

# stanowski\_problem2

May 10, 2025

## 2. Improve the architecture

Experiment with different numbers of layers, size of layers, number of filters, size of filters. You are required to make those adjustment to get the highest accuracy. Watch out for overfitting – we want the highest testing accuracy! Please provide a PDF file of the result, the best test accuracy and the architecture (different numbers of layers, size of layers, number of filters, size of filters)

```
[6]: import numpy as np
import torch
import torch.nn as nn
import torch.optim as optim

from datetime import datetime

import torchvision
import torchvision.transforms as transforms

from torchvision.datasets import FashionMNIST
import matplotlib.pyplot as plt
%matplotlib inline

from torch.utils.data import random_split
from torch.utils.data import DataLoader
import torch.nn.functional as F

from PIL import Image
```

```
[7]: github_labels = {
    0: "T-shirt/top",
    1: "Trouser",
    2: "Pullover",
    3: "Dress",
    4: "Coat",
    5: "Sandal",
    6: "Shirt",
    7: "Sneaker",
    8: "Bag",
    9: "Ankle boot"
```

```

}

fmnist_dataset = FashionMNIST(root = 'data/', download=True, train = True,
    ↪transform = transforms.ToTensor())

print(fmnist_dataset)

```

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100%|      | 29.5k/29.5k [00:00<00:00, 121kB/s]
100%|      | 4.42M/4.42M [00:01<00:00, 2.25MB/s]
100%|      | 5.15k/5.15k [00:00<00:00, 8.94MB/s]

```

```

Dataset FashionMNIST
  Number of datapoints: 60000
  Root location: data/
  Split: Train
  StandardTransform
Transform: ToTensor()

```

```

[9]: train_data, validation_data = random_split(fmnist_dataset, [50000, 10000])
    ## Print the length of train and validation datasets
    print("length of Train Datasets: ", len(train_data))
    print("length of Validation Datasets: ", len(validation_data))

    batch_size = 128
    train_loader = DataLoader(train_data, batch_size, shuffle = True) # true, bo
    ↪tasujemy dla lepszego uczenia się
    val_loader = DataLoader(validation_data, batch_size, shuffle = False) # fal

    test_dataset = FashionMNIST(root = 'data/', train = False, transform =
    ↪transforms.ToTensor())
    test_loader = DataLoader(test_dataset, batch_size = 256, shuffle = False)

```

```

length of Train Datasets: 50000
length of Validation Datasets: 10000

```

```

[10]: def accuracy(outputs, labels):
    _, preds = torch.max(outputs, dim = 1)
    return(torch.tensor(torch.sum(preds == labels).item())/ len(preds)))

class OptimizedCNN(nn.Module):
    def __init__(self, conv_channels=[16, 32], kernel_size=3, fc_size=128):
        super(OptimizedCNN, self).__init__()
        self.convs = nn.ModuleList()

```

```

        in_channels = 1
        for out_channels in conv_channels:
            self.convs.append(
                nn.Sequential(
                    nn.Conv2d(in_channels, out_channels,
↪kernel_size=kernel_size, padding=kernel_size // 2),
                    nn.ReLU(),
                    nn.MaxPool2d(2),
                )
            )
            in_channels = out_channels

        # size after convolutions
        self.flatten_size = out_channels * (28 // (2 ** len(conv_channels))) ** 2
↪2

        self.fc = nn.Linear(self.flatten_size, fc_size)
        self.out = nn.Linear(fc_size, 10)

    def forward(self, x):
        for conv in self.convs:
            x = conv(x)
        x = x.view(x.size(0), -1)
        x = self.fc(x)
        output = self.out(x)
        return output, x

cnn = OptimizedCNN()
print(cnn)

```

```

OptimizedCNN(
  (convs): ModuleList(
    (0): Sequential(
      (0): Conv2d(1, 16, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
      (1): ReLU()
      (2): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1,
ceiling_mode=False)
    )
    (1): Sequential(
      (0): Conv2d(16, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
      (1): ReLU()
      (2): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1,
ceiling_mode=False)
    )
  )
  (fc): Linear(in_features=1568, out_features=128, bias=True)
  (out): Linear(in_features=128, out_features=10, bias=True)
)

```

)

```
[11]: from torch.autograd import Variable

def train(num_epochs, cnn, loaders):
    cnn.train()
    optimizer = optim.Adam(cnn.parameters(), lr=0.01)
    loss_func = nn.CrossEntropyLoss()

    all_accuracies = []

    total_step = len(loaders)

    for epoch in range(num_epochs):
        epoch_loss = 0.0
        correct = 0
        total = 0

        for i, (images, labels) in enumerate(loaders):
            b_x = Variable(images) # batch x
            b_y = Variable(labels) # batch y
            output = cnn(b_x)[0]
            loss = loss_func(output, b_y)

            epoch_loss += loss.item()

            optimizer.zero_grad()
            loss.backward()
            optimizer.step()

            _, predicted = torch.max(output.data, 1)
            total += labels.size(0)
            correct += (predicted == labels).sum().item()

            if (i+1) % 100 == 0:
                print(f"Epoch [{epoch+1}/{num_epochs}], Step [{i+1}/
↪ {total_step}], Loss: {loss.item():.4f}")

        avg_loss = epoch_loss / total_step
        accuracy = 100 * correct / total

        all_accuracies.append(accuracy)

        print(f"Epoch [{epoch+1}/{num_epochs}] - Loss: {avg_loss:.4f}, Accuracy:
↪ {accuracy:.2f}%")

    return all_accuracies
```

```

[12]: architectures = [
    {'conv_channels': [8, 16], 'kernel_size': 3, 'fc_size': 64},
    {'conv_channels': [16, 32], 'kernel_size': 3, 'fc_size': 128},
    {'conv_channels': [32, 64], 'kernel_size': 5, 'fc_size': 128},
    {'conv_channels': [32, 128], 'kernel_size': 5, 'fc_size': 256},
    {'conv_channels': [8, 16, 32], 'kernel_size': 3, 'fc_size': 128},
    {'conv_channels': [16, 32, 64], 'kernel_size': 3, 'fc_size': 256},
    {'conv_channels': [16, 32, 128], 'kernel_size': 5, 'fc_size': 256},
    {'conv_channels': [8, 16, 32, 64], 'kernel_size': 3, 'fc_size': 256},
    {'conv_channels': [16, 32, 64, 128], 'kernel_size': 3, 'fc_size': 256},
    {'conv_channels': [16, 32, 64, 128], 'kernel_size': 5, 'fc_size': 256},
]

results = []

for config in architectures:
    print(f"Testing architecture: {config}")

    # Tworzenie modelu
    cnn = OptimizedCNN(conv_channels=config['conv_channels'],
                       kernel_size=config['kernel_size'],
                       fc_size=config['fc_size'])

    # counting initial accuracies and losses
    cnn.eval()
    with torch.no_grad():
        correct = 0
        total = 0
        epoch_loss = 0.0
        for images, labels in train_loader:
            test_output, _ = cnn(images)
            loss = nn.CrossEntropyLoss()(test_output, labels)
            epoch_loss += loss.item()

            pred_y = torch.max(test_output, 1)[1].data.squeeze()
            correct += (pred_y == labels).sum().item()
            total += labels.size(0)

        initial_accuracy = correct / total
        initial_loss = epoch_loss / total # avg starting loss

    print(f"Initial accuracy: {initial_accuracy:.2f}")

    # saving the first accuracy
    accuracies = [initial_accuracy]

    # training

```

```

train_accuracies = train(num_epochs=5, cnn=cnn, loaders=train_loader)

accuracies.extend(train_accuracies)

# accuracy after training
cnn.eval()
with torch.no_grad():
    correct = 0
    total = 0
    for images, labels in train_loader:
        test_output, _ = cnn(images)
        pred_y = torch.max(test_output, 1)[1].data.squeeze()
        correct += (pred_y == labels).sum().item()
        total += labels.size(0)
    final_accuracy = correct / total

print(f"Final accuracy: {final_accuracy:.2f}")

results.append({
    'config': config,
    'initial_accuracy': initial_accuracy,
    'final_accuracy': final_accuracy,
    'accuracies': accuracies
})

```

Testing architecture: {'conv\_channels': [8, 16], 'kernel\_size': 3, 'fc\_size': 64}

Initial accuracy: 0.12

```

Epoch [1/5], Step [100/391], Loss: 0.6208
Epoch [1/5], Step [200/391], Loss: 0.3589
Epoch [1/5], Step [300/391], Loss: 0.3651
Epoch [1/5] - Loss: 0.4961, Accuracy: 81.95%
Epoch [2/5], Step [100/391], Loss: 0.2894
Epoch [2/5], Step [200/391], Loss: 0.2846
Epoch [2/5], Step [300/391], Loss: 0.2823
Epoch [2/5] - Loss: 0.3459, Accuracy: 87.61%
Epoch [3/5], Step [100/391], Loss: 0.2716
Epoch [3/5], Step [200/391], Loss: 0.3100
Epoch [3/5], Step [300/391], Loss: 0.3763
Epoch [3/5] - Loss: 0.3223, Accuracy: 88.34%
Epoch [4/5], Step [100/391], Loss: 0.1752
Epoch [4/5], Step [200/391], Loss: 0.2606
Epoch [4/5], Step [300/391], Loss: 0.2913
Epoch [4/5] - Loss: 0.3045, Accuracy: 88.95%
Epoch [5/5], Step [100/391], Loss: 0.4153
Epoch [5/5], Step [200/391], Loss: 0.2127
Epoch [5/5], Step [300/391], Loss: 0.2228

```

Epoch [5/5] - Loss: 0.2974, Accuracy: 89.13%  
Final accuracy: 0.90  
Testing architecture: {'conv\_channels': [16, 32], 'kernel\_size': 3, 'fc\_size': 128}  
Initial accuracy: 0.11  
Epoch [1/5], Step [100/391], Loss: 0.6252  
Epoch [1/5], Step [200/391], Loss: 0.5313  
Epoch [1/5], Step [300/391], Loss: 0.3325  
Epoch [1/5] - Loss: 0.5195, Accuracy: 81.03%  
Epoch [2/5], Step [100/391], Loss: 0.3809  
Epoch [2/5], Step [200/391], Loss: 0.3743  
Epoch [2/5], Step [300/391], Loss: 0.3179  
Epoch [2/5] - Loss: 0.3581, Accuracy: 87.02%  
Epoch [3/5], Step [100/391], Loss: 0.2859  
Epoch [3/5], Step [200/391], Loss: 0.3096  
Epoch [3/5], Step [300/391], Loss: 0.4571  
Epoch [3/5] - Loss: 0.3306, Accuracy: 87.95%  
Epoch [4/5], Step [100/391], Loss: 0.3472  
Epoch [4/5], Step [200/391], Loss: 0.3263  
Epoch [4/5], Step [300/391], Loss: 0.3443  
Epoch [4/5] - Loss: 0.3246, Accuracy: 87.98%  
Epoch [5/5], Step [100/391], Loss: 0.3452  
Epoch [5/5], Step [200/391], Loss: 0.4301  
Epoch [5/5], Step [300/391], Loss: 0.4237  
Epoch [5/5] - Loss: 0.3143, Accuracy: 88.54%  
Final accuracy: 0.88  
Testing architecture: {'conv\_channels': [32, 64], 'kernel\_size': 5, 'fc\_size': 128}  
Initial accuracy: 0.07  
Epoch [1/5], Step [100/391], Loss: 0.6502  
Epoch [1/5], Step [200/391], Loss: 0.5616  
Epoch [1/5], Step [300/391], Loss: 0.4712  
Epoch [1/5] - Loss: 0.5335, Accuracy: 81.18%  
Epoch [2/5], Step [100/391], Loss: 0.3825  
Epoch [2/5], Step [200/391], Loss: 0.3091  
Epoch [2/5], Step [300/391], Loss: 0.4531  
Epoch [2/5] - Loss: 0.3670, Accuracy: 86.75%  
Epoch [3/5], Step [100/391], Loss: 0.3813  
Epoch [3/5], Step [200/391], Loss: 0.3803  
Epoch [3/5], Step [300/391], Loss: 0.3532  
Epoch [3/5] - Loss: 0.3379, Accuracy: 87.64%  
Epoch [4/5], Step [100/391], Loss: 0.3026  
Epoch [4/5], Step [200/391], Loss: 0.3686  
Epoch [4/5], Step [300/391], Loss: 0.3926  
Epoch [4/5] - Loss: 0.3268, Accuracy: 88.09%  
Epoch [5/5], Step [100/391], Loss: 0.3103  
Epoch [5/5], Step [200/391], Loss: 0.2955  
Epoch [5/5], Step [300/391], Loss: 0.2464

Epoch [5/5] - Loss: 0.3166, Accuracy: 88.46%  
Final accuracy: 0.90  
Testing architecture: {'conv\_channels': [32, 128], 'kernel\_size': 5, 'fc\_size': 256}  
Initial accuracy: 0.12  
Epoch [1/5], Step [100/391], Loss: 0.4200  
Epoch [1/5], Step [200/391], Loss: 0.3113  
Epoch [1/5], Step [300/391], Loss: 0.3817  
Epoch [1/5] - Loss: 0.8555, Accuracy: 75.47%  
Epoch [2/5], Step [100/391], Loss: 0.3825  
Epoch [2/5], Step [200/391], Loss: 0.4202  
Epoch [2/5], Step [300/391], Loss: 0.3434  
Epoch [2/5] - Loss: 0.3716, Accuracy: 86.36%  
Epoch [3/5], Step [100/391], Loss: 0.3296  
Epoch [3/5], Step [200/391], Loss: 0.2441  
Epoch [3/5], Step [300/391], Loss: 0.4808  
Epoch [3/5] - Loss: 0.3435, Accuracy: 87.36%  
Epoch [4/5], Step [100/391], Loss: 0.2894  
Epoch [4/5], Step [200/391], Loss: 0.2525  
Epoch [4/5], Step [300/391], Loss: 0.4302  
Epoch [4/5] - Loss: 0.3381, Accuracy: 87.59%  
Epoch [5/5], Step [100/391], Loss: 0.2498  
Epoch [5/5], Step [200/391], Loss: 0.2961  
Epoch [5/5], Step [300/391], Loss: 0.5788  
Epoch [5/5] - Loss: 0.3324, Accuracy: 87.88%  
Final accuracy: 0.88  
Testing architecture: {'conv\_channels': [8, 16, 32], 'kernel\_size': 3, 'fc\_size': 128}  
Initial accuracy: 0.09  
Epoch [1/5], Step [100/391], Loss: 0.5000  
Epoch [1/5], Step [200/391], Loss: 0.4549  
Epoch [1/5], Step [300/391], Loss: 0.4301  
Epoch [1/5] - Loss: 0.5669, Accuracy: 78.94%  
Epoch [2/5], Step [100/391], Loss: 0.4523  
Epoch [2/5], Step [200/391], Loss: 0.2915  
Epoch [2/5], Step [300/391], Loss: 0.3820  
Epoch [2/5] - Loss: 0.3826, Accuracy: 86.03%  
Epoch [3/5], Step [100/391], Loss: 0.2183  
Epoch [3/5], Step [200/391], Loss: 0.1814  
Epoch [3/5], Step [300/391], Loss: 0.2286  
Epoch [3/5] - Loss: 0.3497, Accuracy: 87.20%  
Epoch [4/5], Step [100/391], Loss: 0.4163  
Epoch [4/5], Step [200/391], Loss: 0.2425  
Epoch [4/5], Step [300/391], Loss: 0.3581  
Epoch [4/5] - Loss: 0.3359, Accuracy: 87.76%  
Epoch [5/5], Step [100/391], Loss: 0.3414  
Epoch [5/5], Step [200/391], Loss: 0.3722  
Epoch [5/5], Step [300/391], Loss: 0.3254



Epoch [5/5] - Loss: 0.3209, Accuracy: 88.24%  
Final accuracy: 0.89  
Testing architecture: {'conv\_channels': [16, 32, 64], 'kernel\_size': 3, 'fc\_size': 256}  
Initial accuracy: 0.10  
Epoch [1/5], Step [100/391], Loss: 0.4405  
Epoch [1/5], Step [200/391], Loss: 0.3529  
Epoch [1/5], Step [300/391], Loss: 0.3977  
Epoch [1/5] - Loss: 0.5933, Accuracy: 78.03%  
Epoch [2/5], Step [100/391], Loss: 0.4256  
Epoch [2/5], Step [200/391], Loss: 0.4038  
Epoch [2/5], Step [300/391], Loss: 0.3146  
Epoch [2/5] - Loss: 0.4046, Accuracy: 85.14%  
Epoch [3/5], Step [100/391], Loss: 0.3795  
Epoch [3/5], Step [200/391], Loss: 0.3286  
Epoch [3/5], Step [300/391], Loss: 0.2286  
Epoch [3/5] - Loss: 0.3721, Accuracy: 86.21%  
Epoch [4/5], Step [100/391], Loss: 0.4698  
Epoch [4/5], Step [200/391], Loss: 0.3507  
Epoch [4/5], Step [300/391], Loss: 0.4996  
Epoch [4/5] - Loss: 0.3583, Accuracy: 86.90%  
Epoch [5/5], Step [100/391], Loss: 0.3953  
Epoch [5/5], Step [200/391], Loss: 0.2462  
Epoch [5/5], Step [300/391], Loss: 0.4510  
Epoch [5/5] - Loss: 0.3499, Accuracy: 87.06%  
Final accuracy: 0.88  
Testing architecture: {'conv\_channels': [16, 32, 128], 'kernel\_size': 5, 'fc\_size': 256}  
Initial accuracy: 0.10  
Epoch [1/5], Step [100/391], Loss: 0.6413  
Epoch [1/5], Step [200/391], Loss: 0.5520  
Epoch [1/5], Step [300/391], Loss: 0.3026  
Epoch [1/5] - Loss: 0.6272, Accuracy: 77.17%  
Epoch [2/5], Step [100/391], Loss: 0.5112  
Epoch [2/5], Step [200/391], Loss: 0.3273  
Epoch [2/5], Step [300/391], Loss: 0.3440  
Epoch [2/5] - Loss: 0.3991, Accuracy: 85.36%  
Epoch [3/5], Step [100/391], Loss: 0.4714  
Epoch [3/5], Step [200/391], Loss: 0.3159  
Epoch [3/5], Step [300/391], Loss: 0.2785  
Epoch [3/5] - Loss: 0.3695, Accuracy: 86.51%  
Epoch [4/5], Step [100/391], Loss: 0.3712  
Epoch [4/5], Step [200/391], Loss: 0.3743  
Epoch [4/5], Step [300/391], Loss: 0.3086  
Epoch [4/5] - Loss: 0.3649, Accuracy: 86.50%  
Epoch [5/5], Step [100/391], Loss: 0.4469  
Epoch [5/5], Step [200/391], Loss: 0.2688  
Epoch [5/5], Step [300/391], Loss: 0.4433

Epoch [5/5] - Loss: 0.3532, Accuracy: 86.94%  
Final accuracy: 0.88  
Testing architecture: {'conv\_channels': [8, 16, 32, 64], 'kernel\_size': 3, 'fc\_size': 256}  
Initial accuracy: 0.10  
Epoch [1/5], Step [100/391], Loss: 0.6515  
Epoch [1/5], Step [200/391], Loss: 0.5515  
Epoch [1/5], Step [300/391], Loss: 0.4490  
Epoch [1/5] - Loss: 0.5650, Accuracy: 78.80%  
Epoch [2/5], Step [100/391], Loss: 0.4381  
Epoch [2/5], Step [200/391], Loss: 0.2122  
Epoch [2/5], Step [300/391], Loss: 0.3626  
Epoch [2/5] - Loss: 0.3699, Accuracy: 86.49%  
Epoch [3/5], Step [100/391], Loss: 0.2792  
Epoch [3/5], Step [200/391], Loss: 0.2327  
Epoch [3/5], Step [300/391], Loss: 0.2504  
Epoch [3/5] - Loss: 0.3375, Accuracy: 87.73%  
Epoch [4/5], Step [100/391], Loss: 0.3097  
Epoch [4/5], Step [200/391], Loss: 0.2822  
Epoch [4/5], Step [300/391], Loss: 0.4463  
Epoch [4/5] - Loss: 0.3171, Accuracy: 88.39%  
Epoch [5/5], Step [100/391], Loss: 0.2973  
Epoch [5/5], Step [200/391], Loss: 0.2471  
Epoch [5/5], Step [300/391], Loss: 0.1167  
Epoch [5/5] - Loss: 0.3061, Accuracy: 88.81%  
Final accuracy: 0.88  
Testing architecture: {'conv\_channels': [16, 32, 64, 128], 'kernel\_size': 3, 'fc\_size': 256}  
Initial accuracy: 0.10  
Epoch [1/5], Step [100/391], Loss: 0.5589  
Epoch [1/5], Step [200/391], Loss: 0.5134  
Epoch [1/5], Step [300/391], Loss: 0.4339  
Epoch [1/5] - Loss: 0.5998, Accuracy: 77.30%  
Epoch [2/5], Step [100/391], Loss: 0.4366  
Epoch [2/5], Step [200/391], Loss: 0.3899  
Epoch [2/5], Step [300/391], Loss: 0.2504  
Epoch [2/5] - Loss: 0.3790, Accuracy: 86.06%  
Epoch [3/5], Step [100/391], Loss: 0.3497  
Epoch [3/5], Step [200/391], Loss: 0.3458  
Epoch [3/5], Step [300/391], Loss: 0.3171  
Epoch [3/5] - Loss: 0.3447, Accuracy: 87.43%  
Epoch [4/5], Step [100/391], Loss: 0.3295  
Epoch [4/5], Step [200/391], Loss: 0.1892  
Epoch [4/5], Step [300/391], Loss: 0.3939  
Epoch [4/5] - Loss: 0.3228, Accuracy: 88.20%  
Epoch [5/5], Step [100/391], Loss: 0.2682  
Epoch [5/5], Step [200/391], Loss: 0.3719  
Epoch [5/5], Step [300/391], Loss: 0.3468

```

Epoch [5/5] - Loss: 0.3224, Accuracy: 88.30%
Final accuracy: 0.89
Testing architecture: {'conv_channels': [16, 32, 64, 128], 'kernel_size': 5,
'fc_size': 256}
Initial accuracy: 0.10
Epoch [1/5], Step [100/391], Loss: 0.8628
Epoch [1/5], Step [200/391], Loss: 0.7326
Epoch [1/5], Step [300/391], Loss: 0.5651
Epoch [1/5] - Loss: 0.9575, Accuracy: 62.76%
Epoch [2/5], Step [100/391], Loss: 0.3649
Epoch [2/5], Step [200/391], Loss: 0.3942
Epoch [2/5], Step [300/391], Loss: 0.4608
Epoch [2/5] - Loss: 0.4760, Accuracy: 82.50%
Epoch [3/5], Step [100/391], Loss: 0.3162
Epoch [3/5], Step [200/391], Loss: 0.4044
Epoch [3/5], Step [300/391], Loss: 0.4841
Epoch [3/5] - Loss: 0.4405, Accuracy: 83.82%
Epoch [4/5], Step [100/391], Loss: 0.3238
Epoch [4/5], Step [200/391], Loss: 0.3368
Epoch [4/5], Step [300/391], Loss: 0.3994
Epoch [4/5] - Loss: 0.4110, Accuracy: 84.89%
Epoch [5/5], Step [100/391], Loss: 0.4570
Epoch [5/5], Step [200/391], Loss: 0.3203
Epoch [5/5], Step [300/391], Loss: 0.3062
Epoch [5/5] - Loss: 0.4009, Accuracy: 85.27%
Final accuracy: 0.85

```

```

[13]: import matplotlib.pyplot as plt

print(results)

for result in results:
    plt.plot(result['accuracies'], label='Accuracy')
    plt.title(f"Accuracy per Epoch ({result['config']}")
    plt.xlabel("Epoch")
    plt.ylabel("Accuracy (%)")
    plt.legend()

plt.show()

```

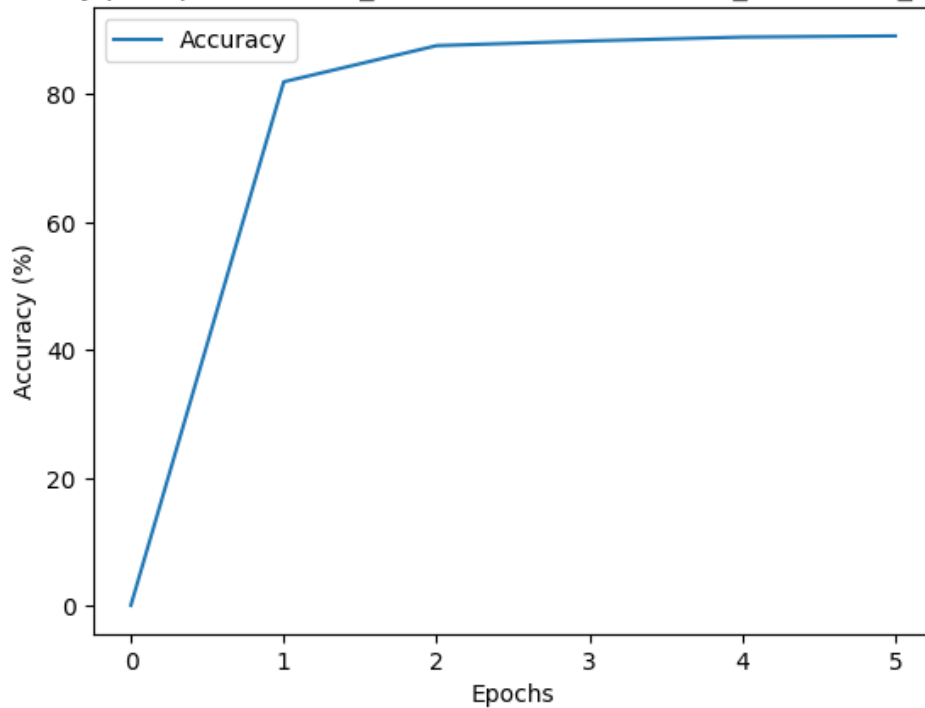
```

[{'config': {'conv_channels': [8, 16], 'kernel_size': 3, 'fc_size': 64},
'initial_accuracy': 0.12446, 'final_accuracy': 0.89696, 'accuracies': [0.12446,
81.952, 87.606, 88.338, 88.946, 89.128]}, {'config': {'conv_channels': [16, 32],
'kernel_size': 3, 'fc_size': 128}, 'initial_accuracy': 0.11168,
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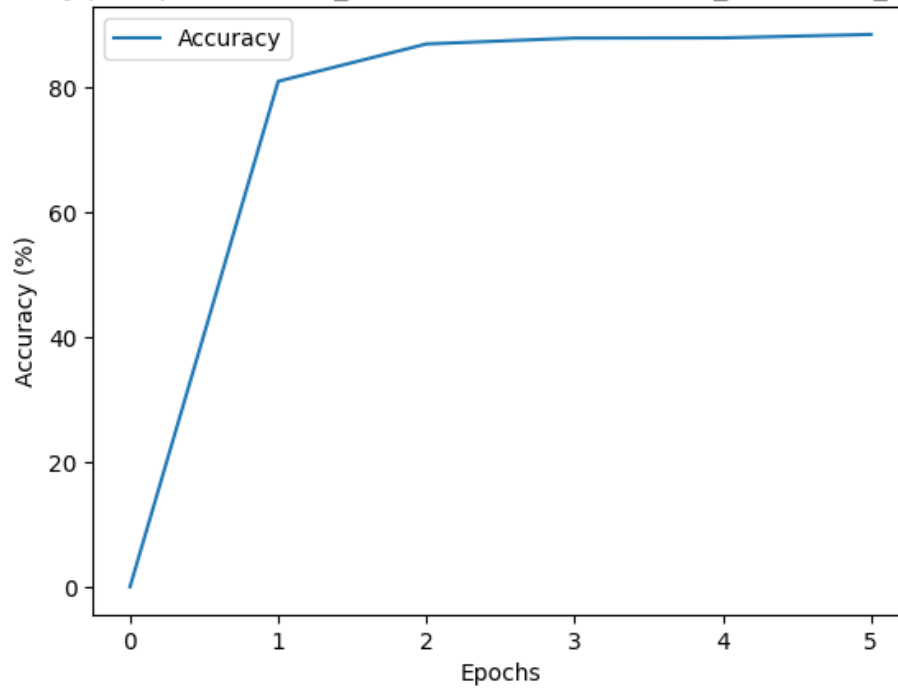
```

```
{'conv_channels': [32, 128], 'kernel_size': 5, 'fc_size': 256},
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88.806]}, {'config': {'conv_channels': [16, 32, 64, 128], 'kernel_size': 3,
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62.76, 82.502, 83.824, 84.89, 85.27]}]}
```

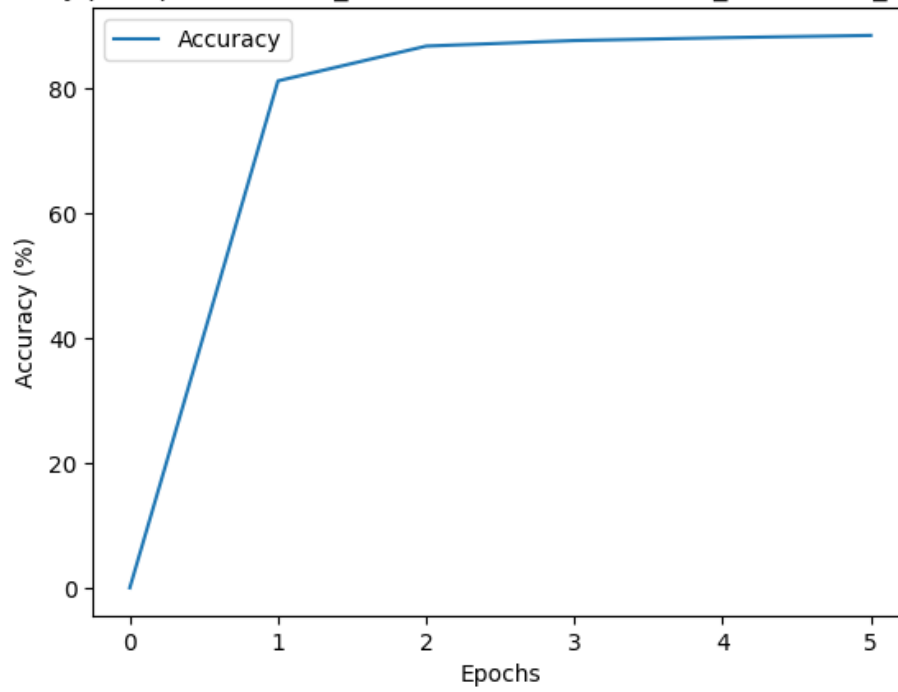
Accuracy per Epoch ({'conv\_channels': [8, 16], 'kernel\_size': 3, 'fc\_size': 64})



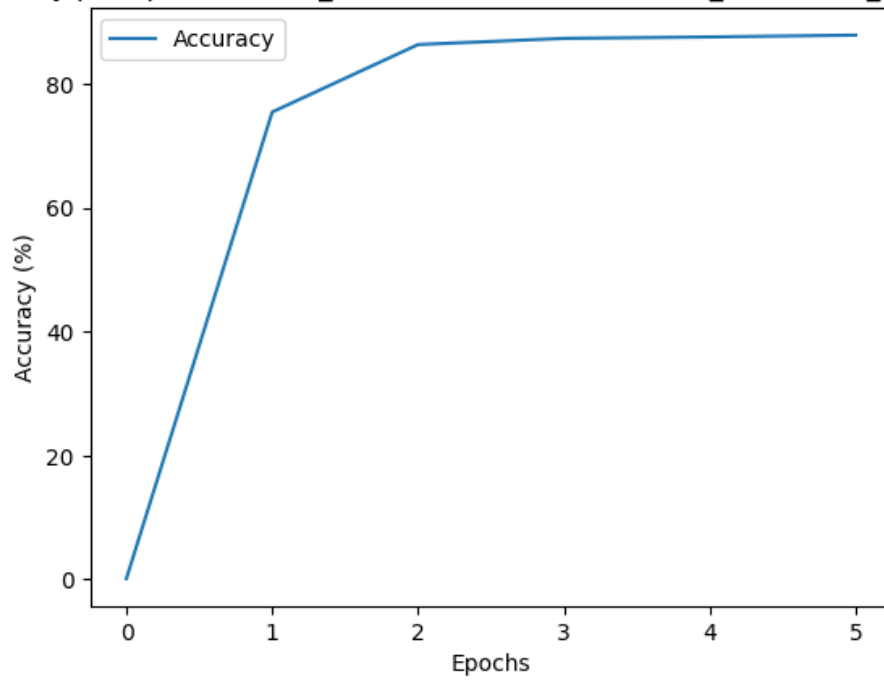
Accuracy per Epoch ({'conv\_channels': [16, 32], 'kernel\_size': 3, 'fc\_size': 128})



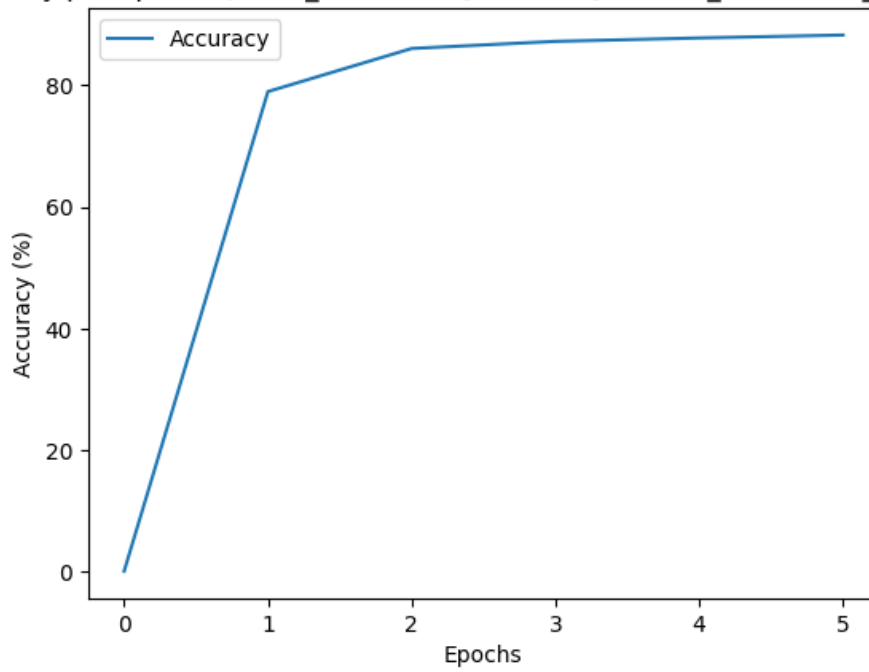
Accuracy per Epoch ({'conv\_channels': [32, 64], 'kernel\_size': 5, 'fc\_size': 128})



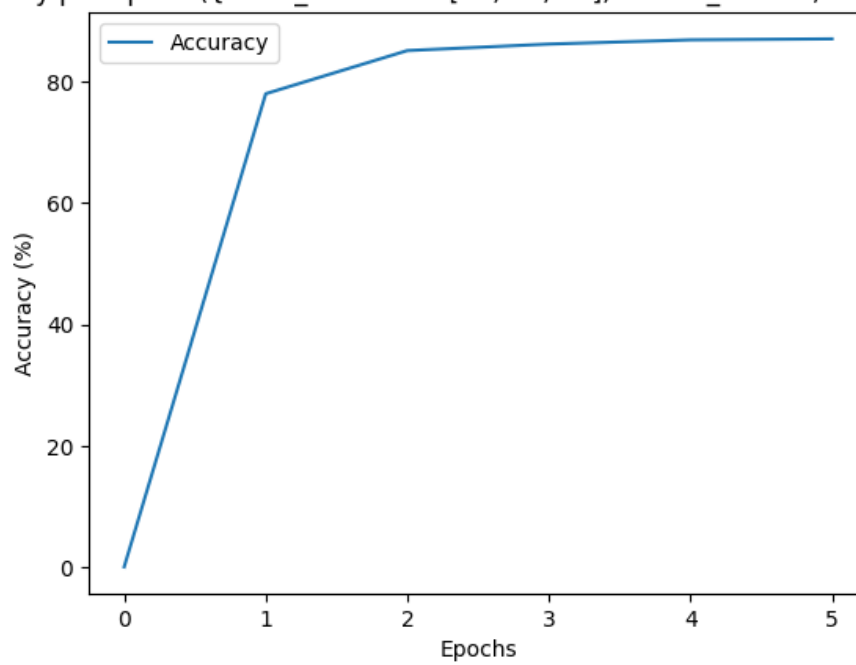
Accuracy per Epoch ({'conv\_channels': [32, 128], 'kernel\_size': 5, 'fc\_size': 256})



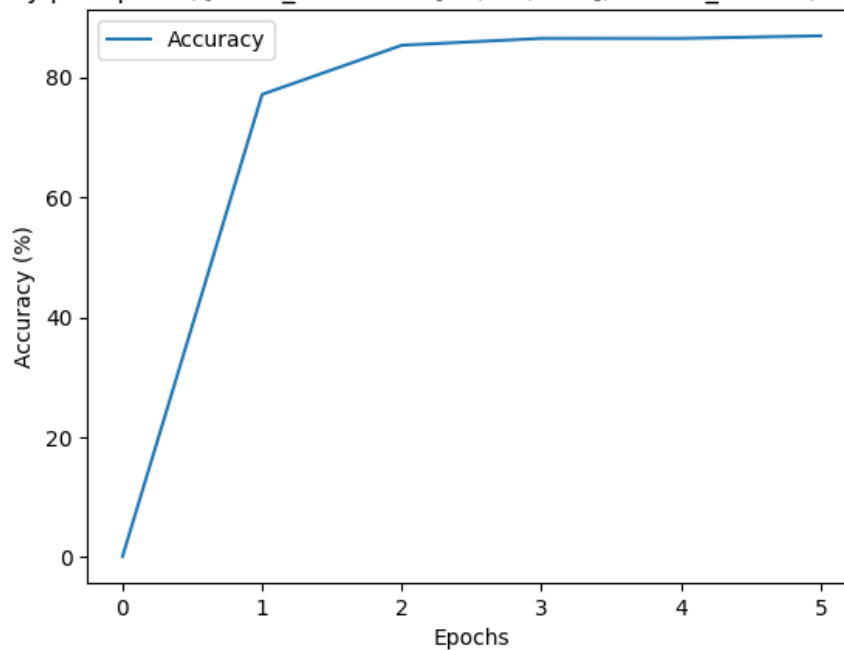
Accuracy per Epoch ({'conv\_channels': [8, 16, 32], 'kernel\_size': 3, 'fc\_size': 128})



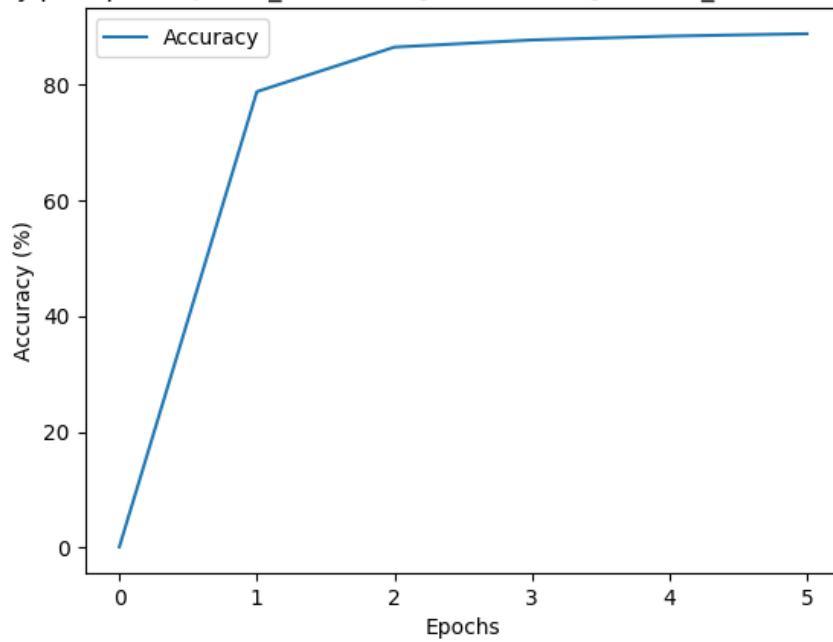
Accuracy per Epoch ({'conv\_channels': [16, 32, 64], 'kernel\_size': 3, 'fc\_size': 256})



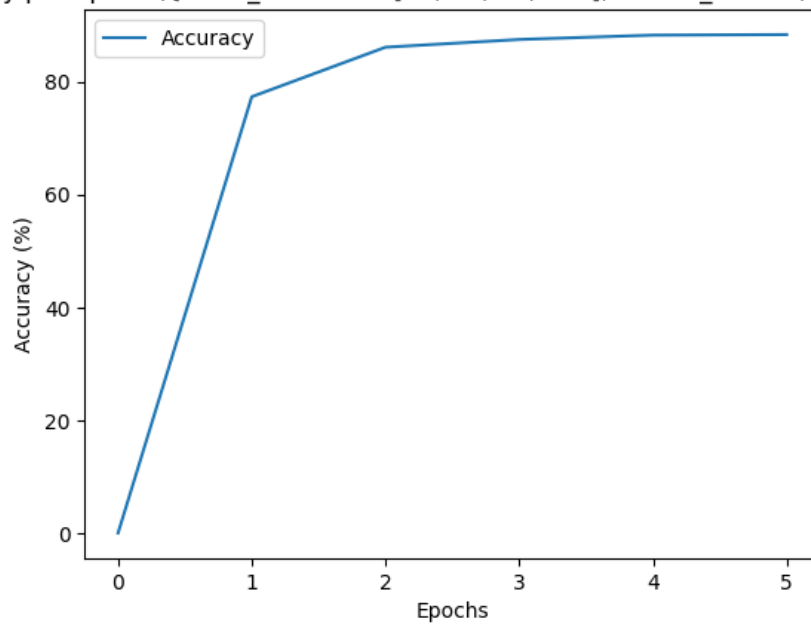
Accuracy per Epoch ({'conv\_channels': [16, 32, 128], 'kernel\_size': 5, 'fc\_size': 256})



Accuracy per Epoch ({'conv\_channels': [8, 16, 32, 64], 'kernel\_size': 3, 'fc\_size': 256})

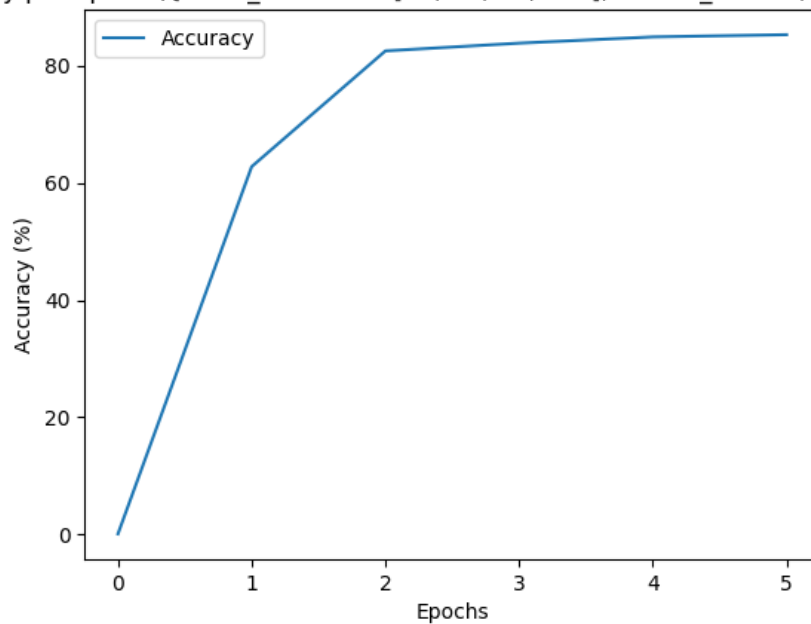


Accuracy per Epoch ({'conv\_channels': [16, 32, 64, 128], 'kernel\_size': 3, 'fc\_size': 256})





Accuracy per Epoch ({'conv\_channels': [16, 32, 64, 128], 'kernel\_size': 5, 'fc\_size': 256})



```
[16]: best_model = max(results, key=lambda x: x['final_accuracy'])

print("Best architecture:")
print(f"Config: {best_model['config']}")
print(f"Initial accuracy: {best_model['initial_accuracy']:.4f}")
print(f"Final accuracy: {best_model['final_accuracy']:.4f}")
```

Best architecture:

Config: {'conv\_channels': [8, 16], 'kernel\_size': 3, 'fc\_size': 64}

Initial accuracy: 0.1245

Final accuracy: 0.8970