Train a Machine Learning Model to detect ink in a papyrus fragment

In [10]:

```
import torch
import torch.nn as nn
import torch.optim as optim
import numpy as np
import glob
import PIL.Image as Image
import torch.utils.data as data
import matplotlib.pyplot as plt
import matplotlib.patches as patches
from tqdm import tqdm
from ipywidgets import interact, fixed

PREFIX = '/input/ink/train/1/'
BUFFER = 30  # Buffer size in x and y direction
Z_START = 27 # First slice in the z direction to use
Z_DIM = 10   # Number of slices in the z direction
TRAINING_STEPS = 30000
LEARNING_RATE = 0.03
BATCH_SIZE = 32
DEVICE = torch.device("cuda" if torch.cuda.is_available() else "cpu")

plt.imshow(Image.open(PREFIX+"ir.png"), cmap="gray")
```

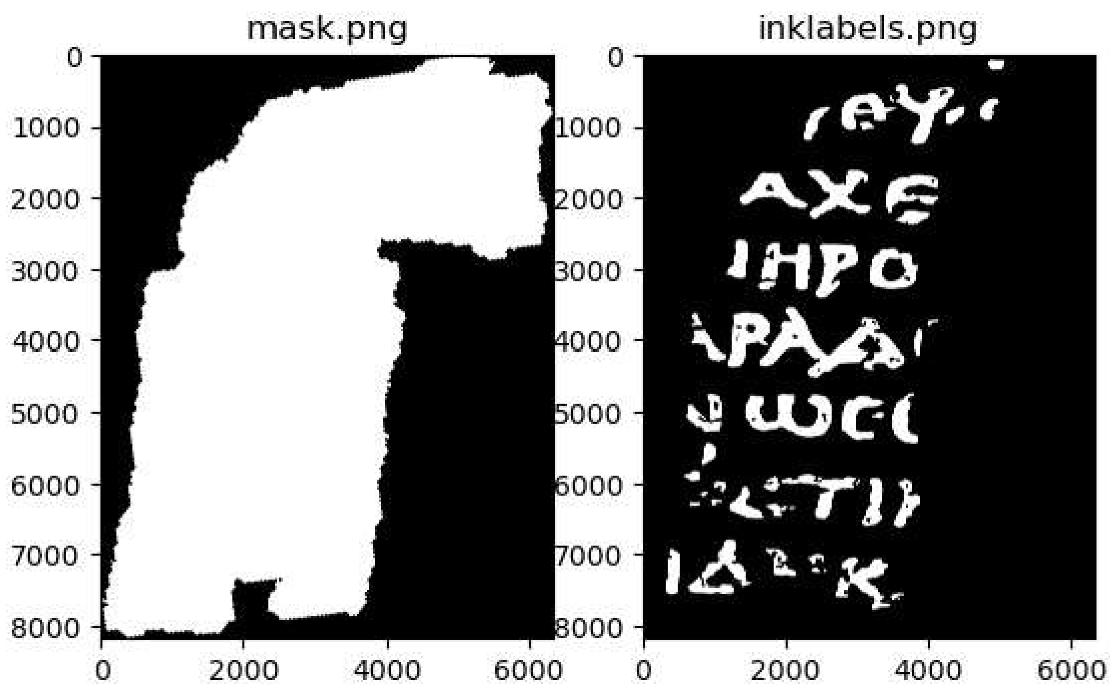
Out[10]:

```
<matplotlib.image.AxesImage at 0x7fa15062eb10>
```

Let's load these binary images:

- **mask.png**: a mask of which pixels contain data, and which pixels we should ignore.
- **inklabels.png**: our label data: whether a pixel contains ink or no ink.

In [11]:
```
mask = np.array(Image.open(PREFIX+"mask.png").convert('1'))
label = torch.from_numpy(np.array(Image.open(PREFIX+"inklabels.png"))).gt(0).float().t
fig, (ax1, ax2) = plt.subplots(1, 2)
ax1.set_title("mask.png")
ax1.imshow(mask, cmap='gray')
ax2.set_title("inklabels.png")
ax2.imshow(label.cpu(), cmap='gray')
plt.show()
```

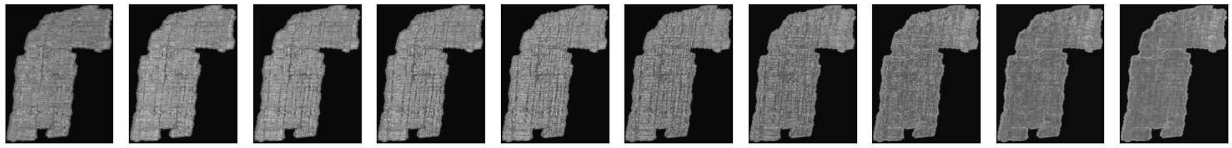


"Next, we'll load the 3D X-ray of the fragment. It is represented as a .tif image stack, which consists of an array of 16-bit grayscale images. Each image corresponds to a "slice" in the z-direction, ranging from below the papyrus to above the papyrus. We'll convert it into a 4D tensor of 32-bit floats and adjust the pixel values to fall within the range [0, 1].

To conserve memory, we will load only the innermost slices (Z_DIM of them). We can examine these slices when we've completed the process."

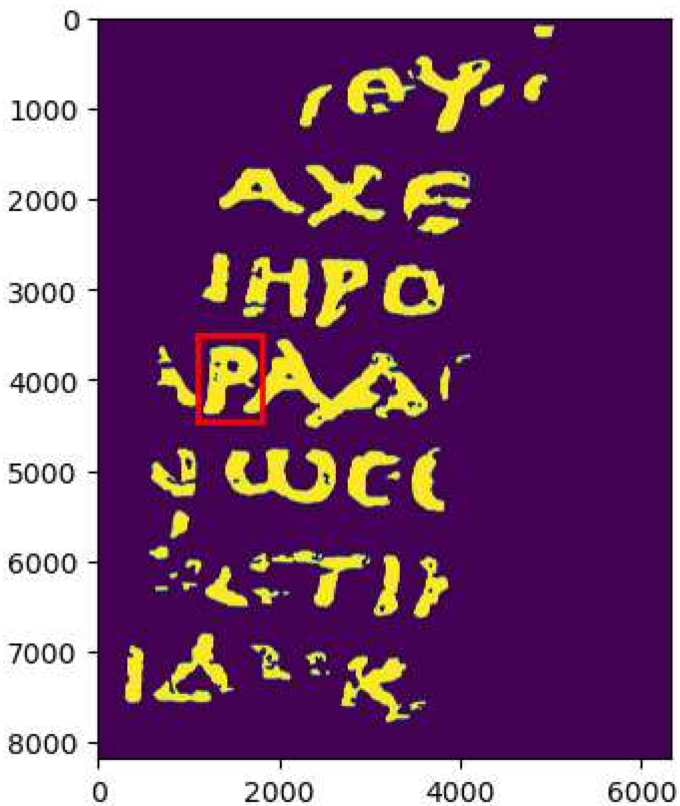
In [12]:
```
# Load the 3d x-ray scan, one slice at a time
images = [np.array(Image.open(filename), dtype=np.float32)/65535.0 for filename in tqd
image_stack = torch.stack([torch.from_numpy(image) for image in images], dim=0).to(DEV

fig, axes = plt.subplots(1, len(images), figsize=(15, 3))
for image, ax in zip(images, axes):
  ax.imshow(np.array(Image.fromarray(image).resize((image.shape[1]//20, image.shape[0]
  ax.set_xticks([]); ax.set_yticks([])
fig.tight_layout()
plt.show()
```

```
100%|██████████| 10/10 [00:02<00:00,  3.74it/s]
```



Now, we'll generate a dataset of subvolumes. For our evaluation, we'll focus on a small rectangle around the letter "P." We will exclude those pixels from the training set. (It's actually a Greek letter "rho," which bears a resemblance to our "P."

In [13]:
```
rect = (1100, 3500, 700, 950)
fig, ax = plt.subplots()
ax.imshow(label.cpu())
patch = patches.Rectangle((rect[0], rect[1]), rect[2], rect[3], linewidth=2, edgecolor
ax.add_patch(patch)
plt.show()
```

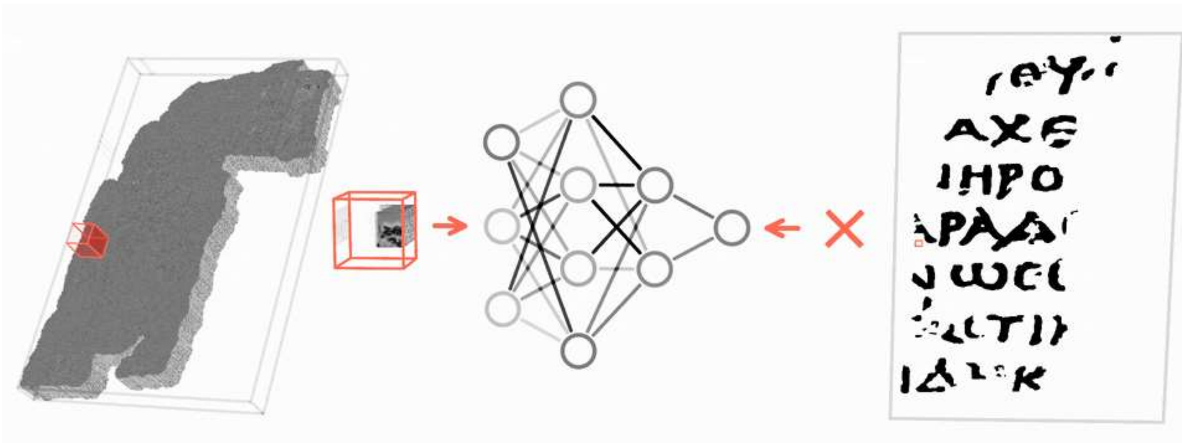


Now, we'll define a PyTorch dataset and model.

In [14]:
```
class SubvolumeDataset(data.Dataset):
    def __init__(self, image_stack, label, pixels):
        self.image_stack = image_stack
        self.label = label
        self.pixels = pixels
    def __len__(self):
        return len(self.pixels)
    def __getitem__(self, index):
        y, x = self.pixels[index]
        subvolume = self.image_stack[:, y-BUFFER:y+BUFFER+1, x-BUFFER:x+BUFFER+1].view
        inklabel = self.label[y, x].view(1)
        return subvolume, inklabel
```

```
model = nn.Sequential(
    nn.Conv3d(1, 16, 3, 1, 1), nn.MaxPool3d(2, 2),
    nn.Conv3d(16, 32, 3, 1, 1), nn.MaxPool3d(2, 2),
    nn.Conv3d(32, 64, 3, 1, 1), nn.MaxPool3d(2, 2),
    nn.Flatten(start_dim=1),
    nn.LazyLinear(128), nn.ReLU(),
    nn.LazyLinear(1), nn.Sigmoid()
).to(DEVICE)
```

Now, we'll train the model. Conceptually it looks like this:



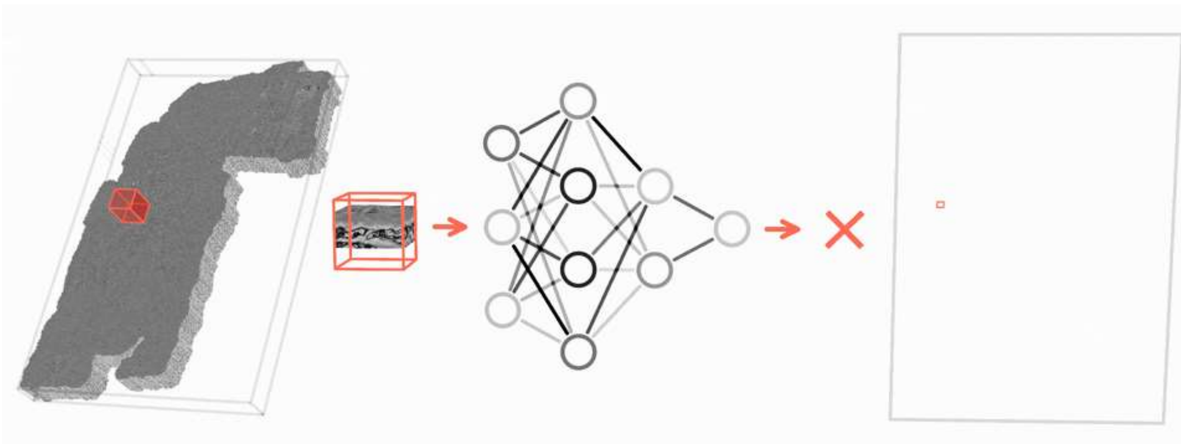
In [15]:
```
print("Generating pixel lists...")
# Split the dataset into train and val.
# Create a Boolean array of the same shape as the bitmask, initially all True
not_border = np.zeros(mask.shape, dtype=bool)
not_border[BUFFER:mask.shape[0]-BUFFER, BUFFER:mask.shape[1]-BUFFER] = True
arr_mask = np.array(mask) * not_border
inside_rect = np.zeros(mask.shape, dtype=bool) * arr_mask
# Sets all indexes with inside_rect array to True
inside_rect[rect[1]:rect[1]+rect[3]+1, rect[0]:rect[0]+rect[2]+1] = True
# Set the pixels within the inside_rect to False
outside_rect = np.ones(mask.shape, dtype=bool) * arr_mask
outside_rect[rect[1]:rect[1]+rect[3]+1, rect[0]:rect[0]+rect[2]+1] = False
pixels_inside_rect = np.argwhere(inside_rect)
pixels_outside_rect = np.argwhere(outside_rect)

print("Training...")
train_dataset = SubvolumeDataset(image_stack, label, pixels_outside_rect)
train_loader = data.DataLoader(train_dataset, batch_size=BATCH_SIZE, shuffle=True)
criterion = nn.BCELoss()
optimizer = optim.SGD(model.parameters(), lr=LEARNING_RATE)
scheduler = torch.optim.lr_scheduler.OneCycleLR(optimizer, max_lr=LEARNING_RATE, total
model.train()
# running_loss = 0.0
for i, (subvolumes, inklabels) in tqdm(enumerate(train_loader), total=TRAINING_STEPS):
    if i >= TRAINING_STEPS:
        break
    optimizer.zero_grad()
    outputs = model(subvolumes.to(DEVICE))
    loss = criterion(outputs, inklabels.to(DEVICE))
    loss.backward()
    optimizer.step()
    scheduler.step()
```

```
#     running_loss += loss.item()
#     if i % 3000 == 3000-1:
#         print("Loss:", running_loss / 3000)
#         running_loss = 0.0
```

```
Generating pixel lists...
Training...
```

```
100%|██████████| 30000/30000 [08:20<00:00, 59.90it/s]
```

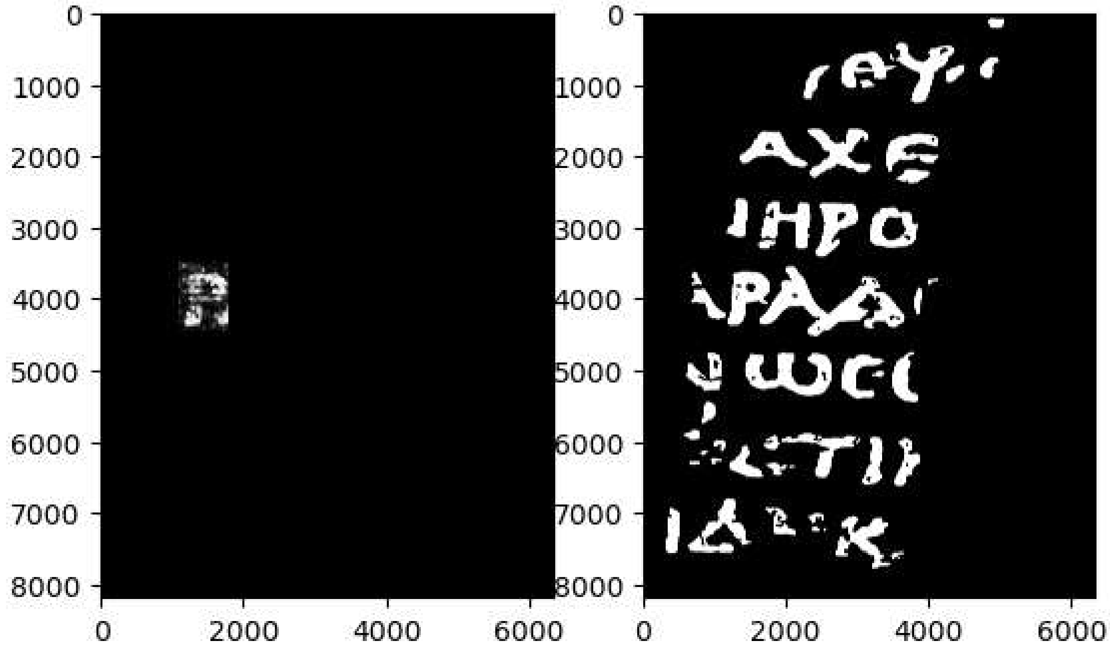
Finally, we'll create a prediction image. We'll employ the model to predict the presence of ink for each pixel within our designated rectangle, which corresponds to the validation set. Conceptually, it appears as follows:



In [16]:

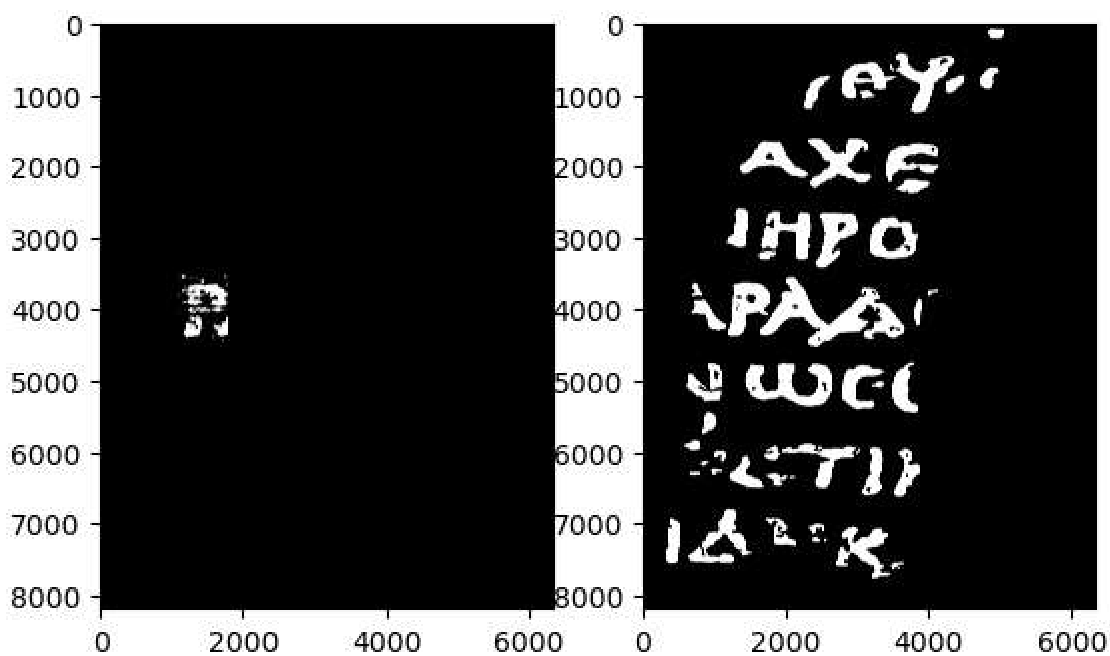
```
eval_dataset = SubvolumeDataset(image_stack, label, pixels_inside_rect)
eval_loader = data.DataLoader(eval_dataset, batch_size=BATCH_SIZE, shuffle=False)
output = torch.zeros_like(label).float()
model.eval()
with torch.no_grad():
    for i, (subvolumes, _) in enumerate(tqdm(eval_loader)):
        for j, value in enumerate(model(subvolumes.to(DEVICE))):
            output[tuple(pixels_inside_rect[i*BATCH_SIZE+j])] = value

fig, (ax1, ax2) = plt.subplots(1, 2)
ax1.imshow(output.cpu(), cmap='gray')
ax2.imshow(label.cpu(), cmap='gray')
plt.show()
```

```
100%|██████████| 20833/20833 [01:23<00:00, 248.26it/s]
```



Since our output needs to be binary, we must select a threshold, such as a 40% confidence level.

In [17]:
```
THRESHOLD = 0.4
fig, (ax1, ax2) = plt.subplots(1, 2)
ax1.imshow(output.gt(THRESHOLD).cpu(), cmap='gray')
ax2.imshow(label.cpu(), cmap='gray')
plt.show()
```



In [18]:
```
def rle(output):
    pixels = np.where(output.flatten().cpu() > THRESHOLD, 1, 0).astype(np.uint8)
    pixels[0] = 0
    pixels[-1] = 0
    runs = np.where(pixels[1:] != pixels[:-1])[0] + 2
    runs[1::2] = runs[1::2] - runs[:-1:2]
    return ' '.join(str(x) for x in runs)
```

```
rle_output = rle(output)


print("Id,Predicted\na," + rle_output + "\nb," + rle_output, file=open('result.csv', '
```