Importing Libraries

```
import numpy as np
import os
import json
from tqdm import tqdm

from skimage.transform import resize
from skimage.feature import hog
from skimage.io import imread
from skimage.filters import gabor

from sklearn.manifold import TSNE
from sklearn.svm import SVC
from sklearn.ensemble import RandomForestClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score, precision_s
from sklearn.model_selection import train_test_split
from sklearn.multioutput import MultiOutputClassifier

import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
```

Extracing both features sequentially in a single function

```
def extract_combined_features(image_path, target_siz  =(
    # Read and preprocess the image
    image = imread(image_path, as_gray=True)
    image_resized = resize(image, target_size, anti_ali

    # Extract HOG features
    hog_features = hog(image_resized, orientations=9, p
                       cells_per_block=(2, 2), block_no

    # Extract Gabor features
    gabor_responses = []
    orientations = [0, np.pi / 4, np.pi / 2, 3 * np.pi
    frequencies = [0.2, 0.4, 0.6, 0.8]
    for theta in orientations:
        for frequency in frequencies:
            filtered, _ = gabor(image_resized, frequenc
            gabor_responses.extend(np.abs(filtered).fla
```

```
    hist, _ = np.histogram(gabor_responses, bins=20, ra
    hist = hist.astype(float) / hist.sum()  # Normalize

    # Combine HOG and Gabor features
    combined_features = np.hstack([hog_features, hist])
    return combined_features
```

```
combined_features = []
labels = []

subject_ids = ['SN001', 'SN002', 'SN003', 'SN004', 'SN0
subject_ids = ['SN001', 'SN002', 'SN003', 'SN026', 'SN0
cropped_dir = "croppedImg"

for subject_id in tqdm(subject_ids, desc="Processing su
    json_file = os.path.join('json', f'{subject_id}.jso
    subject_dir = os.path.join(cropped_dir, subject_id)
    with open(json_file, 'r') as file:
        data = json.load(file)
        for frame_data in data:
            img_path = os.path.join(subject_dir, f"{fra
            if os.path.exists(img_path):
                try:
                    # Extract combined features
                    features = extract_combined_feature
                    combined_features.append(features)
                    # Extract labels (AU intensities) w
                    au_intensities = [frame_data.get(f'
                    labels.append(au_intensities)
                except Exception as e:
                    print(f"Error processing {img_path}
            else:
                print(f"Warning: The file {img_path} do
```

```
Processing subjects: 100%|██████████| 10/10 [1:00:58<00:00,
365.89s/it]
```

Visualizing Dataset using t-SNE

```
X = np.array(combined_features)
y = np.array(labels)
# Simplify or correct y if necessary, here's a hypothet
y_simplified = np.array([labels[0] for labels in y])  #
```

```
# Initialize t-SNE
tsne = TSNE(n_components=2, verbose=1, perplexity=40, n
X_tsne = tsne.fit_transform(X)


sns.set(style="whitegrid")
# Plot the result of t-SNE
plt.figure(figsize=(10, 6))
scatter = plt.scatter(X_tsne[:, 0], X_tsne[:, 1], c=y_s
plt.colorbar(scatter)
plt.title('t-SNE visualization of Combined Features')
plt.xlabel('Dimension 1')
plt.ylabel('Dimension 2')
plt.show()
```

```
/opt/homebrew/lib/python3.10/site-
packages/sklearn/manifold/_t_sne.py:800: FutureWarning: The
default initialization in TSNE will change from 'random' to
'pca' in 1.2.
  warnings.warn(
/opt/homebrew/lib/python3.10/site-
packages/sklearn/manifold/_t_sne.py:810: FutureWarning: The
default learning rate in TSNE will change from 200.0 to 'auto'
in 1.2.
  warnings.warn(

[t-SNE] Computing 121 nearest neighbors...
[t-SNE] Indexed 48450 samples in 0.074s...
[t-SNE] Computed neighbors for 48450 samples in 401.643s...
[t-SNE] Computed conditional probabilities for sample 1000 /
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[t-SNE] Computed conditional probabilities for sample 2000 /
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[t-SNE] Computed conditional probabilities for sample 3000 /
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[t-SNE] Computed conditional probabilities for sample 4000 /
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[t-SNE] Computed conditional probabilities for sample 7000 /
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[t-SNE] Computed conditional probabilities for sample 8000 /
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[t-SNE] Computed conditional probabilities for sample 9000 /
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[t-SNE] Computed conditional probabilities for sample 10000 /
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```
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[t-SNE] Computed conditional probabilities for sample 11000 /
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[t-SNE] Computed conditional probabilities for sample 12000 /
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[t-SNE] Computed conditional probabilities for sample 13000 /
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[t-SNE] Computed conditional probabilities for sample 35000 /
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[t-SNE] Computed conditional probabilities for sample 37000 /
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[t-SNE] Computed conditional probabilities for sample 41000 /
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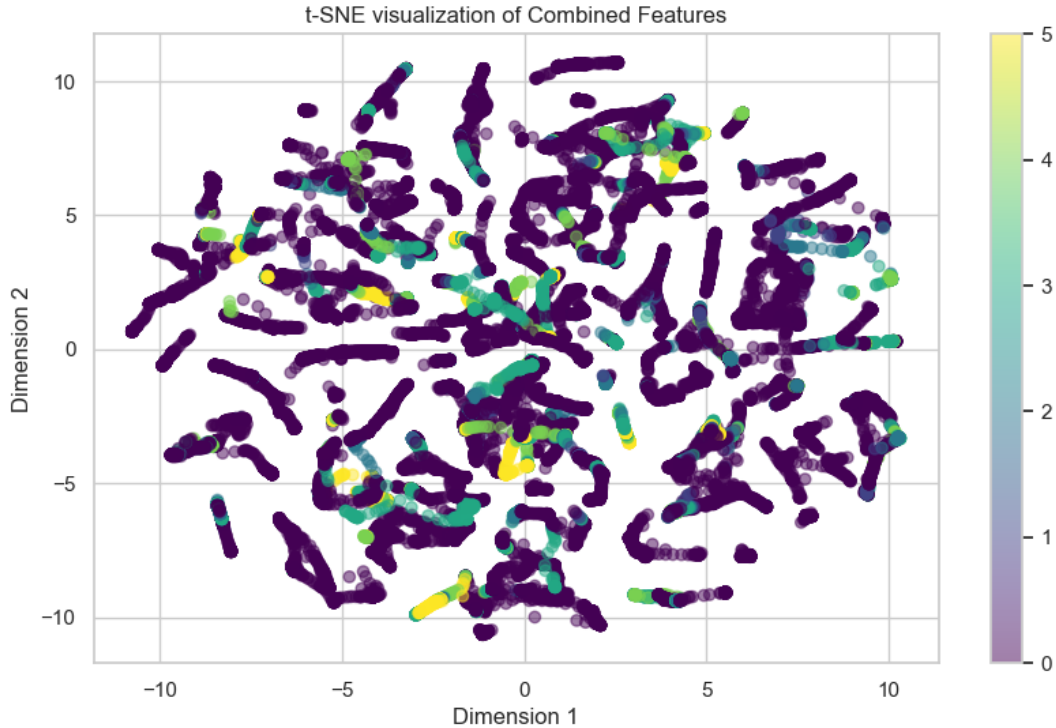
[t-SNE] Computed conditional probabilities for sample 47000 /
48450
[t-SNE] Computed conditional probabilities for sample 48000 /
48450
[t-SNE] Computed conditional probabilities for sample 48450 /
48450
[t-SNE] Mean sigma: 0.801275
[t-SNE] KL divergence after 250 iterations with early
exaggeration: 77.826805
[t-SNE] KL divergence after 300 iterations: 3.737837
```



Transforming the data using MultiLabelBinarizer

```
X_train, X_test, y_train, y_test = train_test_split( X,

from sklearn.preprocessing import MultiLabelBinarizer

mlb = MultiLabelBinarizer()
y_train = mlb.fit_transform(y_train)
y_test = mlb.transform(y_test)
```

Comparing RF and KNN

```
# Wrap classifiers to handle multi-label data
multi_target_rf = RandomForestClassifier()
multi_target_knn = MultiOutputClassifier(KNeighborsClas

models = {
    'Random Forest': multi_target_rf,
    'KNN': multi_target_knn
}

results = {}
for name, model in models.items():
    model.fit(X_train, y_train)
```

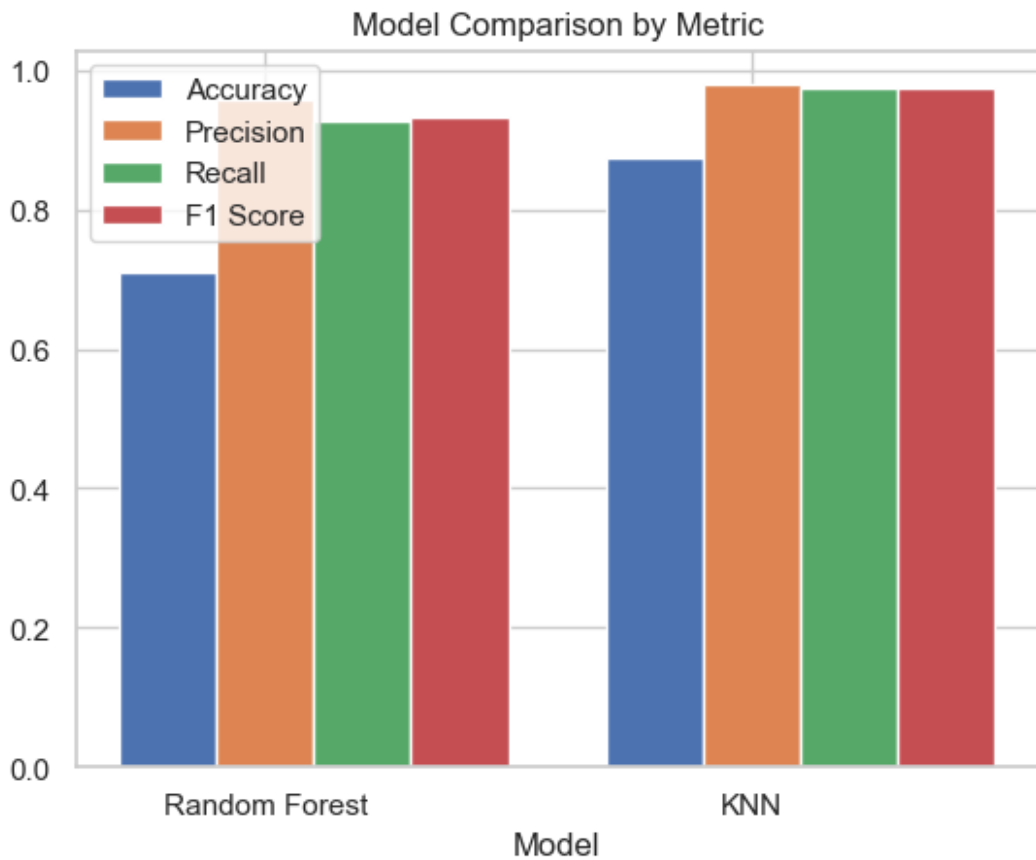
```python
        y_pred = model.predict(X_test)
        results[name] = {
            'Accuracy': accuracy_score(y_test, y_pred),  #
            'Precision': precision_score(y_test, y_pred, av
            'Recall': recall_score(y_test, y_pred, average=
            'F1 Score': f1_score(y_test, y_pred, average='s
        }

    # Visualization remains the same
    n_groups = len(results)
    index = np.arange(n_groups)
    bar_width = 0.2

    # Create the plot
    fig, ax = plt.subplots()
    for i, metric in enumerate(['Accuracy', 'Precision', 'R
        scores = [results[model][metric] for model in model
        ax.bar(index + i * bar_width, scores, bar_width, la

    ax.set_xlabel('Model')
    ax.set_title('Model Comparison by Metric')
    ax.set_xticks(index + bar_width)
    ax.set_xticklabels(models.keys())
    ax.legend()

    plt.show()
```



Running Random Forest Classifier

```
# Initialize and train the Random Forest model
rf_model = RandomForestClassifier()
rf_model.fit(X_train, y_train)

# Predict on the test set
y_pred = rf_model.predict(X_test)

# Initialize dictionaries to store the metrics
accuracy_scores = {}
precision_scores = {}
recall_scores = {}
f1_scores = {}

# Calculate metrics for each AU
for i, class_label in enumerate(mlb.classes_):
    accuracy_scores[class_label] = accuracy_score(y_tes
    precision_scores[class_label] = precision_score(y_t
    recall_scores[class_label] = recall_score(y_test[:,
    f1_scores[class_label] = f1_score(y_test[:, i], y_p
```

```
        # Calculate average metrics across all AUs
        average_accuracy = np.mean(list(accuracy_scores.values(
        average_precision = np.mean([score for score in precisi
        average_recall = np.mean([score for score in recall_sco
        average_f1 = np.mean([score for score in f1_scores.valu

        # Print or return the results
        print("Accuracy per AU:", accuracy_scores)
        print("Precision per AU:", precision_scores)
        print("Recall per AU:", recall_scores)
        print("F1 Score per AU:", f1_scores)
        print("Average Accuracy:", average_accuracy)
        print("Average Precision:", average_precision)
        print("Average Recall:", average_recall)
        print("Average F1 Score:", average_f1)
```

```
Accuracy per AU: {0: 1.0, 1: 0.8958376332989336, 2:
0.8972824217406261, 3: 0.9338837289301686, 4:
0.9173718610251118, 5: 0.9679394564843481}
Precision per AU: {0: 1.0, 1: 0.9284827414949094, 2: 0.88, 3:
0.9112132124674035, 4: 0.9721407624633431, 5:
0.9743589743589743}
Recall per AU: {0: 1.0, 1: 0.7530715005035247, 2:
0.9420724094881399, 3: 0.9675632911392406, 4:
0.359349593495935, 5: 0.29185867895545314}
F1 Score per AU: {0: 1.0, 1: 0.8316281138790036, 2:
0.9099788965933072, 3: 0.9385431988233037, 4:
0.5247328848436882, 5: 0.4491725768321513}
Average Accuracy: 0.9353858502465314
Average Precision: 0.9443659484641049
Average Recall: 0.7189859122637156
Average F1 Score: 0.775675945161909
```

Running K-NN Classifier

```
        # Initialize and train the K-Nearest Neighbors model
        knn_model = KNeighborsClassifier()
        knn_model.fit(X_train, y_train)

        # Predict on the test set
        y_pred = knn_model.predict(X_test)

        # Initialize dictionaries to store the metrics
        accuracy_scores = {}
        precision_scores = {}
        recall_scores = {}
```

```
        f1_scores = {}

        # Calculate metrics for each AU
        for i, class_label in enumerate(mlb.classes_):
            accuracy_scores[class_label] = accuracy_score(y_tes
            precision_scores[class_label] = precision_score(y_t
            recall_scores[class_label] = recall_score(y_test[:,
            f1_scores[class_label] = f1_score(y_test[:, i], y_p

        # Calculate average metrics across all AUs
        average_accuracy = np.mean(list(accuracy_scores.values(
        average_precision = np.mean([score for score in precisi
        average_recall = np.mean([score for score in recall_sco
        average_f1 = np.mean([score for score in f1_scores.valu

        # Print or return the results
        print("Accuracy per AU:", accuracy_scores)
        print("Precision per AU:", precision_scores)
        print("Recall per AU:", recall_scores)
        print("F1 Score per AU:", f1_scores)
        print("Average Accuracy:", average_accuracy)
        print("Average Precision:", average_precision)
        print("Average Recall:", average_recall)
        print("Average F1 Score:", average_f1)
```

```
Accuracy per AU: {0: 1.0, 1: 0.9477124183006536, 2:
0.9486068111455108, 3: 0.9785345717234262, 4:
0.9751633986928104, 5: 0.9901616787065703}
Precision per AU: {0: 1.0, 1: 0.9350300020691082, 2:
0.9546763490672343, 3: 0.9787990518830656, 4:
0.9211123723041997, 5: 0.9110032362459547}
Recall per AU: {0: 1.0, 1: 0.9101711983887211, 2:
0.9519350811485643, 3: 0.9800896624472574, 4:
0.8796747967479674, 5: 0.8648233486943164}
F1 Score per AU: {0: 1.0, 1: 0.922433149622372, 2:
0.9533037444520848, 3: 0.9794439320068521, 4:
0.8999168283892431, 5: 0.8873128447596531}
Average Accuracy: 0.9733631464281619
Average Precision: 0.9501035019282603
Average Recall: 0.9311156812378045
Average F1 Score: 0.9404017498717008
```