Installing The Requirements

In [1]:
```
# pip install torch torchvision matplotlib
```

Loading The Requirements

In [2]:
```
import torch
import torchvision.models as models
import torchvision.transforms as transforms
import matplotlib.pyplot as plt
from PIL import Image
import numpy as np
import math
import os
```

Load and preprocess image

In [3]:
```
transform = transforms.Compose([
    transforms.Resize((224, 224)),
    transforms.ToTensor(),
    transforms.Normalize(mean=[0.485, 0.456, 0.406],  # VGG16 normalization
                         std=[0.229, 0.224, 0.225])
])

image_path = "/kaggle/input/art-style-transfert/a-women-portrait-beautiful-y
original_image = Image.open(image_path).convert("RGB")
input_tensor = transform(original_image).unsqueeze(0)  # [1, 3, 224, 224]
```

Load VGG16 pretrained model

In [4]:
```
vgg16 = models.vgg16(pretrained=True).features.eval()
```

```
/usr/local/lib/python3.11/dist-packages/torchvision/models/_utils.py:208: Us
erWarning: The parameter 'pretrained' is deprecated since 0.13 and may be re
moved in the future, please use 'weights' instead.
  warnings.warn(
/usr/local/lib/python3.11/dist-packages/torchvision/models/_utils.py:223: Us
erWarning: Arguments other than a weight enum or `None` for 'weights' are de
precated since 0.13 and may be removed in the future. The current behavior i
s equivalent to passing `weights=VGG16_Weights.IMAGENET1K_V1`. You can also
use `weights=VGG16_Weights.DEFAULT` to get the most up-to-date weights.
  warnings.warn(msg)
```

Define conv block layer indices

In [5]:
```
block_layers = [4, 9, 16, 23, 30]
```

Extract features after each block

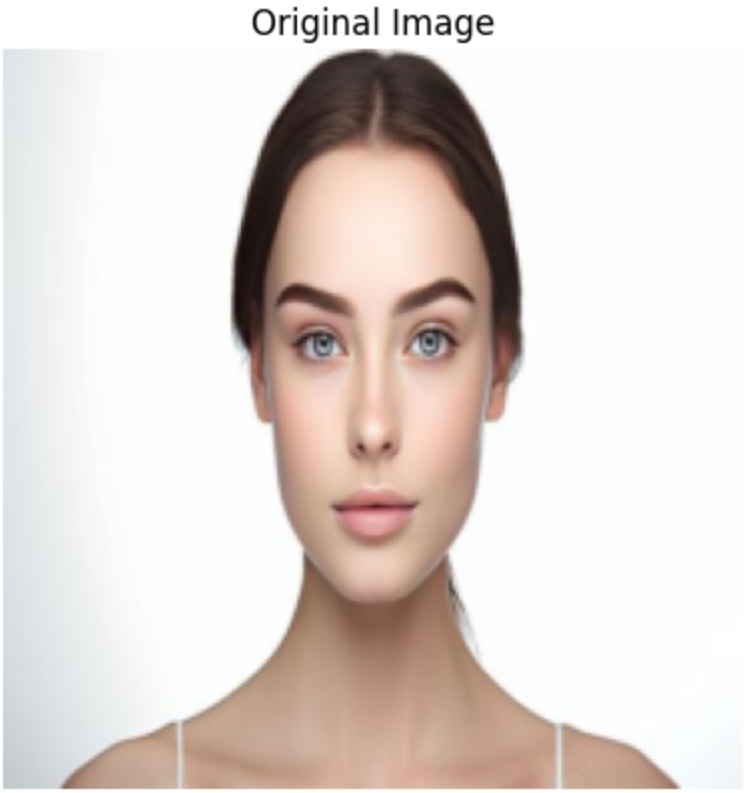
In [6]:
```
features = []
x = input_tensor.clone()
with torch.no_grad():
    for i, layer in enumerate(vgg16):
        x = layer(x)
        if i in block_layers:
            features.append(x.cpu())
```

Utility: Plot all channels in a grid

In [7]:
```
def plot_feature_maps(feature_map, title_prefix="Block"):
    num_channels = feature_map.shape[1]
    grid_cols = 8
    grid_rows = math.ceil(num_channels / grid_cols)

    fig, axs = plt.subplots(grid_rows, grid_cols, figsize=(grid_cols * 1.5,
    axs = axs.flatten()

    for i in range(num_channels):
        axs[i].imshow(feature_map[0, i], cmap='viridis')
        axs[i].axis('off')
        axs[i].set_title(f"C{i}")

    for i in range(num_channels, len(axs)):
        axs[i].axis('off')

    plt.suptitle(f"{title_prefix} - All {num_channels} Feature Maps", fontsi
    plt.tight_layout()
    plt.subplots_adjust(top=0.92)
    plt.show()
```

Visualize original image

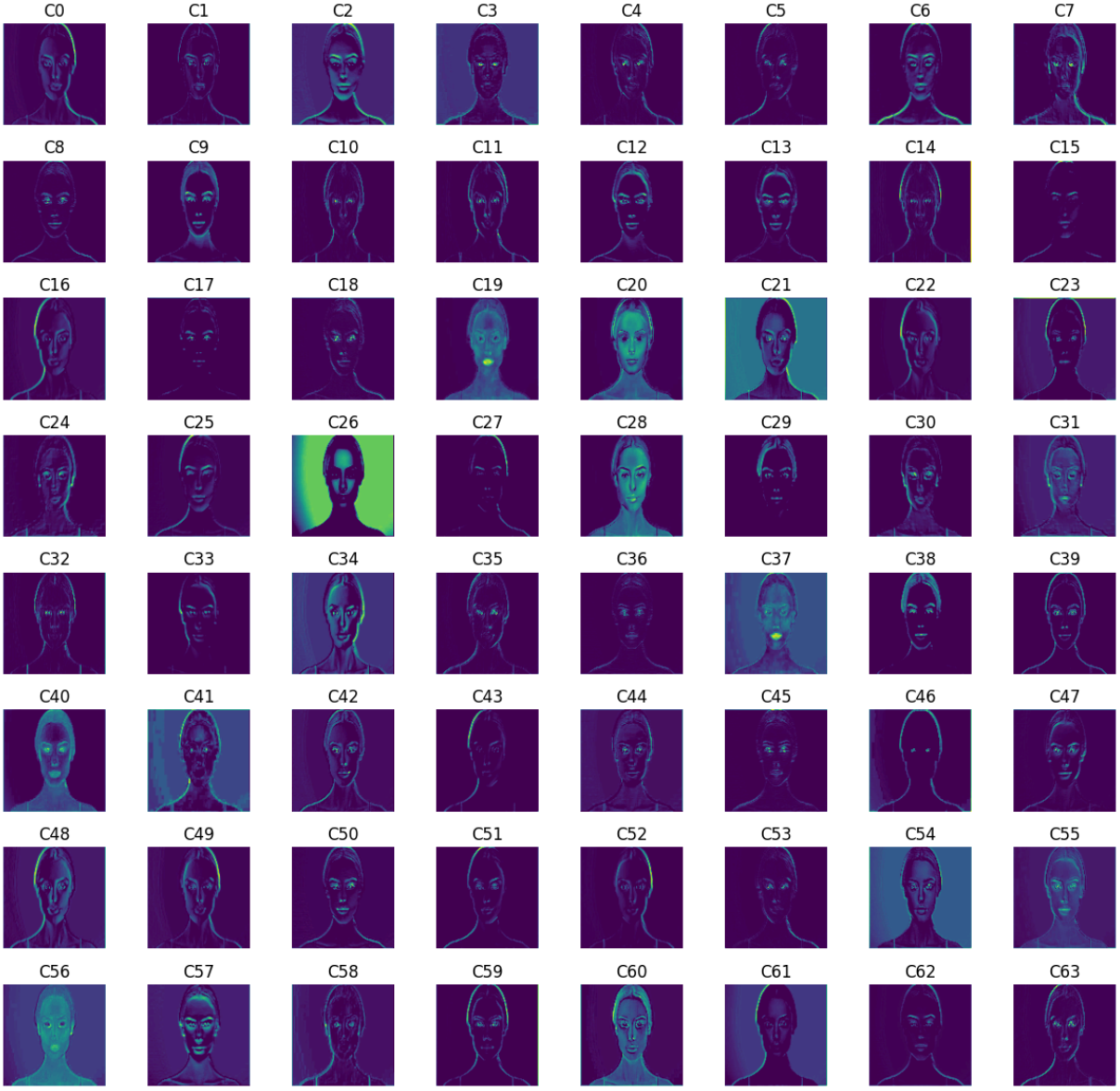
In [8]:
```
def denormalize(tensor):
    mean = torch.tensor([0.485, 0.456, 0.406]).reshape(3, 1, 1)
    std = torch.tensor([0.229, 0.224, 0.225]).reshape(3, 1, 1)
    return tensor * std + mean

plt.imshow(np.transpose(denormalize(input_tensor[0]).numpy(), (1, 2, 0)))
plt.title("Original Image")
plt.axis("off")
plt.show()
```



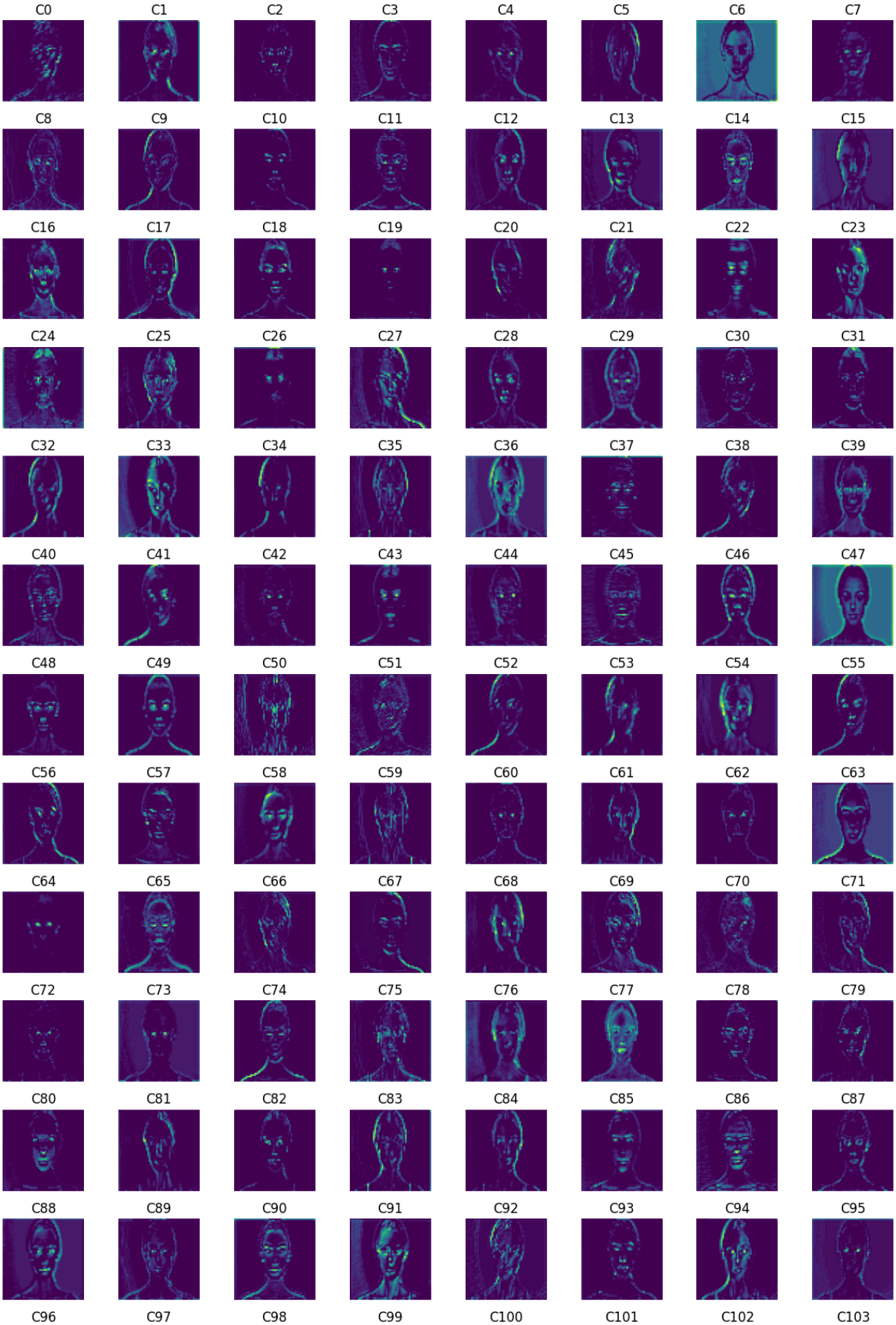
Visualize all channels for each block

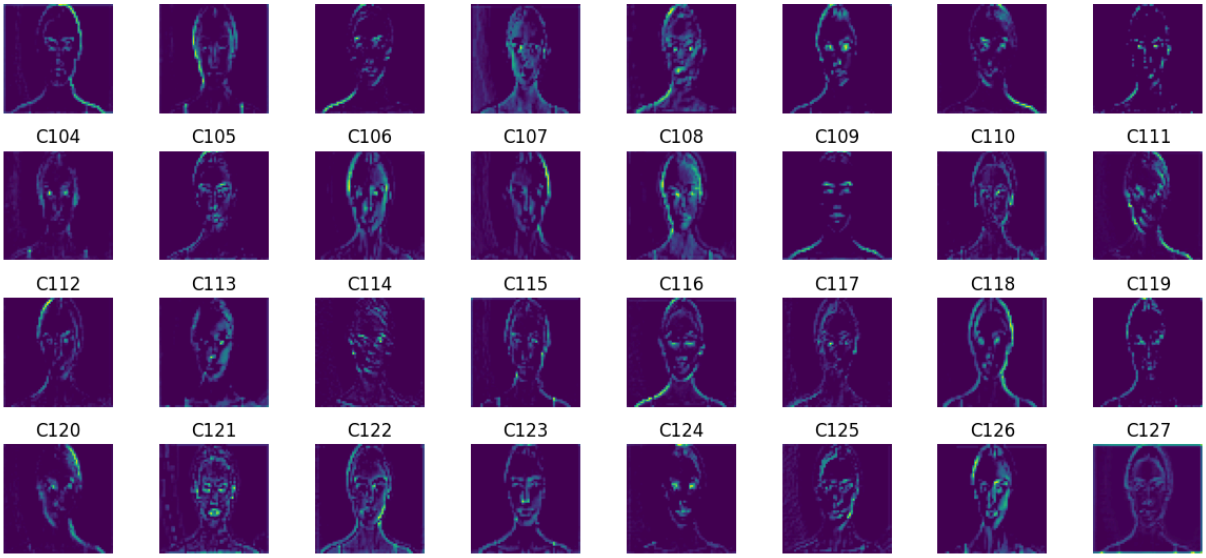
In [9]:
```
for i, feat in enumerate(features):
    plot_feature_maps(feat, title_prefix=f"Block {i+1}")
```

Block 1 - All 64 Feature Maps



Block 2 - All 128 Feature Maps

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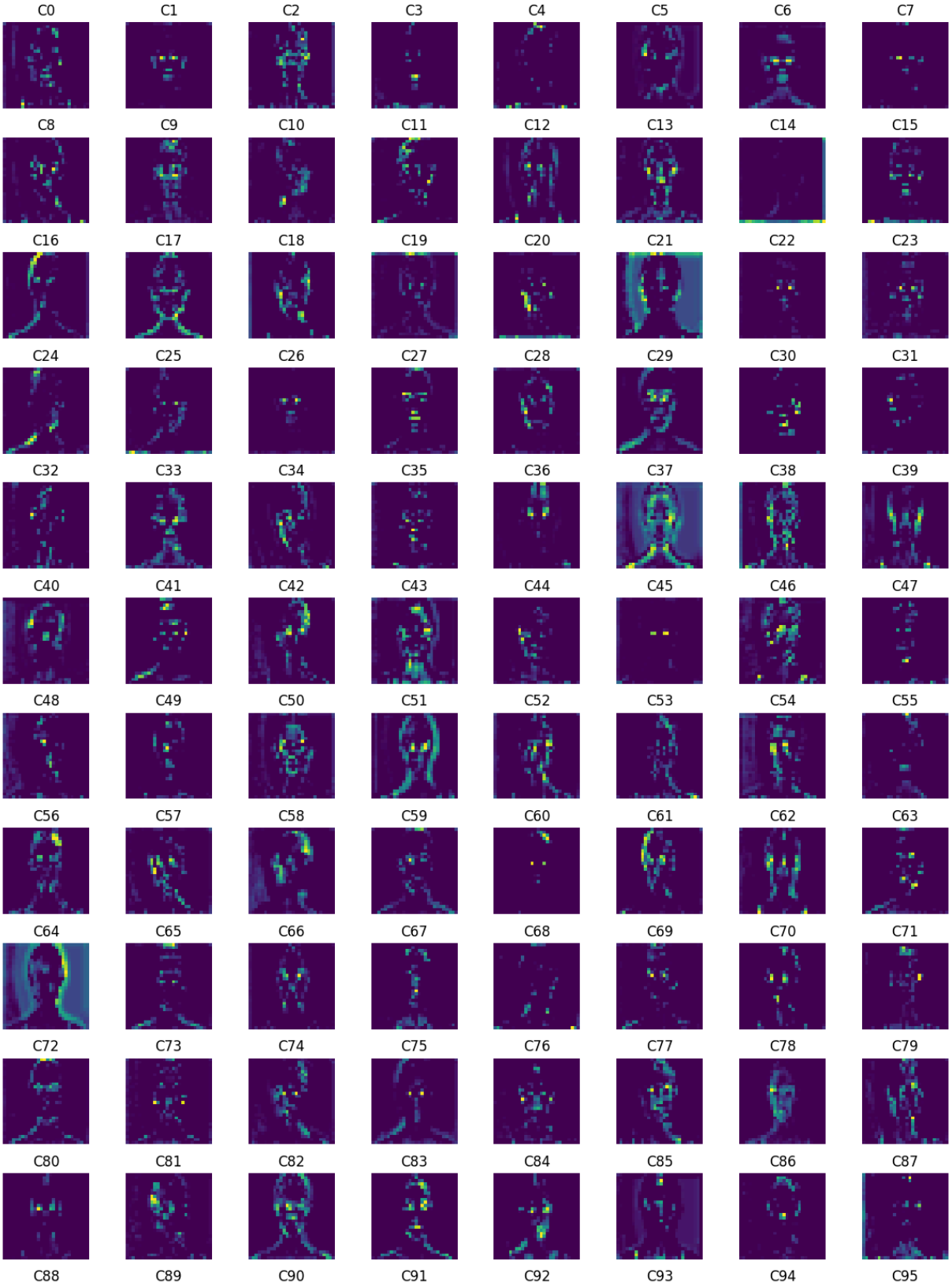
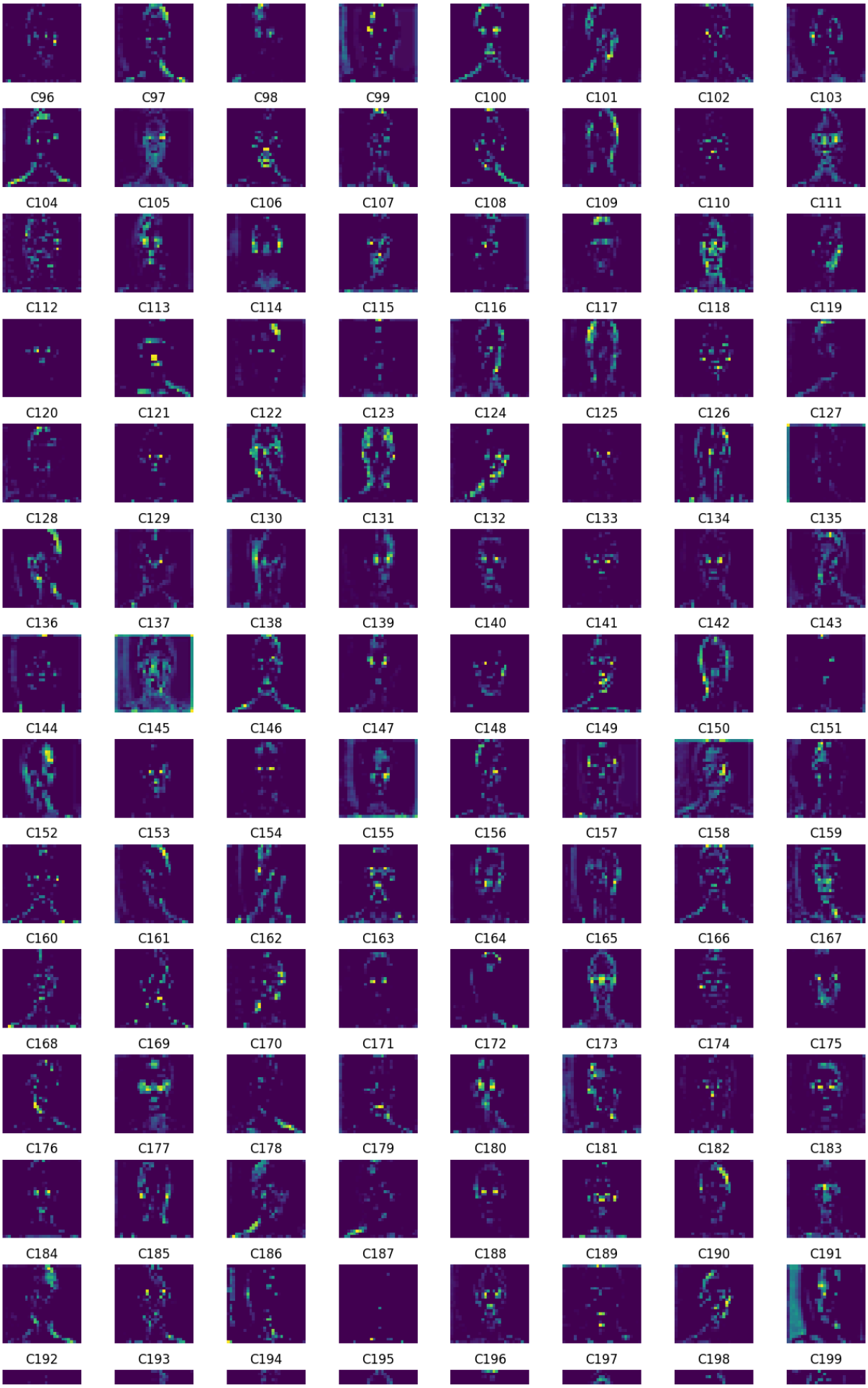
Block 3 - All 256 Feature Maps

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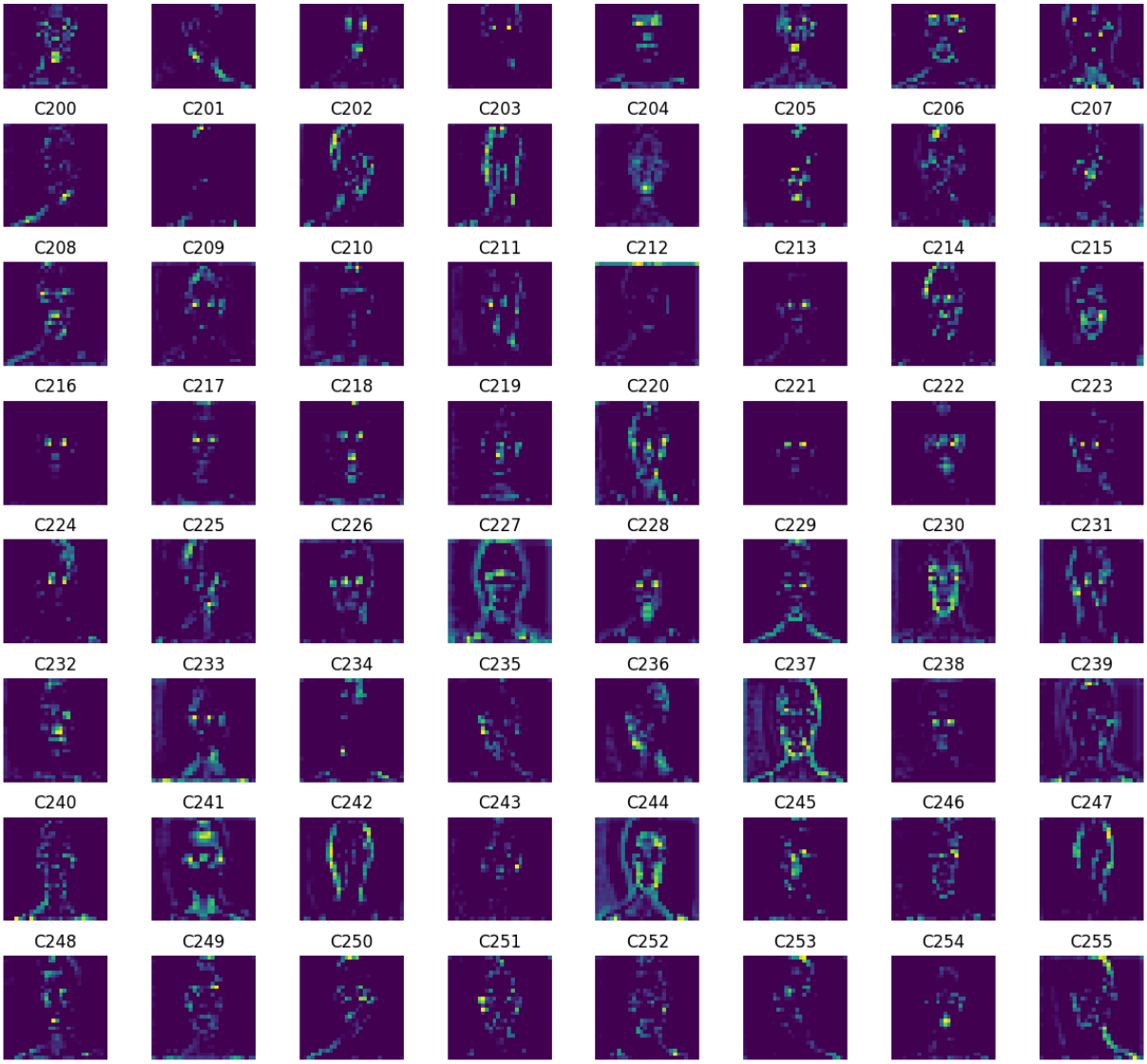
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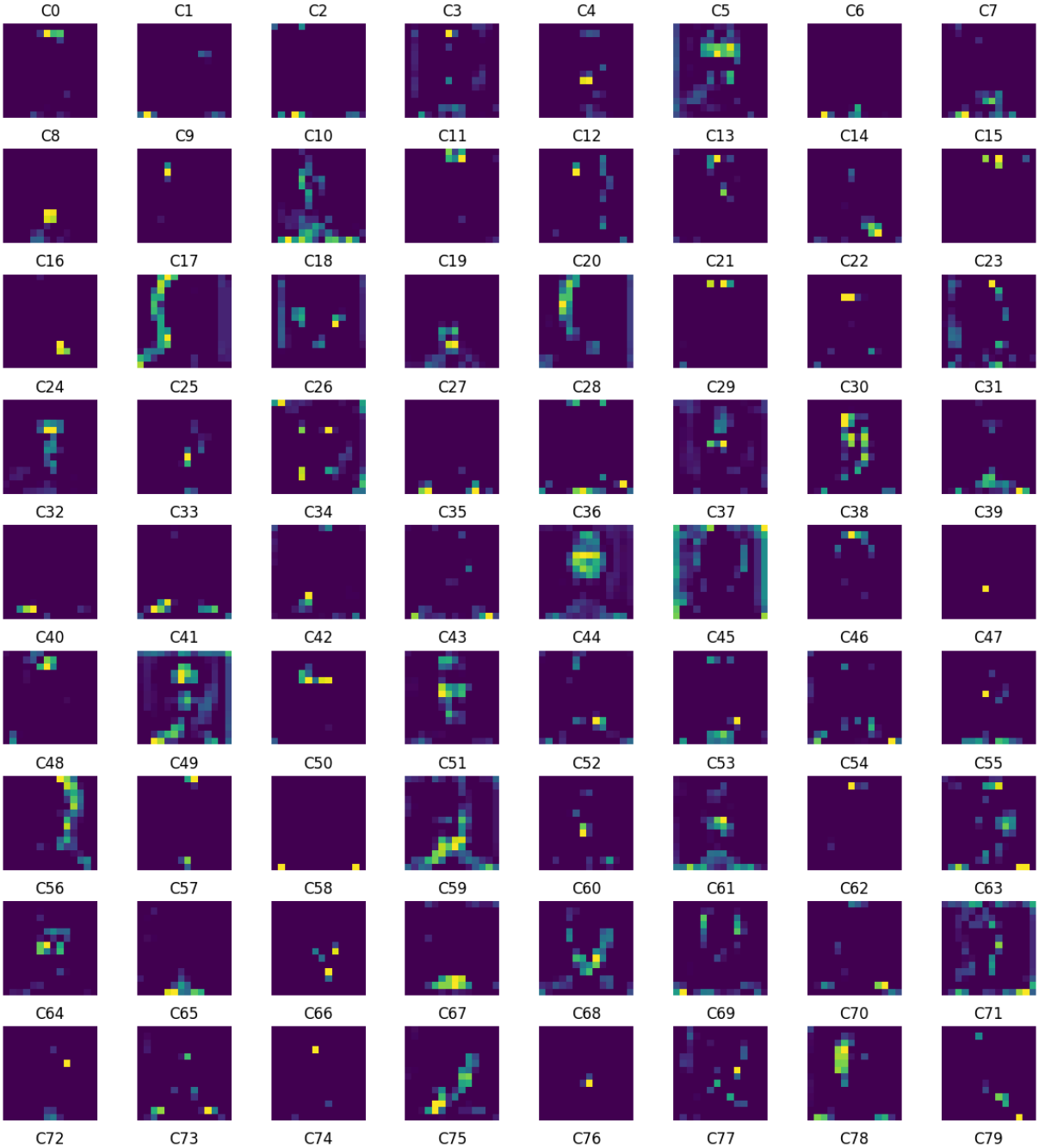
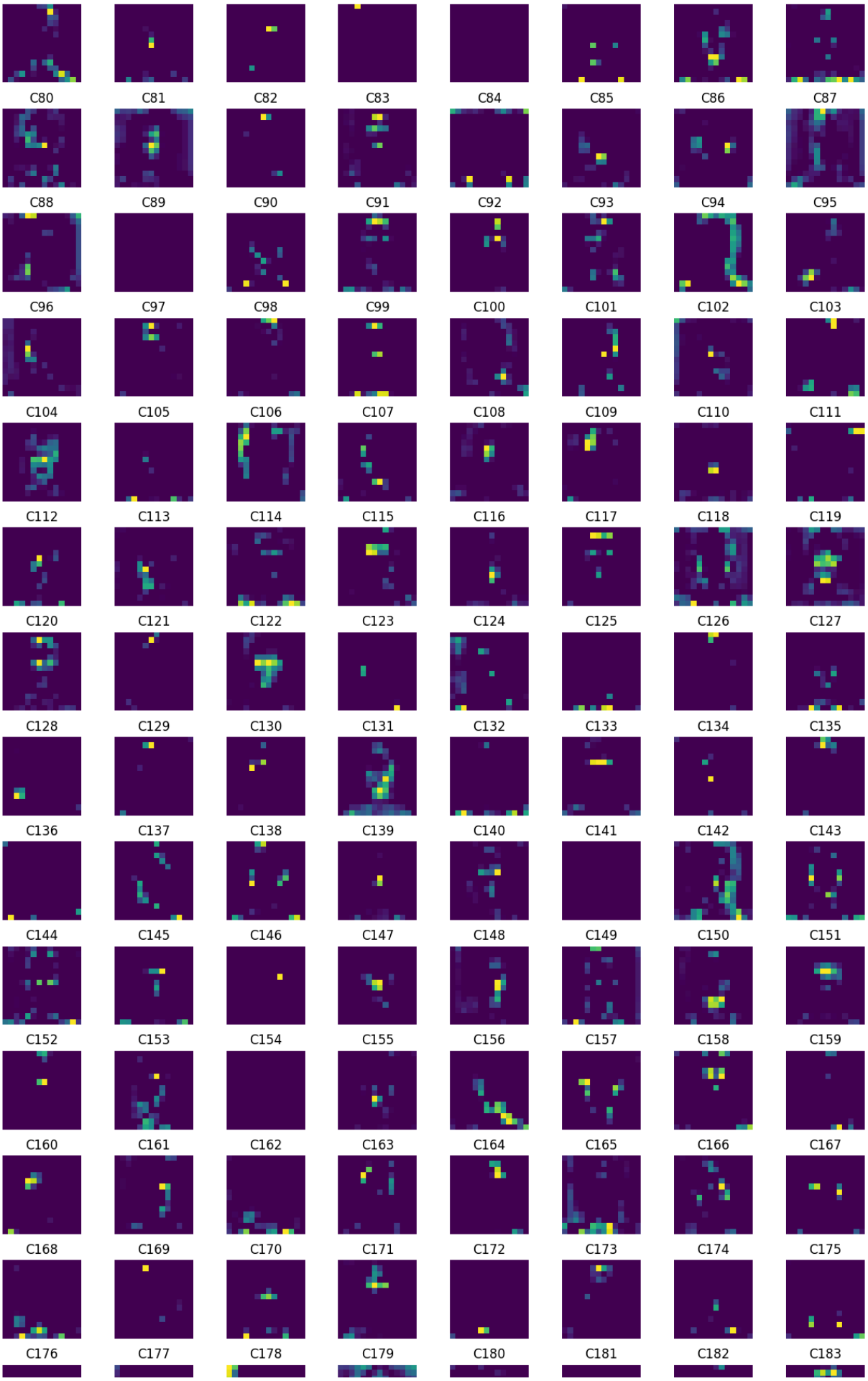
Block 4 - All 512 Feature Maps

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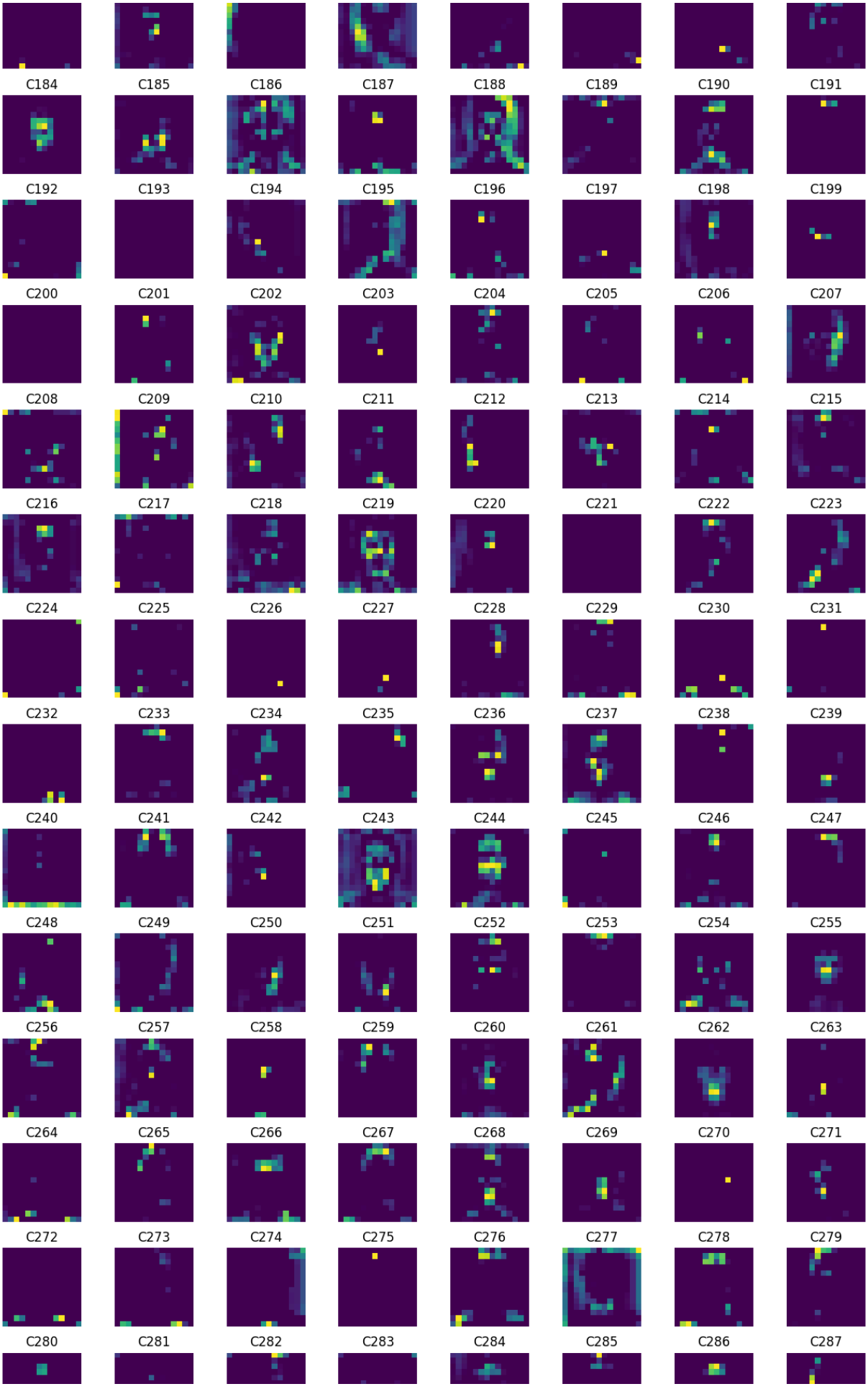
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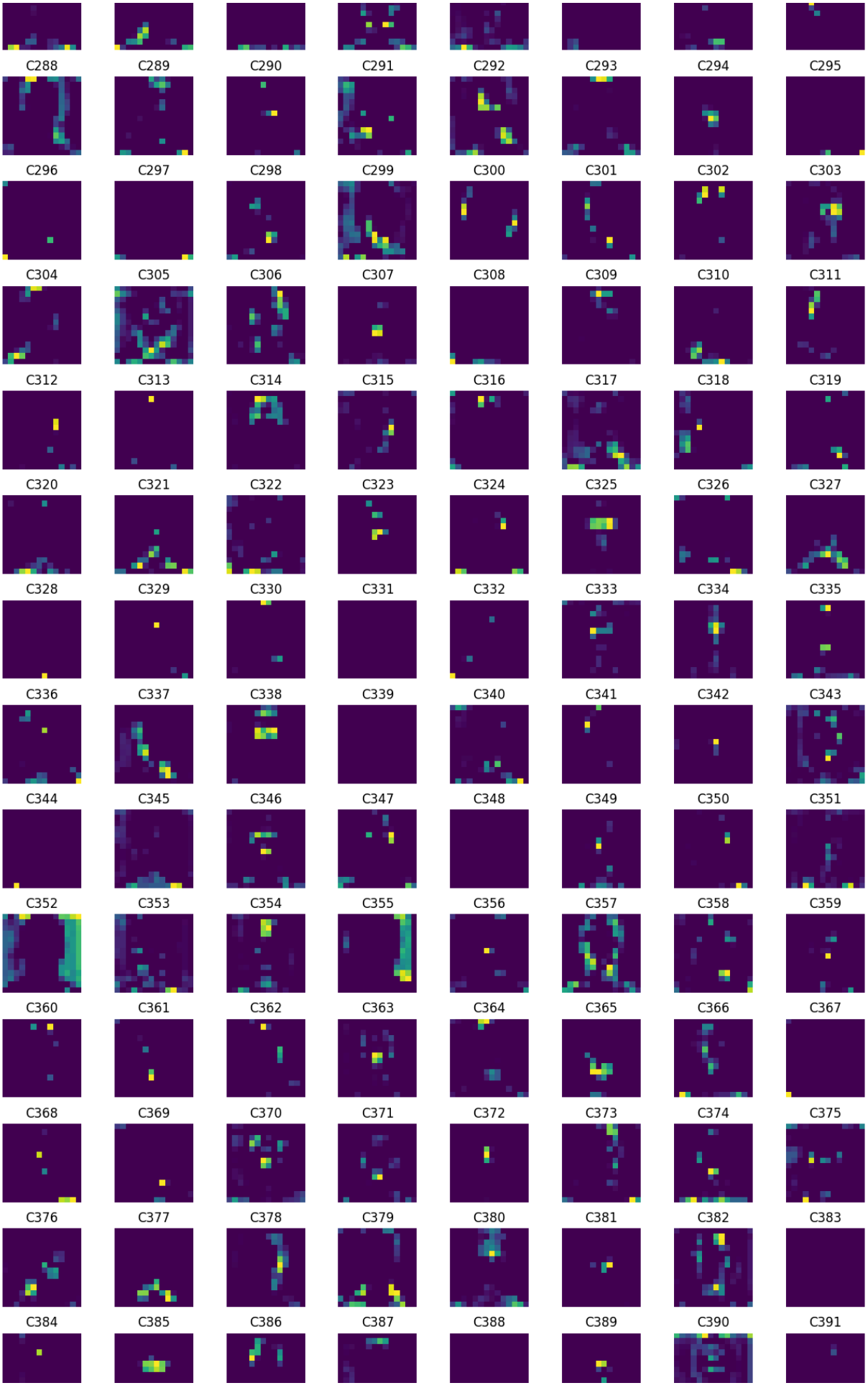
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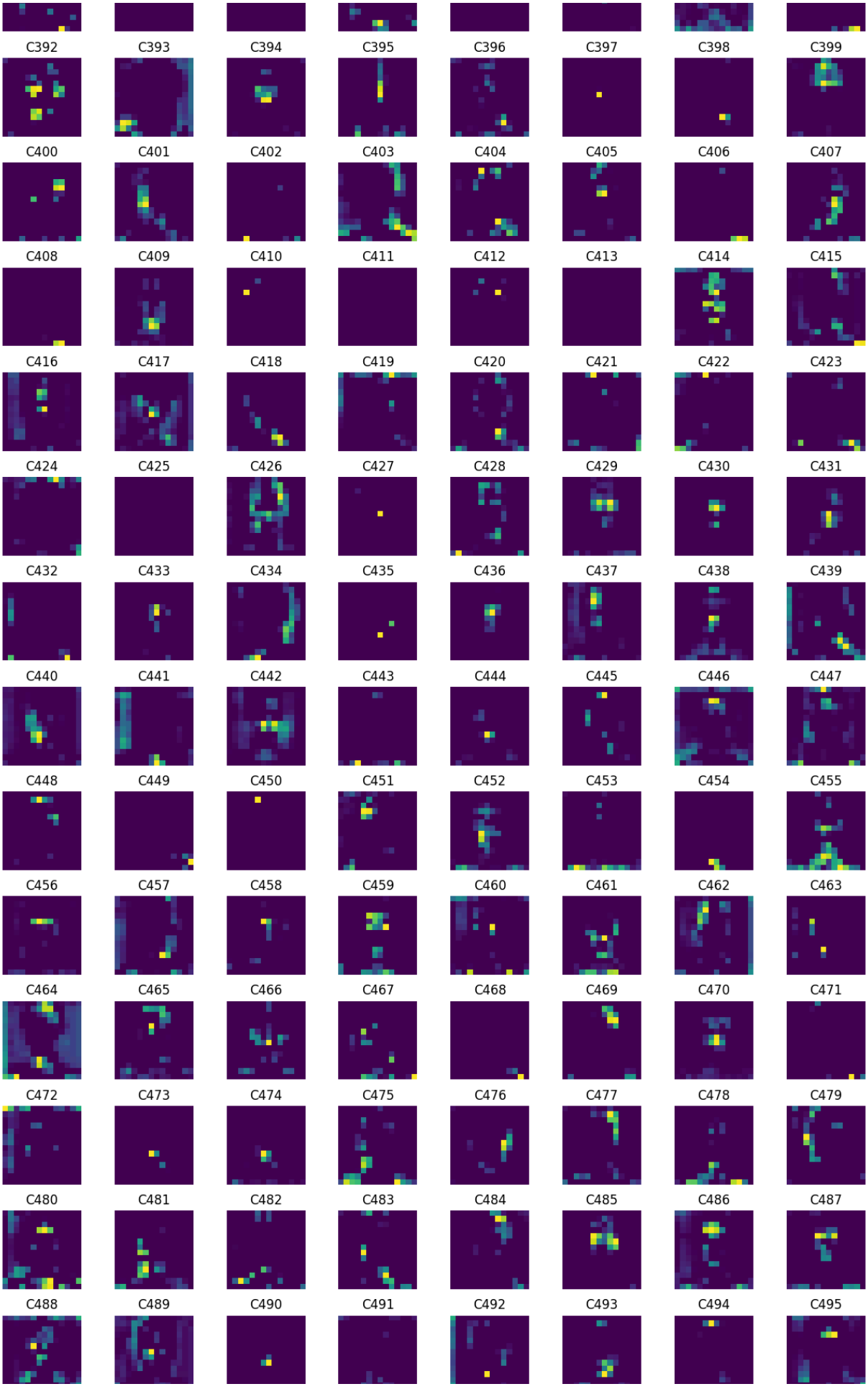
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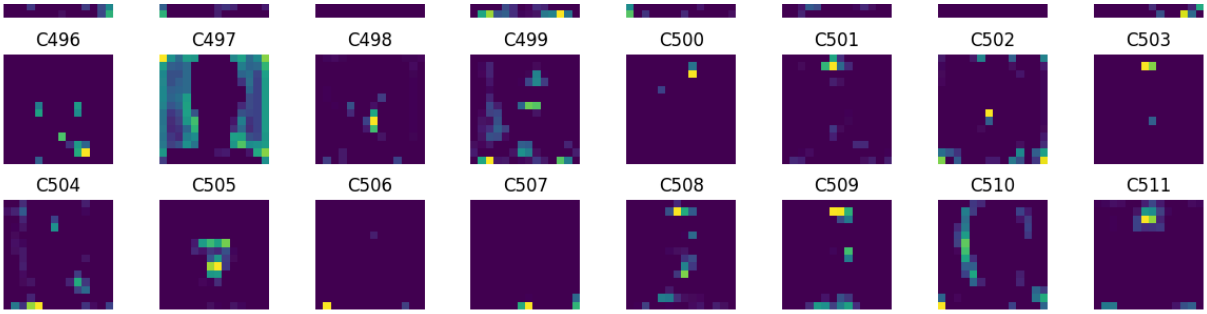
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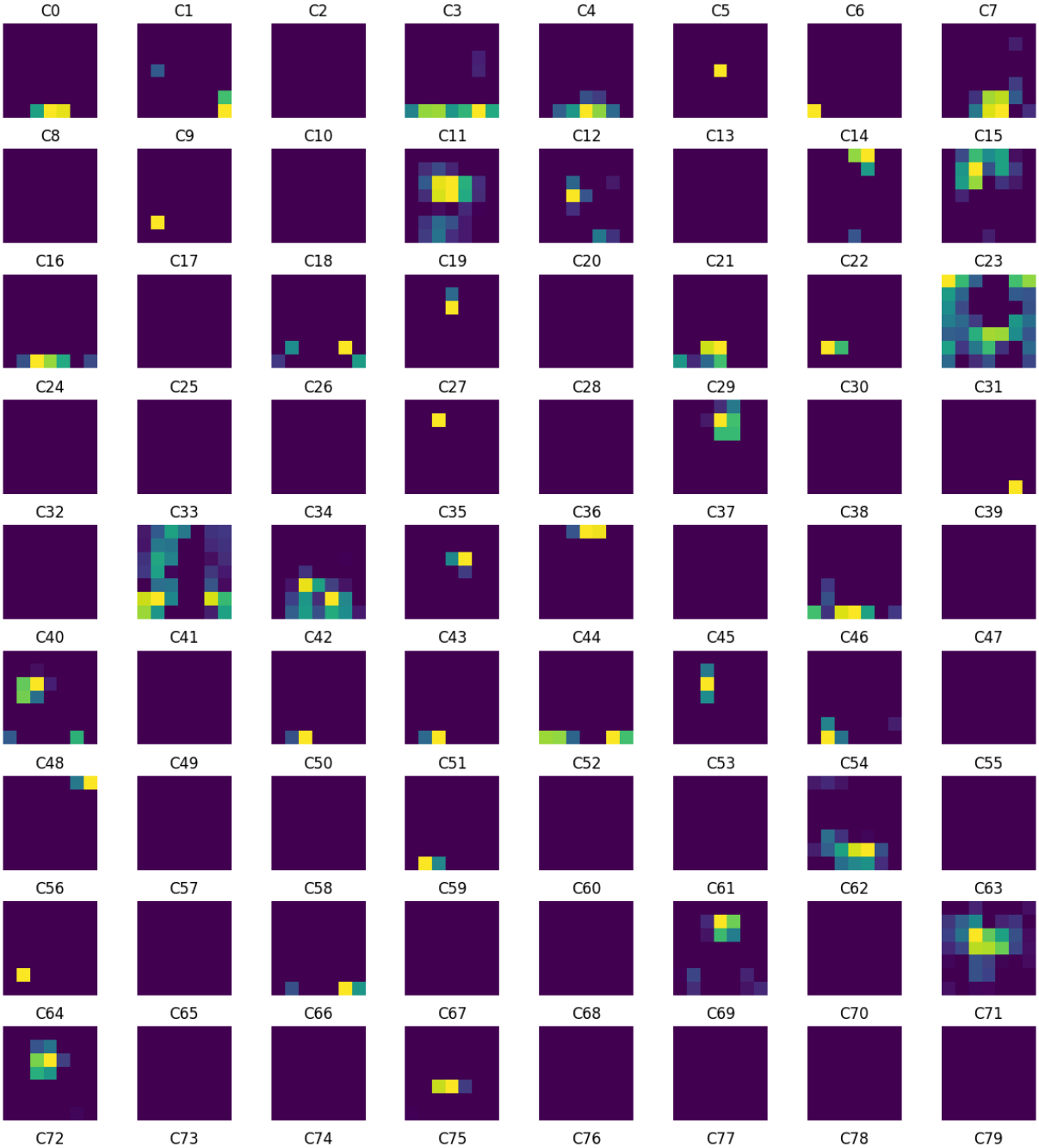
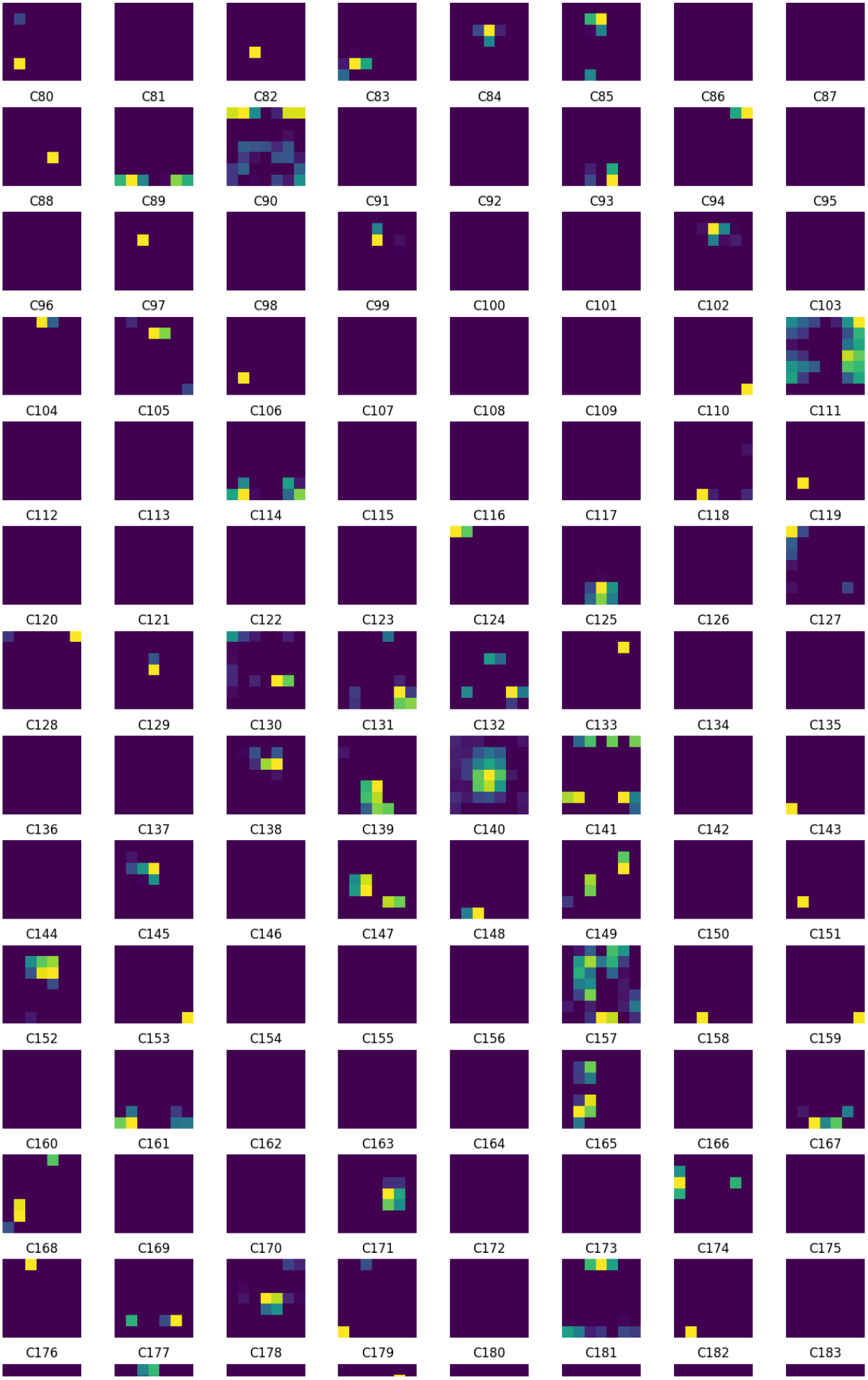
Block 5 - All 512 Feature Maps

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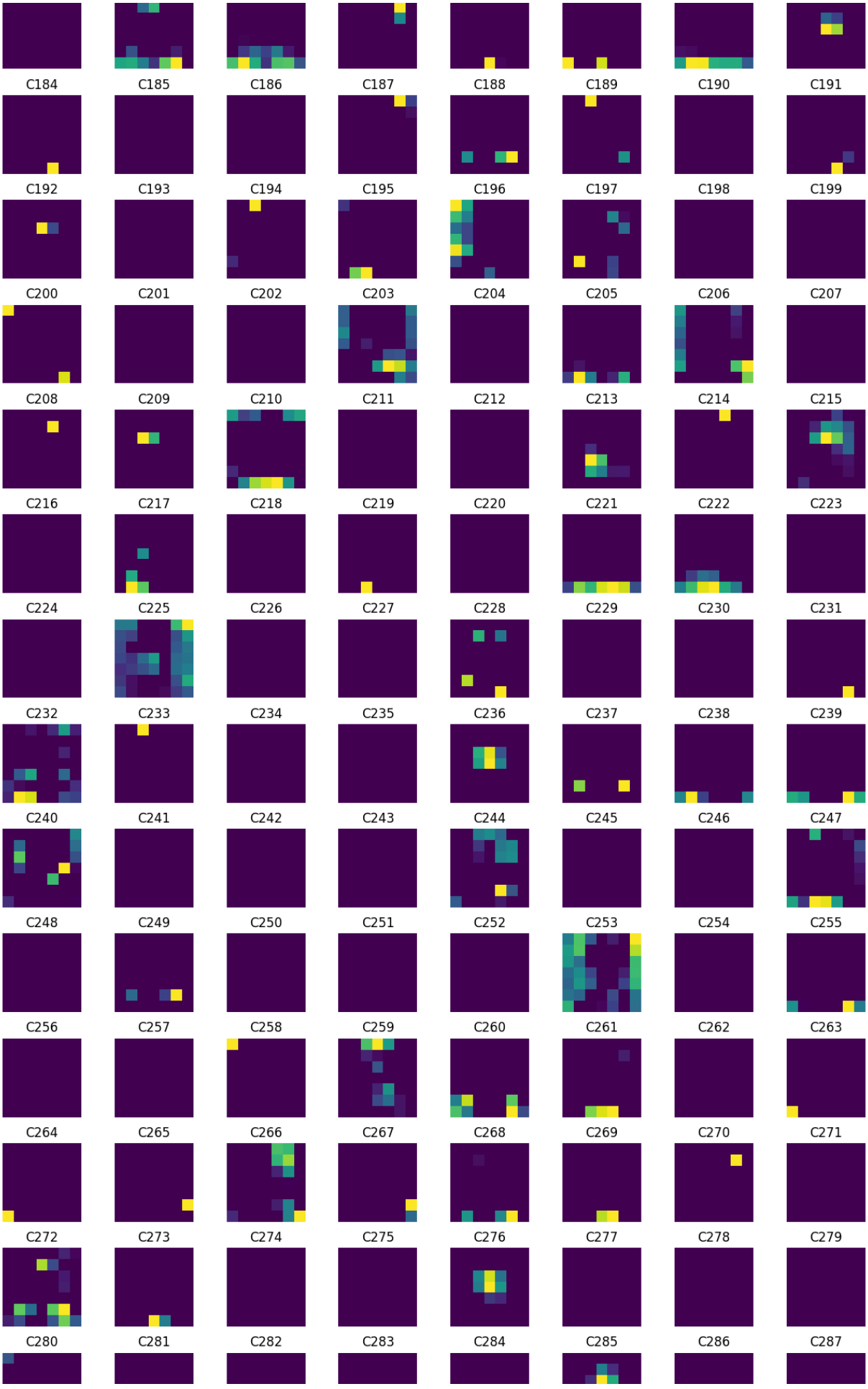
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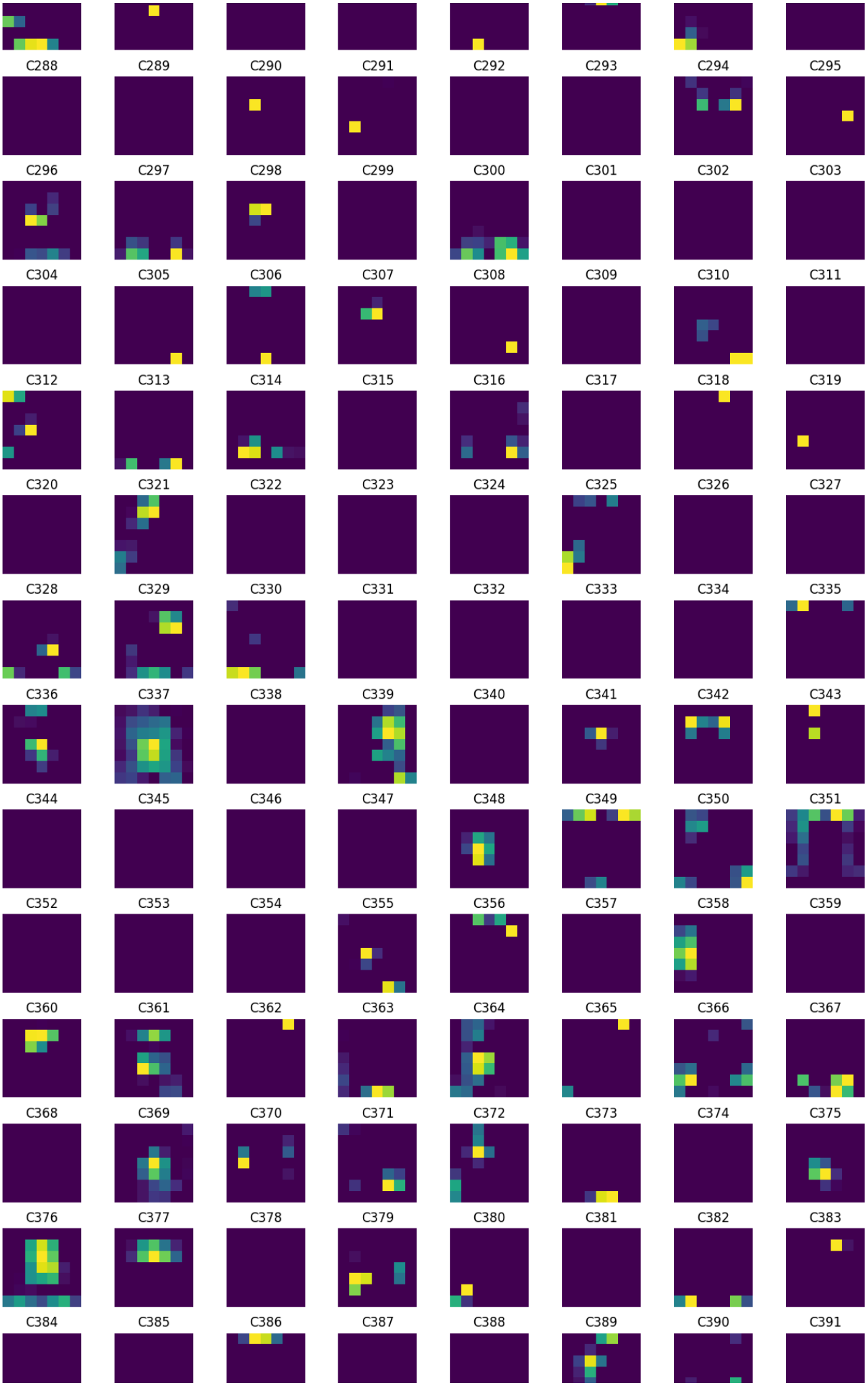
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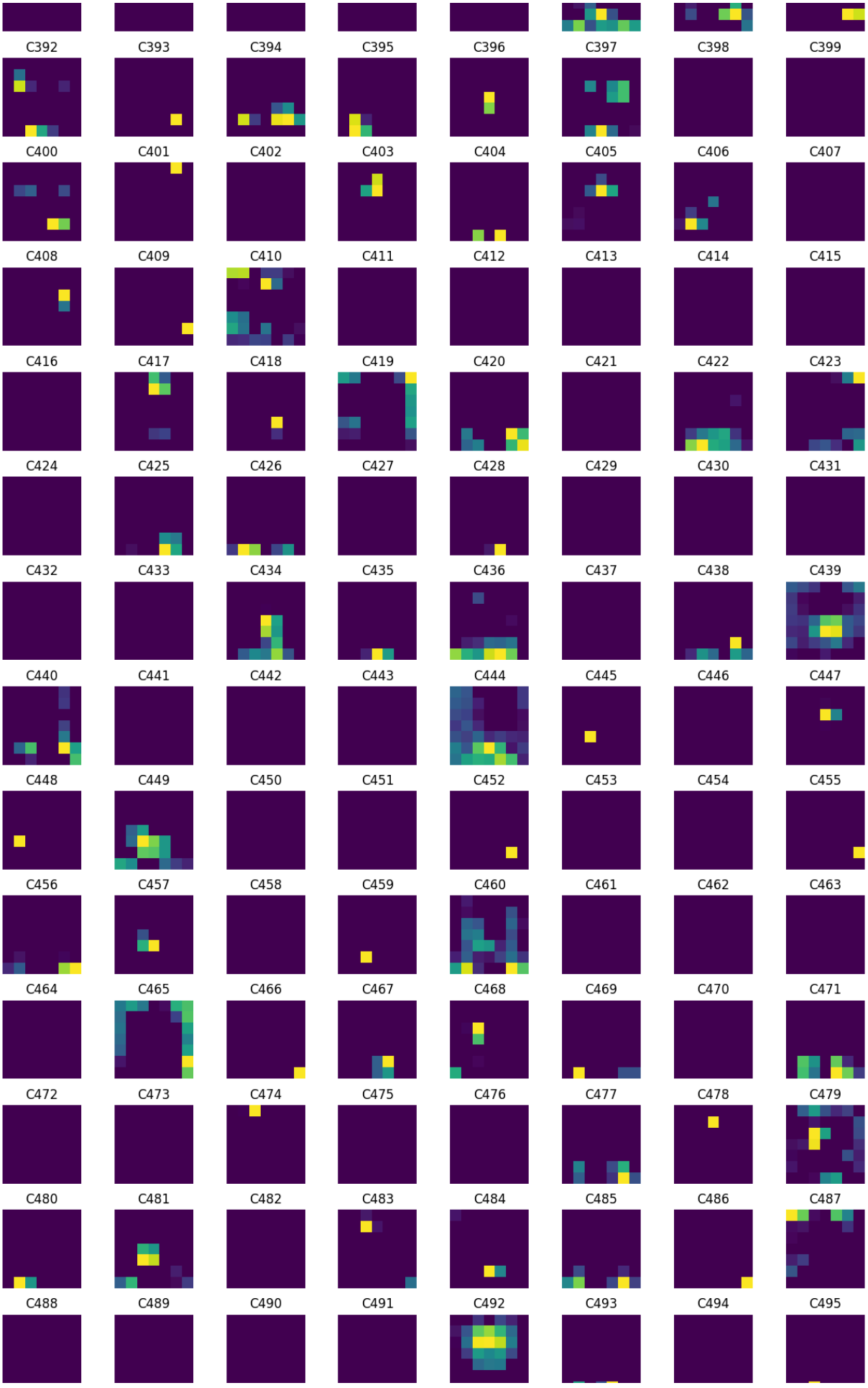
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