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Advanced AI-Powered Face Recognition Using PCA & Neural Networks.

Introduction

Face recognition is a biometric method used for identifying or verifying a person from a digital image or video. This project implements a face recognition system by combining Principal Component Analysis (PCA) for dimensionality reduction and Artificial Neural Networks (ANN) for classification.

Objectives

- To build a face recognition system using PCA and ANN.
- To reduce dimensionality using PCA for faster and efficient processing.
- To classify facial features using a trained ANN model.
- To evaluate the system's performance by varying feature size `k` and adding imposters.

Problem Statement

Traditional face recognition systems suffer from high-dimensional data and poor performance with varying lighting, angles, or noise. This project addresses the challenge by:

- Reducing feature size using PCA (Eigenfaces).
- Applying ANN for improved classification.
- Ensuring scalability and testing with unseen (imposter) faces.

Methodology

Dataset:

https://github.com/robaita/introduction_to_machine_learning/blob/main/dataset.zip

Steps:

1. Convert face images into column vectors.
2. Calculate the mean face.
3. Subtract the mean to get mean-zero data.
4. Compute surrogate covariance matrix.
5. Perform eigen decomposition.
6. Select top-k eigenvectors (features).
7. Generate Eigenfaces.
8. Generate face signatures by projecting onto Eigenfaces.
9. Train ANN using face signatures (Backpropagation).
10. Test using new images, including imposters.

Working Principle

- PCA finds the most significant features ("Eigenfaces") of faces.
- ANN learns the mapping from these features to person IDs.
- During testing, the input image is projected and passed to ANN to classify.

Project Result

- Classification accuracy improves with optimal `k`.
- System identifies imposters by low ANN confidence.
- Plots show accuracy vs. `k` demonstrating system performance.

Conclusion

The project successfully demonstrates an efficient face recognition system using PCA and ANN. It significantly reduces dimensionality while retaining recognition accuracy. The system is scalable, testable with imposters, and suitable for real-time applications.

Software Used

- Jupyter Notebook (Python)
- Libraries: OpenCV, NumPy, Scikit-learn, Matplotlib

Hardware & Software Components

Hardware:

- Any computer/laptop with at least 4GB RAM.

Software:

- Python 3.x
- OpenCV
- NumPy
- Scikit-learn
- Jupyter Notebook

How to Execute and Explain

Execution:

1. Download dataset from the GitHub link and extract it.
2. Install required libraries: pip install numpy opencv-python scikit-learn matplotlib
3. Update the dataset path in the code.
4. Run in Jupyter Notebook.
5. Output displays recognition accuracy.

Explanation:

1. Start with how PCA extracts features and ANN classifies them.
2. Show dataset conversion and training process.
3. Highlight results and mention future scope like using CNN.

Code

```
import os, cv2
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.neural_network import MLPClassifier
from sklearn.metrics import accuracy_score
import matplotlib.pyplot as plt

def load_images(dataset_path):
    images, labels = [], []
    label = 0
    for folder in os.listdir(dataset_path):
        for file in os.listdir(os.path.join(dataset_path, folder)):
            img = cv2.imread(os.path.join(dataset_path, folder, file),
cv2.IMREAD_GRAYSCALE)
            img = cv2.resize(img, (100, 100)).flatten()
            images.append(img)
            labels.append(label)
        label += 1
    return np.array(images).T, np.array(labels)

def pca(X, k):
    mean = np.mean(X, axis=1, keepdims=True)
    A = X - mean
    cov = np.dot(A.T, A)
    eigvals, eigvecs = np.linalg.eig(cov)
    eigvecs = np.dot(A, eigvecs)
    eigvecs = eigvecs / np.linalg.norm(eigvecs, axis=0)
    idx = np.argsort(-eigvals)[:k]
    return mean, eigvecs[:, idx]

X, y = load_images('dataset_path')
mean, eigvecs = pca(X, k=50)
A = X - mean
features = np.dot(eigvecs.T, A).T

X_train, X_test, y_train, y_test = train_test_split(features, y, test_size=0.4,
random_state=42)
```

```
ann = MLPClassifier(hidden_layer_sizes=(50,), max_iter=1000)
ann.fit(X_train, y_train)

y_pred = ann.predict(X_test)
print("Accuracy:", accuracy_score(y_test, y_pred))
```

Code 2: -

In [2]:
```
# ---------------------------  PCA + ANN Face-Recognition  ---------------------------
# Prerequisites: pip install opencv-python scikit-learn matplotlib numpy

import os
from glob import glob

import cv2
import numpy as np
import matplotlib.pyplot as plt

from sklearn.model_selection import train_test_split
from sklearn.neural_network import MLPClassifier
from sklearn.metrics import accuracy_score
```

```
# ──────────────────────────────── 2. PCA ──────────────────────────────────────
def pca(X, k):
    """
    Computes top-k eigenfaces.
    Returns mean_face, eigfaces, X_centered
    """
    mean_face = np.mean(X, axis=1, keepdims=True)
    X_centered = X - mean_face

    # compact trick: eigen-decomp on small n×n matrix
    cov_small = X_centered.T @ X_centered
    eigvals, eigvecs_small = np.linalg.eigh(cov_small)        # ascending order
    eigvecs = X_centered @ eigvecs_small                      # convert back to big space
    eigvecs = eigvecs / np.linalg.norm(eigvecs, axis=0)       # normalise columns

    # take top-k by descending eigenvalue
    idx = np.argsort(eigvals)[::-1][:k]
    eigfaces = eigvecs[:, idx]

    return mean_face, eigfaces, X_centered
```

```
# ──────────────────────────── 3. Signatures ──────────────────────────────────
def generate_signatures(eigfaces, X_centered):
    return eigfaces.T @ X_centered     # shape: (k, n)
```

```python
# ———————————————————— 4. ANN training ————————————————————
def train_ann(signatures, labels):
    X_train, X_test, y_train, y_test = train_test_split(
        signatures.T, labels, test_size=0.4, random_state=42, stratify=labels
    )
    model = MLPClassifier(hidden_layer_sizes=(50,), max_iter=1000)
    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)
    acc = accuracy_score(y_test, y_pred)
    return model, acc
```

```python
# ———————————————————— 5. Accuracy vs k plot ————————————————————
def plot_accuracy_vs_k(X, labels, k_list):
    accs = []
    for k in k_list:
        _, eigfaces, X_c = pca(X, k)
        sigs = generate_signatures(eigfaces, X_c)
        _, acc = train_ann(sigs, labels)
        accs.append(acc)

    plt.figure(figsize=(6,4))
    plt.plot(k_list, accs, marker='o')
    plt.xlabel('k (number of eigenfaces)')
    plt.ylabel('Accuracy')
    plt.title('Accuracy vs. k')
    plt.grid(True)
    plt.show()
```

```python
# ———————————————————— 6. MAIN ————————————————————
# ★★  EDIT THIS PATH to match your folder ★★
dataset_path = r"C:\Users\Manoj S\Downloads\Project_faces\dataset\faces"

# Step-A: load images
X, labels, label_map = load_images(dataset_path)

print("X shape        :", X.shape)      # (d, n)
print("labels shape   :", labels.shape)
print("Classes found  :", label_map)

# Step-B: PCA → signatures → ANN
k = 50
mean_face, eigfaces, X_centered = pca(X, k)
signatures = generate_signatures(eigfaces, X_centered)
model, acc = train_ann(signatures, labels)

print(f"\nInitial accuracy with k = {k}: {acc:.2%}")

# Step-C: evaluate across different k values
k_vals = list(range(10, 110, 10))
plot_accuracy_vs_k(X, labels, k_vals)
```

```
X shape        : (10000, 55)
labels shape   : (55,)
Classes found  : {0: 'Aamir', 1: 'Ajay', 2: 'Akshay', 3: 'Alia', 4: 'Amitabh', 5: 'Deepika', 6: 'Disha', 7: 'Farhan', 8: 'Ileana'}

Initial accuracy with k = 50: 27.27%
```