt.hist(bar, color=colors[i], label=colors[i], **params)
plt.legend(fontsize=20)
```

