EE219-Lab1

October 4, 2025

1 Lab 1 Numpy CNN for inference

In this lab, you are required to fill in the blanks with your code **independently** to complete the inference process of a CNN. Note that there's a bonus at the end of this lab.

Requirements

1. **Complete the codes independently.**
2. **Make sure your results are reproducible.**
3. **Do not change the structure of the CNN and the given codes.**
4. **Do not add additional libraries.**

[11]:
```
import numpy as np
```

We will define a CNN to classify CIFAR-10 images. The network provided is similar to AlexNet, and it has the following architecture:

Layer	Type	Input Shape	Output Shape	Activation
conv1	Convolutional	3x33x33	96x27x27	ReLU
pool1	Max pool	96x27x27	96x13x13	None
conv2	Convolutional	96x13x13	256x13x13	ReLU
pool2	Max pool	256x13x13	256x6x6	None
conv3	Convolutional	256x6x6	384x6x6	ReLU
conv4	Convolutional	384x6x6	384x6x6	ReLU
conv5	Convolutional	384x6x6	256x6x6	ReLU
pool3	Max pool	256x6x6	256x3x3	None
fc1	Fully-connected	2304	1024	ReLU
fc2	Fully-connected	1024	512	ReLU
fc3	Fully-connected	512	10	None

Note that pool1 and pool2 employ 3×3 pooling, whereas pool3 utilizes 2×2 pooling to align with the output shape of conv5.

Next, we will build convolution, relu, max-pooling and fully-connected layers using **numpy** respectively (only forward propagation is required for inference).

[12]:
```python
class ReLU():
    def __init__(self):
        self.mask = None

    def forward(self,input):
        # TODO (5 pts)
        # forward propagation for relu layer
        self.mask = (input <= 0)
        out = input.copy()
        out[self.mask] = 0

        return out
```

[13]:
```python
class ConvLayer:
    def __init__(self, input_channels, output_channels, kernel_size, stride,␣
 ↪padding):
        self.input_channels = input_channels
        self.kernel_size = kernel_size
        self.stride = stride
        self.padding = padding

    def forward(self, x, weight):
        """
        input x: (N, C, H, W) [batchsize, input channels, x_height, x_width]
        input w: (K, C, R, S) [output channels, input channels, w_height,␣
 ↪w_width]
        output: (N, K, P, Q) [batchsize, output channels, output_height,␣
 ↪output_width]
        """
        N, C, H, W = x.shape
        K, C, R, S = weight.shape

        # TODO (5 pts)
        # complete padding operation
        if self.padding > 0:
            #       padding    padding
            x_padded = np.pad(x,
                                pad_width=((0, 0), (0, 0), (self.padding, self.
 ↪padding), (self.padding, self.padding)),
                                mode='constant',
                                constant_values=0)
        else:
            x_padded = x

        # TODO (5 pts)
        # compute output size using self.padding and self.stride
        P =1 + int((H + 2*self.padding - R) / self.stride)
```

```
        Q =1 + int((W + 2*self.padding - S) / self.stride)

        output = np.zeros((N, K, P, Q))
        # TODO (20 pts)
        # complete convolution operation
        for n in range(N):  #
            for k in range(K):  #
                for i in range(P):  #
                    for j in range(Q):  #
                        #
                        h_start = i * self.stride
                        h_end = h_start + R
                        w_start = j * self.stride
                        w_end = w_start + S

                        #     (C, R, S)
                        x_window = x_padded[n, :, h_start:h_end, w_start:w_end]

                        #
                        output[n, k, i, j] = np.sum(x_window * weight[k, :, :, :
↪])
        return output
```

[14]:
```
class MaxPooling2D:
    def __init__(self, pool_size=(2, 2), stride=2):
        self.pool_size = pool_size
        self.stride = stride

    def forward(self, x):
        """
        input x: (N, C, H, W) [batchsize, input channels, x_height, x_width]
        output: (N, C, pooled_height, pooled_width)
        """
        N, C, H, W = x.shape
        # TODO (5 pts)
        # compute output size using self.pool_size and self.stride
        if isinstance(self.pool_size, tuple):
            pool_h, pool_w = self.pool_size
        else:
            pool_h = pool_w = self.pool_size
        pooled_height = int(1 + (H - pool_h) / self.stride)
        pooled_width = int(1 + (W - pool_w) / self.stride)

        output = np.zeros((N, C, pooled_height, pooled_width))
        # TODO (10 pts)
        # complete max-pooling operation
        for n in range(N):  #
```

```
            for c in range(C):  #
                for i in range(pooled_height):  #
                    for j in range(pooled_width):  #
                        #
                        h_start = i * self.stride
                        h_end = h_start + pool_h
                        w_start = j * self.stride
                        w_end = w_start + pool_w

                        #
                        window = x[n, c, h_start:h_end, w_start:w_end]

                        #
                        output[n, c, i, j] = np.max(window)


        return output
```

[15]:
```
class fclayer():
    def __init__(self, in_features, out_features):
        self.in_features = in_features
        self.out_features = out_features

    def forward(self, x, weight):
        # TODO (10 pts)
        # complete forward propagation of fully-connected layer
         #
        if x.ndim > 2:
            x = x.reshape(x.shape[0], -1)  #  batch

        #
        assert x.shape[1] == self.in_features, f"   {x.shape[1]}    {self.
 ↪in_features}  "
        assert weight.shape == (self.in_features, self.out_features), "    "

        #     : output = x · weight
        output = np.dot(x, weight)

        return output
```

[16]:
```
# load trained parameters
ckpt = np.load('./model.npz')
```

[ ]:
```
def lenet_inf(x,ckpt):
    # TODO (20 pts)
    # build the CNN network using classes above
    # Layer 1: conv1 - Input: 3x33x33, Output: 96x27x27
```

```
    conv1 = ConvLayer(input_channels=3, output_channels=96, kernel_size=7, stride=1, padding=0)
    conv1_out = conv1.forward(x, ckpt['conv1.weight'])
    relu1_out = ReLU().forward(conv1_out)

    # Layer 2: pool1 - Input: 96x27x27, Output: 96x13x13
    pool1 = MaxPooling2D(pool_size=3, stride=2)
    pool1_out = pool1.forward(relu1_out)

    # Layer 3: conv2 - Input: 96x13x13, Output: 256x13x13
    #    kernel_size  5  3     (256, 96, 5, 5)
    conv2 = ConvLayer(input_channels=96, output_channels=256, kernel_size=5, stride=1, padding=2)  # padding=2
    conv2_out = conv2.forward(pool1_out, ckpt['conv2.weight'])
    relu2_out = ReLU().forward(conv2_out)

    # Layer 4: pool2 - Input: 256x13x13, Output: 256x6x6
    pool2 = MaxPooling2D(pool_size=3, stride=2)
    pool2_out = pool2.forward(relu2_out)

    # Layer 5: conv3 - Input: 256x6x6, Output: 384x6x6
    conv3 = ConvLayer(input_channels=256, output_channels=384, kernel_size=3, stride=1, padding=1)
    conv3_out = conv3.forward(pool2_out, ckpt['conv3.weight'])
    relu3_out = ReLU().forward(conv3_out)

    # Layer 6: conv4 - Input: 384x6x6, Output: 384x6x6
    conv4 = ConvLayer(input_channels=384, output_channels=384, kernel_size=3, stride=1, padding=1)
    conv4_out = conv4.forward(relu3_out, ckpt['conv4.weight'])
    relu4_out = ReLU().forward(conv4_out)

    # Layer 7: conv5 - Input: 384x6x6, Output: 256x6x6
    conv5 = ConvLayer(input_channels=384, output_channels=256, kernel_size=3, stride=1, padding=1)
    conv5_out = conv5.forward(relu4_out, ckpt['conv5.weight'])
    relu5_out = ReLU().forward(conv5_out)

    # Layer 8: pool3 - Input: 256x6x6, Output: 256x3x3
    pool3 = MaxPooling2D(pool_size=2, stride=2)
    pool3_out = pool3.forward(relu5_out)

    # Flatten for fully connected layers
    # Input: (N, 256, 3, 3) -> Flatten to (N, 256*3*3) = (N, 2304)
    flattened = pool3_out.reshape(pool3_out.shape[0], -1)

    # Layer 9: fc1 - Input: 2304, Output: 1024
```

```
    #     (1024, 2304)   (2304, 1024)
    fc1_weight_transposed = ckpt['fc1.weight'].T  #
    fc1 = fclayer(in_features=2304, out_features=1024)
    fc1_out = fc1.forward(flattened, fc1_weight_transposed)
    #
    relu6_out = ReLU().forward(fc1_out)

    # Layer 10: fc2 - Input: 1024, Output: 512
    fc2_weight_transposed = ckpt['fc2.weight'].T  #
    fc2 = fclayer(in_features=1024, out_features=512)
    fc2_out = fc2.forward(relu6_out, fc2_weight_transposed)
    #
    relu7_out = ReLU().forward(fc2_out)

    # Layer 11: fc3 - Input: 512, Output: 10
    fc3_weight_transposed = ckpt['fc3.weight'].T  #
    fc3 = fclayer(in_features=512, out_features=10)
    output = fc3.forward(relu7_out, fc3_weight_transposed)
    #
    return output
```

Execute the **cifar10_extraction.py** script to obtain the CIFAR-10 dataset.

[18]:
```
# you may need to install PIL package if not installed
# e.g. 'pip install pillow'
%run cifar10_extraction.py
```

```
Files already downloaded and verified
Train set done, 50000 images
Test set done, 10000 images
Dataset saved to /home/ubuntu/data/CIFAR10/datasets
```

[19]:
```
# you may need to install some packages if not installed
# e.g. 'conda install imageio' for imageio.v2, 'pip install pillow' for PIL

import imageio.v2 as imageio
import os
import random
from PIL import Image

# in this lab we will only infer 1 random picture from CIFAR-10 datasets to␣
 ↪save running time

test_folder = '/home/ubuntu/data/CIFAR10/datasets/test'
image_files = [f for f in os.listdir(test_folder) if f.endswith('.png') and f.
 ↪startswith('test_')]
```

```
random_image_file = random.choice(image_files)
image_path = os.path.join(test_folder, random_image_file)

input_image = imageio.imread(image_path)

# TODO (3 pts)
# resize the image to 33x33x3 to fit the input of the network
# Hint: use 'PIL' package, e.g. Image.fromarray()
pil_image = Image.fromarray(input_image)
resized_image = np.array(pil_image.resize((33, 33), Image.Resampling.LANCZOS))

# TODO (3 pts)
# normalize the pixels into [0,1] to maintain consistency with the training process
# models learn patterns based on the specific input distribution they were trained on
# this scaling ensures input features operate within the range the model's architecture and parameters were optimized for
image = resized_image.astype(np.float32) / 255.0


# TODO (4 pts)
# alter the size of the pixel matrix from (33,33,3) to (1,3,33,33) to fit convolution layer
image = image.transpose(2, 0, 1)  #   (33,33,3)    (3,33,33)
image = np.expand_dims(image, axis=0)  #   batch : (1,3,33,33)

# Verify output
print(f"Using test image: {image_path}")
print(f"Processed image shape: {image.shape}")  # should show (1, 3, 33, 33)
```

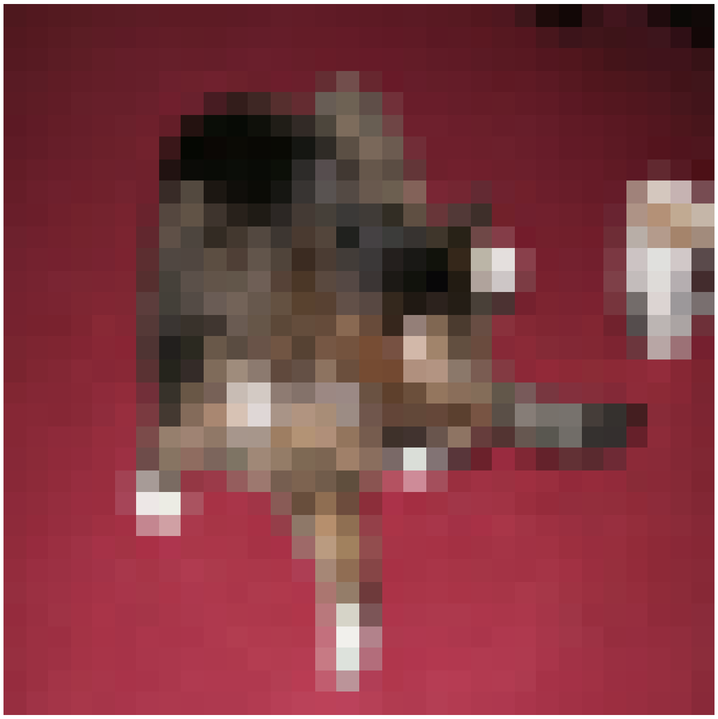
```
Using test image: /home/ubuntu/data/CIFAR10/datasets/test/test_4077.png
Processed image shape: (1, 3, 33, 33)
```

[20]:

```
classes = ['airplane', 'automobile', 'bird', 'cat', 'deer',
               'dog', 'frog', 'horse', 'ship', 'truck']

label_file_path = test_folder + '/label.txt'

ground_truth = None
with open(label_file_path, 'r') as f:
    for line in f:
        if line.startswith(random_image_file):
            ground_truth = int(line.strip().split()[1])
            break

# TODO (10 pts)
```

```python
# inference using lenet_inf created above
#   npz
print("Available keys in model.npz:", ckpt.files)

# npz
ckpt_dict = {}
for key in ckpt.files:
    ckpt_dict[key] = ckpt[key]
    print(f"{key}: shape = {ckpt[key].shape}")

output = lenet_inf(image, ckpt_dict)
label = np.argmax(output, axis=1)[0]

import matplotlib.pyplot as plt

# visualize the picture to be classified
print(f"Predicted label: {label} ({classes[label]})")
print(f"Ground truth: {ground_truth} ({classes[ground_truth]})")
plt.imshow(input_image)
plt.axis('off')
plt.show()
```

```
Available keys in model.npz: ['conv1.weight', 'conv2.weight', 'conv3.weight',
'conv4.weight', 'conv5.weight', 'fc1.weight', 'fc2.weight', 'fc3.weight']
conv1.weight: shape = (96, 3, 7, 7)
conv2.weight: shape = (256, 96, 5, 5)
conv3.weight: shape = (384, 256, 3, 3)
conv4.weight: shape = (384, 384, 3, 3)
conv5.weight: shape = (256, 384, 3, 3)
fc1.weight: shape = (1024, 2304)
fc2.weight: shape = (512, 1024)
fc3.weight: shape = (10, 512)
Predicted label: 6 (frog)
Ground truth: 3 (cat)
```



Bonus: Calculate the number of computations and parameters. Visualize your results directly in the outputs of your codes.

[ ]:
```
import matplotlib.pyplot as plt
import numpy as np

def visualize_model_analysis(results, total_params, total_flops):
    """

    """
    plt.figure(figsize=(15, 10))

    # 1. Parameters by Layer
    plt.subplot(2, 2, 1)
    layer_names = [r['layer'] for r in results if r['params'] > 0]
    layer_params = [r['params'] for r in results if r['params'] > 0]
    colors = plt.cm.Set3(np.linspace(0, 1, len(layer_names)))

    bars = plt.bar(layer_names, [p/1e6 for p in layer_params], color=colors)
    plt.title('Parameters by Layer (Millions)', fontsize=14, fontweight='bold')
    plt.xlabel('Layers')
    plt.ylabel('Parameters (M)')
    plt.xticks(rotation=45)
    plt.grid(axis='y', alpha=0.3)
```

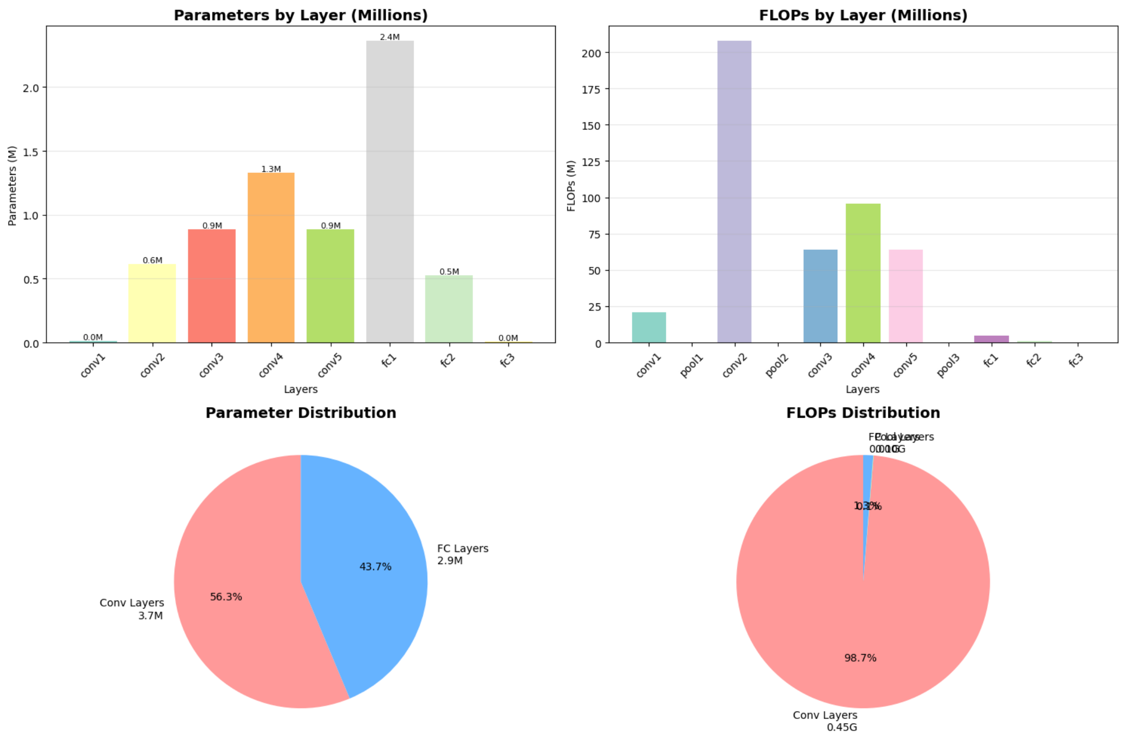
```
    # Add value labels on bars
    for bar, value in zip(bars, layer_params):
        plt.text(bar.get_x() + bar.get_width()/2, bar.get_height(),
                 f'{value/1e6:.1f}M', ha='center', va='bottom', fontsize=8)

    # 2. FLOPs by Layer
    plt.subplot(2, 2, 2)
    layer_names_flops = [r['layer'] for r in results]
    layer_flops = [r['flops'] for r in results]
    colors_flops = plt.cm.Set3(np.linspace(0, 1, len(layer_names_flops)))

    bars = plt.bar(layer_names_flops, np.array(layer_flops)/1e6, color=colors_flops)
    plt.title('FLOPs by Layer (Millions)', fontsize=14, fontweight='bold')
    plt.xlabel('Layers')
    plt.ylabel('FLOPs (M)')
    plt.xticks(rotation=45)
    plt.grid(axis='y', alpha=0.3)

    # 3. Parameter Distribution Pie Chart
    plt.subplot(2, 2, 3)
    conv_params = sum(r['params'] for r in results if 'conv' in r['layer'])
    fc_params = sum(r['params'] for r in results if 'fc' in r['layer'])

    sizes = [conv_params, fc_params]
    labels = [f'Conv Layers\n{conv_params/1e6:.1f}M', f'FC Layers\n{fc_params/1e6:.1f}M']
    colors = ['#ff9999', '#66b3ff']
    plt.pie(sizes, labels=labels, colors=colors, autopct='%1.1f%%', startangle=90)
    plt.title('Parameter Distribution', fontsize=14, fontweight='bold')

    # 4. FLOPs Distribution Pie Chart
    plt.subplot(2, 2, 4)
    conv_flops = sum(r['flops'] for r in results if 'conv' in r['layer'])
    pool_flops = sum(r['flops'] for r in results if 'pool' in r['layer'])
    fc_flops = sum(r['flops'] for r in results if 'fc' in r['layer'])

    sizes = [conv_flops, pool_flops, fc_flops]
    labels = [
        f'Conv Layers\n{conv_flops/1e9:.2f}G',
        f'Pool Layers\n{pool_flops/1e9:.2f}G',
        f'FC Layers\n{fc_flops/1e9:.2f}G'
    ]
    colors = ['#ff9999', '#99ff99', '#66b3ff']
```

```
    plt.pie(sizes, labels=labels, colors=colors, autopct='%1.1f%%',␣
↪startangle=90)
    plt.title('FLOPs Distribution', fontsize=14, fontweight='bold')

    plt.tight_layout()
    plt.show()

#
print("MODEL COMPLEXITY ANALYSIS")
print("=" * 50)
print(f"Total Parameters: {total_params:,} ({total_params/1e6:.2f} Million)")
print(f"Total FLOPs: {total_flops:,} ({total_flops/1e9:.2f} GFLOPs)")
print(f"FLOPs per image: {total_flops/1e9:.2f} GFLOPs")
print("=" * 50)

#
visualize_model_analysis(results, total_params, total_flops)

#
print("\nDETAILED ANALYSIS REPORT")
print("=" * 50)

#
conv_layers = [r for r in results if 'conv' in r['layer']]
fc_layers = [r for r in results if 'fc' in r['layer']]

print(f"\nConvolutional Layers Analysis:")
for layer in conv_layers:
    params_m = layer['params'] / 1e6
    print(f"  {layer['layer']}: {layer['params']:,} params ({params_m:.2f}M)")

print(f"\nFully Connected Layers Analysis:")
for layer in fc_layers:
    params_m = layer['params'] / 1e6
    print(f"  {layer['layer']}: {layer['params']:,} params ({params_m:.2f}M)")

print(f"\nEfficiency Analysis:")
print(f"  FLOPs per parameter: {total_flops/total_params:.1f} FLOPs/param")
print(f"  Model size (32-bit float): {total_params * 4 / 1e6:.2f} MB")

#
print(f"\nMemory Usage Analysis:")
print(f"  Feature maps memory (approx): ~{(96*27*27 + 256*13*13 + 384*6*6*3 +␣
↪256*3*3) * 4 / 1e6:.2f} MB")
print(f"  Weights memory: {total_params * 4 / 1e6:.2f} MB")
print(f"  Total memory (inference): ~{(total_params * 4 / 1e6) + 10:.2f} MB") ␣
↪#
```

```python
#
print(f"\nComparison with Classic Models (approximate):")
print(f"  LeNet-5: ~60K parameters, ~0.001 GFLOPs")
print(f"  AlexNet: ~60M parameters, ~0.7 GFLOPs")
print(f"  VGG-16: ~138M parameters, ~16 GFLOPs")
print(f"  ResNet-18: ~11M parameters, ~1.8 GFLOPs")
print(f"  This Model: ~{total_params/1e6:.1f}M parameters, ~{total_flops/1e9:.2f} GFLOPs")

print(f"\nModel Characteristics:")
print(f"   Moderate size: {total_params/1e6:.1f}M parameters")
print(f"   Efficient: {total_flops/1e9:.2f} GFLOPs per image")
print(f"   Balanced: Good FLOPs/parameter ratio ({total_flops/total_params:.1f})")
print(f"   Suitable for: Real-time inference on modern hardware")

#
print(f"\nPerformance Estimation (on modern GPU):")
print(f"  Theoretical throughput: ~{1000/(total_flops/1e9/5):.0f} FPS (assuming 5 TFLOPs GPU)")
print(f"  Batch processing (32 images): ~{32*1000/(total_flops/1e9/5):.0f} FPS")

#
print(f"\nDETAILED LAYER BREAKDOWN")
print("=" * 80)
print(f"{'Layer':<10} {'Input Shape':<15} {'Output Shape':<15} {'Params':<12} {'FLOPs':<15} {'Params %':<10}")
print("-" * 80)

for r in results:
    input_str = f"{r['input_shape']}"
    output_str = f"{r['output_shape']}"
    params_str = f"{r['params']:,}"
    flops_str = f"{r['flops']:,}"
    params_pct = f"{(r['params']/total_params*100):.1f}%"

    print(f"{r['layer']:<10} {input_str:<15} {output_str:<15} {params_str:<12} {flops_str:<15} {params_pct:<10}")

print("-" * 80)
```

```
MODEL COMPLEXITY ANALYSIS
==================================================
Total Parameters: 6,615,338 (6.62 Million)
Total FLOPs: 457,211,552 (0.46 GFLOPs)
FLOPs per image: 0.46 GFLOPs
```

==



DETAILED ANALYSIS REPORT
==

Convolutional Layers Analysis:
  conv1: 14,112 params (0.01M)
  conv2: 614,400 params (0.61M)
  conv3: 884,736 params (0.88M)
  conv4: 1,327,104 params (1.33M)
  conv5: 884,736 params (0.88M)

Fully Connected Layers Analysis:
  fc1: 2,360,320 params (2.36M)
  fc2: 524,800 params (0.52M)
  fc3: 5,130 params (0.01M)

Efficiency Analysis:
  FLOPs per parameter: 69.1 FLOPs/param
  Model size (32-bit float): 26.46 MB

Memory Usage Analysis:
  Feature maps memory (approx): ~0.63 MB

```
  Weights memory: 26.46 MB
  Total memory (inference): ~36.46 MB

Comparison with Classic Models (approximate):
  LeNet-5: ~60K parameters, ~0.001 GFLOPs
  AlexNet: ~60M parameters, ~0.7 GFLOPs
  VGG-16: ~138M parameters, ~16 GFLOPs
  ResNet-18: ~11M parameters, ~1.8 GFLOPs
  This Model: ~6.6M parameters, ~0.46 GFLOPs

Model Characteristics:
   Moderate size: 6.6M parameters
   Efficient: 0.46 GFLOPs per image
   Balanced: Good FLOPs/parameter ratio (69.1)
   Suitable for: Real-time inference on modern hardware

Performance Estimation (on modern GPU):
  Theoretical throughput: ~10936 FPS (assuming 5 TFLOPs GPU)
  Batch processing (32 images): ~349947 FPS

DETAILED LAYER BREAKDOWN
================================================================================
Layer      Input Shape     Output Shape    Params       FLOPs          Params %
--------------------------------------------------------------------------------
conv1      (3, 33, 33)     (96, 27, 27)    14,112       20,575,296     0.2%
pool1      (96, 27, 27)    (96, 13, 13)    0            146,016        0.0%
conv2      (96, 13, 13)    (256, 13, 13)   614,400      207,667,200    9.3%
pool2      (256, 13, 13)   (256, 6, 6)     0            82,944         0.0%
conv3      (256, 6, 6)     (384, 6, 6)     884,736      63,700,992     13.4%
conv4      (384, 6, 6)     (384, 6, 6)     1,327,104    95,551,488     20.1%
conv5      (384, 6, 6)     (256, 6, 6)     884,736      63,700,992     13.4%
pool3      (256, 6, 6)     (256, 3, 3)     0            9,216          0.0%
fc1        (2304,)         (1024,)         2,360,320    4,718,592      35.7%
fc2        (1024,)         (512,)          524,800      1,048,576      7.9%
fc3        (512,)          (10,)           5,130        10,240         0.1%
--------------------------------------------------------------------------------
```

Write down your answer below.