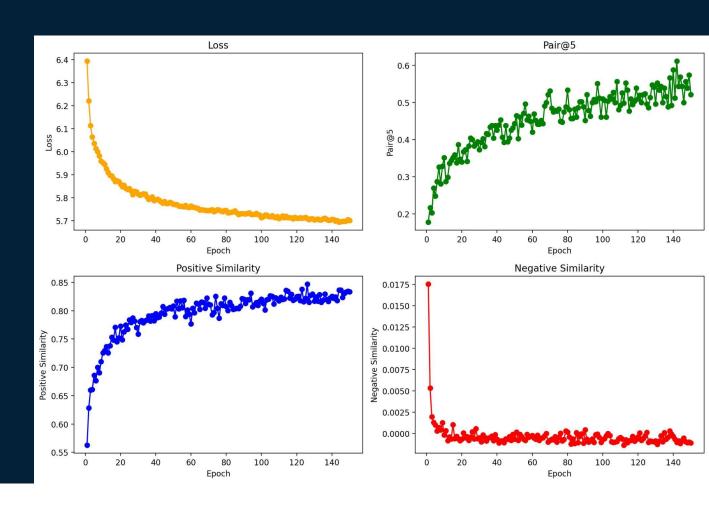


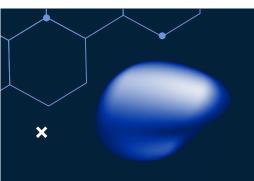




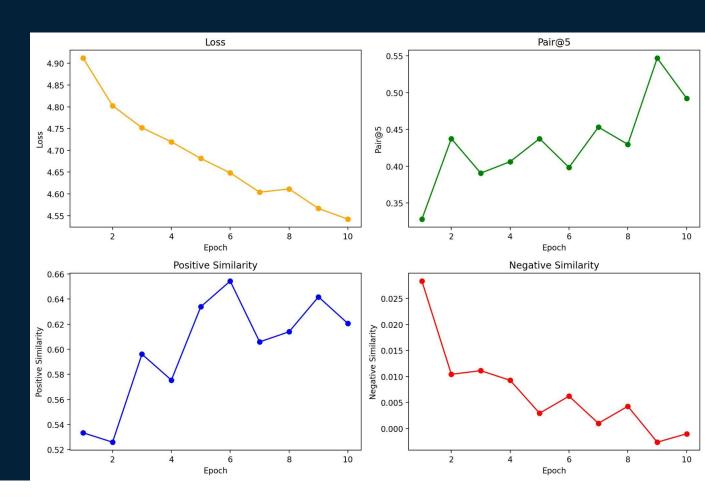


Parameter		
Image Size	144x144	
Batch Size	512	
Learning Rate	0.003	
Feature Dimension	256	



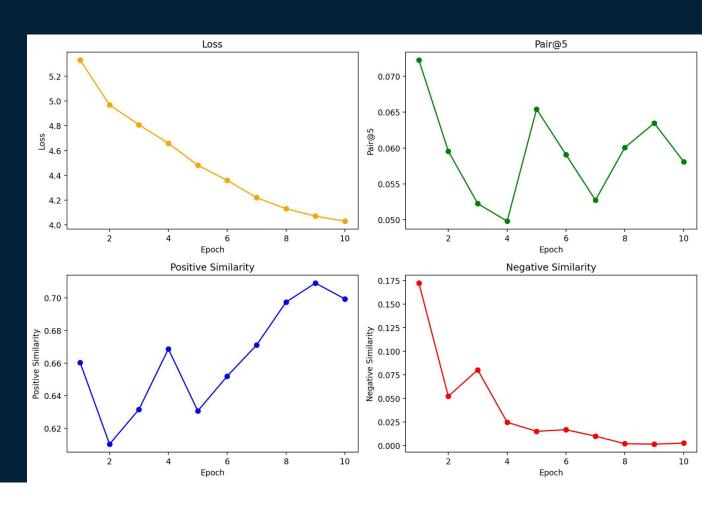


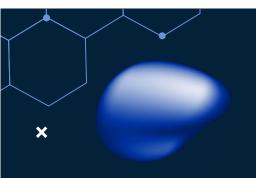
Parameter Image Size 224x224 Batch Size 128 Learning Rate 0.001 Feature Dimension 384



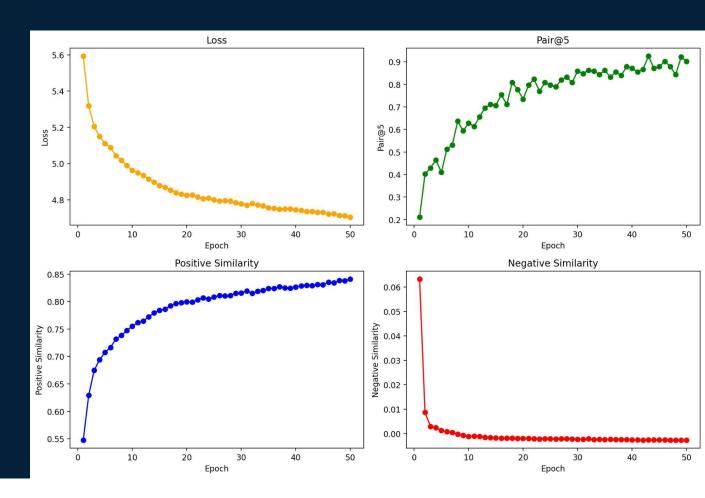


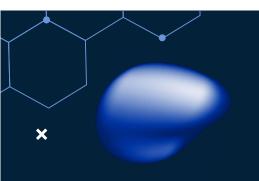
Parameter			
Image Size	192x192		
Batch Size	256		
Learning Rate	0.01		
Feature Dimension	256		





Parameter Image Size 224x224 Batch Size 256 Learning Rate 0.003 Feature Dimension 256

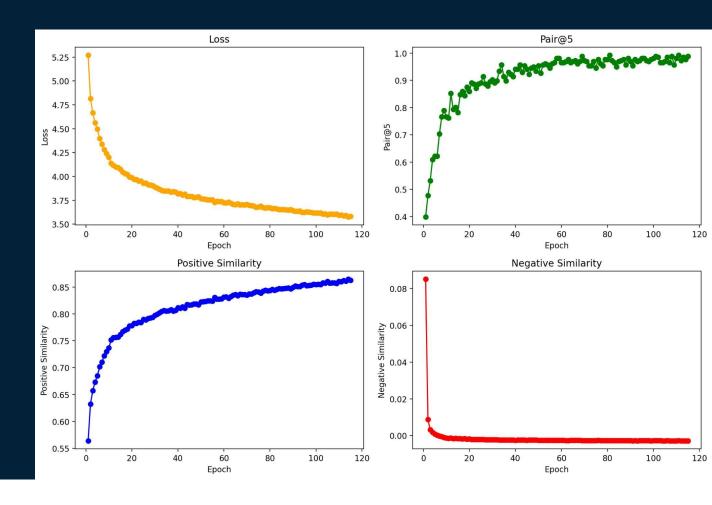


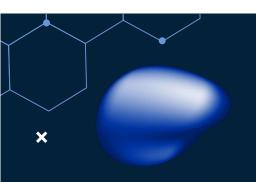


Training Final



Parameter		
lmage Size	224x224	
Batch Size	256	
Learning Rate	0.003	
Feature Dimension	512	





Encoder Versuch 1



Layer	Kanäle	Größe (H×W)	Neuronen
Input	3	224×224	150.528
Stem	64	112x112	802.816
Layer 1	128	56×56	401.408
Layer 2	256	28×28	200.704
Layer 3	512	14×14	100.352
Convo Out	512	14×14	100.352
GAP + FC	512	٦×٦	512

Stem:

→ Kantenerkennung

Layer 1, 2 & 3:

- → Conv2D
- → GroupNorm
- → ReLu

GAP:

→ Global Average Pooling

FC:

→ Fully Connected Layer

×

Encoder Final

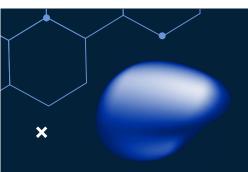
Layer	Kanäle	Größe (H×W)	Neuronen
Input	3	224×224	150.528
Stem	64	56×56	200.704
Layer 1	64	56×56	200.704
Layer 2	128	28×28	100.352
Layer 3	256	14×14	50.176
Layer 4	512	7×7	25.088
GAP + FC	512]×]	512

Stem:

→ Cov2D + MaxPooling

Layer 1, 2 & 3:

- → 2 Blöcke a 2 Conv2D
- → BatchNorm
- → ReLu
- → Skip-Connection



Encoder



```
# Stem
self.conv1 = nn.Conv2d(3, self.in_ch, kernel_size=7, stride=2, padding=3, bias=False)
self.bn1 = nn.BatchNorm2d(self.in_ch)
self.relu = nn.ReLU(inplace=True)
self.maxpool = nn.MaxPool2d(kernel_size=3, stride=2, padding=1)

# Stages (2,2,2,2)
self.layer1 = self._make_layer( BasicBlock, 64, blocks=2, stride=1)
self.layer2 = self._make_layer( BasicBlock, 128, blocks=2, stride=2)
self.layer3 = self._make_layer( BasicBlock, 256, blocks=2, stride=2)
self.layer4 = self._make_layer( BasicBlock, 512, blocks=2, stride=2)
# Global Average Pooling
self.gap = nn.AdaptiveAvgPool2d((1, 1))
```

Stem:

→ low-level Features (Kanten & Texturen)

GAP:

→ 1 Wert pro Kanal

BasicBlock

```
self.conv1 = conv3x3(in_ch, out_ch, stride)
self.bn1 = nn.BatchNorm2d(out_ch)
self.relu = nn.ReLU(inplace=True)
self.conv2 = conv3x3(out_ch, out_ch)
self.bn2 = nn.BatchNorm2d(out_ch)
self.downsample = downsample # passt die Skip-Connection an (Form/Stride)
```

Skip-Connection:

- eigene Identität kann gelernt werden
- → Gradientenfluss bleibt stabil





Python-Pakete

torch / torch.nn / torch.nn.functional

 Modelle und Layer (Convolution, Linear, Batchnorm)

torchvision / torchvision.transform

→ Datenvorbereitung & Augmentierung

torch.utils.data

DataLoader, Batch-Bildung

torch.optim

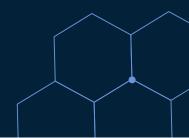
Gewichte von Encoder & Projektionskopf anpassen

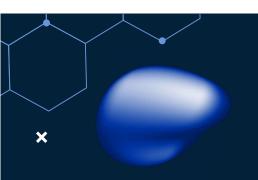
torch.load / torch.save

→ Modell speichern & laden

torch.cuda.amp

Speicher sparen &Trainingsbeschleunigung





UL vs. SSL



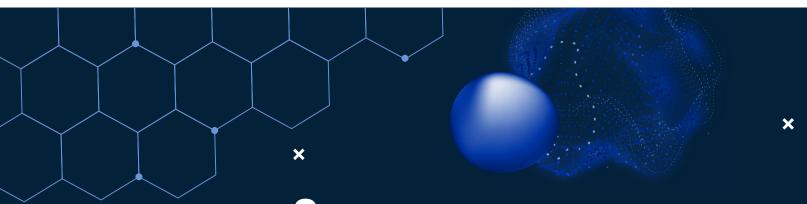


Anwendung









Wir brauchten

Kleine App

- Bildervergleich
- → Duplikate angezeigt
- → Möglichkeit gibt, Bilder zu behalten oder zu entfernen





DuplicAlt

Lokal verwendbar

→ Offline & Nativ

Einfach und intuitiv

→ Minimalistisches Design

Ordnerauswahl

Kompletter Foto-Ordner

Direkter Vergleich

→ Gegenüberstellung der Duplikate

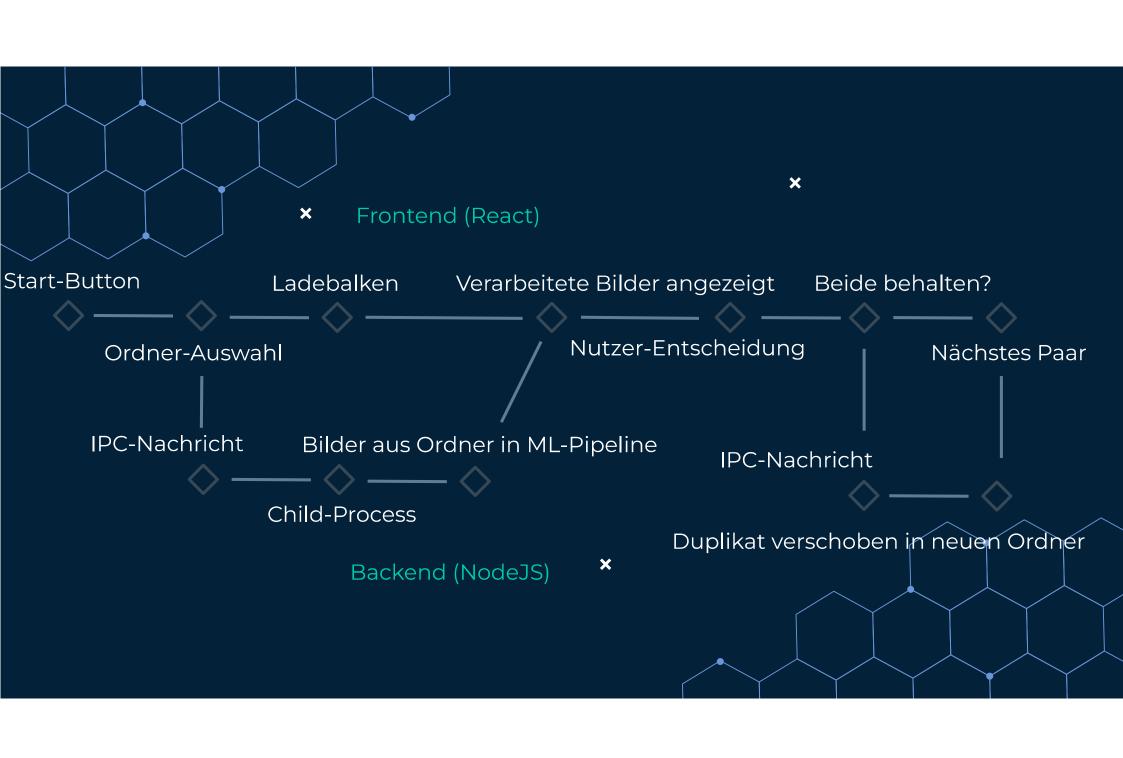
Lightweight

→ Nur das Notwendigste

Backups

→ Fotos nicht gelöscht, sondern verschoben





Finaler Build

Dependencies

- Verschiedene Komponenten
- Vollständige Python-Integration
- Aufblasen einer kompakten App

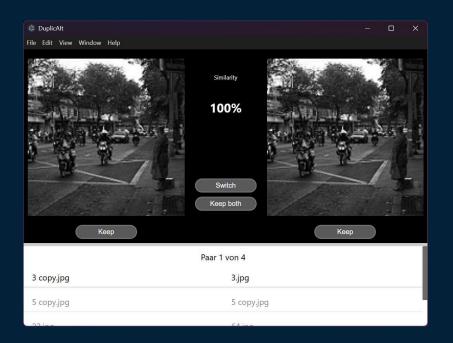
Distribution

- Unabhängige Anwendung
- Native Erfahrung im Zentrum
- Electron Forge bündelt alles

Finaler Build

Darstellung und UI

- Modernisierte Elemente
- Dunkles UI für hohen Kontrast
- Keine Überladung, organisiert
- Wichtige Kernpositionen





Demo



×





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[1] Chen, T., Kornblith, S., Norouzi, M., & Hinton, G. (2020). A simple framework for contrastive learning of visual representations. In H. Larochelle, M. Ranzato, R. Hadsell, M. F. Balcan, & H. Lin (Eds.), Advances in Neural Information Processing Systems (Vol. 33, pp. 1597–1607). Curran Associates, Inc. https://arxiv.org/abs/2002.05709
[2] Le, Q. V., Ranzato, M., Monga, R., Devin, M., Chen, K., Corrado, G. S., Dean, J., & Ng, A. Y. (2012). Building high-level features using large scale unsupervised learning. In Proceedings of the 29th International Conference on Machine Learning (pp. 507–514). Omnipress.



