Introduction

Please see the Github repository for more information:

https://github.com/Createdd/computervision_ue

This notebook is available on Google Colab:

https://colab.research.google.com/drive/1UXrw17Lsbt-hsOIerbMG4JuFzpn73DWK

> Be aware that you would need to set up your google drive with the corresponding data if you like to use the google colab notebook!

Google Colab related

```
gpu_info = !nvidia-smi
gpu_info = '\n'.join(gpu_info)
if gpu_info.find('failed') >= 0:
  print('Not connected to a GPU')
else:
  print(gpu_info)
```

```
Thu Jan 20 21:24:37 2022
+-----------------------------------------------------------------------------+
| NVIDIA-SMI 495.46       Driver Version: 460.32.03    CUDA Version: 11.2     |
|-------------------------------+----------------------+----------------------+
| GPU  Name        Persistence-M| Bus-Id        Disp.A | Volatile Uncorr. ECC |
| Fan  Temp  Perf  Pwr:Usage/Cap|         Memory-Usage | GPU-Util  Compute M. |
|                               |                      |               MIG M. |
|===============================+======================+======================|
|   0  Tesla P100-PCIE...  Off  | 00000000:00:04.0 Off |                    0 |
| N/A   34C    P0    27W / 250W |      0MiB / 16280MiB |      0%      Default |
|                               |                      |                  N/A |
+-------------------------------+----------------------+----------------------+

+-----------------------------------------------------------------------------+
| Processes:                                                                  |
|  GPU   GI   CI        PID   Type   Process name                  GPU Memory |
|        ID   ID                                                   Usage      |
|=============================================================================|
|  No running processes found                                                 |
+-----------------------------------------------------------------------------+
```

```
from google.colab import drive
drive.mount('/content/drive')

%cd /content/drive/MyDrive/cv_data
```

```
Mounted at /content/drive
```

```
/content/drive/MyDrive/cv_data
```

```
# !apt install unzip
# !unzip ./data_WiSAR.zip -d .

%ls
```

```
data/  data_WiSAR.zip  integrated/  logs/  method.gdoc  model/  model_plot.png
```

Data loading

```
import torchvision
import torch
import matplotlib.pyplot as plt
import numpy as np

!pip install ipython-autotime
```

```
Collecting ipython-autotime
  Downloading ipython_autotime-0.3.1-py2.py3-none-any.whl (6.8 kB)
Requirement already satisfied: ipython in /usr/local/lib/python3.7/dist-packag
Requirement already satisfied: decorator in /usr/local/lib/python3.7/dist-pack
Requirement already satisfied: traitlets>=4.2 in /usr/local/lib/python3.7/dist
Requirement already satisfied: prompt-toolkit<2.0.0,>=1.0.4 in /usr/local/lib/
Requirement already satisfied: setuptools>=18.5 in /usr/local/lib/python3.7/di
Requirement already satisfied: pickleshare in /usr/local/lib/python3.7/dist-pa
Requirement already satisfied: pexpect in /usr/local/lib/python3.7/dist-packag
Requirement already satisfied: pygments in /usr/local/lib/python3.7/dist-packa
Requirement already satisfied: simplegeneric>0.8 in /usr/local/lib/python3.7/d
Requirement already satisfied: six>=1.9.0 in /usr/local/lib/python3.7/dist-pac
Requirement already satisfied: wcwidth in /usr/local/lib/python3.7/dist-packag
Requirement already satisfied: ptyprocess>=0.5 in /usr/local/lib/python3.7/dis
Installing collected packages: ipython-autotime
Successfully installed ipython-autotime-0.3.1
```

Load data and set parameters

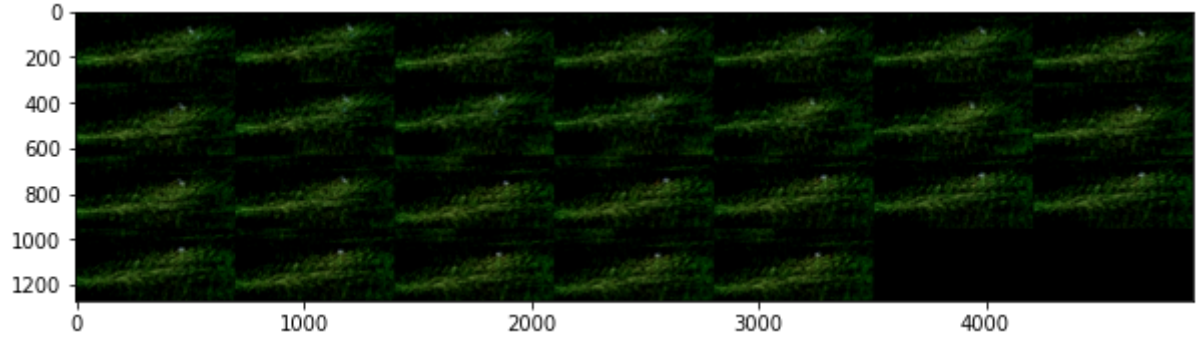
- Specifying the path to the images and using the DataLoader functions to efficiently feed the Keras Model image data.
- Display example of images

```
from torchvision import datasets, transforms

#####
# To make the google colab notebook work you need to upload the data on your go
# data_dir = './data'
data_dir = './integrated'

train_dir = data_dir + '/train'
```

```
validation_dir = data_dir + '/validation'
test_dir = data_dir + '/test'

target_size = (1024, 1024)
channel = (3,)
input_size = target_size + channel
batch_size=16
```

```
train_transforms = transforms.Compose([
                                       transforms.ToTensor(),
                                        transforms.Normalize([0.5, 0.5, 0.5],
                                                             [0.5, 0.5, 0.5])])
train_data = datasets.ImageFolder(train_dir,
                                  transform=train_transforms)
train_loader = torch.utils.data.DataLoader(train_data,
                                           batch_size=32)

def imshow(img):
    plt.figure(figsize=(10,8))
    plt.imshow(img.permute(1,2,0))


image, labels = next(iter(train_loader))
imshow(torchvision.utils.make_grid(image,nrow=7))
```

```
Clipping input data to the valid range for imshow with RGB data ([0..1] for fl
```




```
from keras.preprocessing.image import ImageDataGenerator


data_gen = ImageDataGenerator(rescale=1 / 255)

train_generator = data_gen.flow_from_directory(
    train_dir,
    target_size = target_size,
    # color_mode='grayscale',
    class_mode='input',
    batch_size=batch_size)

test_generator = data_gen.flow_from_directory(
    test_dir,
    target_size = target_size,
    # color_mode='grayscale',
    class_mode='input',
```

```
    batch_size=batch_size)

validation_generator = data_gen.flow_from_directory(
    validation_dir,
    target_size = target_size,
    # color_mode='grayscale',
    class_mode='input',
    batch_size=batch_size)
```

```
Found 26 images belonging to 26 classes.
Found 13 images belonging to 13 classes.
Found 11 images belonging to 11 classes.
```

Build architecture

- Building the Keras Deep Convolutional Autoencoder Model
- Add an own SSIM loss function

```
import tensorflow as tf
from tensorflow.keras import layers
from tensorflow.keras.models import Model

input = layers.Input(shape=input_size)

# Encoder
x = layers.Conv2D(32, (3, 3), activation="relu", padding="same")(input)
x = layers.MaxPooling2D((2, 2), padding="same")(x)
x = layers.Conv2D(32, (3, 3), activation="relu", padding="same")(x)
x = layers.MaxPooling2D((2, 2), padding="same")(x)

# Decoder
x = layers.Conv2DTranspose(32, (3, 3), strides=2, activation="relu", padding="s
x = layers.Conv2DTranspose(32, (3, 3), strides=2, activation="relu", padding="s
x = layers.Conv2D(3, (3, 3), activation="sigmoid", padding="same")(x)


def SSIMLoss(y_true, y_pred):
  return 1 - tf.reduce_mean(tf.image.ssim(y_true, y_pred,1.0))

autoencoder = Model(input, x)
optimizer = tf.keras.optimizers.Adam(lr = 0.0005)
autoencoder.compile(optimizer=optimizer, loss=SSIMLoss)

autoencoder.summary()

#########################################
# for plotting architecture
# from keras.utils.vis_utils import plot_model
# plot_model(autoencoder, to_file='model_plot.png', show_shapes=True, show_laye
```

```
Model: "model_27"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
```

```
=================================================================
 input_2 (InputLayer)        [(None, 1024, 1024, 3)]   0

 conv2d_3 (Conv2D)           (None, 1024, 1024, 32)    896

 max_pooling2d_2 (MaxPooling  (None, 512, 512, 32)     0
 2D)

 conv2d_4 (Conv2D)           (None, 512, 512, 32)      9248

 max_pooling2d_3 (MaxPooling  (None, 256, 256, 32)     0
 2D)

 conv2d_transpose_2 (Conv2DT  (None, 512, 512, 32)     9248
 ranspose)

 conv2d_transpose_3 (Conv2DT  (None, 1024, 1024, 32)   9248
 ranspose)

 conv2d_5 (Conv2D)           (None, 1024, 1024, 3)     867

=================================================================
Total params: 29,507
Trainable params: 29,507
Non-trainable params: 0
_________________________________________________________________
time: 116 ms (started: 2022-01-20 17:32:00 +00:00)
/usr/local/lib/python3.7/dist-packages/keras/optimizer_v2/adam.py:105: UserWar
  super(Adam, self).__init__(name, **kwargs)
```

Train Model

- Set up Tensorboard for debugging the model
- Train and save the model

```
%load_ext tensorboard
%reload_ext tensorboard

from keras.callbacks import TensorBoard
import tensorflow as tf
import datetime, os

## remove old logs
import shutil
shutil.rmtree("logs", ignore_errors=False)
###

logdir = os.path.join("logs", datetime.datetime.now().strftime("%Y%m%d-%H%M%S")
tensorboard_callback = tf.keras.callbacks.TensorBoard(logdir, histogram_freq=1)
```

```
The tensorboard extension is already loaded. To reload it, use:
  %reload_ext tensorboard
time: 22.9 ms (started: 2022-01-20 17:32:00 +00:00)
```

```
# https://keras.io/api/models/model_training_apis/
# %load_ext autotime

# hist=autoencoder.fit(
#                 x = train_generator,
#                 epochs=100,
#                 #batch_size=128, # doesnt need to be specified when generator
#                 #shuffle=True,
#                 validation_data=(validation_generator),
#                 callbacks=[tensorboard_callback]
#                 )


# autoencoder.save('./model/autoencoder.h5')
autoencoder = keras.models.load_model('./model/autoencoder.h5')
predictions = autoencoder.predict(validation_generator)
```

```
The autotime extension is already loaded. To reload it, use:
  %reload_ext autotime
Epoch 1/100
2/2 [==============================] - 4s 2s/step - loss: 0.2251 - val_loss:
Epoch 2/100
2/2 [==============================] - 2s 2s/step - loss: 0.2176 - val_loss:
Epoch 3/100
2/2 [==============================] - 3s 1s/step - loss: 0.2161 - val_loss:
Epoch 4/100
2/2 [==============================] - 2s 2s/step - loss: 0.2158 - val_loss:
Epoch 5/100
2/2 [==============================] - 2s 2s/step - loss: 0.2156 - val_loss:
Epoch 6/100
2/2 [==============================] - 2s 2s/step - loss: 0.2154 - val_loss:
Epoch 7/100
2/2 [==============================] - 3s 1s/step - loss: 0.2154 - val_loss:
Epoch 8/100
2/2 [==============================] - 2s 2s/step - loss: 0.2152 - val_loss:
Epoch 9/100
2/2 [==============================] - 2s 2s/step - loss: 0.2150 - val_loss:
Epoch 10/100
2/2 [==============================] - 3s 1s/step - loss: 0.2148 - val_loss:
Epoch 11/100
2/2 [==============================] - 2s 2s/step - loss: 0.2146 - val_loss:
Epoch 12/100
2/2 [==============================] - 3s 1s/step - loss: 0.2145 - val_loss:
Epoch 13/100
2/2 [==============================] - 3s 1s/step - loss: 0.2142 - val_loss:
Epoch 14/100
2/2 [==============================] - 3s 1s/step - loss: 0.2139 - val_loss:
Epoch 15/100
2/2 [==============================] - 2s 2s/step - loss: 0.2136 - val_loss:
Epoch 16/100
2/2 [==============================] - 3s 1s/step - loss: 0.2132 - val_loss:
Epoch 17/100
2/2 [==============================] - 2s 2s/step - loss: 0.2126 - val_loss:
Epoch 18/100
2/2 [==============================] - 3s 1s/step - loss: 0.2122 - val_loss:
Epoch 19/100
2/2 [==============================] - 2s 2s/step - loss: 0.2114 - val_loss:
Epoch 20/100
```

```
2/2 [==============================] - 3s 1s/step - loss: 0.2107 - val_loss:
Epoch 21/100
2/2 [==============================] - 3s 1s/step - loss: 0.2097 - val_loss:
Epoch 22/100
2/2 [==============================] - 2s 2s/step - loss: 0.2083 - val_loss:
Epoch 23/100
2/2 [==============================] - 2s 2s/step - loss: 0.2068 - val_loss:
Epoch 24/100
2/2 [==============================] - 3s 1s/step - loss: 0.2051 - val_loss:
Epoch 25/100
2/2 [==============================] - 2s 2s/step - loss: 0.2024 - val_loss:
Epoch 26/100
2/2 [==============================] - 2s 2s/step - loss: 0.1994 - val_loss:
Epoch 27/100
2/2 [==============================] - 2s 2s/step - loss: 0.1957 - val_loss:
Epoch 28/100
```

```
# Used for debugging Model
# %tensorboard --logdir logs
# ## notebook.display(port=6006, height=1000)

# from tensorboard import notebook
# notebook.list()
```

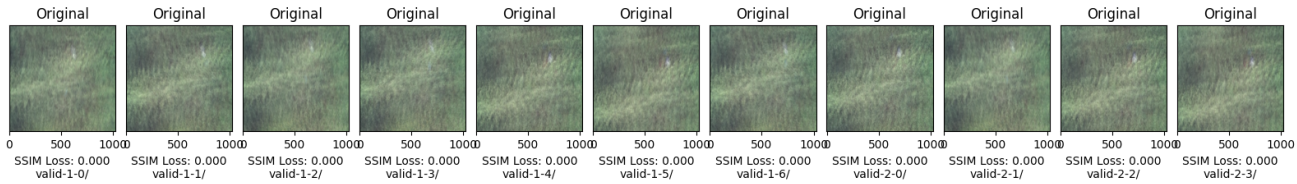
```
time: 1.57 ms (started: 2022-01-20 17:36:13 +00:00)
```

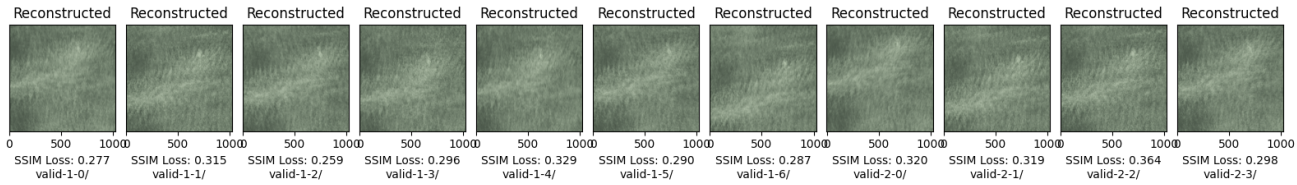
Display results

```
def display(array1, array2, target_size=(28,28)):

    n = 10

    indices = np.random.randint(len(array1), size=n)
    images1 = array1[indices, :]
    images2 = array2[indices, :]

    plt.figure(figsize=(20, 4))
    for i, (image1, image2) in enumerate(zip(images1, images2)):
        ax = plt.subplot(2, n, i + 1)
        plt.imshow(image1.reshape(target_size))
        plt.gray()
        ax.get_xaxis().set_visible(False)
        ax.get_yaxis().set_visible(False)

        ax = plt.subplot(2, n, i + 1 + n)
        plt.imshow(image2.reshape(target_size))
        plt.gray()
        ax.get_xaxis().set_visible(False)
        ax.get_yaxis().set_visible(False)

    plt.show()

```

```
time: 12.7 ms (started: 2022-01-20 17:36:14 +00:00)
```

```
plt.figure(figsize=(20, 14), dpi=100)
plt.subplots_adjust( wspace=0.1, hspace=0.07)
plt_a=1

n=11
for i in range(n):

    gen_file_name = validation_generator.filenames[i]
    img = next(validation_generator)[0][i]
    loss_orig = SSIMLoss(img,img)
    loss_reconstructed = SSIMLoss(img,predictions[i])

    ax = plt.subplot(3, n, plt_a)
    plt.imshow(img)
    ax.get_xaxis().set_visible(True)
    ax.get_yaxis().set_visible(False)
    ax.set_title(f"Original")
    label = f'SSIM Loss: {loss_orig:.3f}\n{gen_file_name[:10]}'
    ax.set_xlabel(label)


    ax = plt.subplot(3, n, plt_a + n )
    plt.imshow(predictions[i])
    ax.get_xaxis().set_visible(True)
    ax.get_yaxis().set_visible(False)
    ax.set_title(f"Reconstructed")
    label = f'SSIM Loss: {loss_reconstructed:.3f}\n{gen_file_name[:10]}'
    ax.set_xlabel(label)

    plt_a+=1
plt.show()
```





Get activations

- for showing reconstructions activations and detecting anomalies

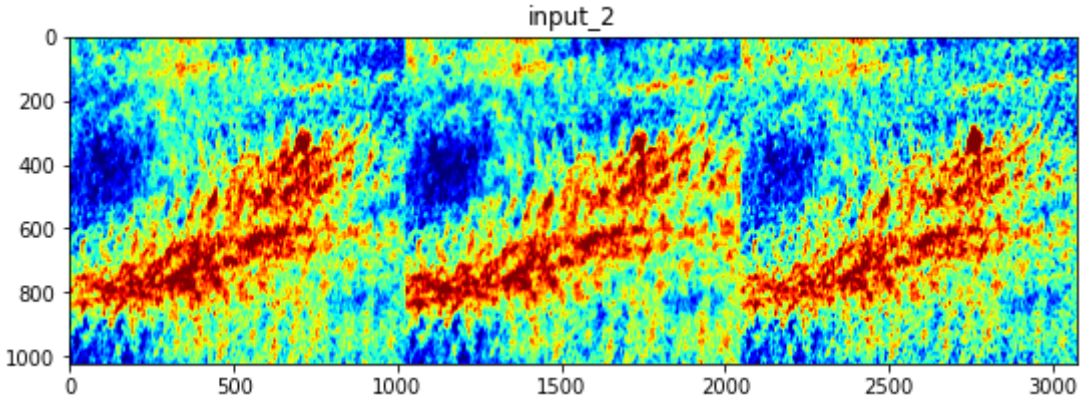
```
!pip install keract
from keract import get_activations

input_sample = next(validation_generator)[0][10]
input_sample_expanded = np.expand_dims(input_sample, axis=0)

activations = get_activations(autoencoder, input_sample_expanded, nested=True)
for layer_name, acts in activations.items():
        print(layer_name, acts.shape,'\n', end=' ')
```

```
Requirement already satisfied: keract in /usr/local/lib/python3.7/dist-package
input_2 (1, 1024, 1024, 3)
 conv2d_3 (1, 1024, 1024, 32)
 max_pooling2d_2 (1, 512, 512, 32)
 conv2d_4 (1, 512, 512, 32)
 max_pooling2d_3 (1, 256, 256, 32)
 conv2d_transpose_2 (1, 512, 512, 32)
 conv2d_transpose_3 (1, 1024, 1024, 32)
 conv2d_5 (1, 1024, 1024, 3)
 time: 3.46 s (started: 2022-01-20 17:36:23 +00:00)
```

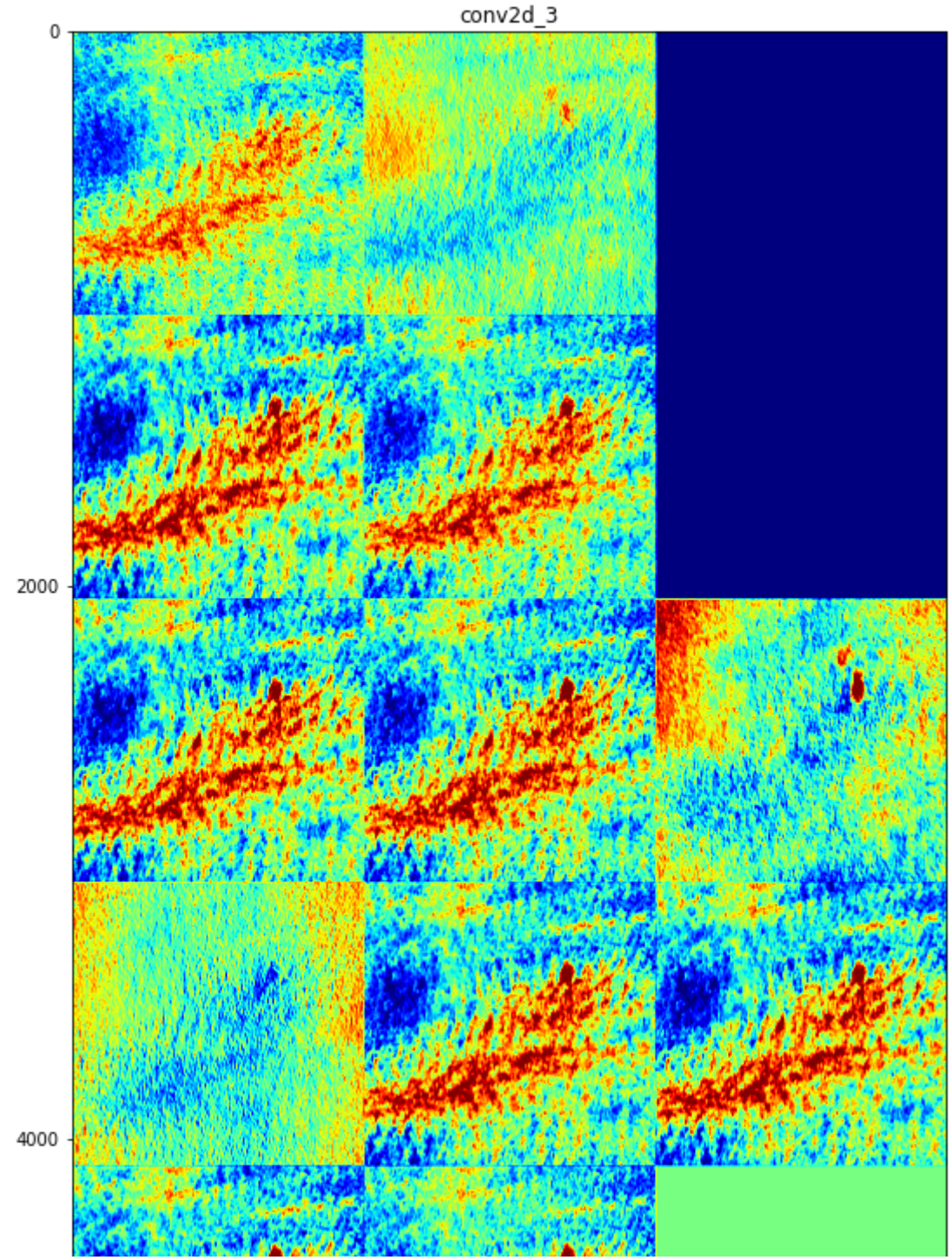
```
# base from https://towardsdatascience.com/visualizing-intermediate-activation-

from matplotlib.pyplot import figure


layer_names = []
for layer in autoencoder.layers[:12]:
    layer_names.append(layer.name) # Names of the layers, so you can have them


activations = get_activations(autoencoder, next(validation_generator)[0][-2:-1]
all_acts = list(activations.items())
activations = all_acts#[-2:]
```

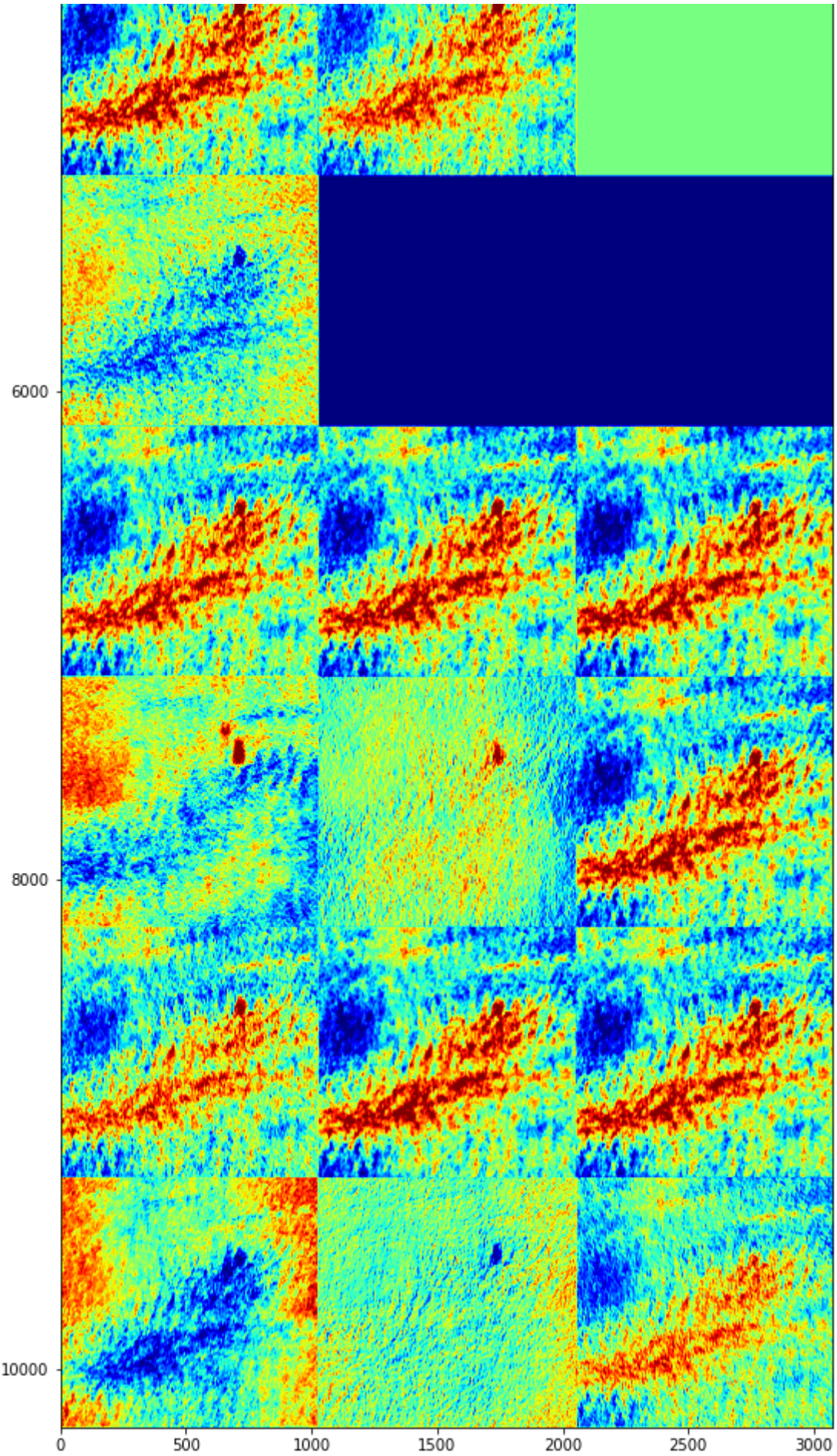
```
print(validation_generator.filenames[8])

images_per_row = 3

for layer_name, layer_activation in activations: # Displays the feature maps
    figure(figsize=(12, 8), dpi=80)
    n_features = layer_activation.shape[-1] # Number of features in the feature
    size = layer_activation.shape[1] #The feature map has shape (1, size, size,
    print(n_features)

    if n_features > 1:
      n_cols = n_features // images_per_row
      display_grid = np.zeros((size * n_cols, images_per_row * size))


      for col in range(n_cols): # Tiles each filter into a big horizontal grid
          for row in range(images_per_row):
              channel_image = layer_activation[0,
                                               :, :,
                                               col * images_per_row + row]
              channel_image -= channel_image.mean()
              channel_image /= channel_image.std()
              channel_image *= 64
              channel_image += 128
              channel_image = np.clip(channel_image, 0, 255).astype('uint8')
              display_grid[col * size : (col + 1) * size,
                           row * size : (row + 1) * size] = channel_image
      scale = 3. / size
      plt.figure(figsize=(scale * display_grid.shape[1],
                          scale * display_grid.shape[0]))
      plt.title(layer_name)
      plt.grid(False)
      plt.imshow(display_grid, aspect='auto', cmap='jet')
      plt.show()

    else:

      plt.imshow(np.expand_dims(last_act[0,:,:,1], axis=0).reshape(target_size)
      plt.title(layer_name)
      plt.show()
```

```
valid-2-1/cropped_image_all.png
3
<Figure size 960x640 with 0 Axes>
```

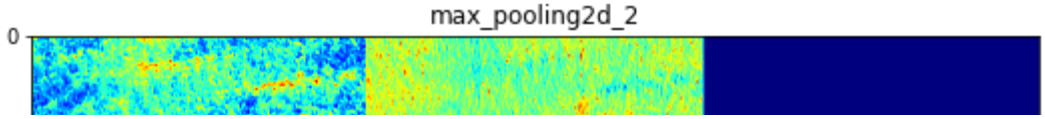


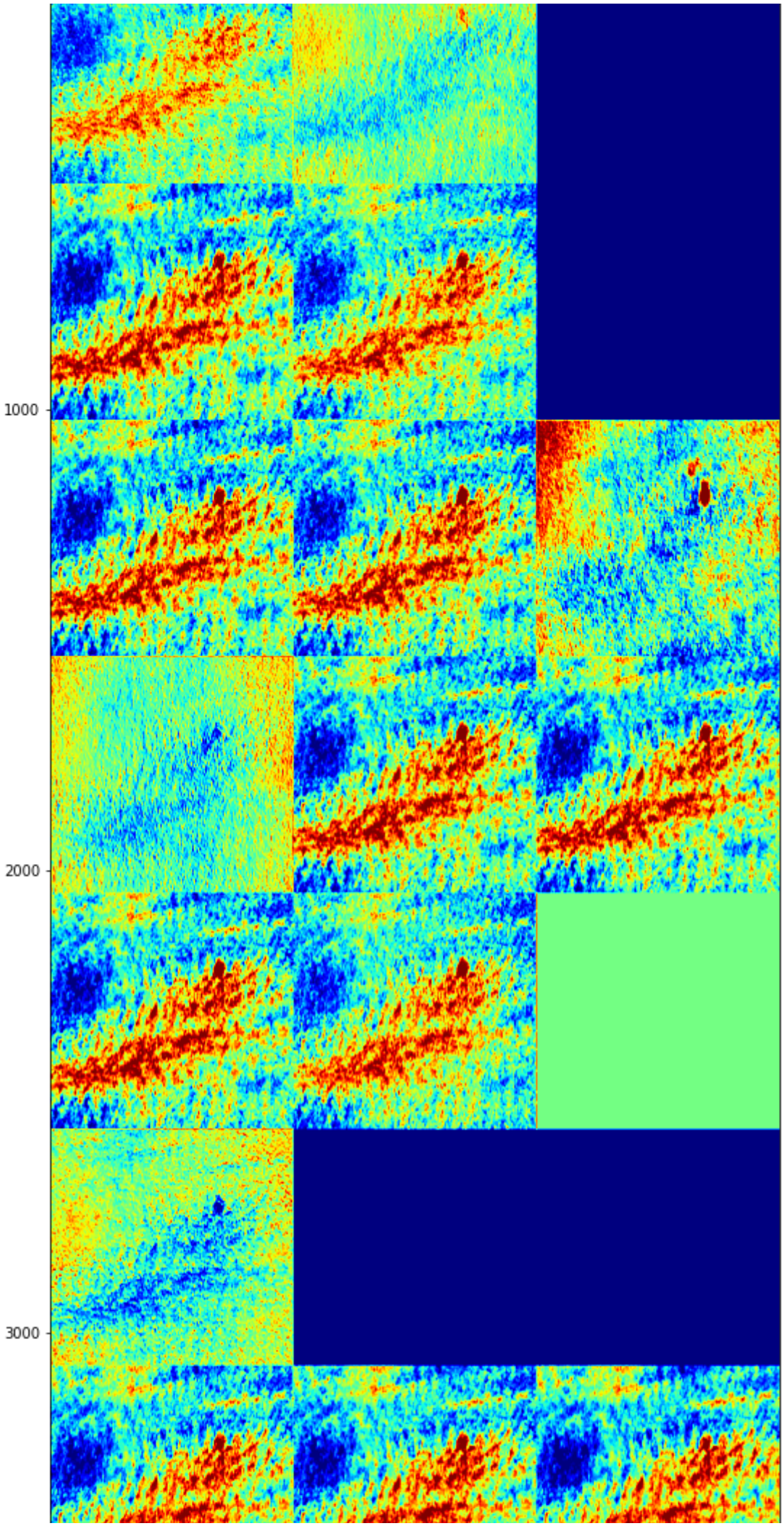

```
32
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:35: RuntimeWarnir
<Figure size 960x640 with 0 Axes>
```

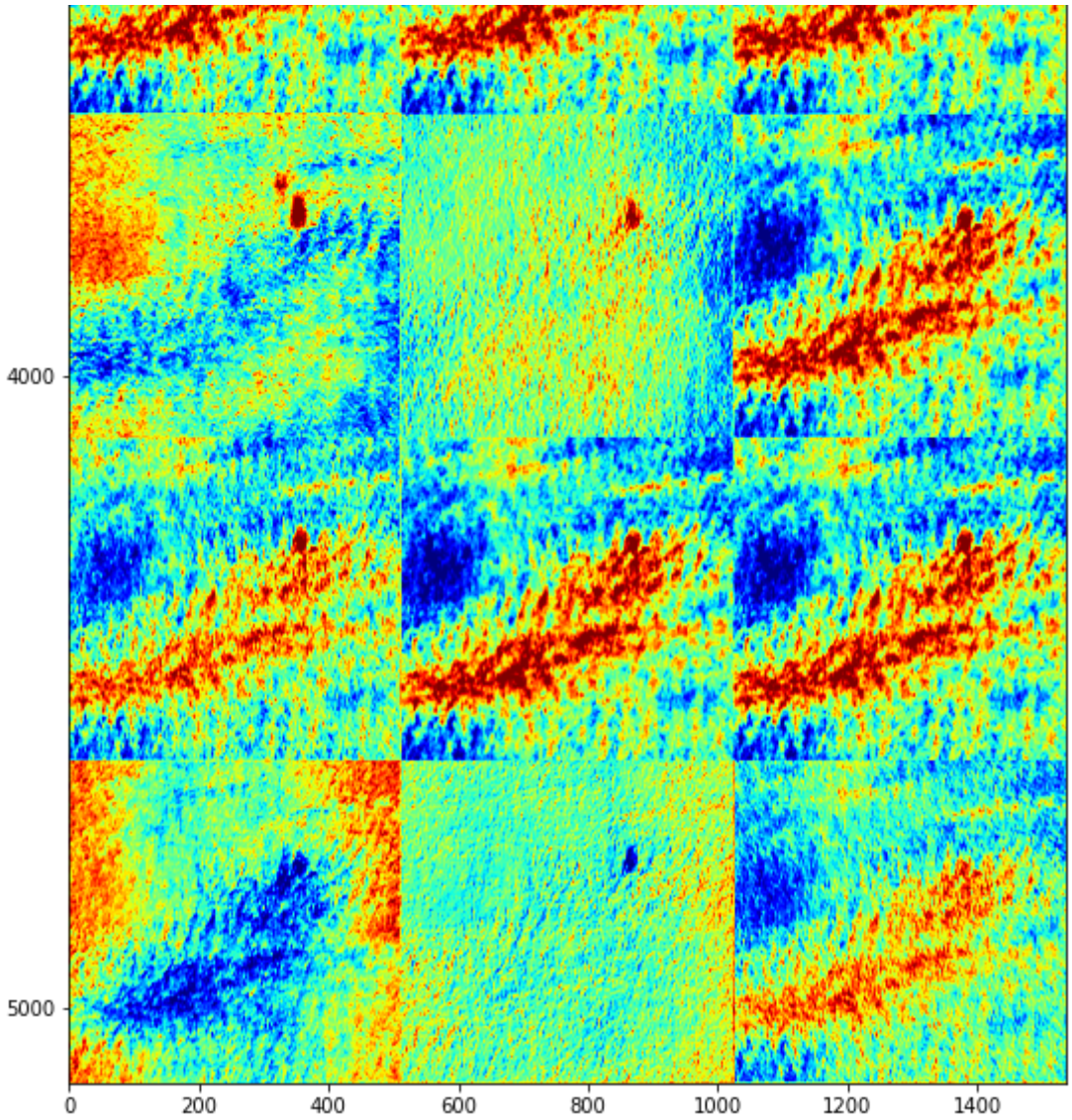




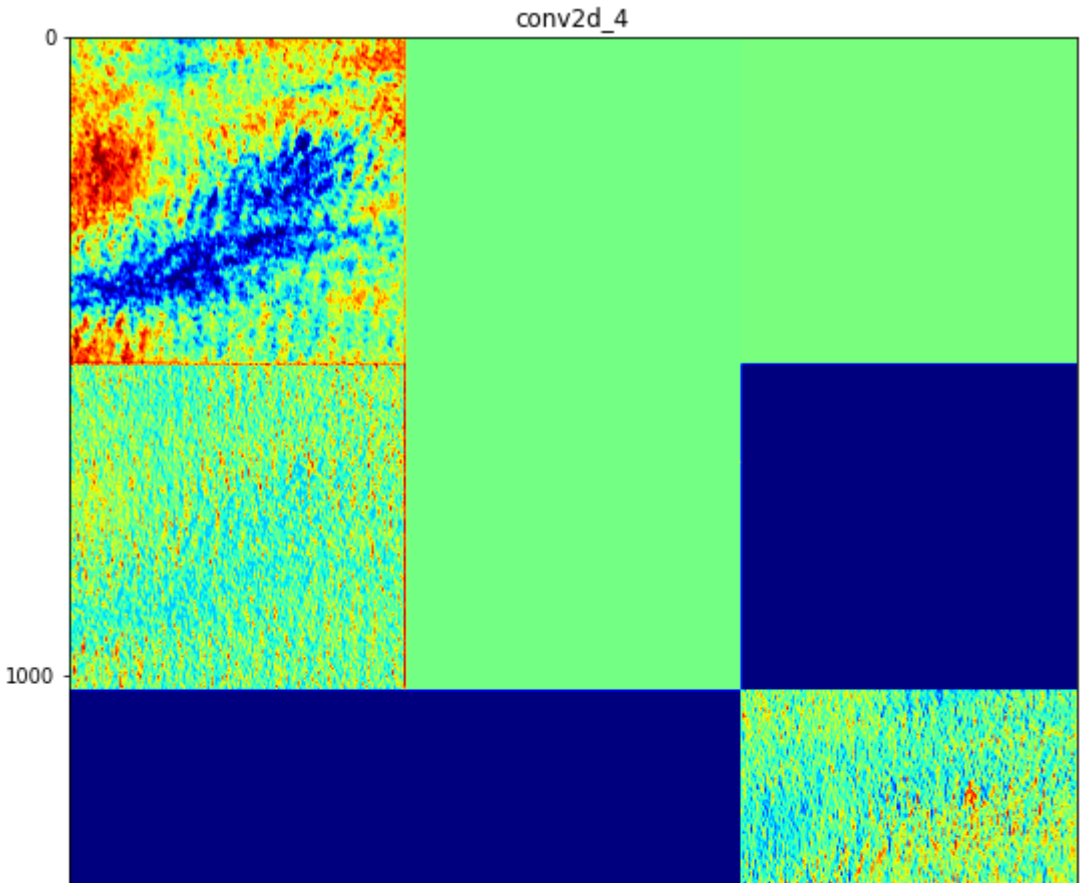

```
32
<Figure size 960x640 with 0 Axes>
```

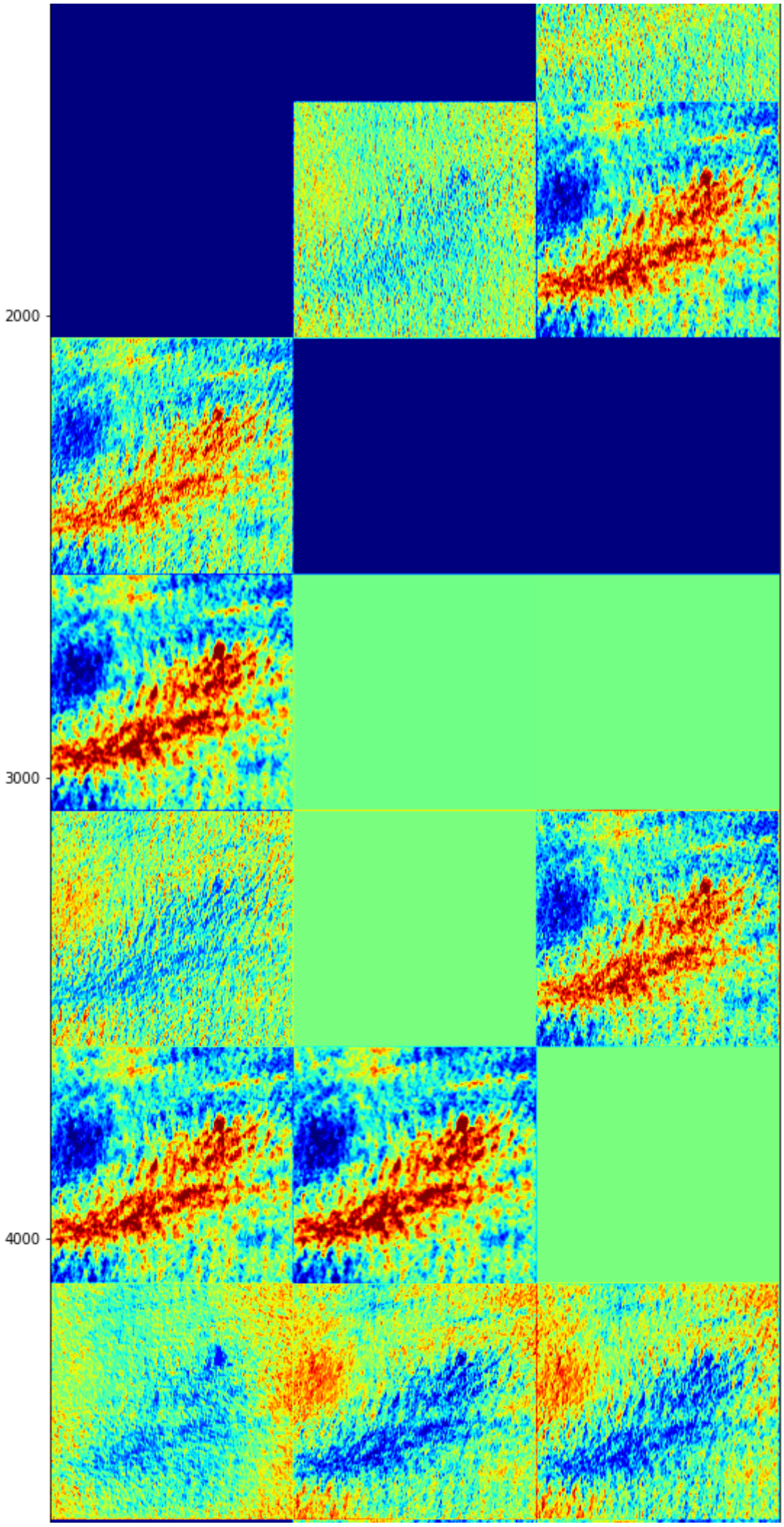


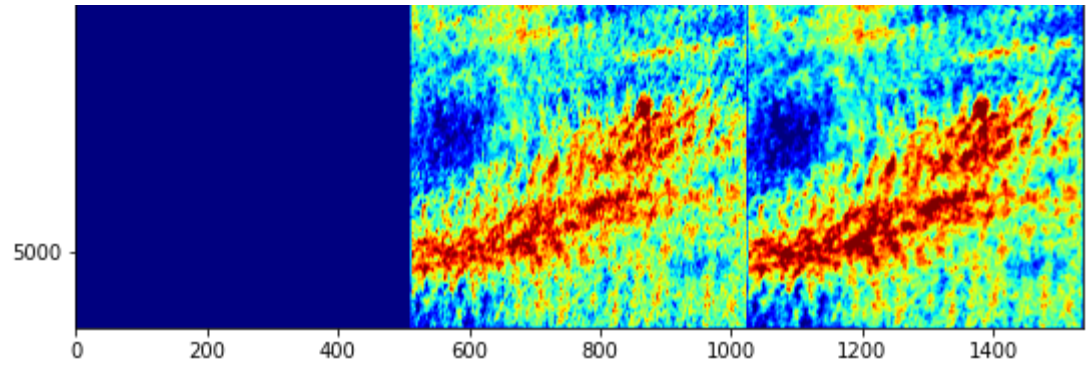

1000
2000
3000



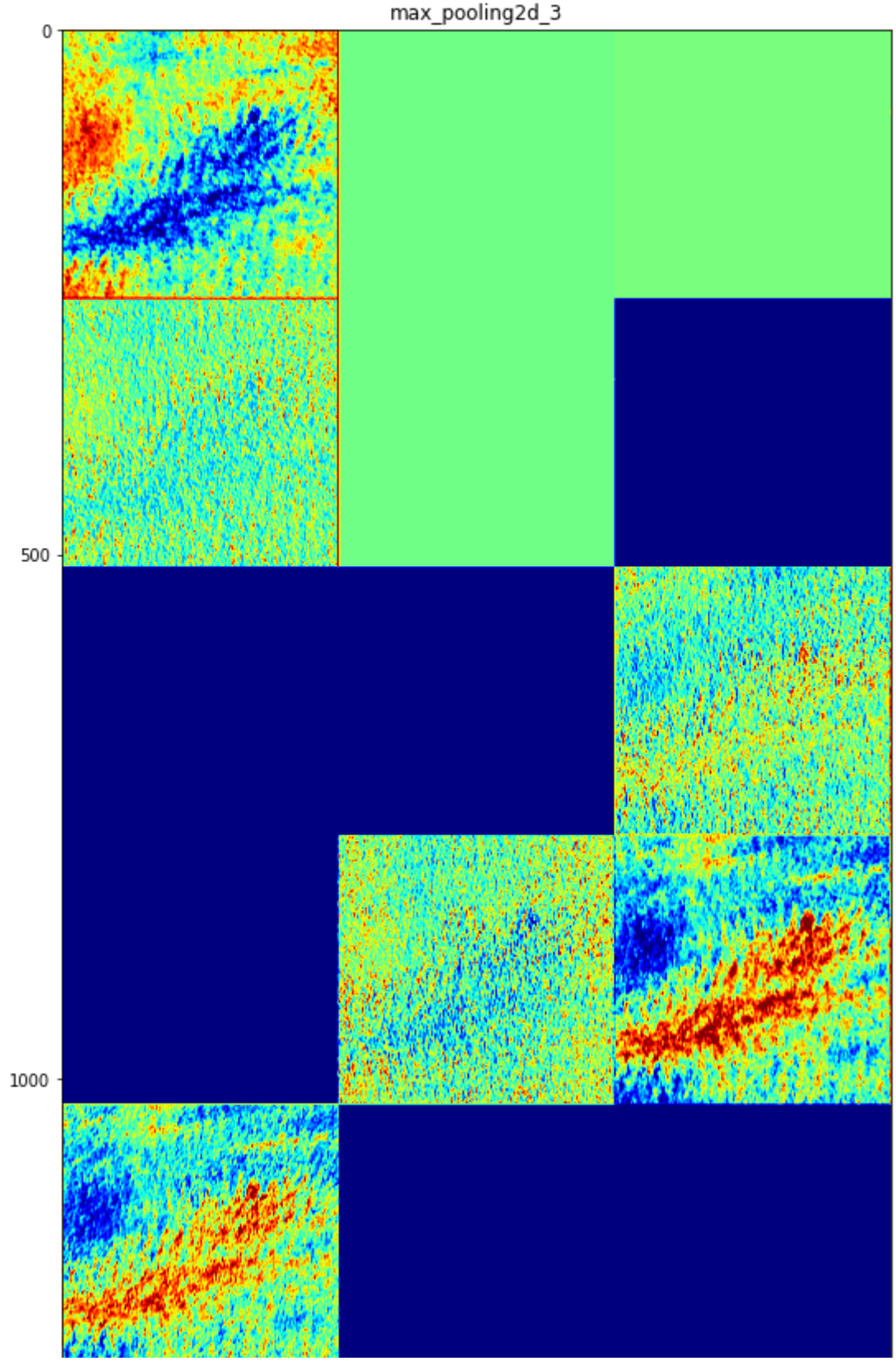

```
32
<Figure size 960x640 with 0 Axes>
```

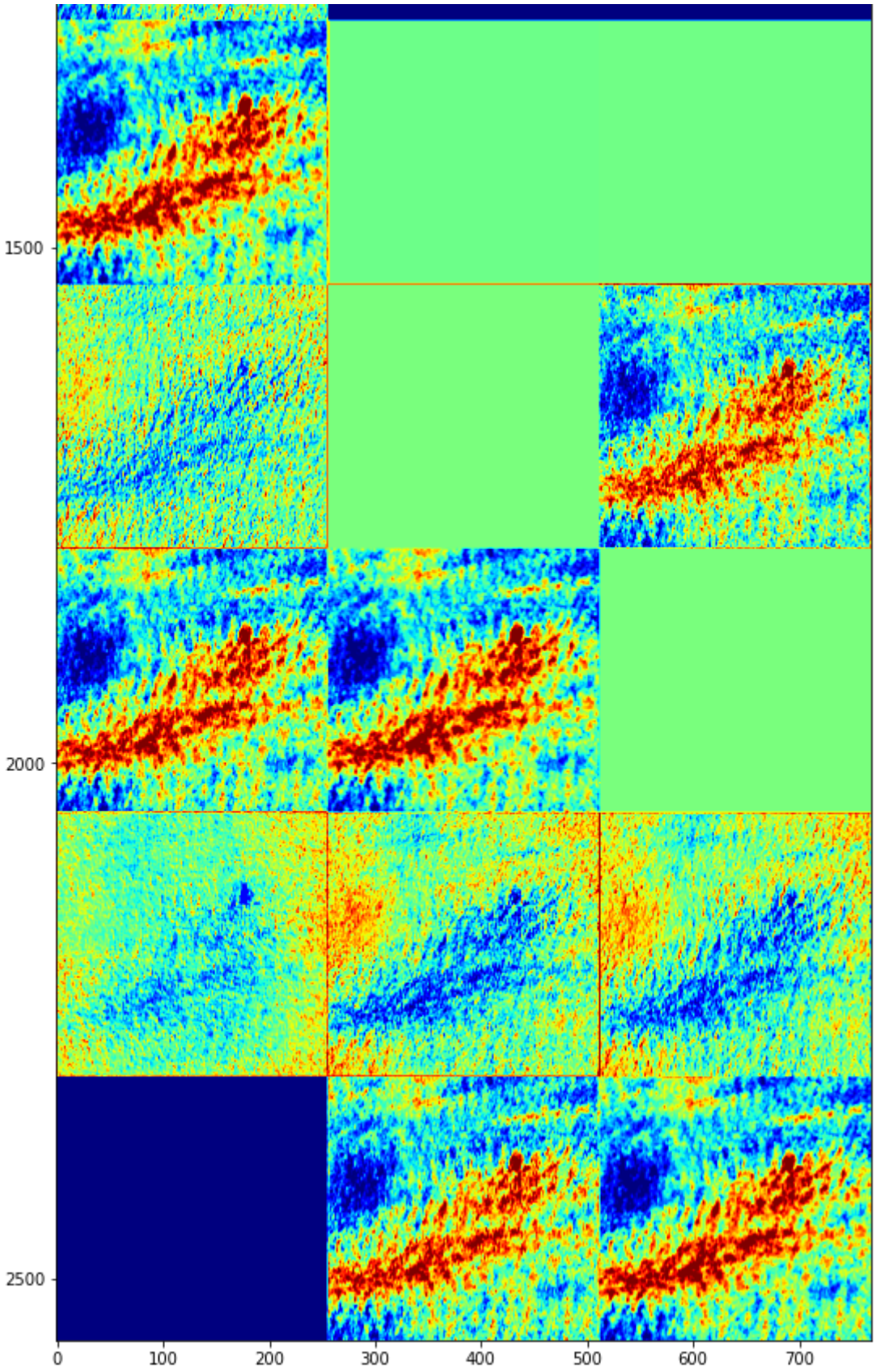



2000
3000
4000

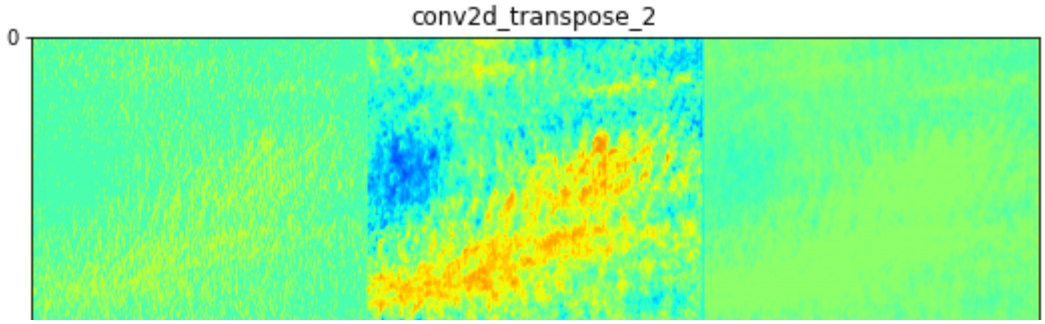


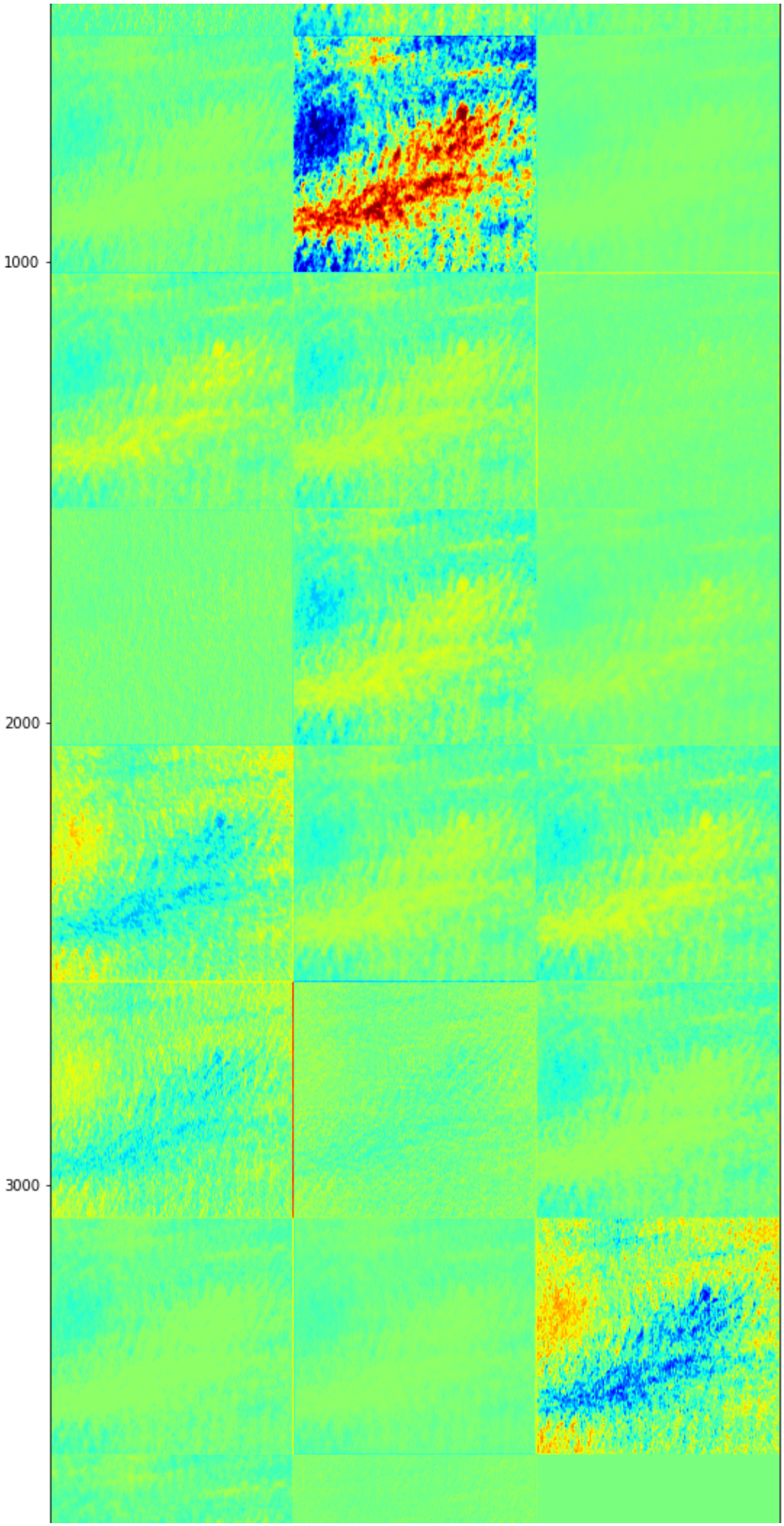

```
32
<Figure size 960x640 with 0 Axes>
```

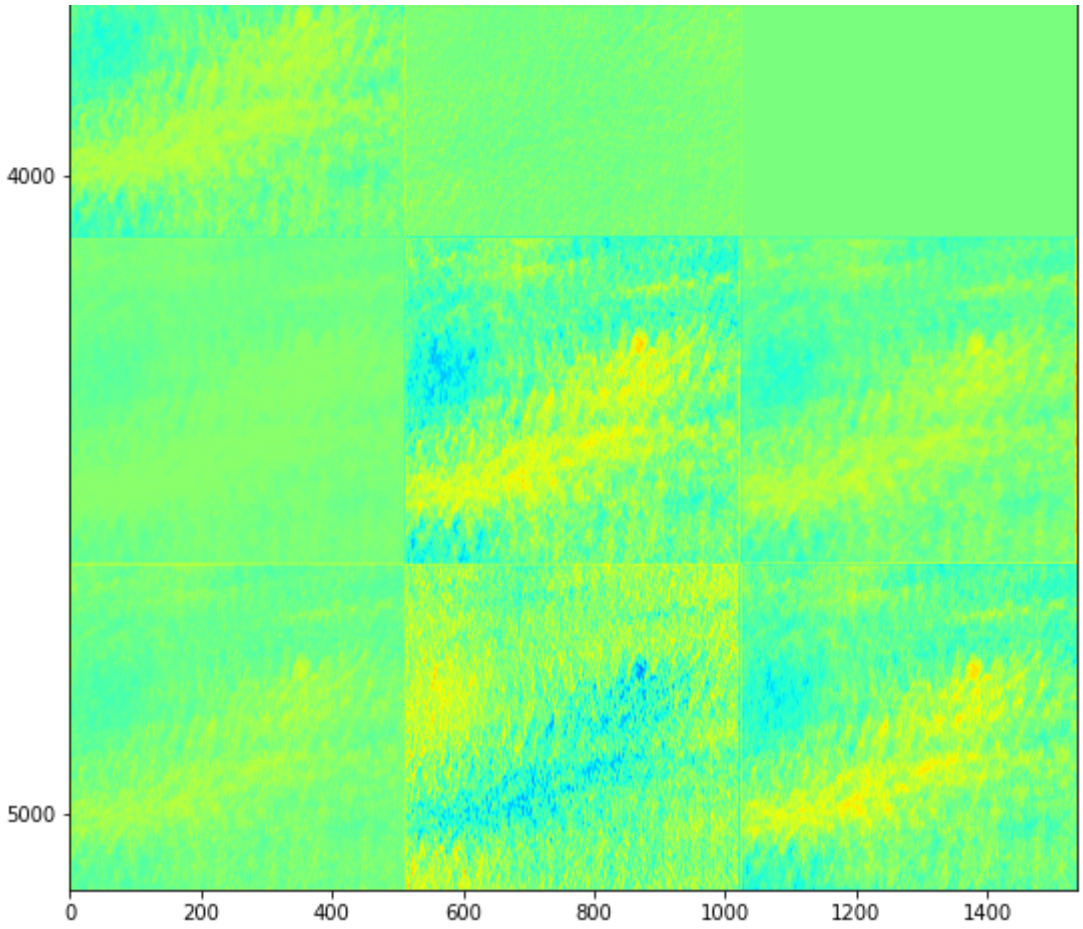




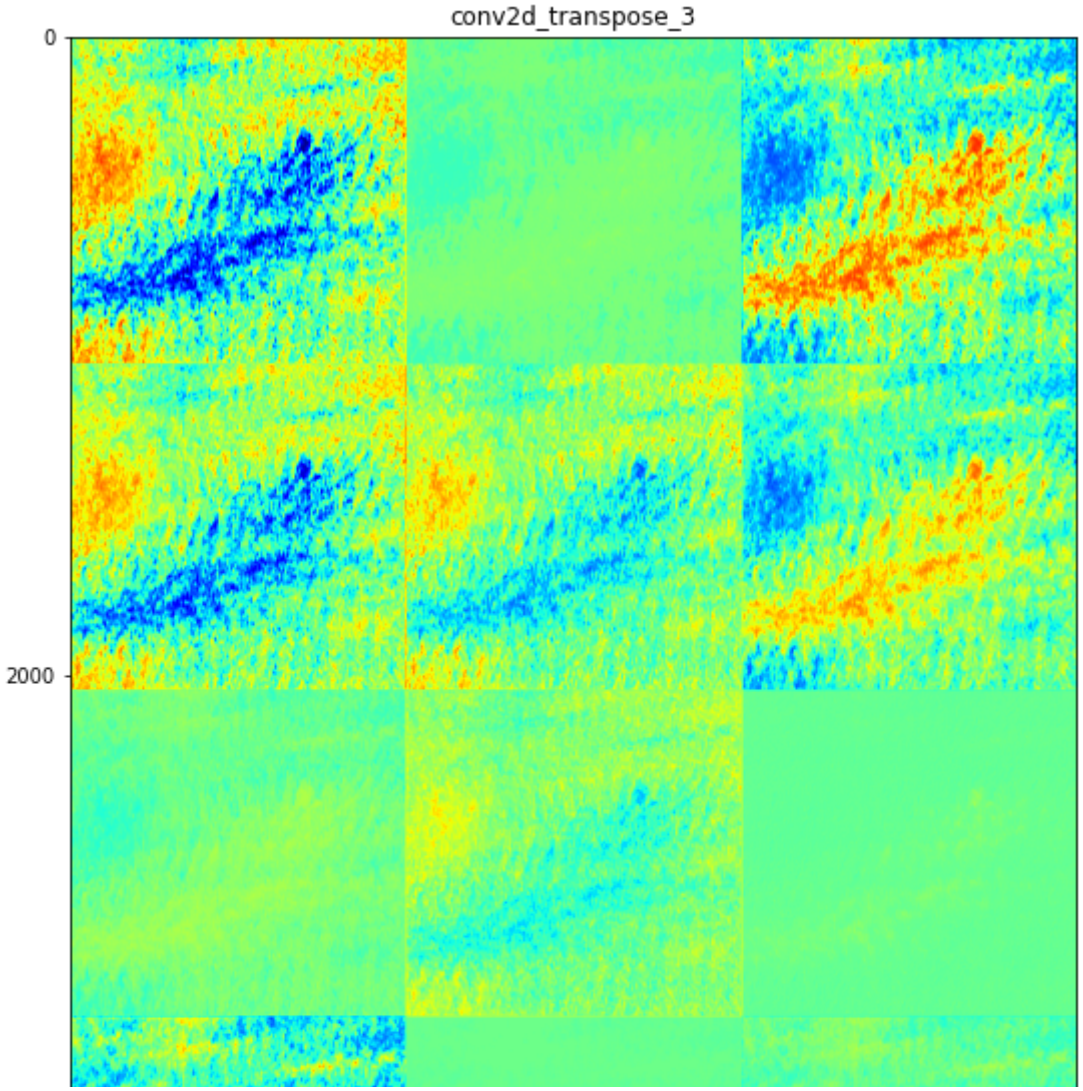

```
32
<Figure size 960x640 with 0 Axes>
```

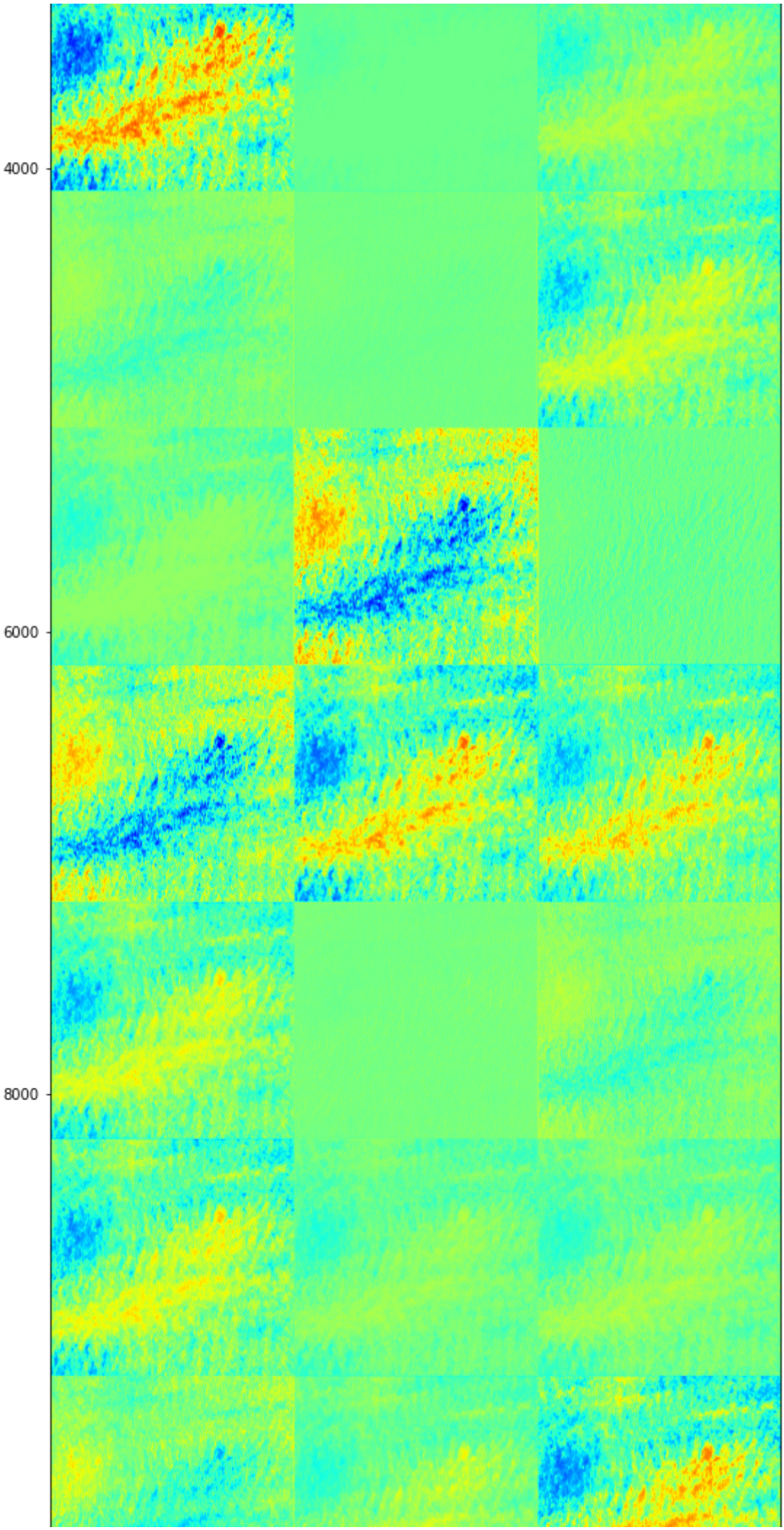


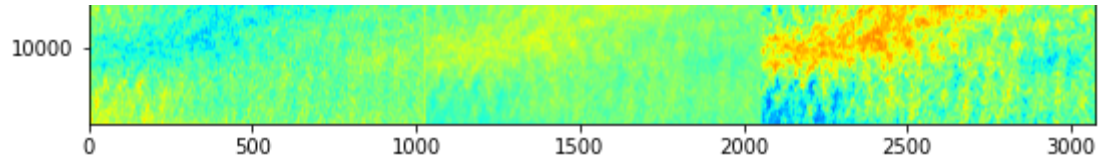

1000
2000
3000




```
32
<Figure size 960x640 with 0 Axes>
```



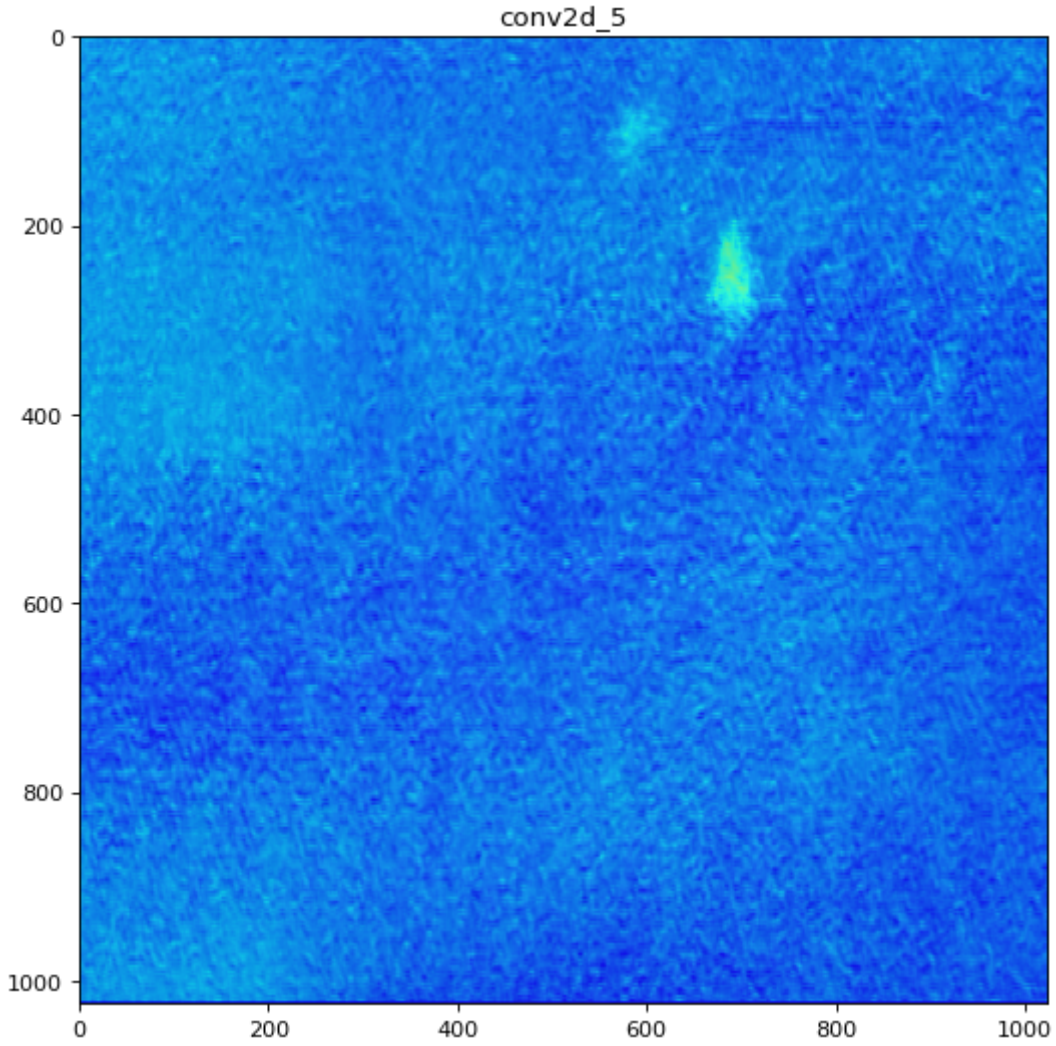

4000
6000
8000

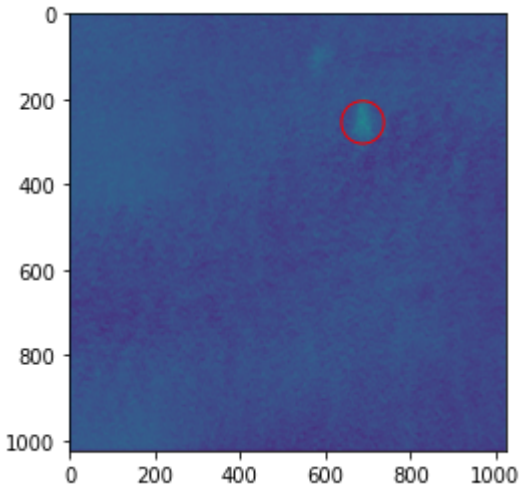


Selecting specific layer and visualize anomalies

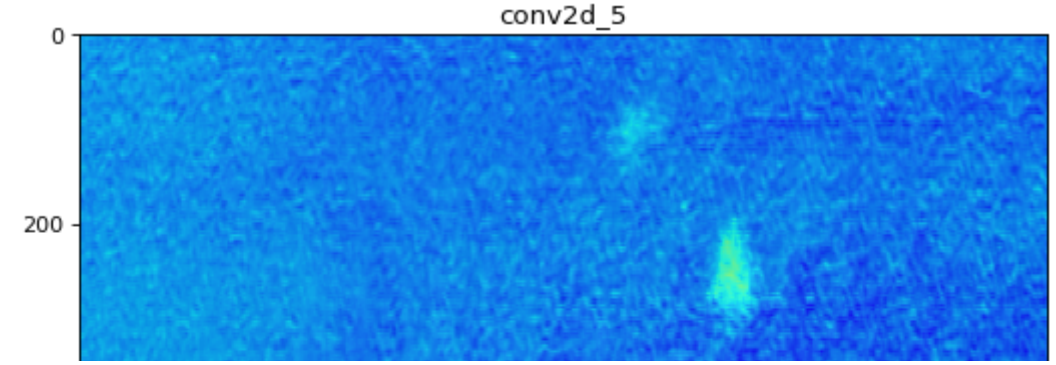
```
import cv2
import matplotlib.patches as patches

def draw_circles(img):
    radius = 41
    g_blured = cv2.GaussianBlur(img, (radius, radius), 0)
    (minVal, maxVal, minLoc, maxLoc) = cv2.minMaxLoc(g_blured)

    fig, ax = plt.subplots()
    ax.imshow(img)
    circ = patches.Circle((maxLoc), 50, color='red', fill=False)
    ax.add_patch(circ)

    plt.show()



def plot_activation(img):
    img_expanded = np.expand_dims(img, axis=0)

    activations = get_activations(autoencoder, img, nested=True)
    all_acts = list(activations.items())
    last_act_tuple = all_acts[1] # taking the conv2d layer
    last_layer, last_act = last_act_tuple
    print(last_layer, last_act.shape)
    ######
    channel_highest_location = 21 # -> manually defined by looking at the activ
    ######

    activation_img = np.expand_dims(last_act[0,:,:,channel_highest_location],

    figure(figsize=(12, 8), dpi=80)
    plt.imshow(np.squeeze(img_expanded))
    plt.imshow(np.squeeze(activation_img), cmap='jet', alpha=0.85)
    plt.title(layer_name)
    plt.show()

    draw_circles(np.squeeze(np.expand_dims(last_act[0,:,:,channel_highest_loca


for i in range(validation_generator.samples):
  nr_img = i
  input_sample = next(validation_generator)[0][nr_img]
  input_sample = np.expand_dims(input_sample, axis=0)
  print(validation_generator.filenames[nr_img])
  plot_activation(input_sample)
```

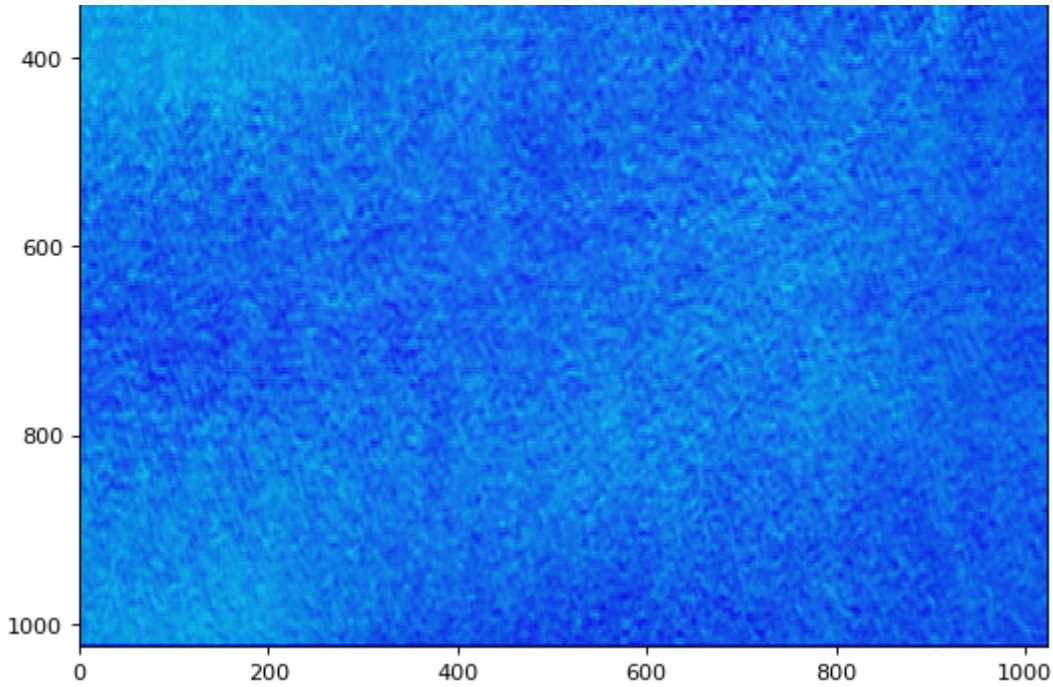
```
valid-1-0/cropped_image_all.png
conv2d_3 (1, 1024, 1024, 32)
```

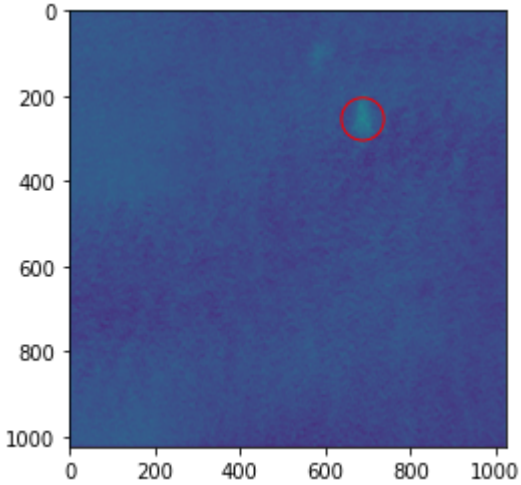




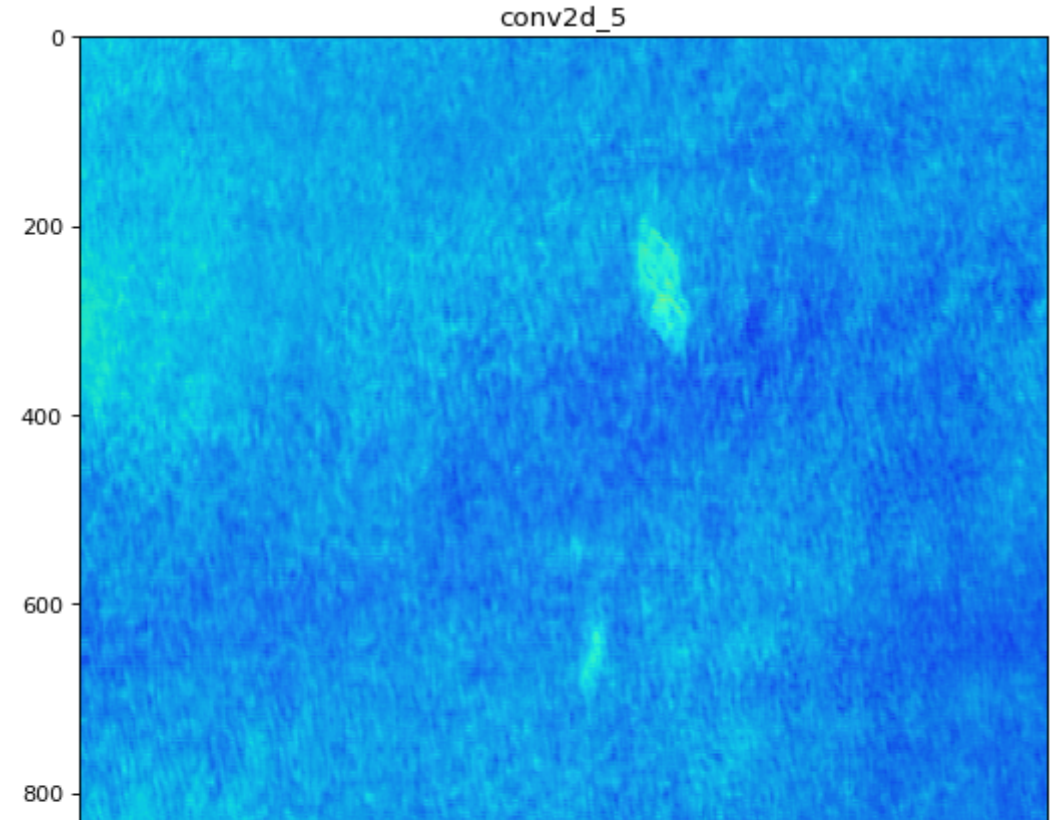

```
valid-1-1/cropped_image_all.png
conv2d_3 (1, 1024, 1024, 32)
```

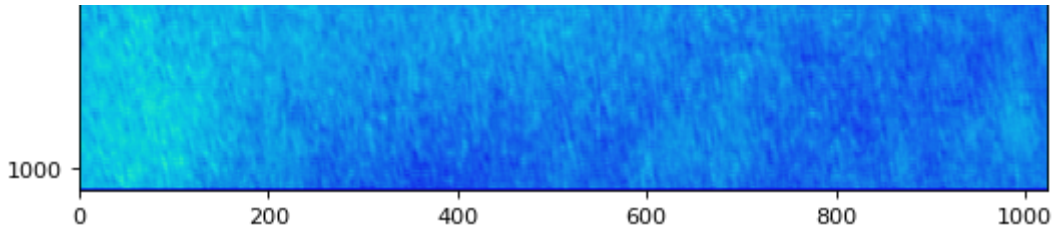


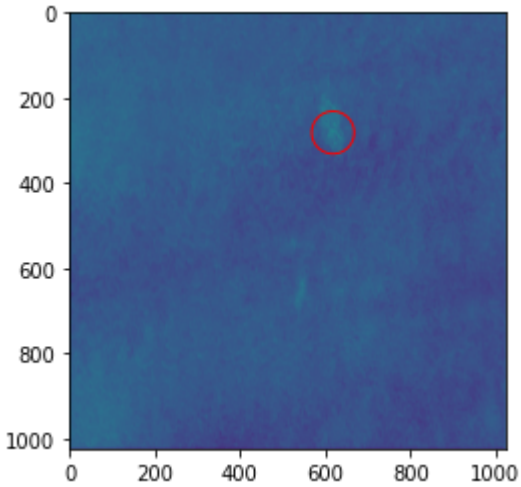




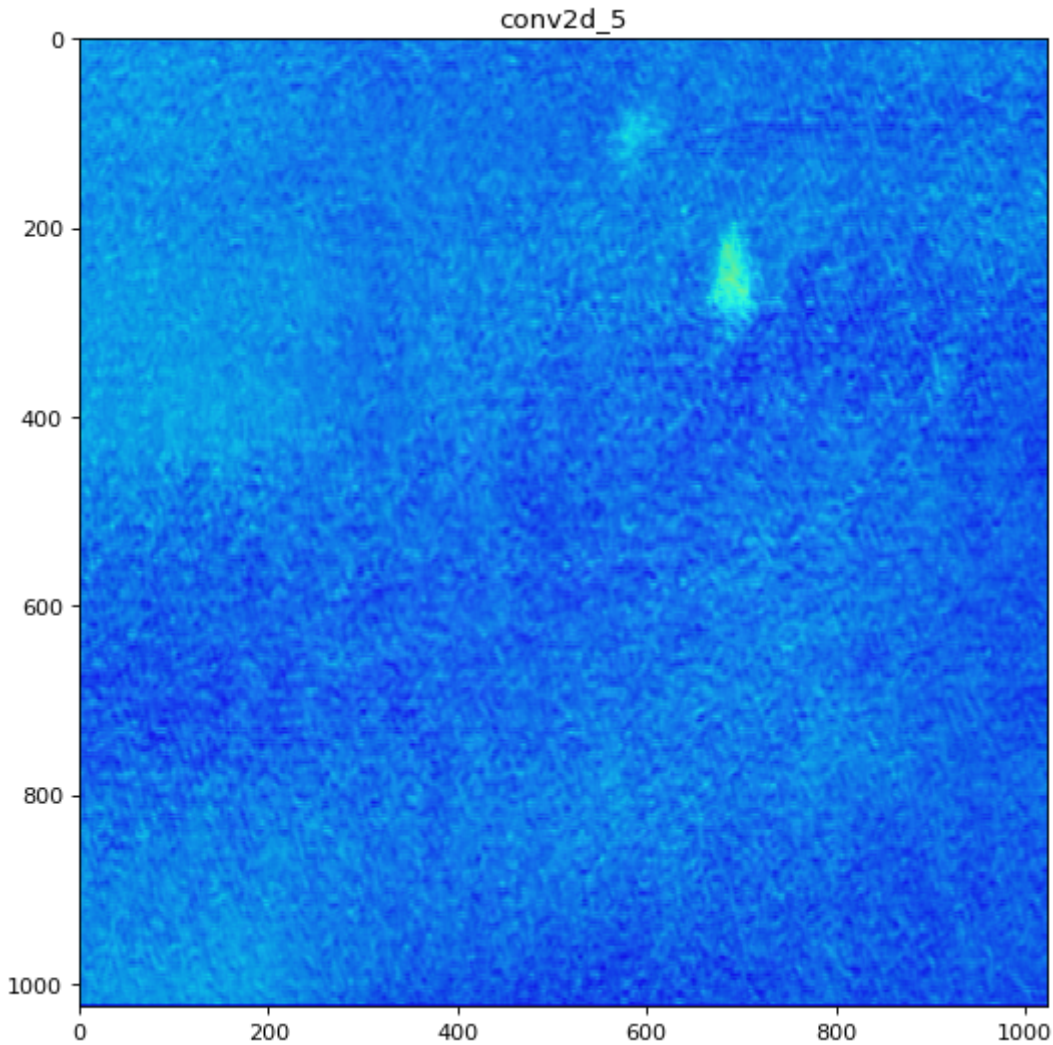

```
valid-1-2/cropped_image_all.png
conv2d_3 (1, 1024, 1024, 32)
```

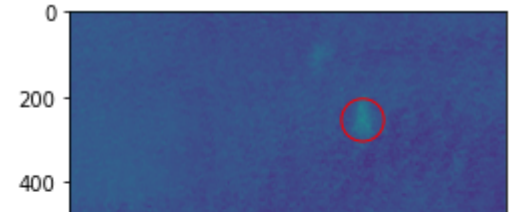


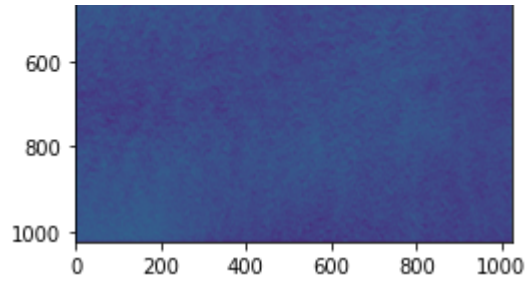




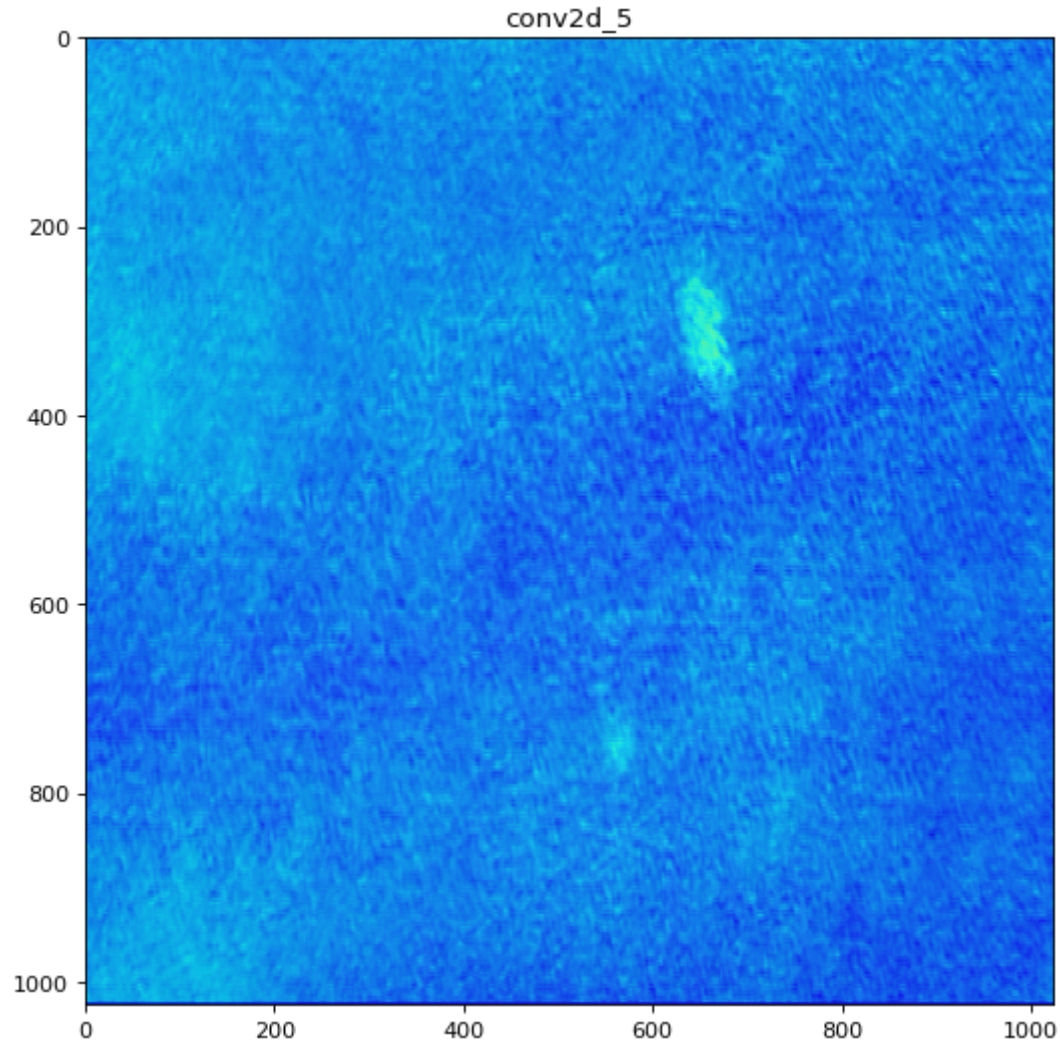

```
valid-1-3/cropped_image_all.png
conv2d_3 (1, 1024, 1024, 32)
```

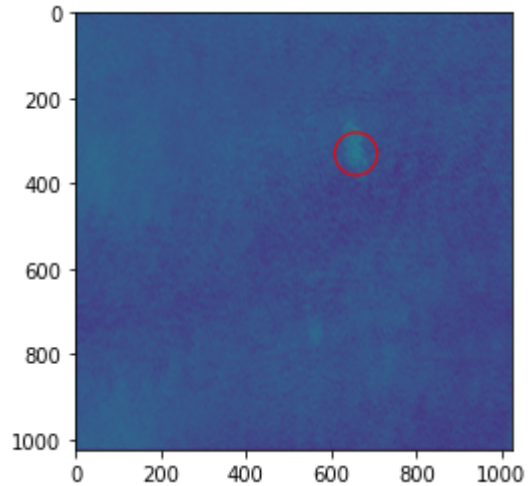




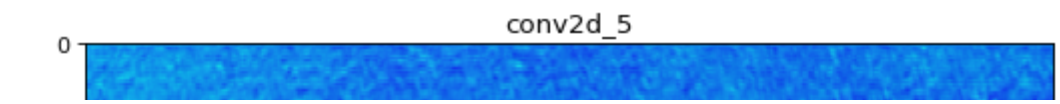


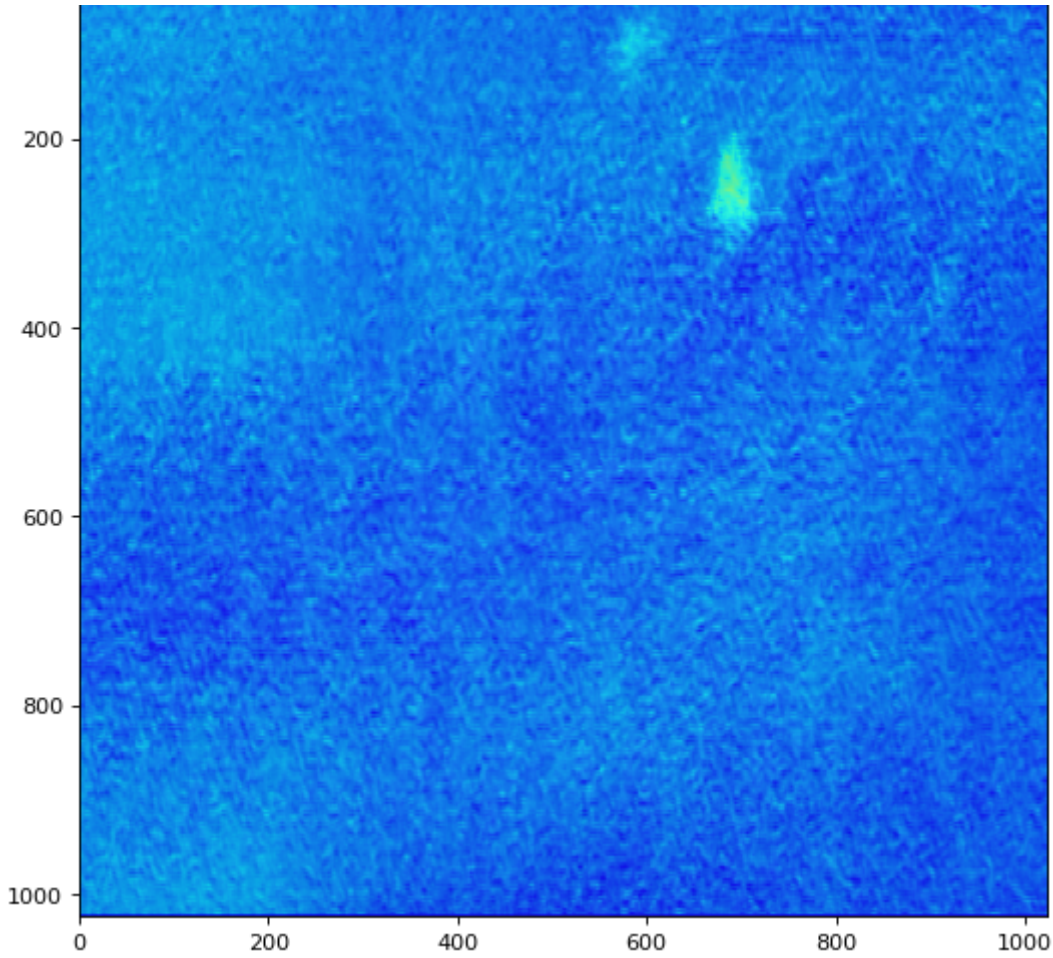

```
valid-1-4/cropped_image_all.png
conv2d_3 (1, 1024, 1024, 32)
```

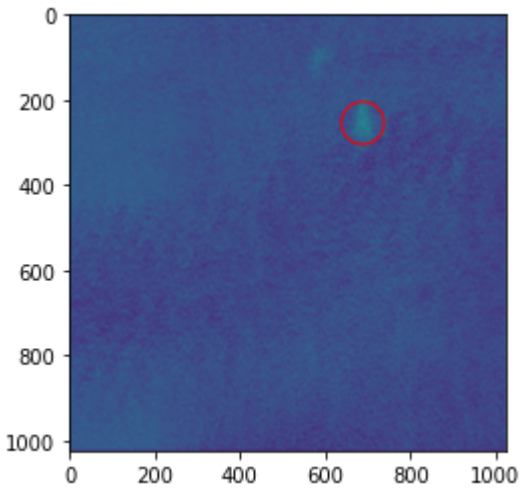




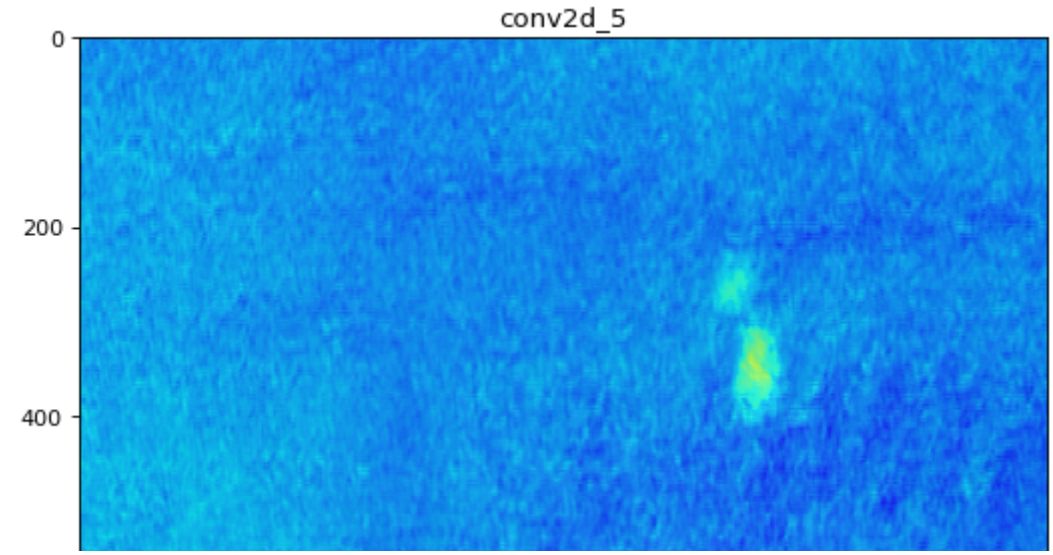

```
valid-1-5/cropped_image_all.png
conv2d_3 (1, 1024, 1024, 32)
```

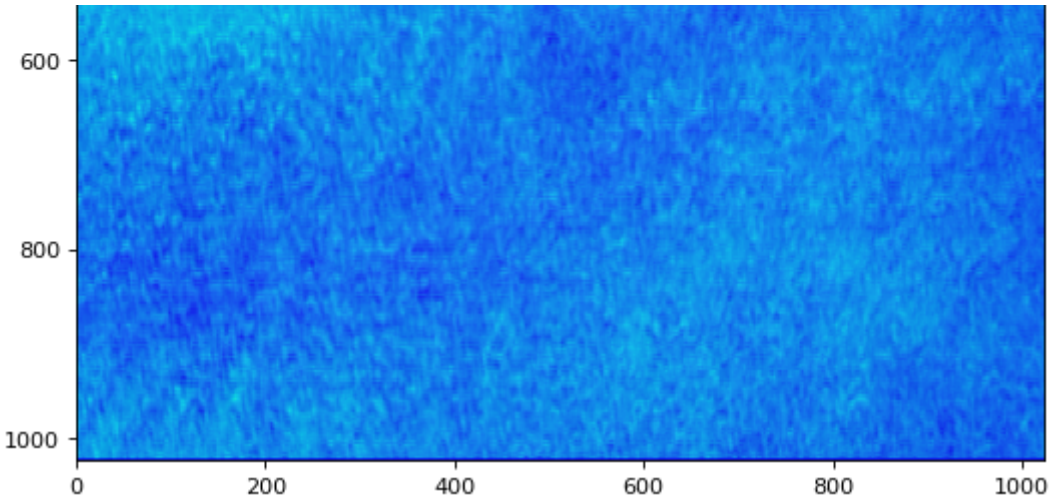


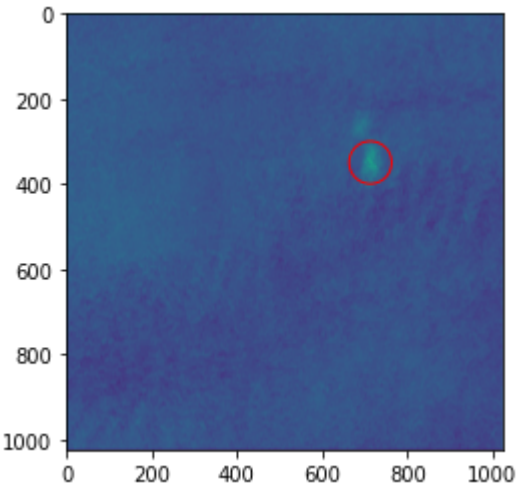




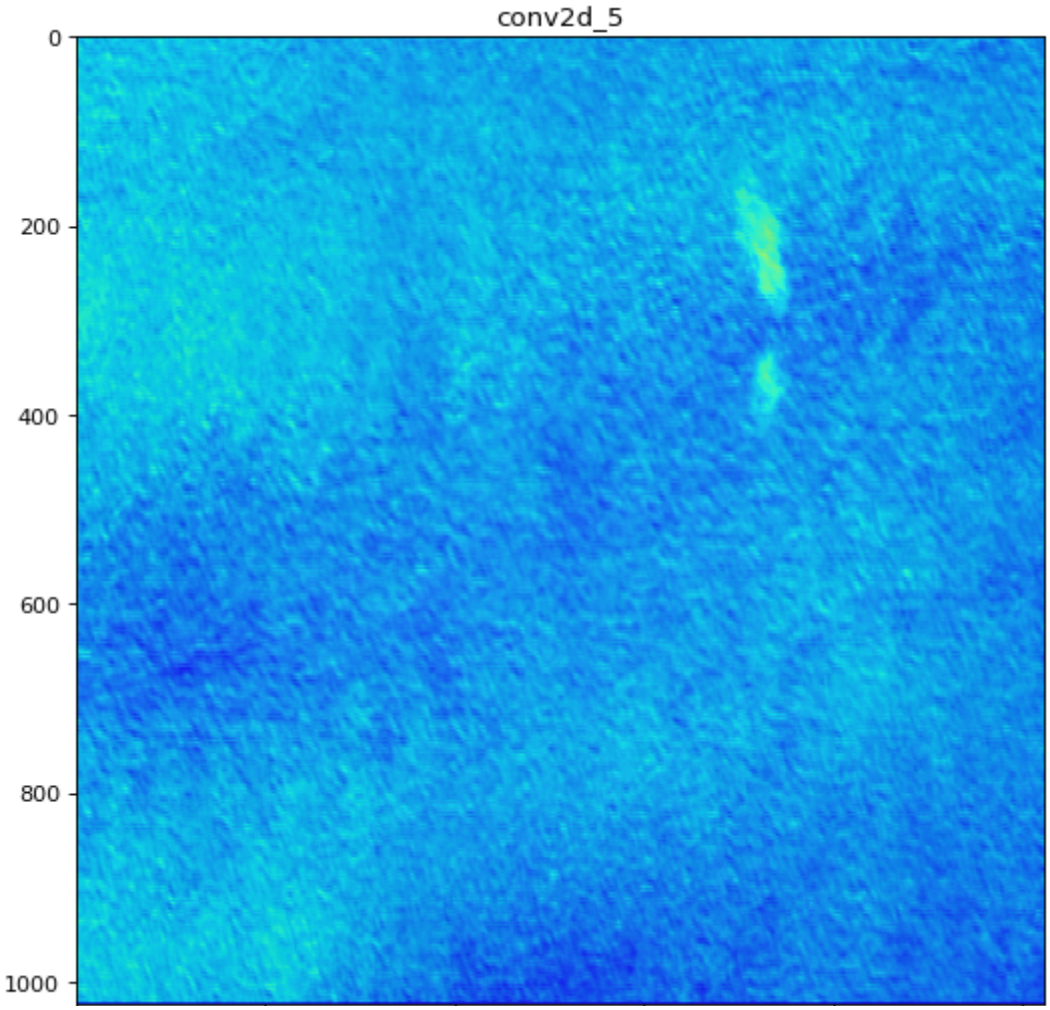

```
valid-1-6/cropped_image_all.png
conv2d_3 (1, 1024, 1024, 32)
```

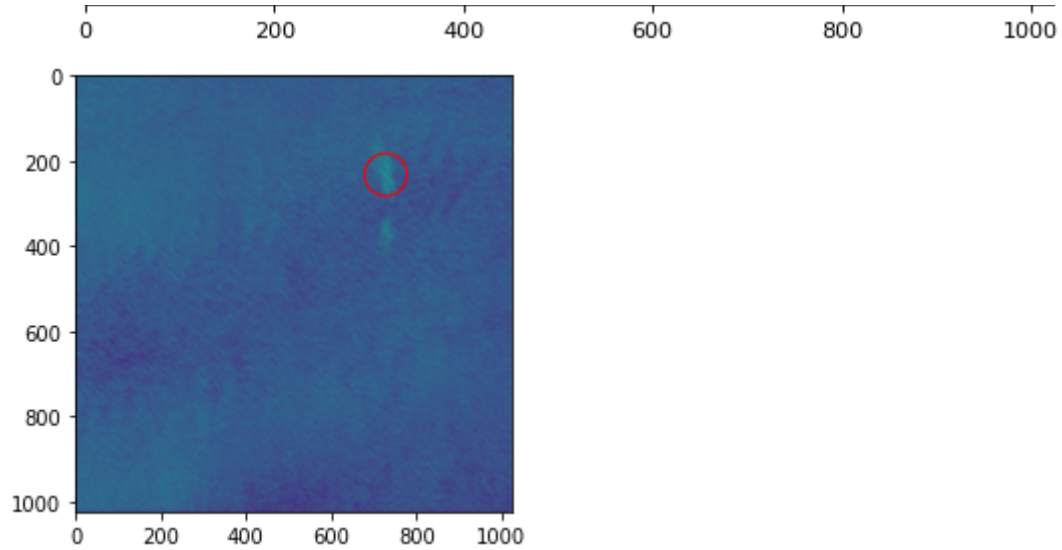




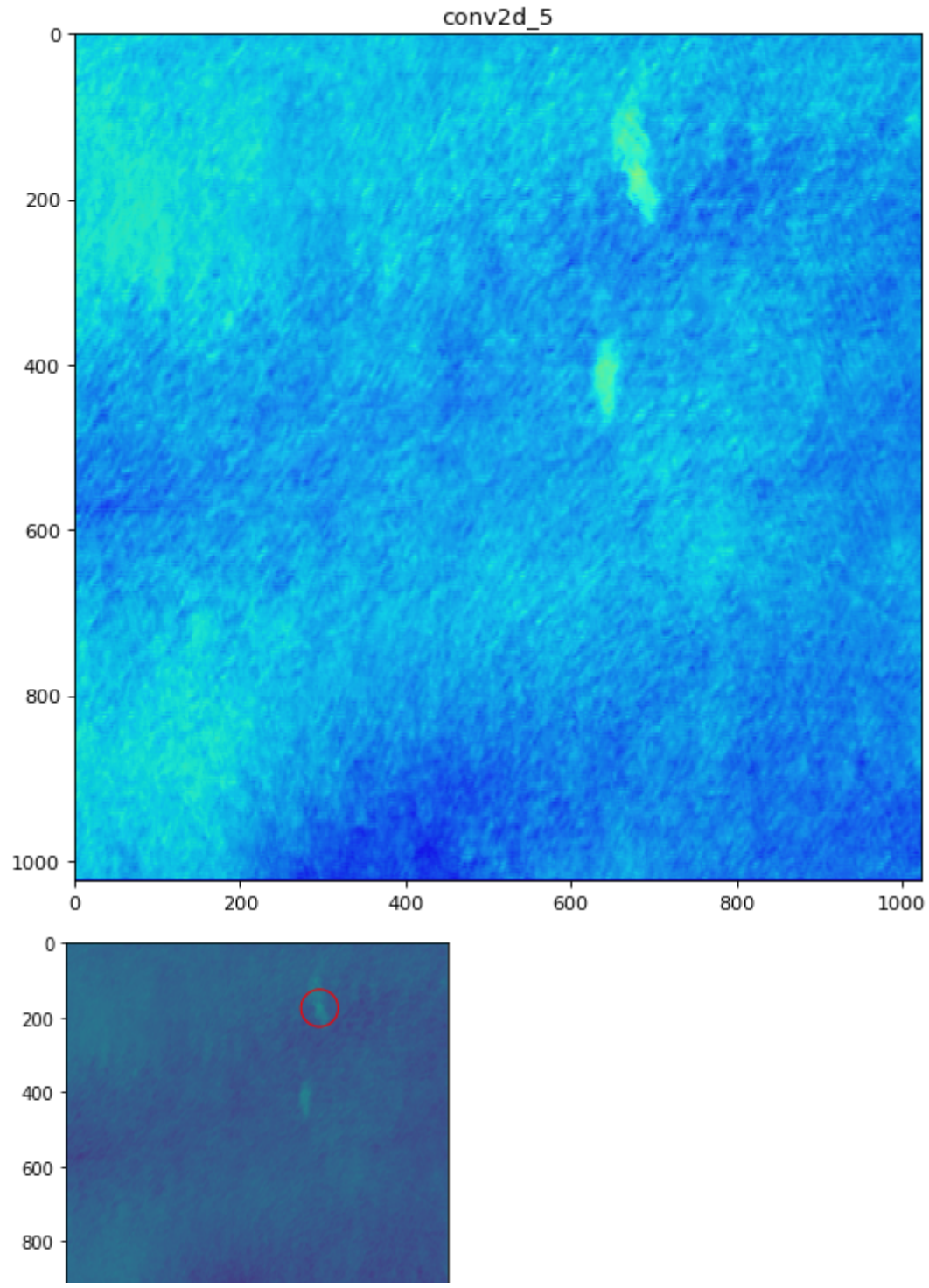


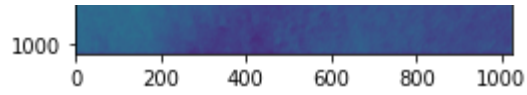

```
valid-2-0/cropped_image_all.png
conv2d_3 (1, 1024, 1024, 32)
```



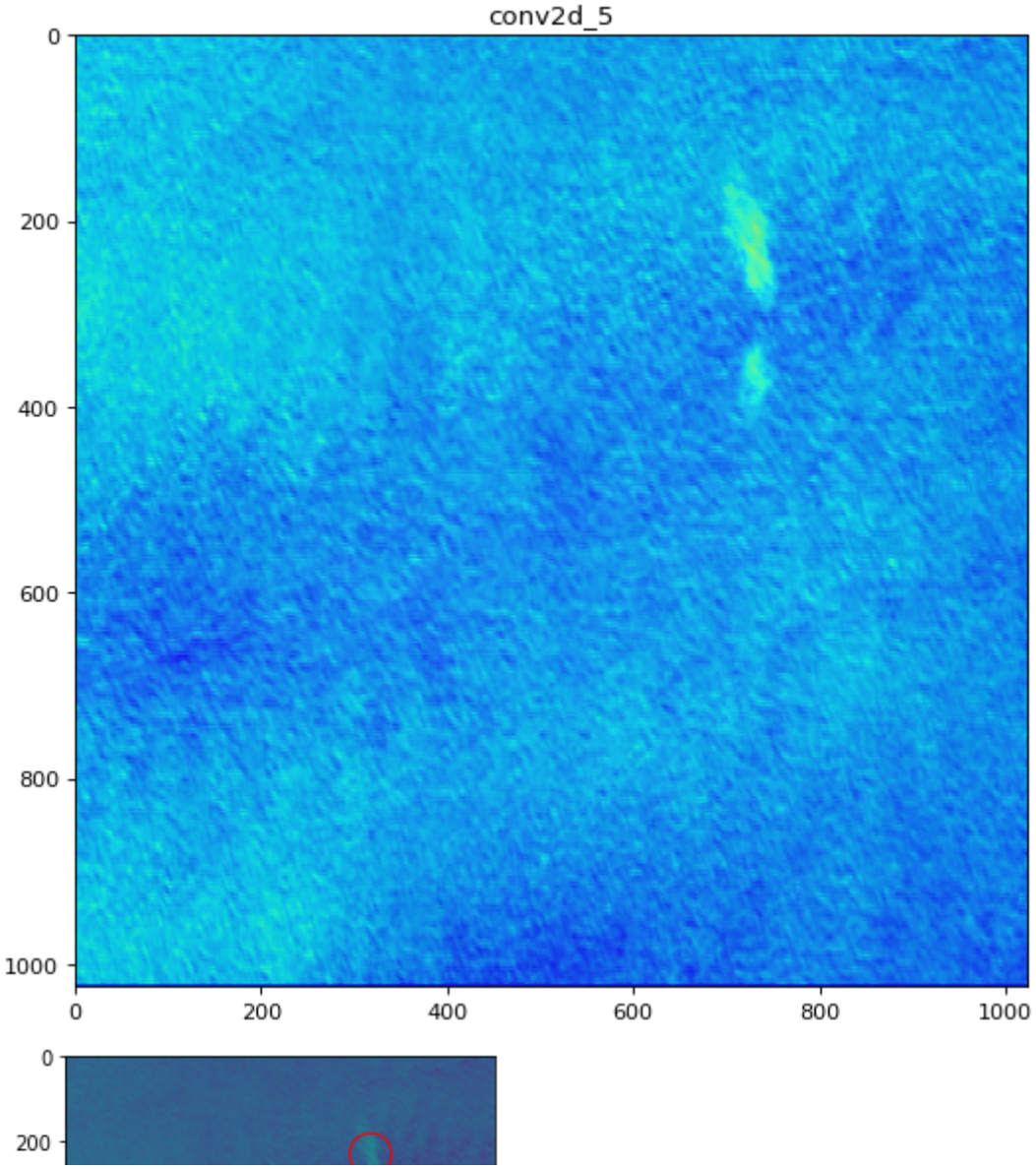



```
valid-2-1/cropped_image_all.png
conv2d_3 (1, 1024, 1024, 32)
```






```
valid-2-2/cropped_image_all.png
conv2d_3 (1, 1024, 1024, 32)
```



Resources

Research regarding autoencoder for anomaly detection

- Morales-Forero, A., & Bassetto, S. (2019, December). Case Study: A Semi-Supervised Methodology for Anomaly Detection and Diagnosis. In 2019 IEEE International Conference on Industrial Engineering and Engineering Management (IEEM) (p. 4) (pp. 1031-1037). IEEE.
- Sakurada, M., & Yairi, T. (2014, December). Anomaly detection using autoencoders with nonlinear dimensionality reduction. In Proceedings of the MLSDA 2014 2nd Workshop on Machine Learning for Sensory Data Analysis (p. 4). ACM.
- An, J., & Cho, S. (2015). Variational autoencoder based anomaly detection using reconstruction probability. Special Lecture on IE, 2, 1-18.

- Zhou, C., & Paffenroth, R. C. (2017, August). Anomaly detection with robust deep autoencoders. In Proceedings of the 23rd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (pp. 665-674). ACM.
- Ribeiro, Manassés; Lazzaretti, André Eugênio; Lopes, Heitor Silvério (2018). "A study of deep convolutional auto-encoders for anomaly detection in videos". Pattern Recognition Letters. 105: 13–22. doi:10.1016/j.patrec.2017.07.016
- Nalisnick, Eric; Matsukawa, Akihiro; Teh, Yee Whye; Gorur, Dilan; Lakshminarayanan, Balaji (2019-02-24). "Do Deep Generative Models Know What They Don't Know?". arXiv:1810.09136
- Xiao, Zhisheng; Yan, Qing; Amit, Yali (2020). "Likelihood Regret: An Out-of-Distribution Detection Score For Variational Auto-encoder". Advances in Neural Information Processing Systems. 33. arXiv:2003.02977

Implementation related

Some of the resources that have been used through the implementaion

- https://anomagram.fastforwardlabs.com/#/
- https://benjoe.medium.com/anomaly-detection-using-pytorch-autoencoder-and-mnist-31c5c2186329
- https://blog.keras.io/building-autoencoders-in-keras.html
- https://docs.opencv.org/3.4/d7/d4d/tutorial_py_thresholding.html
- https://github.com/SubhamIO/AnomalyDetection---Deep-AUTOENCODERS/blob/main/AnamolydetectionAE.ipynb
- https://github.com/cerlymarco/MEDIUM_NoteBook/blob/master/Anomaly_Detection_Image/Anomaly_Detection_Image.ipynb
- https://github.com/olonok69/Survival-Analisys/blob/master/Anomaly_Detection_Image.ipynb
- https://keras.io/examples/vision/autoencoder/
- https://medium.com/analytics-vidhya/anomaly-detection-in-images-autoencoders-b780abf88f51
- https://medium.com/analytics-vidhya/image-anomaly-detection-using-autoencoders-ae937c7fd2d1
- https://medium.com/analytics-vidhya/unsupervised-learning-and-convolutional-autoencoder-for-image-anomaly-detection-b783706eb59e
- https://stackoverflow.com/questions/57614072/visualizing-layers-of-autoencoder
- https://towardsdatascience.com/anomaly-detection-in-images-777534980aeb
- https://towardsdatascience.com/anomaly-detection-using-autoencoders-5b032178a1ea
- https://towardsdatascience.com/hands-on-anomaly-detection-with-variational-autoencoders-d4044672acd5

- https://towardsdatascience.com/visualizing-intermediate-activation-in-convolutional-neural-networks-with-keras-260b36d60d0
- https://www.machinecurve

```

```

```

# unused
# show similarity differences


# from skimage.metrics import structural_similarity as compare_ssim
# import imutils
# import cv2
# from google.colab.patches import cv2_imshow

# print(len(validation_generator.filenames))
# nr_img = 10

# gen_file_name = validation_generator.filenames[nr_img]
# img = next(validation_generator)[0][nr_img]

# a_img = img
# b_img =predictions[1]

# a_img = cv2.cvtColor(a_img, cv2.COLOR_BGR2GRAY)
# b_img = cv2.cvtColor(b_img, cv2.COLOR_BGR2GRAY)

# a = np.squeeze(a_img)
# b = np.squeeze(b_img)

# loss_orig = SSIMLoss(img,img)
# loss_reconstructed = SSIMLoss(img,predictions[nr_img])


# (score, diff) = compare_ssim(a, b, full=True)
# diff = (diff * 255).astype("uint8")


# thresh = cv2.threshold(diff, 0, 255,
#   #  cv2.THRESH_BINARY_INV |
#   #  cv2.THRESH_OTSU)[1]
#   cv2.THRESH_BINARY)[1]
#   # cv2.THRESH_TRUNC)[1]
# cnts = cv2.findContours(thresh.copy(), cv2.RETR_EXTERNAL,
#   cv2.CHAIN_APPROX_SIMPLE)
# cnts = imutils.grab_contours(cnts)

# print(f'SSIM: {score} \n Diff: {diff}')#' \n {thresh} \n {cnts}')

# # loop over the contours
```

```
# for c in cnts:
#   # compute the bounding box of the contour and then draw the
#   # bounding box on both input images to represent where the two
#   # images differ
#   (x, y, w, h) = cv2.boundingRect(c)
#   cv2.rectangle(a_img, (x, y), (x + w, y + h), (0, 0, 255), 2)
#   cv2.rectangle(b_img, (x, y), (x + w, y + h), (0, 0, 255), 2)
# # show the output images
# plt.figure(figsize=(12, 8), dpi=80)
# plt.title(gen_file_name)
# plt.imshow(np.expand_dims(b_img, axis=0).reshape(target_size), cmap='jet')

# # cv2_imshow(a_img)
# # cv2_imshow(b_img)
# cv2_imshow(diff)
# cv2_imshow(thresh)
```

time: 7.15 ms (started: 2022-01-20 17:36:59 +00:00)

✓ 3s completed at 10:26 PM