AI Capstone Project 1 report

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1. Data link:
2. Research Question: The objective of this project is to **classify images of the five members of NJZ** using different machine learning methods such as HOG + SVM and CNN and others.

The motivation of this project is that a lot of people cannot tell the difference between the memebers of k-pop girl group, while it is very easy for the fans to regonize them. For me, I was frustrated at the beginning, while I can tell the differences very easily right now. I think the main cause is that the makeups making each of them looks alike. While in different stages they come up with different makeups, making it harder to find the similarities in each members.  
This is an interesting topic, so I want to know that if the computers can “learn” to regonize them in a relatively small data set.

1. Dataset Documentation:

Datatype: The main data type is image. To be more specific it is .jpg.

Numbers: For each member, there are at least 180 photos. The total number of photos is 1125. (there are five members in NJZ!)

Collection methods: The data is collected from internet, include fan made websites, social media, pinterest, and others. The data is downloaded by myself, I tried to use web scrawler but there are always some bugs, thus I quit.

Data Preprocessing: Face Detection and Cropping using MTCNN. I use MTCNN (Multi-task Cascaded Convolutional Networks) to detect faces, once a face is detected, the script extract the photo with extra 20% padding to ensure that the cropped image contain some spaces around the face. This helps the regonition model to improve performance by reducing noises.

1. Methods Used:
2. **HOG+SVM**: I use **HOG (Histogram of Oriented Gradients)**, a feature descriptor that counts occurrences of gradient orientation in localized portions of an image.180 photos per member is used. Given a overall 900 pictures data set.

HOG parameters: Each image is resized to 64\*64 pixel, and turned into grayscale. And then using the hog function from the skimage.feature module with the following parameters:

* Orientations: 9 (The number of orientation bins for the gradient histograms)
* Pixels percell: (8, 8) (The size of the cell over which gradients are computed)
* Cells per block: (2, 2) (The number of cells that make up a block, used for normalization)

SVM: And then I use Support Vector Machine, which is trained on the feature vectors from the HOG discription, to classify the images into one of the five members of NJZ.

Cross-Validation: The performance of the SVM classifier is assessed using **StratifiedKFold cross-validation**. This method splits the dataset into 5 parts, trains the model on 4 parts, and tests it on the remaining part.

Libraries Used:

OpenCV, skimage.feature, scikit-learn, Matplotlib

Results:

The data used is 180 randomly selected pictures for each member.

For 5 folds, the model use 36 pictures for testing each time.

Cross-validation scores: [0.68, 0.68, 0.64, 0.67, 0.61]

Mean CV accuracy: 0.658 ± 0.025

|  |  |  |  |
| --- | --- | --- | --- |
|  | Precision | Recall | F1-Score |
| Danielle | 0.62 | 0.64 | 0.63 |
| Hanni | 0.67 | 0.69 | 0.68 |
| Minji | 0.63 | 0.62 | 0.62 |
| Hyein | 0.67 | 0.66 | 0.66 |
| Haerin | 0.72 | 0.68 | 0.70 |
| accuracy |  |  | 0.66 |
| macro avg | 0.66 | 0.66 | 0.66 |
| weighted avg | 0.66 | 0.66 | 0.66 |

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Predicted  label  True lable | Danielle | Hanni | Minji | Hyein | Haerin |
| Danielle | 116 | 14 | 21 | 12 | 17 |
| Hanni | 18 | 124 | 11 | 21 | 6 |
| Minji | 21 | 19 | 112 | 12 | 16 |
| Hyein | 15 | 19 | 18 | 118 | 10 |
| Haerin | 18 | 9 | 17 | 13 | 123 |

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AI 產生的內容可能不正確。The result of HOG+SVM is quite impressive, even though its accuracy is less than 0.8. It still shows potential in a relatively small dataset.

1. **CNN:** Use the Convolutional Neural Network classifier is to classify the facial images of the five NJZ members. CNN can extract the features through convolution operations, without the feature extraction step.

180 pictures for each member as dataset, given a total 900 pictures dataset.

Data preprocessing: The images are resized to 128\*128 pixels and normalized by scaling pixel values to the range [0, 1].

CNN detail discription: Optimizer: Use Adam Optimizer to adapt the learning rate during training to improve convergence. Loss Function: categorical cross-entropy loss function is used.

Cross-Validation: 5-fold Stratified Cross-Validation is used to evaluate the model's performance.

Early Stopping: To prevent overfitting, stop the training when the validation accuracy does not improve for 5 consecutive epochs.

Libraries Used:

TensorFlow / Keras, OpenCV, NumPy, Matplotlib, Scikit-learn.

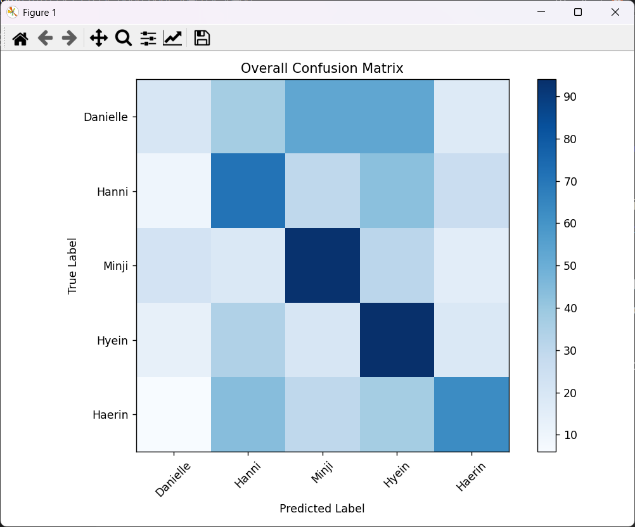
Results:

Cross-validation results:

Fold 1: 0.3722 Fold 2: 0.3333 Fold 3: 0.3944 Fold 4: 0.4500 Fold 5: 0.3444

Mean CV accuracy: 0.3789 ± 0.0415

|  |  |  |  |
| --- | --- | --- | --- |
| Class | Precision | Recall | F1-Score |
| Danielle | 0.28 | 0.11 | 0.16 |
| Hanni | 0.35 | 0.39 | 0.37 |
| Minji | 0.41 | 0.52 | 0.46 |
| Hyein | 0.36 | 0.52 | 0.43 |
| Haerin | 0.45 | 0.35 | 0.39 |
| Accuracy |  |  | 0.38 |
| Macro avg | 0.37 | 0.38 | 0.36 |
| Weighted avg | 0.37 | 0.38 | 0.36 |



|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | Danielle | Hanni | Minji | Hyein | Haerin |
| Danielle | 20 | 37 | 53 | 53 | 17 |
| Hanni | 10 | 71 | 30 | 43 | 26 |
| Minji | 22 | 19 | 93 | 31 | 15 |
| Hyein | 13 | 34 | 20 | 94 | 19 |
| Haerin | 6 | 44 | 30 | 37 | 63 |

The performance of CNN is not good, since the accuracy is only 0.38, slightly better than 0.2 (pure guessing).

This might because of the differences between each member is not very large. Also the dataset is quite small, which is not very suitable for deap-learning models like CNN.

1. HOG+K-mean clustering: Use K-means clustering to group facial images and test if the algorithm can segregate different members based on the extracted features.

Image preprocessing: Images are converted to grayscale and resized to 128x128 pixels to standardize the input.

HOG: Same as the SVM part. The hog function from skimage.feature is used to extract HOG features with the following parameters:

* Orientations: 9 (bins for gradient directions)
* Pixels per cell: (8, 8) (size of the cell for gradient calculation)
* Cells per block: (2, 2) (number of cells per block for normalization)

K-Means Clustering: K-Means attempts to partition the dataset into **5 clusters** (since there are 5 members) based on the feature similarities between images.

n\_clusters: 5 (number of clusters, corresponding to the 5 members)

n\_init: 10 (number of initializations of the centroid to avoid local minima)

Libraries Used:

OpenCV, NumPy, Matplotlib, scikit-learn, scipy, skimage.feature.

Result: I use ARI, NMI and Confusion Matrix with Hungarian algorithm to align the clusters with the true labels.

**Adjusted Rand Index (ARI)**: 0.0484

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aligned confusion matrix:

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | Danielle | Hanni | Minji | Hyein | Haerin |
| Danielle | 32 | 30 | 59 | 41 | 18 |
| Hanni | 10 | 49 | 36 | 21 | 64 |
| Minji | 27 | 43 | 85 | 21 | 4 |
| Hyein | 19 | 33 | 63 | 54 | 11 |
| Haerin | 19 | 22 | 38 | 31 | 70 |

Clustering Accuracy (after alignment): 0.3222

The result of k-means clustering is not very good, either.

I think it is because of the HOG feature are alike for human faces, making it harder for the algorithm to distinguish and form different clusters.

5. Experiments:

1. Dataset quantaties:

I perform HOG+SVM with the same parameters as above, with different dataset number (50, 100, 150, 180 per member)  
For 50 images per member (total 250 pictures):

Cross-validation scores: [0.52, 0.68, 0.6, 0.58, 0.54]

Mean CV accuracy: 0.5840 ± 0.0557

|  |  |  |  |
| --- | --- | --- | --- |
| Class | Precision | Recall | F1-Score |
| Danielle | 0.64 | 0.56 | 0.60 |
| Hanni | 0.60 | 0.54 | 0.57 |
| Minji | 0.53 | 0.56 | 0.54 |
| Hyein |  |  | 0.58 |
| Haerin | 0.59 | 0.58 | 0.58 |
| Accuracy | 0.59 | 0.58 | 0.58 |
| Macro avg | 0.64 | 0.56 | 0.60 |
| Weighted avg | 0.60 | 0.54 | 0.57 |

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | Danielle | Hanni | Minji | Hyein | Haerin |
| Danielle | 35 | 4 | 4 | 1 | 6 |
| Hanni | 5 | 28 | 3 | 9 | 5 |
| Minji | 5 | 5 | 28 | 3 | 9 |
| Hyein | 8 | 8 | 2 | 27 | 5 |
| Haerin | 6 | 4 | 7 | 5 | 28 |

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For 100 images per member (total 500 pictures):

Cross-validation scores: [0.61 0.61 0.62 0.68 0.7 ]

Mean CV accuracy: 0.6440 ± 0.0383

|  |  |  |  |
| --- | --- | --- | --- |
| Class | Precision | Recall | F1-Score |
| Danielle | 0.62 | 0.67 | 0.64 |
| Hanni | 0.72 | 0.66 | 0.69 |
| Minji | 0.60 | 0.68 | 0.64 |
| Hyein | 0.65 | 0.65 | 0.65 |
| Haerin | 0.64 | 0.56 | 0.60 |
| Accuracy |  |  | **0.64** |
| Macro avg | 0.65 | 0.64 | 0.64 |
| Weighted avg | 0.65 | 0.64 | 0.64 |

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | Danielle | Hanni | Minji | Hyein | Haerin |
| Danielle | 67 | 7 | 11 | 8 | 7 |
| Hanni | 8 | 66 | 6 | 14 | 6 |
| Minji | 6 | 5 | 68 | 10 | 11 |
| Hyein | 11 | 8 | 9 | 65 | 7 |
| Haerin | 16 | 6 | 19 | 3 | 56 |

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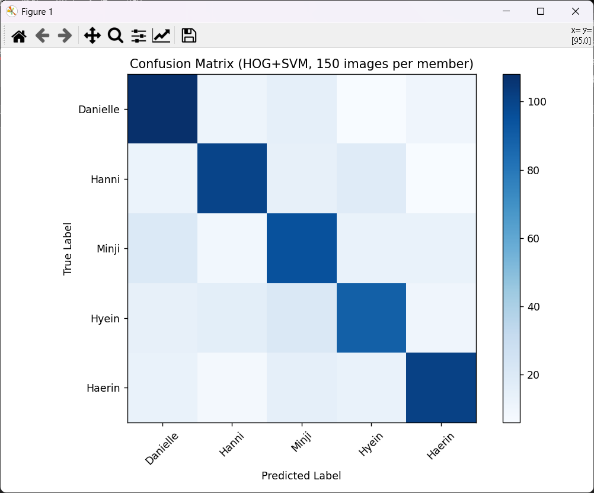
For 150 images per member (total 750 pictures):

Cross-validation scores: [0.6867, 0.6333, 0.6467, 0.66, 0.66]

Mean CV accuracy: 0.6573 ± 0.0177

|  |  |  |  |
| --- | --- | --- | --- |
| Class | Precision | Recall | F1-Score |
| Danielle | 0.65 | 0.72 | 0.68 |
| Hanni | 0.69 | 0.67 | 0.68 |
| Minji | 0.59 | 0.63 | 0.61 |
| Hyein | 0.64 | 0.59 | 0.62 |
| Haerin | 0.72 | 0.67 | 0.70 |
| Accuracy |  |  | **0.66** |
| Macro avg | 0.66 | 0.66 | 0.66 |
| Weighted avg | 0.66 | 0.66 | 0.66 |

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | Danielle | Hanni | Minji | Hyein | Haerin |
| Danielle | 108 | 11 | 15 | 6 | 10 |
| Hanni | 12 | 100 | 14 | 18 | 6 |
| Minji | 20 | 9 | 95 | 13 | 13 |
| Hyein | 14 | 16 | 21 | 89 | 10 |
| Haerin | 13 | 8 | 15 | 13 | 101 |



For 180 images per member (total 900 pictures):

Cross-validation scores: [0.6611, 0.6833, 0.6889, 0.6389, 0.6222]

Mean CV accuracy: 0.6589 ± 0.0255

|  |  |  |  |
| --- | --- | --- | --- |
| Class | Precision | Recall | F1-Score |
| Danielle | 0.62 | 0.72 | 0.66 |
| Hanni | 0.65 | 0.65 | 0.65 |
| Minji | 0.62 | 0.60 | 0.61 |
| Hyein | 0.67 | 0.64 | 0.66 |
| Haerin | 0.75 | 0.69 | 0.72 |
| Accuracy |  |  | **0.66** |
| Macro avg | 0.66 | 0.66 | 0.66 |
| Weighted avg | 0.66 | 0.66 | 0.66 |

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|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | Danielle | Hanni | Minji | Hyein | Haerin |
| Danielle | 129 | 9 | 18 | 11 | 13 |
| Hanni | 17 | 117 | 18 | 21 | 7 |
| Minji | 27 | 18 | 108 | 12 | 15 |
| Hyein | 17 | 26 | 15 | 115 | 7 |
| Haerin | 18 | 10 | 16 | 12 | 124 |

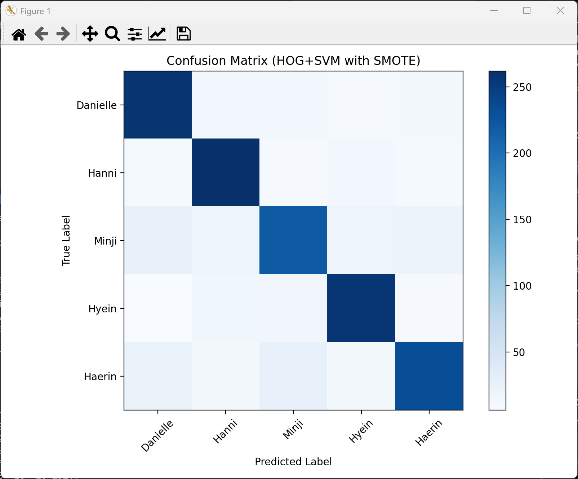
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AI 產生的內容可能不正確。As shown in this picture, the accuracy increases as the size of dataset increases. However, the magnitude of increase slows down when number of dataset changes from 150 to 180. I think that is because when the size become larger, you have to add more data than before (two times more, for instance) to see a significant change.

2. SMOTE oversampling:  
 Since the dataset of mine is imbalanced (some member have photos more that 270). I use SMOTE to oversample every member’s dataset to 300, resulting a total 1500 unit dataset.  
Result: Cross-validation scores: [0.8233, 0.8167, 0.85, 0.83, 0.76]  
Mean CV accuracy: 0.8160 ± 0.0301

|  |  |  |  |
| --- | --- | --- | --- |
| Class | Precision | Recall | F1-Score |
| Danielle | 0.81 | 0.85 | 0.83 |
| Hanni | 0.82 | 0.87 | 0.85 |
| Minji | 0.78 | 0.73 | 0.75 |
| Hyein | 0.84 | 0.85 | 0.85 |
| Haerin | 0.83 | 0.77 | 0.80 |
| Accuracy |  |  | **0.82** |
| Macro avg | 0.82 | 0.82 | 0.82 |
| Weighted avg | 0.82 | 0.82 | 0.82 |

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | Danielle | Hanni | Minji | Hyein | Haerin |
| Danielle | 256 | 13 | 13 | 8 | 10 |
| Hanni | 9 | 262 | 8 | 12 | 9 |
| Minji | 24 | 18 | 219 | 18 | 21 |
| Hyein | 6 | 16 | 15 | 255 | 8 |
| Haerin | 22 | 10 | 26 | 10 | 232 |



The result is very good, compared to the original method (with 180 photos each member). This is expected because with oversampling we manage to use the whole data set and thus improve the accuracy.

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AI 產生的內容可能不正確。3. PCA Components:

Use PCA to reduce the dimensions of features. Thus reduce the time needed for evaluation and remove some noises that might affect the performance.  
I use SMOTE to oversampling to 300 data for each member, for a total of 1500 data points. Test differenr amount of PCA components: 20, 100, 200, 400, 600, 800, 1000, 1200, and full (1764)  
The result shows that when the dimensions increases to a certain number, the accuracy remain approximately the same. This is useful when dataset is large since reduce dimensions can improve efficiency greatly.

6. Discussion:

1.Based on your experiments, are the results and observed behaviors what you expect?

Ans: Yes, the experiments results are similar from what I expected. However, I’m amazed by the power of SMOTE oversampling. At first I expected the accuracy will improve for like 0.05 at most. But it increased for 0.15, greater than 0.8. Which is way higher than I expected.

2.Discuss factors that affect the performance, including dataset characteristics.

Ans: The quantity, quality, diversity of dataset are very important. For this assignment, some photo’s quality is relatively bad (with low resolution) or some photos are very alike (taked from the same activity/performance). Which I think also affect the performance greatly.

3.Describe experiments that you would do if there were more time available.

Ans: I would like to do experiments about different quality of pictures, for instance, limit and resize the images to 256\*256 pixel, and see if the performance improve. However, this will increase the complexity of cauculation and increase time needed. I would also like to increase the number of dataset till the CNN method would work. But that would require a lot of data, which does not seems feasable.

4.Indicate what you have learned from the experiments as well as your remaining questions.

Ans: The experiment of PCA makes me realize that reduce the number of dimensions in a acceptable range would not reduce performance. In the future if I have to implement models with high-dimensional data, I would think of this and thus reduce the time needed for training.

I think that the remaining questions is that I still don’t know how many photos need for CNN to perform normally. And also how many photos need for SVM to achieve a human like accuracy (for at least 0.95 would be nice).

Appendex:

The first one is the one I use to crop the photos (as preprocessing):

import os

import cv2

from mtcnn import MTCNN

import numpy as np

import shutil

# Root directories

input\_root\_dir = "Hyein\_renamed\_photo\_dataset"  # Renamed dataset with ASCII names

output\_root\_dir = "NJZ\_cropped\_faces\_dataset"  # Cropped faces

original\_successful\_dir = "NJZ\_original\_successful\_dataset"  # Originals of successful crops

# List of members to process (modify this as needed)

members\_to\_process = ["Hyein"]  # Example: process Minji and Hanni only

# Supported image extensions

image\_extensions = (".jpg", ".jpeg", ".png")

# Initialize MTCNN face detector

detector = MTCNN()

# Create output directories

if not os.path.exists(output\_root\_dir):

    os.makedirs(output\_root\_dir)

if not os.path.exists(original\_successful\_dir):

    os.makedirs(original\_successful\_dir)

# Function to generate a unique filename

def get\_unique\_filename(base\_path, filename):

    base, ext = os.path.splitext(filename)  # Split into name and extension (e.g., "hanni\_001", ".jpg")

    # Extract the original number (e.g., "001" from "hanni\_001")

    prefix, num = base.rsplit("\_", 1) if "\_" in base and base.rsplit("\_", 1)[-1].isdigit() else (base, "0")

    counter = 1

    new\_filename = filename

    new\_path = os.path.join(base\_path, new\_filename)

    while os.path.exists(new\_path):

        new\_filename = f"{prefix}\_{counter}\_{num}{ext}"  # e.g., "hanni\_1\_001.jpg"

        new\_path = os.path.join(base\_path, new\_filename)

        counter += 1

    return new\_filename

# Function to crop face from an image

def crop\_face(image\_path, output\_path, original\_output\_path):

    # Read the image

    img = cv2.imread(image\_path)

    if img is None:

        print(f"Failed to load {image\_path}")

        return False

    # Convert to RGB (MTCNN expects RGB)

    img\_rgb = cv2.cvtColor(img, cv2.COLOR\_BGR2RGB)

    # Detect faces

    faces = detector.detect\_faces(img\_rgb)

    if len(faces) == 0:

        print(f"No face detected in {image\_path}")

        return False

    # Use the first detected face (assume one face per image)

    face = faces[0]

    x, y, w, h = face['box']

    # Add padding around the face (20% of the bounding box size)

    padding = int(max(w, h) \* 0.2)

    x = max(0, x - padding)

    y = max(0, y - padding)

    w = min(img.shape[1] - x, w + 2 \* padding)

    h = min(img.shape[0] - y, h + 2 \* padding)

    # Crop the face

    cropped = img[y:y+h, x:x+w]

    # Save the cropped image with unique name

    unique\_output\_filename = get\_unique\_filename(os.path.dirname(output\_path), os.path.basename(output\_path))

    unique\_output\_path = os.path.join(os.path.dirname(output\_path), unique\_output\_filename)

    cv2.imwrite(unique\_output\_path, cropped)

    # Copy the original image with unique name

    unique\_original\_filename = get\_unique\_filename(os.path.dirname(original\_output\_path), os.path.basename(original\_output\_path))

    unique\_original\_output\_path = os.path.join(os.path.dirname(original\_output\_path), unique\_original\_filename)

    shutil.copy2(image\_path, unique\_original\_output\_path)

    if unique\_output\_filename != os.path.basename(output\_path):

        print(f"  Renamed {os.path.basename(output\_path)} to {unique\_output\_filename} in cropped folder")

    if unique\_original\_filename != os.path.basename(original\_output\_path):

        print(f"  Renamed {os.path.basename(original\_output\_path)} to {unique\_original\_filename} in original folder")

    return True

# Process specified members

total\_successful\_crops = 0

total\_failed\_crops = 0

for member\_to\_process in members\_to\_process:

    member\_input\_path = os.path.join(input\_root\_dir, member\_to\_process)

    member\_output\_path = os.path.join(output\_root\_dir, member\_to\_process)

    original\_member\_output\_path = os.path.join(original\_successful\_dir, member\_to\_process)

    if os.path.isdir(member\_input\_path):

        # Create output folders

        if not os.path.exists(member\_output\_path):

            os.makedirs(member\_output\_path)

        if not os.path.exists(original\_member\_output\_path):

            os.makedirs(original\_member\_output\_path)

        print(f"Processing {member\_to\_process}...")

        total\_images = 0

        successful\_crops = 0

        failed\_crops = 0

        # Loop through images

        for filename in os.listdir(member\_input\_path):

            if filename.lower().endswith(image\_extensions):

                total\_images += 1

                input\_path = os.path.join(member\_input\_path, filename)

                output\_path = os.path.join(member\_output\_path, filename)

                original\_output\_path = os.path.join(original\_member\_output\_path, filename)

                # Crop and save the face

                if crop\_face(input\_path, output\_path, original\_output\_path):

                    successful\_crops += 1

                else:

                    failed\_crops += 1

        # Update global counts

        total\_successful\_crops += successful\_crops

        total\_failed\_crops += failed\_crops

        # Print results for this member

        print(f"  {member\_to\_process}: {successful\_crops}/{total\_images} images cropped successfully")

        print(f"  Successful crops: {successful\_crops}")

        print(f"  Failed crops: {failed\_crops}\n")

    else:

        print(f"Folder {member\_to\_process} not found in {input\_root\_dir}")

# Print overall results

print(f"Overall results:")

print(f"  Total successful crops: {total\_successful\_crops}")

print(f"  Total failed crops: {total\_failed\_crops}")

print("Face cropping completed!")

The second one is the code for HOG+SVM

import cv2

import numpy as np

from skimage.feature import hog

from sklearn.model\_selection import StratifiedKFold, cross\_val\_score, cross\_val\_predict

from sklearn.svm import SVC

from sklearn.metrics import classification\_report, confusion\_matrix

import matplotlib.pyplot as plt

import os

from glob import glob

import random

import shutil

# Set random seed for reproducibility

random\_seed = 722

random.seed(random\_seed)

np.random.seed(random\_seed)

# Path to your dataset

dataset\_path = "NJZ\_cropped\_faces\_dataset"

# Define the members

members = ["Danielle", "Hanni", "Minji", "Hyein", "Haerin"]

# Store images and labels

images = []

labels = []

file\_paths = []

# Load images for each member

for idx, member in enumerate(members):

    member\_path = os.path.join(dataset\_path, member)

    image\_paths = glob(os.path.join(member\_path, "\*.jpg"))

    # Randomly select 180 images per member

    if len(image\_paths) > 180:

        image\_paths = random.sample(image\_paths, 180)

    for img\_path in image\_paths:

        # Read image

        img = cv2.imread(img\_path)

        img = cv2.cvtColor(img, cv2.COLOR\_BGR2GRAY)  # Convert to grayscale

        img = cv2.resize(img, (64, 64))  # Resize to consistent dimensions

        # Append image, label, and file path

        images.append(img)

        labels.append(idx)

        file\_paths.append(img\_path)

# Convert to numpy arrays

images = np.array(images)

labels = np.array(labels)

file\_paths = np.array(file\_paths)

# Extract HOG features

print("Extracting HOG features...")

hog\_features = []

for image in images:

    features = hog(image, orientations=9, pixels\_per\_cell=(8, 8),

                   cells\_per\_block=(2, 2), visualize=False)

    hog\_features.append(features)

hog\_features = np.array(hog\_features)

# Perform cross-validation

print("Performing 5-fold cross-validation...")

cv = StratifiedKFold(n\_splits=5, shuffle=True, random\_state=random\_seed)

svm = SVC(kernel='linear', probability=True, random\_state=random\_seed)

# Cross-validation scores (accuracy)

cv\_scores = cross\_val\_score(svm, hog\_features, labels, cv=cv, scoring='accuracy')

print(f"Cross-validation scores: {cv\_scores}")

print(f"Mean CV accuracy: {cv\_scores.mean():.4f} ± {cv\_scores.std():.4f}")

# After computing cv\_scores

from sklearn.model\_selection import cross\_val\_predict

# Get predictions across all folds

y\_pred\_all = cross\_val\_predict(svm, hog\_features, labels, cv=cv)

# Overall classification report

print("\nOverall Classification Report:")

print(classification\_report(labels, y\_pred\_all, target\_names=members))

# Overall confusion matrix

overall\_cm = confusion\_matrix(labels, y\_pred\_all)

print("\nOverall Confusion Matrix:")

print(overall\_cm)

# Visualize

plt.figure(figsize=(8, 6))

plt.imshow(overall\_cm, interpolation='nearest', cmap=plt.cm.Blues)

plt.title("Overall Confusion Matrix (SVM)")

plt.colorbar()

tick\_marks = np.arange(len(members))

plt.xticks(tick\_marks, members, rotation=45)

plt.yticks(tick\_marks, members)

plt.ylabel('True Label')

plt.xlabel('Predicted Label')

plt.tight\_layout()

plt.show()

the third one is for CNN:

import os

import cv2

import numpy as np

import matplotlib.pyplot as plt

from glob import glob

import random

import shutil

from sklearn.model\_selection import StratifiedKFold

from sklearn.metrics import classification\_report, confusion\_matrix

import tensorflow as tf

from tensorflow.keras.models import Sequential

from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense, Dropout

from tensorflow.keras.preprocessing.image import ImageDataGenerator

from tensorflow.keras.optimizers import Adam

from tensorflow.keras.utils import to\_categorical

from tensorflow.keras.callbacks import EarlyStopping

# Set random seed for reproducibility

random\_seed = 42

random.seed(random\_seed)

np.random.seed(random\_seed)

tf.random.set\_seed(random\_seed)

# Path to your dataset

dataset\_path = "NJZ\_cropped\_faces\_dataset"

# Define the members

members = ["Danielle", "Hanni", "Minji", "Hyein", "Haerin"]

# Store images and labels

images = []

labels = []

file\_paths = []

# Load images for each member

for idx, member in enumerate(members):

    member\_path = os.path.join(dataset\_path, member)

    image\_paths = glob(os.path.join(member\_path, "\*.jpg"))

    # Randomly select 180 images per member

    if len(image\_paths) > 180:

        image\_paths = random.sample(image\_paths, 180)

    for img\_path in image\_paths:

        img = cv2.imread(img\_path)

        img = cv2.cvtColor(img, cv2.COLOR\_BGR2RGB)

        img = cv2.resize(img, (128, 128))

        images.append(img)

        labels.append(idx)

        file\_paths.append(img\_path)

# Convert to numpy arrays

images = np.array(images)

labels = np.array(labels)

file\_paths = np.array(file\_paths)

# Normalize pixel values to 0-1

images = images / 255.0

# Function to create CNN model

def create\_model():

    model = Sequential([

        Conv2D(32, (3, 3), activation='relu', padding='same', input\_shape=(128, 128, 3)),

        Conv2D(32, (3, 3), activation='relu', padding='same'),

        MaxPooling2D((2, 2)),

        Dropout(0.25),

        Conv2D(64, (3, 3), activation='relu', padding='same'),

        Conv2D(64, (3, 3), activation='relu', padding='same'),

        MaxPooling2D((2, 2)),

        Dropout(0.25),

        Conv2D(128, (3, 3), activation='relu', padding='same'),

        Conv2D(128, (3, 3), activation='relu', padding='same'),

        MaxPooling2D((2, 2)),

        Dropout(0.25),

        Flatten(),

        Dense(256, activation='relu'),

        Dropout(0.5),

        Dense(5, activation='softmax')

    ])

    model.compile(

        optimizer=Adam(learning\_rate=0.0001),

        loss='categorical\_crossentropy',

        metrics=['accuracy']

    )

    return model

# Perform cross-validation

cv = StratifiedKFold(n\_splits=5, shuffle=True, random\_state=random\_seed)

cv\_scores = []

all\_y\_true = []

all\_y\_pred = []

print("Performing 5-fold cross-validation...")

for fold, (train\_idx, val\_idx) in enumerate(cv.split(images, labels)):

    print(f"\nFold {fold+1}/5")

    # Split data

    X\_train\_fold, X\_val\_fold = images[train\_idx], images[val\_idx]

    y\_train\_fold, y\_val\_fold = labels[train\_idx], labels[val\_idx]

    # Convert to one-hot encoding

    y\_train\_fold\_onehot = to\_categorical(y\_train\_fold, num\_classes=5)

    y\_val\_fold\_onehot = to\_categorical(y\_val\_fold, num\_classes=5)

    # Create data augmentation

    datagen = ImageDataGenerator(

        rotation\_range=20,

        width\_shift\_range=0.2,

        height\_shift\_range=0.2,

        shear\_range=0.2,

        zoom\_range=0.2,

        horizontal\_flip=True,

        fill\_mode='nearest'

    )

    # Create and train model

    model = create\_model()

    # Early stopping

    early\_stopping = EarlyStopping(

        monitor='val\_accuracy',

        patience=5,

        restore\_best\_weights=True

    )

    # Train model

    history = model.fit(

        datagen.flow(X\_train\_fold, y\_train\_fold\_onehot, batch\_size=32),

        epochs=15,

        validation\_data=(X\_val\_fold, y\_val\_fold\_onehot),

        callbacks=[early\_stopping],

        verbose=1

    )

    # Evaluate model

    val\_loss, val\_acc = model.evaluate(X\_val\_fold, y\_val\_fold\_onehot, verbose=0)

    cv\_scores.append(val\_acc)

    print(f"Validation accuracy: {val\_acc:.4f}")

    # Get predictions for this fold

    y\_pred\_proba = model.predict(X\_val\_fold)

    y\_pred = np.argmax(y\_pred\_proba, axis=1)  # Convert probabilities to class labels

    y\_true = y\_val\_fold  # True labels (not one-hot encoded)

    # Store true and predicted labels for overall metrics

    all\_y\_true.extend(y\_true)

    all\_y\_pred.extend(y\_pred)

    # Per-fold classification report

    print(f"\nClassification Report for Fold {fold+1}:")

    print(classification\_report(y\_true, y\_pred, target\_names=members))

    # Per-fold confusion matrix

    cm = confusion\_matrix(y\_true, y\_pred)

    print(f"Confusion Matrix for Fold {fold+1}:\n{cm}")

# Print cross-validation results

print("\nCross-validation results:")

for i, score in enumerate(cv\_scores):

    print(f"Fold {i+1}: {score:.4f}")

print(f"Mean CV accuracy: {np.mean(cv\_scores):.4f} ± {np.std(cv\_scores):.4f}")

# Overall classification report across all folds

print("\nOverall Classification Report:")

print(classification\_report(all\_y\_true, all\_y\_pred, target\_names=members))

# Overall confusion matrix across all folds

overall\_cm = confusion\_matrix(all\_y\_true, all\_y\_pred)

print("\nOverall Confusion Matrix:")

print(overall\_cm)

# Optional: Visualize the overall confusion matrix

plt.figure(figsize=(8, 6))

plt.imshow(overall\_cm, interpolation='nearest', cmap=plt.cm.Blues)

plt.title("Overall Confusion Matrix")

plt.colorbar()

tick\_marks = np.arange(len(members))

plt.xticks(tick\_marks, members, rotation=45)

plt.yticks(tick\_marks, members)

plt.ylabel('True Label')

plt.xlabel('Predicted Label')

plt.tight\_layout()

plt.show()

the fourth one is for K-means:

import os

import cv2

import numpy as np

import matplotlib.pyplot as plt

from glob import glob

import random

from sklearn.cluster import KMeans

from sklearn.metrics import adjusted\_rand\_score, normalized\_mutual\_info\_score, confusion\_matrix

from scipy.optimize import linear\_sum\_assignment

from skimage.feature import hog

# Set random seed for reproducibility

random\_seed = 722

random.seed(random\_seed)

np.random.seed(random\_seed)

# Path to your dataset

dataset\_path = "NJZ\_cropped\_faces\_dataset"

# Define the members

members = ["Danielle", "Hanni", "Minji", "Hyein", "Haerin"]

# Store images and labels

images = []

labels = []

file\_paths = []

# Load images for each member

for idx, member in enumerate(members):

    member\_path = os.path.join(dataset\_path, member)

    image\_paths = glob(os.path.join(member\_path, "\*.jpg"))

    # Randomly select 180 images per member

    if len(image\_paths) > 180:

        image\_paths = random.sample(image\_paths, 180)

    for img\_path in image\_paths:

        img = cv2.imread(img\_path)

        img = cv2.cvtColor(img, cv2.COLOR\_BGR2GRAY)

        img = cv2.resize(img, (128, 128))

        images.append(img)

        labels.append(idx)

        file\_paths.append(img\_path)

# Convert to numpy arrays

images = np.array(images)

labels = np.array(labels)

file\_paths = np.array(file\_paths)

# Extract HOG features

print("Extracting HOG features...")

hog\_features = []

for image in images:

    features = hog(image, orientations=9, pixels\_per\_cell=(8, 8),

                   cells\_per\_block=(2, 2), visualize=False)

    hog\_features.append(features)

hog\_features = np.array(hog\_features)

# Perform K-Means clustering

print("Performing K-Means clustering...")

kmeans = KMeans(n\_clusters=5, random\_state=random\_seed, n\_init=10)

cluster\_labels = kmeans.fit\_predict(hog\_features)

# Evaluation metrics

ari = adjusted\_rand\_score(labels, cluster\_labels)

nmi = normalized\_mutual\_info\_score(labels, cluster\_labels)

print(f"\nEvaluation Metrics:")

print(f"Adjusted Rand Index (ARI): {ari:.4f}")

print(f"Normalized Mutual Information (NMI): {nmi:.4f}")

# Compute initial confusion matrix (before alignment)

cm\_initial = confusion\_matrix(labels, cluster\_labels)

print("\nInitial Confusion Matrix (True Labels vs. Cluster Labels, Unaligned):")

print(cm\_initial)

# Align cluster labels with true labels using the Hungarian algorithm

def align\_labels(true\_labels, cluster\_labels):

    cm = confusion\_matrix(true\_labels, cluster\_labels)

    row\_ind, col\_ind = linear\_sum\_assignment(-cm)  # Maximize diagonal by minimizing -cm

    label\_mapping = {old\_label: new\_label for old\_label, new\_label in zip(col\_ind, row\_ind)}

    aligned\_labels = np.array([label\_mapping[label] for label in cluster\_labels])

    return aligned\_labels

# Get aligned cluster labels

aligned\_cluster\_labels = align\_labels(labels, cluster\_labels)

# Compute aligned confusion matrix

cm\_aligned = confusion\_matrix(labels, aligned\_cluster\_labels)

print("\nAligned Confusion Matrix (True Labels vs. Aligned Cluster Labels):")

print(cm\_aligned)

# Compute clustering accuracy based on aligned labels

clustering\_accuracy = np.sum(np.diag(cm\_aligned)) / np.sum(cm\_aligned)

print(f"\nClustering Accuracy (after alignment): {clustering\_accuracy:.4f}")

# Visualize the aligned confusion matrix

plt.figure(figsize=(8, 6))

plt.imshow(cm\_aligned, interpolation='nearest', cmap=plt.cm.Blues)

plt.title("Aligned Confusion Matrix (K-Means Clustering)")

plt.colorbar()

tick\_marks = np.arange(len(members))

plt.xticks(tick\_marks, members, rotation=45)

plt.yticks(tick\_marks, members)

plt.ylabel('True Label')

plt.xlabel('Aligned Cluster Label')

plt.tight\_layout()

plt.show()

# Analyze cluster composition

print("\nCluster Composition (Number of samples per cluster):")

unique, counts = np.unique(cluster\_labels, return\_counts=True)

for cluster, count in zip(unique, counts):

    print(f"Cluster {cluster}: {count} samples")

the fifth one is for experiment one, dataset difference:

import cv2

import numpy as np

from skimage.feature import hog

from sklearn.model\_selection import StratifiedKFold, cross\_val\_score, cross\_val\_predict

from sklearn.svm import SVC

from sklearn.metrics import classification\_report, confusion\_matrix

import matplotlib.pyplot as plt

import os

from glob import glob

import random

# Set random seed for reproducibility

random\_seed = 722

random.seed(random\_seed)

np.random.seed(random\_seed)

# Path to your dataset

dataset\_path = "NJZ\_cropped\_faces\_dataset"

# Define the members

members = ["Danielle", "Hanni", "Minji", "Hyein", "Haerin"]

# Dataset sizes to experiment with (images per member)

dataset\_sizes = [50, 100, 150, 180]

# Function to load data with a specified size per member

def load\_data(size\_per\_member):

    images = []

    labels = []

    file\_paths = []

    for idx, member in enumerate(members):

        member\_path = os.path.join(dataset\_path, member)

        image\_paths = glob(os.path.join(member\_path, "\*.jpg"))

        # Randomly select the specified number of images per member

        if len(image\_paths) > size\_per\_member:

            image\_paths = random.sample(image\_paths, size\_per\_member)

        for img\_path in image\_paths:

            img = cv2.imread(img\_path)

            img = cv2.cvtColor(img, cv2.COLOR\_BGR2GRAY)

            img = cv2.resize(img, (64,64))

            images.append(img)

            labels.append(idx)

            file\_paths.append(img\_path)

    return np.array(images), np.array(labels), np.array(file\_paths)

# Function to extract HOG features

def extract\_hog\_features(images):

    print("Extracting HOG features...")

    hog\_features = []

    for image in images:

        features = hog(image, orientations=9, pixels\_per\_cell=(8, 8),

                       cells\_per\_block=(2, 2), visualize=False)

        hog\_features.append(features)

    return np.array(hog\_features)

# Store results

results = {}

# Perform experiment for each dataset size

for size in dataset\_sizes:

    print(f"\n=== Experiment with {size} images per member (Total: {size \* len(members)} images) ===")

    # Load data for this size

    images, labels, file\_paths = load\_data(size)

    # Extract HOG features

    hog\_features = extract\_hog\_features(images)

    # Perform cross-validation

    print("Performing 5-fold cross-validation...")

    cv = StratifiedKFold(n\_splits=5, shuffle=True, random\_state=random\_seed)

    svm = SVC(kernel='linear', probability=True, random\_state=random\_seed)

    # Get cross-validation accuracy scores

    cv\_scores = cross\_val\_score(svm, hog\_features, labels, cv=cv, scoring='accuracy')

    print(f"Cross-validation scores: {cv\_scores}")

    print(f"Mean CV accuracy: {cv\_scores.mean():.4f} ± {cv\_scores.std():.4f}")

    # Get predictions for detailed metrics

    y\_pred = cross\_val\_predict(svm, hog\_features, labels, cv=cv)

    # Compute and print classification report

    print("\nClassification Report:")

    report = classification\_report(labels, y\_pred, target\_names=members, output\_dict=True)

    print(classification\_report(labels, y\_pred, target\_names=members))

    # Compute confusion matrix

    cm = confusion\_matrix(labels, y\_pred)

    print("\nConfusion Matrix:")

    print(cm)

    # Store results

    results[size] = {

        'accuracy': cv\_scores.mean(),

        'std': cv\_scores.std(),

        'precision': [report[member]['precision'] for member in members],

        'recall': [report[member]['recall'] for member in members],

        'f1': [report[member]['f1-score'] for member in members],

        'confusion\_matrix': cm

    }

    # Visualize confusion matrix

    plt.figure(figsize=(8, 6))

    plt.imshow(cm, interpolation='nearest', cmap=plt.cm.Blues)

    plt.title(f"Confusion Matrix (HOG+SVM, {size} images per member)")

    plt.colorbar()

    tick\_marks = np.arange(len(members))

    plt.xticks(tick\_marks, members, rotation=45)

    plt.yticks(tick\_marks, members)

    plt.ylabel('True Label')

    plt.xlabel('Predicted Label')

    plt.tight\_layout()

    plt.show()

# Summarize results

print("\n=== Summary of Results ===")

for size in dataset\_sizes:

    print(f"\nDataset Size: {size} images per member (Total: {size \* len(members)})")

    print(f"Mean CV Accuracy: {results[size]['accuracy']:.4f} ± {results[size]['std']:.4f}")

    print("Per-class Precision:", [f"{x:.4f}" for x in results[size]['precision']])

    print("Per-class Recall:", [f"{x:.4f}" for x in results[size]['recall']])

    print("Per-class F1-score:", [f"{x:.4f}" for x in results[size]['f1']])

# Plot accuracy vs. dataset size

plt.figure(figsize=(8, 5))

accuracies = [results[size]['accuracy'] for size in dataset\_sizes]

stds = [results[size]['std'] for size in dataset\_sizes]

plt.errorbar(dataset\_sizes, accuracies, yerr=stds, fmt='-o', capsize=5)

plt.title("Mean CV Accuracy vs. Dataset Size (HOG+SVM)")

plt.xlabel("Images per Member")

plt.ylabel("Mean CV Accuracy")

plt.grid(True)

plt.show()

the sixth one is for experiment two, SMOTE oversampling:

import cv2

import numpy as np

from skimage.feature import hog

from sklearn.model\_selection import StratifiedKFold, cross\_val\_score, cross\_val\_predict

from sklearn.svm import SVC

from sklearn.metrics import classification\_report, confusion\_matrix

from imblearn.over\_sampling import SMOTE

import matplotlib.pyplot as plt

import os

from glob import glob

import random

# Set random seed for reproducibility

random\_seed = 722

random.seed(random\_seed)

np.random.seed(random\_seed)

# Path to your dataset

dataset\_path = "NJZ\_cropped\_faces\_dataset"

# Define the members

members = ["Danielle", "Hanni", "Minji", "Hyein", "Haerin"]

# Target size for oversampling (based on largest class, e.g., Minji/Haerin)

target\_size\_per\_member = 300

# Store images and labels

images = []

labels = []

file\_paths = []

# Load all available images for each member

for idx, member in enumerate(members):

    member\_path = os.path.join(dataset\_path, member)

    image\_paths = glob(os.path.join(member\_path, "\*.jpg"))

    # No cap; use all available images

    print(f"Loaded {len(image\_paths)} images for {member}")

    for img\_path in image\_paths:

        img = cv2.imread(img\_path)

        img = cv2.cvtColor(img, cv2.COLOR\_BGR2GRAY)

        img = cv2.resize(img, (64,64))

        images.append(img)

        labels.append(idx)

        file\_paths.append(img\_path)

# Convert to numpy arrays

images = np.array(images)

labels = np.array(labels)

file\_paths = np.array(file\_paths)

# Extract HOG features

print("\nExtracting HOG features...")

hog\_features = []

for image in images:

    features = hog(image, orientations=9, pixels\_per\_cell=(8, 8),

                   cells\_per\_block=(2, 2), visualize=False)

    hog\_features.append(features)

hog\_features = np.array(hog\_features)

# Apply SMOTE to balance the dataset

print(f"\nApplying SMOTE to oversample to {target\_size\_per\_member} images per member...")

smote = SMOTE(sampling\_strategy={i: target\_size\_per\_member for i in range(len(members))},

              random\_state=random\_seed)

hog\_features\_smote, labels\_smote = smote.fit\_resample(hog\_features, labels)

# Check new dataset size

print(f"New dataset size after SMOTE: {len(labels\_smote)} samples")

unique, counts = np.unique(labels\_smote, return\_counts=True)

for member\_idx, count in zip(unique, counts):

    print(f"{members[member\_idx]}: {count} samples")

# Perform cross-validation on SMOTE-balanced data

print("\nPerforming 5-fold cross-validation on SMOTE-balanced data...")

cv = StratifiedKFold(n\_splits=5, shuffle=True, random\_state=random\_seed)

svm = SVC(kernel='linear', probability=True, random\_state=random\_seed)

# Get cross-validation accuracy scores

cv\_scores = cross\_val\_score(svm, hog\_features\_smote, labels\_smote, cv=cv, scoring='accuracy')

print(f"Cross-validation scores: {cv\_scores}")

print(f"Mean CV accuracy: {cv\_scores.mean():.4f} ± {cv\_scores.std():.4f}")

# Get predictions for detailed metrics

y\_pred = cross\_val\_predict(svm, hog\_features\_smote, labels\_smote, cv=cv)

# Compute and print classification report

print("\nClassification Report:")

report = classification\_report(labels\_smote, y\_pred, target\_names=members, output\_dict=True)

print(classification\_report(labels\_smote, y\_pred, target\_names=members))

# Compute confusion matrix

cm = confusion\_matrix(labels\_smote, y\_pred)

print("\nConfusion Matrix:")

print(cm)

# Visualize confusion matrix

plt.figure(figsize=(8, 6))

plt.imshow(cm, interpolation='nearest', cmap=plt.cm.Blues)

plt.title("Confusion Matrix (HOG+SVM with SMOTE)")

plt.colorbar()

tick\_marks = np.arange(len(members))

plt.xticks(tick\_marks, members, rotation=45)

plt.yticks(tick\_marks, members)

plt.ylabel('True Label')

plt.xlabel('Predicted Label')

plt.tight\_layout()

plt.show()

# Summarize per-class metrics

print("\nPer-class Metrics Summary:")

print("Precision:", [f"{report[member]['precision']:.4f}" for member in members])

print("Recall:", [f"{report[member]['recall']:.4f}" for member in members])

print("F1-score:", [f"{report[member]['f1-score']:.4f}" for member in members])

the seventh one is for experiment three, pca:

import cv2

import numpy as np

from skimage.feature import hog

from sklearn.model\_selection import StratifiedKFold, cross\_val\_score, cross\_val\_predict

from sklearn.svm import SVC

from sklearn.metrics import classification\_report

from sklearn.decomposition import PCA

from imblearn.over\_sampling import SMOTE

import matplotlib.pyplot as plt

import os

from glob import glob

import random

# Set random seed for reproducibility

random\_seed = 722

random.seed(random\_seed)

np.random.seed(random\_seed)

# Path to your dataset

dataset\_path = "NJZ\_cropped\_faces\_dataset"

# Define the members

members = ["Danielle", "Hanni", "Minji", "Hyein", "Haerin"]

# PCA components to test

# pca\_components = [50, 100, 200, 400, 800, 1600, 3200, None]  # Expanded list

pca\_components = [20, 50, 100, 200, 400, 600, 800, 1000, 1200, None]

# Target size for oversampling (based on largest class, e.g., Minji/Haerin)

target\_size\_per\_member = 300

# Store images and labels

images = []

labels = []

file\_paths = []

# Load all available images for each member

for idx, member in enumerate(members):

    member\_path = os.path.join(dataset\_path, member)

    image\_paths = glob(os.path.join(member\_path, "\*.jpg"))

    # Use all available images (no cap)

    print(f"Loaded {len(image\_paths)} images for {member}")

    for img\_path in image\_paths:

        img = cv2.imread(img\_path)

        img = cv2.cvtColor(img, cv2.COLOR\_BGR2GRAY)

        img = cv2.resize(img, (64, 64))

        images.append(img)

        labels.append(idx)

        file\_paths.append(img\_path)

# Convert to numpy arrays

images = np.array(images)

labels = np.array(labels)

file\_paths = np.array(file\_paths)

# Extract HOG features

print("\nExtracting HOG features...")

hog\_features = []

for image in images:

    features = hog(image, orientations=9, pixels\_per\_cell=(8, 8),

                   cells\_per\_block=(2, 2), visualize=False)

    hog\_features.append(features)

hog\_features = np.array(hog\_features)

print(f"Original HOG feature dimensionality: {hog\_features.shape[1]}")

# Apply SMOTE to balance the dataset

print(f"\nApplying SMOTE to oversample to {target\_size\_per\_member} images per member...")

smote = SMOTE(sampling\_strategy={i: target\_size\_per\_member for i in range(len(members))},

              random\_state=random\_seed)

hog\_features\_smote, labels\_smote = smote.fit\_resample(hog\_features, labels)

# Check new dataset size

print(f"New dataset size after SMOTE: {len(labels\_smote)} samples")

unique, counts = np.unique(labels\_smote, return\_counts=True)

for member\_idx, count in zip(unique, counts):

    print(f"{members[member\_idx]}: {count} samples")

# Store results

results = {}

# Perform experiment for each PCA setting

for n\_components in pca\_components:

    if n\_components is None:

        print(f"\n=== Experiment with full HOG features (no PCA, {hog\_features\_smote.shape[1]} components) ===")

        features = hog\_features\_smote

    else:

        print(f"\n=== Experiment with PCA ({n\_components} components) ===")

        pca = PCA(n\_components=n\_components, random\_state=random\_seed)

        features = pca.fit\_transform(hog\_features\_smote)

        print(f"Explained variance ratio: {np.sum(pca.explained\_variance\_ratio\_):.4f}")

    # Perform cross-validation

    print("Performing 5-fold cross-validation...")

    cv = StratifiedKFold(n\_splits=5, shuffle=True, random\_state=random\_seed)

    svm = SVC(kernel='linear', probability=True, random\_state=random\_seed)

    # Get cross-validation accuracy scores

    cv\_scores = cross\_val\_score(svm, features, labels\_smote, cv=cv, scoring='accuracy')

    print(f"Cross-validation scores: {cv\_scores}")

    print(f"Mean CV accuracy: {cv\_scores.mean():.4f} ± {cv\_scores.std():.4f}")

    # Get predictions for detailed metrics (optional, but not plotted)

    y\_pred = cross\_val\_predict(svm, features, labels\_smote, cv=cv)

    # Compute and print classification report (optional, for reference)

    print("\nClassification Report:")

    print(classification\_report(labels\_smote, y\_pred, target\_names=members))

    # Store results

    results[n\_components if n\_components is not None else 'full'] = {

        'accuracy': cv\_scores.mean(),

        'std': cv\_scores.std()

    }

# Summarize results

print("\n=== Summary of Results ===")

for n\_components in results:

    print(f"\nPCA Components: {n\_components}")

    print(f"Mean CV Accuracy: {results[n\_components]['accuracy']:.4f} ± {results[n\_components]['std']:.4f}")

# Plot accuracy vs. PCA components

plt.figure(figsize=(8, 5))

components\_list = [n if n is not None else hog\_features\_smote.shape[1] for n in pca\_components]

accuracies = [results[n if n is not None else 'full']['accuracy'] for n in pca\_components]

stds = [results[n if n is not None else 'full']['std'] for n in pca\_components]

plt.errorbar(components\_list, accuracies, yerr=stds, fmt='-o', capsize=5)

plt.title("Mean CV Accuracy vs. PCA Components (HOG+SVM, 64x64 with SMOTE)")

plt.xlabel("Number of PCA Components")

plt.ylabel("Mean CV Accuracy")

plt.grid(True)

plt.xticks(components\_list, [str(n) if n is not None else 'Full' for n in pca\_components], rotation=45)

plt.tight\_layout()

plt.show()

=== Thanks TAs! ===

一張含有 微笑, 人員, 人的臉孔, 嘴唇 的圖片

AI 產生的內容可能不正確。

Minji, Hanni, Danielle, Haerin, Hyein