ML Assign 2

Date	@October 1, 2024

SECTION C

1.

a. Observations on the Number of Images per Class:

1. **Balanced Dataset**:
    - Each class (e.g., sitting, using laptop, hugging, etc.) contains exactly **840 images**.
    - This indicates a well-balanced dataset, which is beneficial for training machine learning models as it helps to mitigate biases toward any specific class.
2. **Class Diversity**:
    - The presence of a variety of actions (e.g., sitting, hugging, dancing, fighting) suggests that the dataset can potentially capture a wide range of human activities.
    - This diversity is important for creating a model that can generalize well to different situations and contexts.

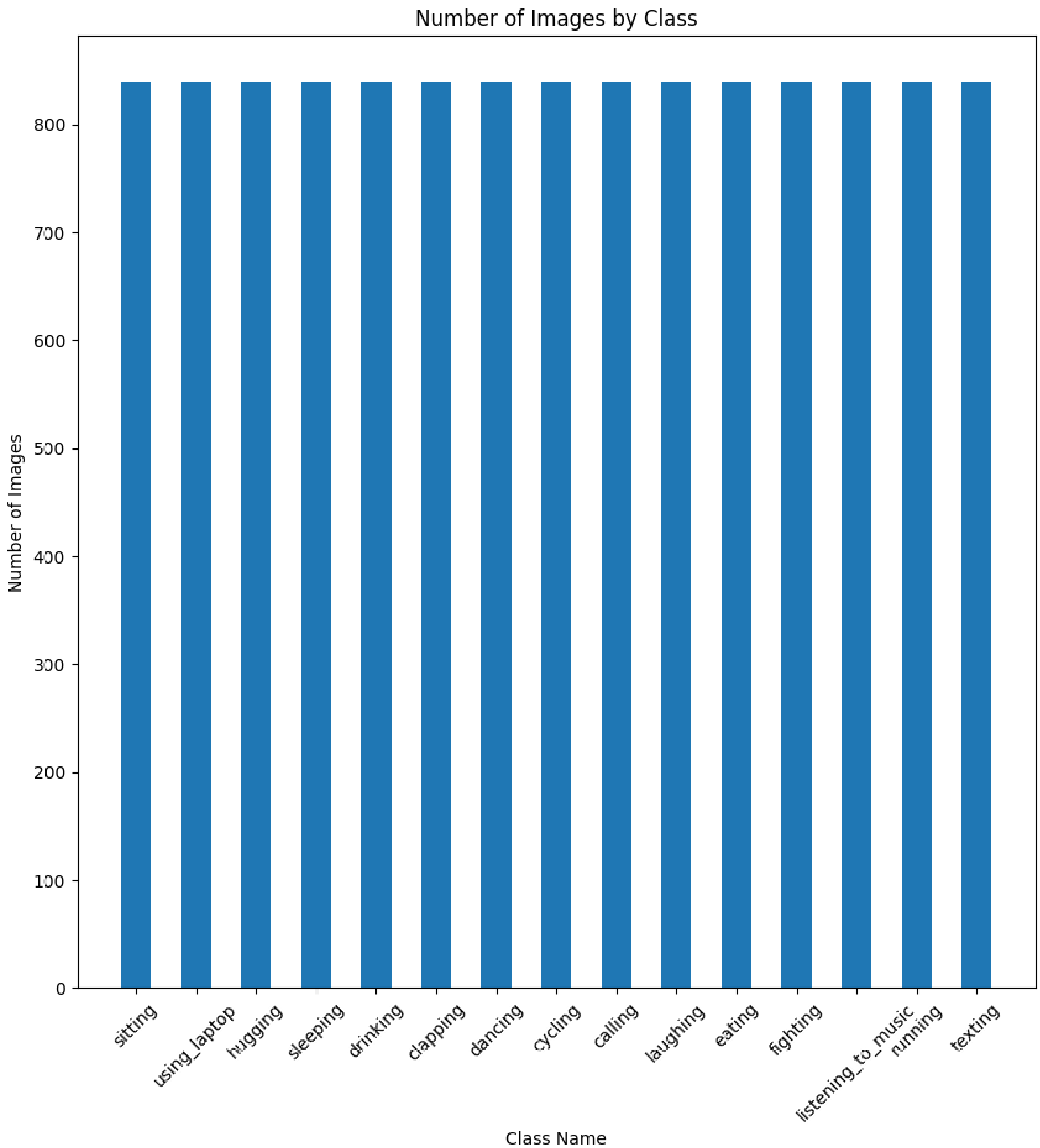
Observations on Image Dimensions:

1. **Image Width and Height Distribution**:
    - The **mean width** is approximately **260 pixels**, while the **mean height** is around **197 pixels**.

- The **standard deviations** of **39.92** (width) and **35.28** (height) indicate some variability in image sizes, but they are relatively small compared to the mean values.

2. **Minimum and Maximum Dimensions**:
   - The **minimum width** and height are both **84 pixels**, which suggests that there are smaller images that might affect the model's performance if they do not contain sufficient detail.
   - The **maximum width** is **478 pixels**, and the maximum height is **318 pixels**, showing that there are larger images in the dataset. This could contribute to better feature extraction.
3. **Interquartile Range**:
   - The **25th percentile (Q1)** and **75th percentile (Q3)** values indicate that **75%** of images have widths between **254 pixels and 276 pixels** and heights between **181 pixels and 194 pixels**.
   - This suggests that most images are relatively close in size, which is helpful when processing images, as it minimizes the variability that the model needs to handle.

b.



→ Each class has the same number of images i.e. 840.


sitting
sitting
sitting
using_laptop
using_laptop
using_laptop
hugging
hugging
hugging
sleeping
sleeping
sleeping
drinking
drinking
drinking
clapping
clapping
clapping
dancing
dancing
dancing
cycling
cycling
cycling
calling
calling
calling
laughing
laughing
laughing
eating
eating
eating
fighting
fighting
fighting
listening_to_music
listening_to_music
listening_to_music
running
running
running
texting
texting
texting

c.

Observations on Class Distribution

1. **Class Count**:
    - All classes have **840 images**, indicating a perfectly balanced dataset with respect to the number of images per class.
2. **Imbalance Ratio**:
    - The **imbalance ratio** calculated as the **maximum class count divided by the minimum class count** yields a value of **1.0** (since both are 840). This indicates no class imbalance is present in the dataset.
    - An imbalance ratio of **1.0** suggests that every class has the same representation, which is ideal for training machine learning models, particularly in classification tasks.

2.

Feature Extraction Observations

In the image classification task, I am using four key feature extraction methods: **Histogram of Oriented Gradients (HOG)**, **color histograms**, **Local Binary Patterns (LBP)**, and **Gray Level Co-occurrence Matrix (GLCM)**. Here are brief observations for each:

1. **Histogram of Oriented Gradients (HOG)**
    - **Focus**: Captures edge and shape information through gradient orientations.
    - **Strength**: Robust to lighting changes and effective for object detection.
    - **Drawback**: High dimensionality may require dimensionality reduction (e.g., PCA).
2. **Color Histograms**
    - **Focus**: Represents color distribution in an image.

    - **Strength**: Useful for differentiating classes based on color.
    - **Drawback**: Sensitive to lighting variations and lacks texture detail.
3. **Local Binary Patterns (LBP)**
    - **Focus**: Encodes texture by thresholding pixel neighborhoods.
    - **Strength**: Efficient and robust to grayscale changes.
    - **Drawback**: Limited to local texture information.
4. **Gray Level Co-occurrence Matrix (GLCM)**
    - **Focus**: Analyzes pixel spatial relationships for texture.
    - **Strength**: Provides statistical features for comprehensive texture analysis.
    - **Drawback**: Can result in high dimensionality and complexity.

3.

Model Evaluation Results

The following are the performance metrics for the four classification models applied to the dataset:

1. Naive Bayes

- **Accuracy**: 0.21
- **Macro Avg Precision**: 0.20
- **Macro Avg Recall**: 0.21
- **Macro Avg F1-Score**: 0.19

Observations:

- Naive Bayes shows low accuracy and has difficulty in correctly classifying most classes, particularly with low precision and recall across the board.

---

2. Decision Tree

- **Accuracy**: 0.15
- **Macro Avg Precision**: 0.15
- **Macro Avg Recall**: 0.15
- **Macro Avg F1-Score**: 0.15

Observations:

- The Decision Tree classifier performed the worst among the models evaluated. Its low accuracy and average metrics indicate that it struggles with the dataset, potentially due to overfitting or poor feature selection.

---

3. Random Forest

- **Accuracy**: 0.31
- **Macro Avg Precision**: 0.30
- **Macro Avg Recall**: 0.31
- **Macro Avg F1-Score**: 0.29

Observations:

- Random Forest exhibited the highest accuracy among the models. It also shows better balance in precision and recall for multiple classes, particularly for class 2 and class 5.

---

4. Perceptron

- **Accuracy**: 0.20
- **Macro Avg Precision**: 0.20
- **Macro Avg Recall**: 0.20
- **Macro Avg F1-Score**: 0.20

Observations:

- The Perceptron model achieved slightly better accuracy than Naive Bayes but still underperformed compared to Random Forest. The precision and recall are consistently low, indicating issues in distinguishing classes.

Best Performing Model: **Random Forest (0.31 accuracy)** – This model outperformed the others, likely benefiting from its ensemble approach which reduces overfitting and improves generalization.