TUBAF

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Scientific Computing Project

Winter Semester 2024/2025

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Content

Task

1. Task

- implement a **Convolutional Neural Network**

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- classify images from 10 categories
- network architecture: **VGG-16**
- hyperparameter tuning via **k-fold cross-validation**
- **evaluation** with performance measurements

Description of the Dataset

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10 classes of images:

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1. bottles	2. mugs/cups	3. spoons	4. knifes	5. forks
6. shoes	7. t-shirts	8. plants	9. chairs	10. bikes

2. Dataset

10 classes of images:

1. bottles 2. mugs/cups 3. spoons 4. knifes 5. forks
6. shoes 7. t-shirts 8. plants 9. chairs 10. bikes

(a) 10. bikes

(b) 2. mugs/cups

(c) 3. spoons

2. Dataset

Augmentation by:

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- horizontal flip
- vertical flip
- crop
- rotation
- blur
- change of brightness
- change of contrast
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- random intensity

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- crop
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- change of brightness
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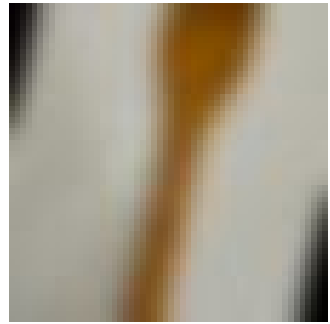
- change of color

- application of up to 4 different augmentations per image
- random intensity
- normalization to 56x56 pixels

2. Dataset

(a) 10. bike

(b) 1. bottles



(c) 3. spoons

Figure: Normalized images of the augmented database with different transformations

Architecture of the Network

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  - deep but uniform architecture
  - many convolutional layers with kernel size 3 followed by a pooling layer
  - simplified: just 4 repetitions of these layers with max-pooling

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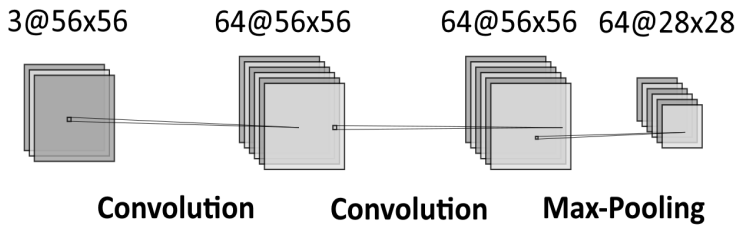

Figure: Inital sequence of 2 convolutional layers with max-pooling

3. Architecture

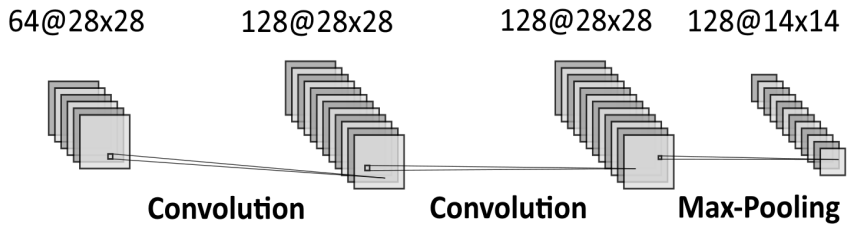

Figure: First repetition with 2 convolutional layers and max-pooling

3. Architecture

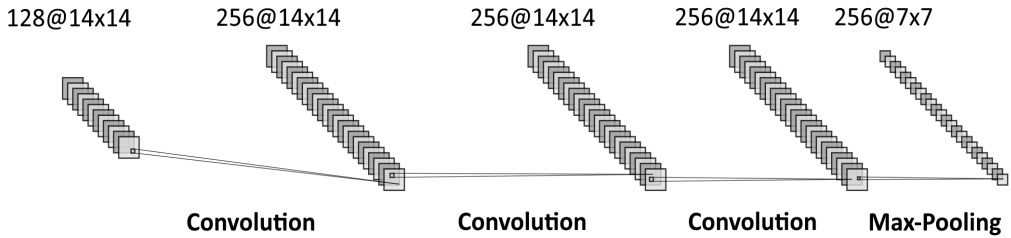

Figure: Second repetition with 3 convolutional layers and max-pooling

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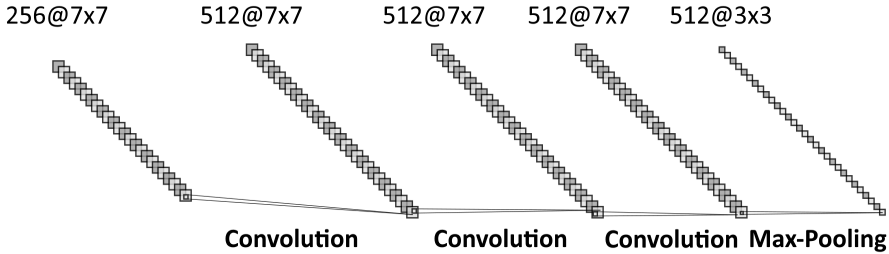

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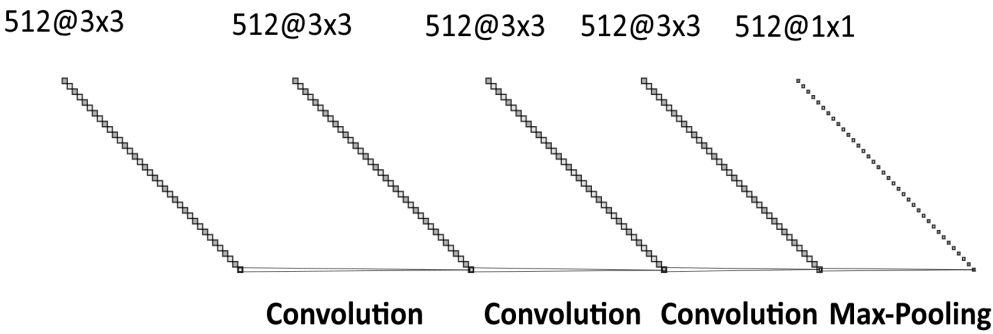

Figure: Fourth repetition with 3 convolutional layers and max-pooling

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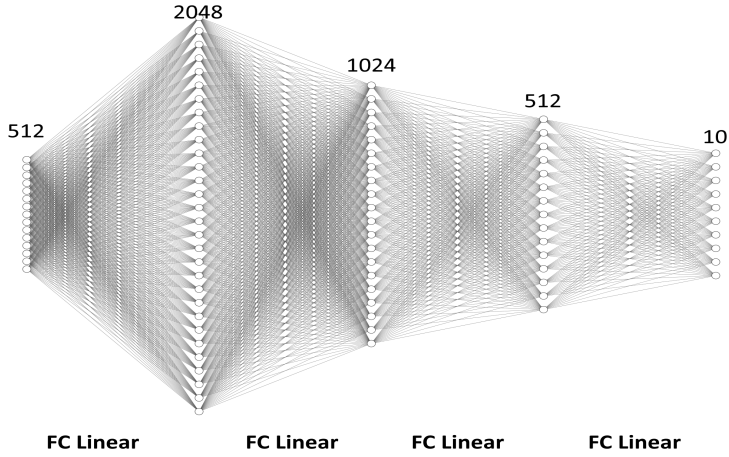

Figure: Fully connected linear layers at the end

Training

4. Training

- hyperparameter tuning via **3-fold cross-validation**

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- hyperparameter tuning via **3-fold cross-validation**
- used for finding best learning rate, batch size for **ADAM** and **SGD**

4. Training - ADAM

- ADAM = Adaptive Moment Estimation

[1] source: A Method for Stochastic Optimization - https://arxiv.org/abs/1412.6980

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- ADAM = Adaptive Moment Estimation
- adapts learning rate for each parameter
- uses estimates of first and second moments of the gradient (mean, uncentered variance)
- leads to faster convergence, better on complex and noisy datasets [1]

[1] source: A Method for Stochastic Optimization - https://arxiv.org/abs/1412.6980

4. Training - ADAM

$$m_t = \beta_1 m_{t-1} + (1 - \beta_1)\nabla_\theta L(\theta_t)$$
$$v_t = \beta_2 v_{t-1} + (1 - \beta_2)(\nabla_\theta L(\theta_t))^2$$
$$\hat{m}_t = \frac{m_t}{1 - \beta_1^t}, \quad \hat{v}_t = \frac{v_t}{1 - \beta_2^t}$$
$$\theta_{t+1} = \theta_t - \eta \frac{\hat{m}_t}{\sqrt{\hat{v}_t} + \epsilon}$$

m_t : first moment (mean of gradients)
v_t : second moment (uncentered variance of gradients)
β_1, β_2 : decay rates for moments
$\hat{m}_t, \hat{v}_t$: bias-corrected estimates
ϵ : small constant (for numerical stability)

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- SGD = Stochastic Gradient Descent

[2] source: Mathematics of Machine Learning lecture script - B. Sprungk

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- SGD = Stochastic Gradient Descent
- updates model parameters using current gradient
- simple and efficient
- but sensitive to learning rate and slower [2]

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Stochastic Gradient Descent [3] uses one randomly selected gradient per step:

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Stochastic Gradient Descent [3] uses one randomly selected gradient per step: Given a starting vector $\mathbf{w}_0 \in \mathbb{R}^p$ and an objective function

$$F(w) = \frac{1}{m} \sum_{i=1}^{m} f_i(w), \qquad f_i : \mathbb{R}^p \to \mathbb{R},$$

calculate for $k = 0, 1, 2, \ldots$ the iterates $\mathbf{w}_{k+1}$ as follows:

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1. draw realization $i_k \in [m]$ of the uniformly random index variable

$$I_k \sim U([m]), \qquad [m] := \{1, \ldots, m\}$$

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where the I_k, $k \in \mathbb{N}$, are stochastically independent,
2. for a given deterministic step size $\eta_k > 0$, calculate

$$\mathbf{w}_{k+1} = \mathbf{w}_k - \eta_k \nabla f_{i_k}(\mathbf{w}_k).$$

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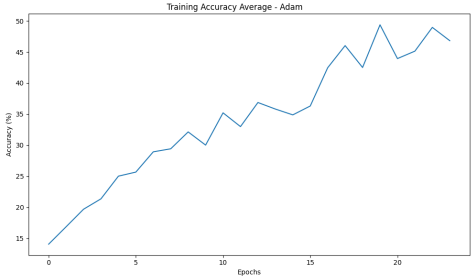
Results

5. Results



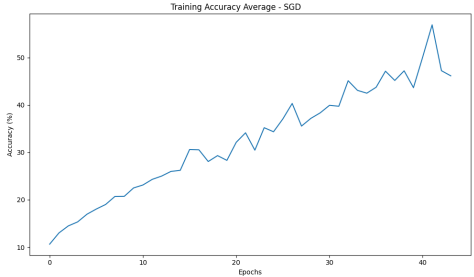


Figure: Average accuracy of ADAM and SGD with respect to training epochs

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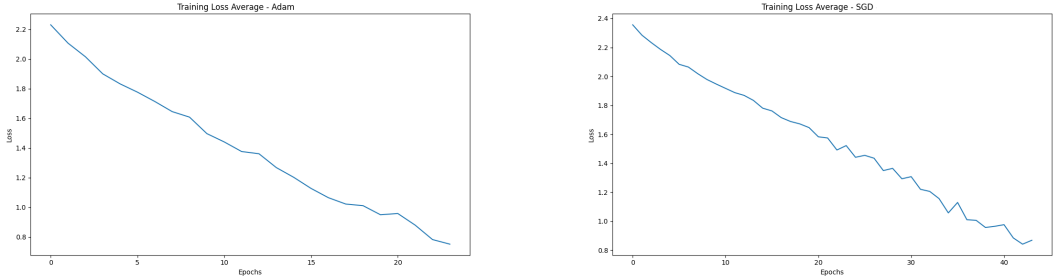

Figure: Average loss of ADAM and SGD with respect to training epochs

5. Results

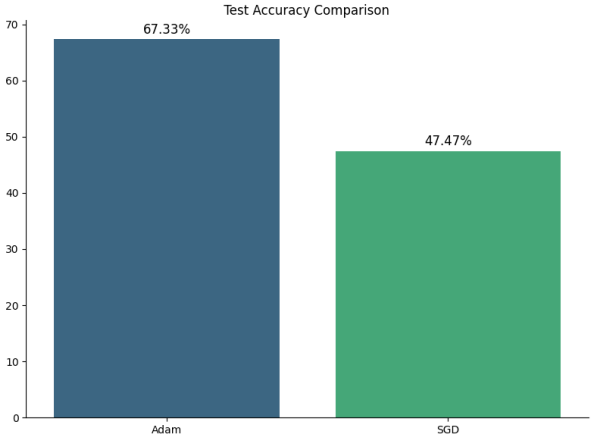

Figure: Comparison of the accuracy of both optimizers over test data

5. Result

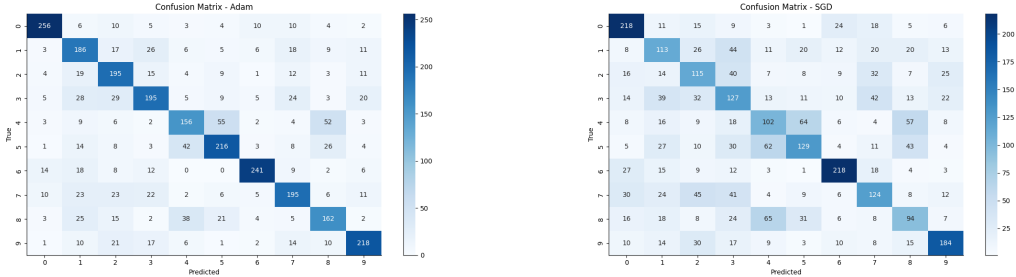

Figure: Confusion matrices for ADAM and SGD for the test data

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- possible ways for improvement:
  - increase image resolution
  - having more computational power / time
  - using more repetitions in the architecture of the VGG-16