

# Progetto di Riconoscimento Facciale

## Deep Learning e Architetture di Reti Neurali

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# Obiettivi del Progetto

- **Face Recognition:** identificazione automatica di persone
- **Look-alike Search:** ricerca di volti simili
- **Architettura modulare:** detector + recognizer
- **Confronto architetture:** DNN, CNN, Transfer Learning, ResNet

## Principio di funzionamento:

- Rimozione logit layer → embedding vettoriale
- Distanza nello spazio n-dimensionale = similarità
- Cosine similarity per confronto embeddings

## Detector (YOLO)

- Localizzazione volti
- Bounding boxes
- Confidence scores

## Recognizer

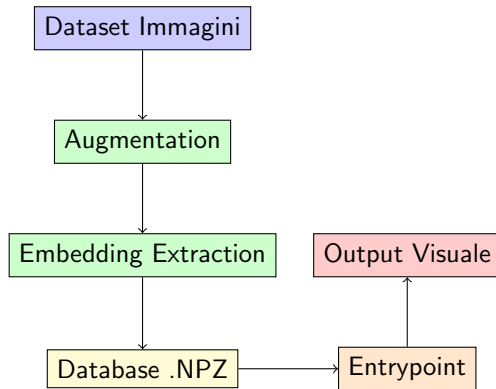
- Generazione embeddings
- Normalizzazione L2
- Confronto similarità

## Moduli di supporto

- `utils.py`: orchestrazione
- `initializer.py`: factory pattern
- `config.py`: configurazione

## Entrypoint

- `main_camera`
- `main_image`
- `main_look_alike`



# Detector: Rilevamento Volti

```
def detect(self, frame):
    results = self.model(frame, conf=self.conf, verbose=False)
    faces = []

    for result in results:
        boxes = result.bboxes.xyxy.cpu().numpy()
        scores = result.bboxes.conf.cpu().numpy()

        for i in range(len(boxes)):
            x1, y1, x2, y2 = map(int, boxes[i])
            faces.append({
                'bbox': (x1, y1, x2, y2),
                'score': float(scores[i])
            })

    return faces
```

# Recognizer: Generazione Embeddings

```
def get_embedding(self, face_bgr: np.ndarray) -> np.ndarray:
    face_tensor = self._preprocess(face_bgr)

    with torch.no_grad():
        if self.use_get_embedding:
            embedding = self.model.get_embedding(face_tensor)
        else:
            embedding = self.model(face_tensor)

    embedding = embedding.cpu().numpy()[0]

    # Normalizzazione L2
    norm = np.linalg.norm(embedding)
    embedding = embedding / norm if norm > 0 else embedding

    return embedding
```

# Riconoscimento: Cosine Similarity

```
def recognize_faces(frame, detector, recognizer,
                    embeddings_array, labels_list, threshold=0.60):
    faces = detector.detect(frame)
    results = []

    for face in faces:
        (x1, y1, x2, y2) = face['bbox']
        face_crop = frame[y1:y2, x1:x2]

        emb = recognizer.get_embedding(face_crop)

        if embeddings_array.size > 0:
            # cosine similarity con embeddings L2-normalizzati
            sims = embeddings_array @ emb
            best_idx = np.argmax(sims)
            best_sim = sims[best_idx]

            if best_sim > threshold:
                name = labels_list[best_idx]
                confidence = (best_sim - threshold) / (1.0 - threshold)

            results.append({'bbox': (x1, y1, x2, y2), 'name': name})

    return results
```



## Organizzazione directory:

- data/dataset/: KB riconoscimento
- data/classify\_images/: immagini da classificare
- data/similarity\_images/: look-alike
- data/test\_images/: testing modelli

## Versioning:

- Hash-based: evita ricomputazione
- File .npz per modello

## Augmentation:

- Random flip
- Brightness adjustment
- Random crop
- Rotazioni

## GUI Features:

- ➊ **Model Selection:** scelta modello recognizer
- ➋ **Import & Process:** aggiunta persone + embedding
- ➌ **Load Images:** caricamento immagini da classificare
- ➍ **Run Scripts:** esecuzione main scripts
- ➎ **Utilities:** manutenzione database embeddings
- ➏ **Model Testing:** test sistematici + metriche
- ➐ **Console Output:** log operazioni real-time

**Comando:** `python -m src.gui_app`

Face Recognition Manager

**Model Selection**

Recognition Model: InceptionResnetV1 (VGGFace2)

Modello pretrained su VGGFace2 (512-dim embeddings)

✓ Model found: C:\Users\Matteo Ghidin\OneDrive - unibs.it\unibs\WAGSTRALE\Deep Learning e Architetture di reti neurali\Code\face\_recognition\models\face\_recognition\vggface2.pt

**1. Import & Process Images**

Target: ☒ Dataset (Camera/Images) ☐ Known People (Look-alike) ☐ People (Look-alike)

Person Name:

Select Images Import & Process ☐ Force reprocess (ignore cache)

No images selected

**2. Load Images to Classify**

Images for recognition: Select Images to Classify No images loaded

**3. Run Main Scripts**

Camera Recognition Image Recognition

Look-alike Offline Look-alike Online

**4. Utilities**

Re-extract All Embeddings Force Re-extract All Show Dataset Info

**5. Model Testing**

Test Images: Load Test Images No test images loaded

Recognition Threshold:  (0.0 - 1.0)

Models to test: ☒ All models ☐ Current model only

Run Model Testing

Note: Test images must be in folders named by person (e.g., test\_images/mario\_rossi\img1.jpg)

Architettura	Parametri	Embedding	Approccio
ResNet (pre-trained)	-	512	State-of-the-art
DNN	51-101M	128-256	Fully connected
CNN	5M-37M	128-256	Convoluzionale
Transfer Learning	variabile	128-256	Fine-tuning

## Dataset utilizzati:

- **LFW**: 13.000 immagini, 5749 identità ( $\geq 10$  img/persona)
- **CelebA**: 200.000 immagini, attributi booleani (male, young, smiling, eyeglasses)

## Architettura:

Input<sub>128×128×3</sub> → Flatten → Dense<sub>n</sub> → ⋯ → Embedding<sub>d</sub> → Classifier

## Configurazioni testate:

Config	Hidden Sizes	Embedding	Dropout	Val Acc (%)
Baseline	[1024, 512]	128	0.5	34.45
Deep	[2048, 1024, 512, 256]	128	0.4	26.94
Optimized	[1536, 768, 384]	256	0.3	44.16

## Limitazioni:

- Alto numero parametri per dati spaziali
- Perdita informazioni strutturali immagine
- Prone a overfitting

# Convolutional Neural Network

## Architettura base:

Conv2D  $\rightarrow$  BatchNorm  $\rightarrow$  ReLU  $\rightarrow$  MaxPool  $\rightarrow \dots \rightarrow$  FC  $\rightarrow$  Embedding

## Variante con Residual Blocks:

- Skip connections:  $\mathbf{y} = F(\mathbf{x}) + \mathbf{x}$
- Mitiga vanishing gradient
- Ispirata a ResNet

## LFW Dataset:

- Best: CNN Optimized
- Accuracy: 78.84%
- Parametri: 36.8M

## CelebA Dataset:

- Best: CNN Deep Residual
- Accuracy: 82.65%
- Parametri: 5.5M

Configurazione	Parametri	Val Acc LFW (%)	Val Acc CelebA (%)
Baseline	17.7M	57.80	80.88
Shallow	34.4M	64.16	81.34
Deep	18.9M	71.56	81.73
Large Kernels	17.8M	60.81	-
GAP	1.3M	13.06	79.03
Optimized	36.9M	<b>78.84</b>	82.40
Deep Residual	5.5M	52.25	<b>82.65</b>

## Osservazioni:

- Residual connections efficaci su CelebA
- Trade-off parametri vs accuracy
- Global Average Pooling riduce parametri ma degrada performance

# Transfer Learning e Fine-Tuning

## Approccio:

- 1 Backbone pre-trained su ImageNet (ResNet18/34/50)
- 2 Custom residual blocks
- 3 Fine-tuning opzionale

## Strategie:

- **Frozen backbone:** feature extraction
- **Fine-tuning:** unfreeze + LR basso ( $10^{-5}$ )

Config	Backbone	Val Acc LFW (%)	Val Acc CelebA (%)
ResNet18 Frozen	ResNet18	75.32	83.12
ResNet18 Finetuned	ResNet18	<b>81.45</b>	<b>85.67</b>
ResNet34 Frozen	ResNet34	77.89	84.21
ResNet50 Frozen	ResNet50	79.12	84.89



# InceptionResnetV1 (Baseline)

## Modello state-of-the-art:

- Pre-trained: VGGFace2, CASIA-WebFace
- Embedding: 512 dimensioni
- Architettura: Inception + Residual connections

## Motivazione:

- Baseline di riferimento
- Prestazioni elevate out-of-the-box
- Robustezza: addestrato su milioni di immagini
- Efficienza: no training da zero

**Utilizzo:** Cosine similarity su embeddings normalizzati L2

## Configurazione:

- **Loss:** CrossEntropyLoss + Label Smoothing
- **Optimizer:** Adam / RMSprop / SGD
- **Scheduler:** ReduceLROnPlateau
- **Regularization:** Dropout, Weight Decay, BatchNorm
- **Early Stopping:** patience=5-10 epoche

## Hyperparameters:

Parametro	DNN	CNN	Transfer Learning
Learning Rate	$10^{-3}$ - $5 \times 10^{-4}$	$10^{-3}$ - $3 \times 10^{-4}$	$10^{-3}$ (frozen), $10^{-5}$ (ft)
Batch Size	64-128	32-64	32-64
Epochs	10-20	35-45	35 (+5 ft)
Weight Decay	$0 - 10^{-4}$	$10^{-5} - 10^{-4}$	$10^{-4}$

## Dropout:

- Rate: 0.3-0.5
- Dopo FC e Conv layers
- Riduce co-adaptation

## Batch Normalization:

- Stabilizza training
- Accelera convergenza
- Dopo Conv/FC, prima ReLU

## Weight Decay:

- L2 regularization
- $\lambda = 10^{-5} - 10^{-4}$
- Penalizza grandi pesi

## Label Smoothing:

- $\epsilon = 0.05 - 0.1$
- Previene overconfidence
- Migliora generalizzazione

## Metodologia:

- Dataset personale: immagini reali
- Dataset AI-generated: Nano-Banana, ChatGPT-5
- Metriche: Accuracy, Precision, Recall

Architettura	Acc Reali (%)	Acc AI-Gen (%)
ResNet Pre-trained	<b>88.1</b>	<b>88.9</b>
Transfer Learning (ResNet18 FT)	50.0	18.5
CNN Optimized	16.7	11.1
CNN Deep Residual	40.5	0.0
DNN Optimized	42.9	77.8

## Punti di forza:

- **ResNet**: best accuracy, robusto
- **Transfer Learning**: ottimo trade-off
- **CNN**: customizzabile, efficiente

## Limitazioni:

- **ResNet**: black-box
- **Transfer Learning**: dipende da backbone
- **CNN**: richiede più training
- **DNN**: molto pesante

## Contributi:

- ➊ Sistema completo face recognition + look-alike
- ➋ Confronto sistematico 4 architetture
- ➌ GUI user-friendly

## Risultati:

- Transfer Learning  $>$  training da zero
- Residual connections essenziali per reti deep
- Regularization critica per generalizzazione
- Dataset quantity  $>$  quality

## Dataset:

- LFW: <https://www.kaggle.com/datasets/jessicali9530/lfw-dataset>
- CelebA: <https://www.kaggle.com/datasets/jessicali9530/celeba-dataset>

## Modelli:

- ResNet: *He et al., CVPR 2016*
- InceptionResnetV1: *Szegedy et al., AAAI 2017*

## Repository:

- Codice:  
[https://github.com/Moryuss/Progetto\\_DeepLearning\\_e\\_architetture\\_di\\_Reti\\_Neurali](https://github.com/Moryuss/Progetto_DeepLearning_e_architetture_di_Reti_Neurali)
- Notebooks: training su Google Colab
- Pesi: <https://github.com/timesler/facenet-pytorch/tree/master?tab=readme-ov-file#pretrained-models>

# Grazie per l'attenzione

Domande?



## Tecnologie:

- **Framework:** PyTorch 2.0
- **Detection:** YOLO v8
- **GUI:** Tkinter
- **Training:** MuHack GPU NVIDIA Quadro RTX 8000 — 48 GB GDDR6

## Struttura codice:

- `src/`: detector, recognizer, utils
- `src/models/`: architetture custom
- `src/`: augmentation, embedding extraction
- `src/main_*.py`: entripoint applicazione

## Face Recognition:

$$\text{Accuracy} = \frac{\text{Correct Matches}}{\text{Total Faces}}$$

## Look-alike Search:

$$\text{Similarity} = \cos(\theta) = \frac{\mathbf{a} \cdot \mathbf{b}}{\|\mathbf{a}\| \|\mathbf{b}\|}$$

## Classification (training):

$$\text{Precision} = \frac{TP}{TP + FP}$$

$$\text{Recall} = \frac{TP}{TP + FN}$$

$$F_1 = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$$