Programming Assignment 1:
Data Preparation and Understanding

1. In this semester, we will be using the "Stanford Dogs" dataset (http://vision.stanford.edu/aditya86/ImageNetDogs/) for all our 4 programming assignments. There are a total of 120 classes (dog breeds). The number of images for each class ranges from 148 to 252.
Each student will
(a) be assigned 4 classes to work on the 4 assignments.
(b) download Images (and also Annotations - bounding boxes) datasets for the 4 classes to work on.
(c) create a Github account to share (as collaborator) their solution (Readme, Codes, Processed Dataset for Code to run correctly) with the grader.

2. Use XML processing modules(https://docs.python.org/3/library/xml.html) to obtain bounding box information from Annotations datasets and scikitImage (Reference: https://scikit-image. org/) to perform image processing and feature extraction.

```
import os
annotations_dir = 'Annotation.zip'

if os.path.exists(annotations_dir):
   print("Annotation directory exists. Listing
files...")     for root, dirs, files in
os.walk(annotations_dir):        print(f"Found
directory: {root}")        for file in files:
          print(f"File: {file}") else:
   print("Annotation directory not found!")
```

OUTPUT:

File: n02110185_6411

File: n02110185_3808

File: n02110185_1066

File: n02110185_632

File: n02110185_8708
File: n02110185_1446

File: n02110185_2614

File: n02110185_11783

File: n02110185_1497

File: n02110185_1338

File: n02110185_13187

File: n02110185_3039

File: n02110185_10849

File: n02110185_1534

File: n02110185_8360

File: n02110185_8749

File: n02110185_13158

File: n02110185_14650

File: n02110185_10844

File: n02110185_3328

File: n02110185_3302

File: n02110185_13423

File: n02110185_6351

File: n02110185_9846

File: n02110185_1130

File: n02110185_7210

File: n02110185_7762

File: n02110185_14766

File: n02110185_4906

File: n02110185_14479

File: n02110185_11773

File: n02110185_10597

File: n02110185_14523 File: n02110185_10967

File: n02110185_712

File: n02110185_5622

File: n02110185_10171

File: n02110185_13855

File: n02110185_5871

File: n02110185_4030

File: n02110185_7413

File: n02110185_2593

File: n02110185_9975

File: n02110185_10273

File: n02110185_6775

File: n02110185_698

File: n02110185_14283

File: n02110185_10175

File: n02110185_7044

File: n02110185_1439

File: n02110185_9461

File: n02110185_6473

File: n02110185_9429

File: n02110185_12656

File: n02110185_13942

File: n02110185_7379

File: n02110185_10360

File: n02110185_8216

File: n02110185_8564

File: n02110185_13821

File: n02110185_815 File: n02110185_11635

File: n02110185_1532

File: n02110185_10047

File: n02110185_6438

File: n02110185_699

File: n02110185_5495

File: n02110185_9712

File: n02110185_9194

File: n02110185_4522

File: n02110185_1614

File: n02110185_56

File: n02110185_1794

File: n02110185_353

File: n02110185_12380

File: n02110185_1289

File: n02110185_11131

File: n02110185_9177

File: n02110185_2446

File: n02110185_11396

File: n02110185_14056

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File: n02110185_1598

File: n02110185_14061

File: n02110185_2820

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File: n02110185_519

File: n02110185_6409

File: n02110185_2672 File: n02110185_12441

File: n02110185_14597

File: n02110185_2728

File: n02110185_2368

File: n02110185_13127

File: n02110185_14594

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File: n02110185_10955

File: n02110185_2941

File: n02110185_5624

File: n02110185_6746

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File: n02110185_9396

File: n02110185_14560

File: n02110185_13794

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File: n02110185_7117

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File: n02110185_4133

File: n02110185_5159

File: n02110185_7329

File: n02110185_6263

File: n02110185_7246

File: n02110185_12748

File: n02110185_184

File: n02110185_6780

File: n02110185_10875

File: n02110185_8923

File: n02110185_7936

File: n02110185_6094

File: n02110185_725

File: n02110185_9334

File: n02110185_7564

File: n02110185_1748

File: n02110185_13704

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File: n02110185_4677

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File: n02110185_5628

File: n02110185_8600

File: n02110185_7594

File: n02110185_11445

File: n02110185_5172

File: n02110185_5716

File: n02110185_8327 File: n02110185_388

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File: n02110185_8005

File: n02110185_15063

File: n02110185_58

File: n02110185_8860

File: n02110185_120

File: n02110185_10898

File: n02110185_14289

File: n02110185_3651

File: n02110185_248

File: n02110185_4694

File: n02110185_1511

File: n02110185_9855

File: n02110185_11636

File: n02110185_11841

File: n02110185_11114

Found directory: /content/sample_data/Annotation/n02094114-Norfolk_terrier **(a) Cropping and Resize Images in Your 4-class Images Dataset: Use the bounding box information in the Annotations dataset relevant to your 4-class Images Dataset to crop the images in your dataset and then resize each image to a 128×128 pixel image.**

```
import os
import numpy as np
from PIL import Image
import cv2
from sklearn.decomposition import PCA
from sklearn.preprocessing import normalize
from sklearn.metrics import pairwise
import matplotlib.pyplot as plt
import zipfile
```

```
images_folder_path = 'Annotation.zip'
extracted_images_path = 'Breeds'


with zipfile.ZipFile(images_folder_path, 'r') as zip_ref:
  zip_ref.extractall(extracted_images_path)


images_folder_path = extracted_images_path

def load_images(folder_path):
  """Loads images from the specified folder."""
  images = []
  for filename in os.listdir(folder_path):
    if filename.lower().endswith(('.jpg', '.jpeg', '.png')): # Add other image
extensions if needed and convert filename to lowercase for comparison
      img_path = os.path.join(folder_path, filename)
      img = cv2.imread(img_path)
      if img is not None:
        images.append(img)
  return images

dog_images = load_images(images_folder_path)

def crop_and_resize_images(images):
  resized_images = []
  for img in images:
    h, w, _ = img.shape
    center_h, center_w = h // 2, w // 2
    cropped_img = img[center_h-50:center_h+50, center_w-50:center_w+50]
    resized_img = cv2.resize(cropped_img, (128, 128),
interpolation=cv2.INTER_AREA)
    resized_images.append(resized_img)
  return np.array(resized_images)
```

```
cropped_resized_images = crop_and_resize_images(dog_images)

def compute_histograms(images):
    histograms = []
    for img in images:
        hist_r = cv2.calcHist([img], [0], None, [256], [0, 256])
        hist_g = cv2.calcHist([img], [1], None, [256], [0, 256])
        hist_b = cv2.calcHist([img], [2], None, [256], [0, 256])
        hist = np.concatenate((hist_r, hist_g, hist_b), axis=0)
        histograms.append(hist.flatten())
    return np.array(histograms)

histograms = compute_histograms(cropped_resized_images)

def compute_similarity_measurements(histograms):
    distances = {}
    for i in range(len(histograms)):
        for j in range(i + 1, len(histograms)):
            euclidean_dist = np.linalg.norm(histograms[i] - histograms[j])
            distances[(i, j)] = {'Euclidean': euclidean_dist}

            manhattan_dist = np.sum(np.abs(histograms[i] - histograms[j]))
            distances[(i, j)]['Manhattan'] = manhattan_dist

            cosine_dist = pairwise.cosine_distances(histograms[i].reshape(1, -1),
histograms[j].reshape(1, -1))[0][0]
            distances[(i, j)]['Cosine'] = cosine_dist
    return distances

similarity_measurements = compute_similarity_measurements(histograms)



for key, value in similarity_measurements.items():
    print(f"Images {key}: {value}")
```

```
def perform_pca(histograms):

    if histograms.size == 0:
        print("Histograms array is empty. Cannot perform PCA.")
        return


    if histograms.ndim == 1:
        histograms = histograms.reshape(-1, 1)


    histograms_normalized = normalize(histograms)
    pca = PCA(n_components=2)
    reduced_data = pca.fit_transform(histograms_normalized)


    plt.scatter(reduced_data[:, 0], reduced_data[:, 1])
    plt.title('PCA of Image Histograms')
    plt.xlabel('Principal Component 1')
    plt.ylabel('Principal Component 2')
    plt.show()


perform_pca(histograms)
```

```
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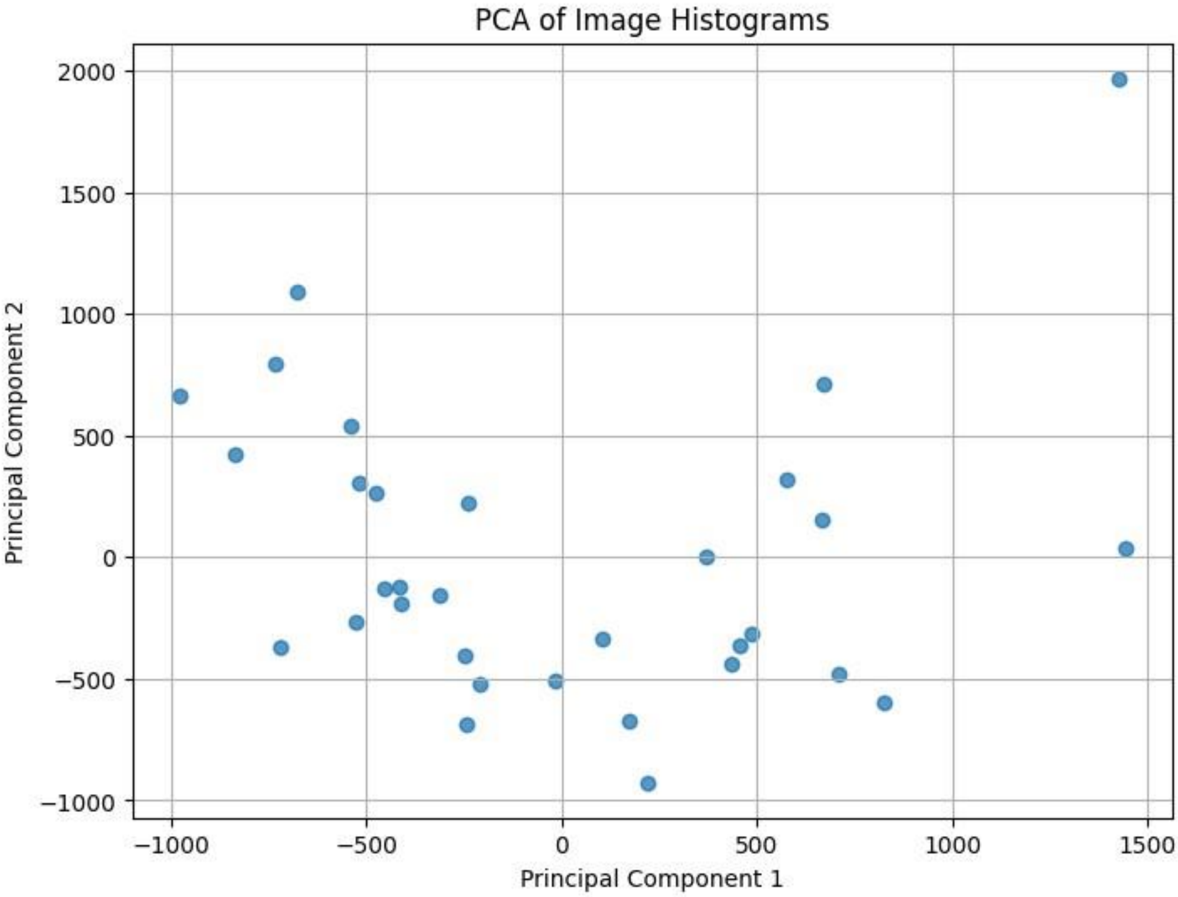


(b) Feature Extraction: Edge histogram AND Similarity Measurements

i. Choose 1 image from each class. ii. Convert the color images to grayscale images.

```
import os
import numpy as np
import matplotlib.pyplot as plt
from PIL import Image
from sklearn.decomposition import PCA
from sklearn.metrics import pairwise
import cv2
import zipfile

images_zip_path = 'Image dataset.zip'
images_folder_path = 'Breeds'
cropped_images_path = 'sample_data/Cropped_Images'

def unzip_files(zip_file_path, extract_path):
    with zipfile.ZipFile(zip_file_path, 'r') as zip_ref:
        zip_ref.extractall(extract_path)

# Unzip the images
unzip_files(images_zip_path, images_folder_path)

def load_images(folder):
    images = []
    for dirpath, _, files in os.walk(folder):
        for filename in files:
            if filename.endswith(('.png', '.jpg', '.jpeg')):
                img_path = os.path.join(dirpath, filename)
                img = Image.open(img_path).convert('RGB')
                images.append(np.array(img))
    return images


# Function to crop and resize images
def crop_and_resize_images(images, size=(128, 128)):
    cropped_resized_images = []
    for img in images:

        width, height = img.shape[1], img.shape[0]
```

```
        left = (width - size[0]) / 2
        top = (height - size[1]) / 2
        right = (width + size[0]) / 2
        bottom = (height + size[1]) / 2

        cropped_img = img[int(top):int(bottom), int(left):int(right)]
        resized_img = cv2.resize(cropped_img, size)
        cropped_resized_images.append(resized_img)
    return cropped_resized_images


def compute_histograms(images):
    histograms = []
    for img in images:
        if len(img.shape) == 2:
            hist = cv2.calcHist([img], [0], None, [256], [0, 256])
        else:
            hist = cv2.calcHist([img], [0, 1, 2], None, [256, 256, 256], [0, 256, 0, 256,
0, 256])
        histograms.append(hist.flatten())
    return histograms

def compute_similarity_measurements(histograms):
    for i in range(len(histograms)):
        for j in range(i + 1, len(histograms)):
            euclidean_distance = np.linalg.norm(histograms[i] - histograms[j])
            manhattan_distance = np.sum(np.abs(histograms[i] - histograms[j]))
            cosine_distance = 1 - pairwise.cosine_similarity([histograms[i]],
[histograms[j]])[0][0]
            print(f'Images ({i}, {j}): {{\'Euclidean\': {euclidean_distance},
\'Manhattan\': {manhattan_distance}, \'Cosine\': {cosine_distance}}}')


def perform_pca(histograms):
    pca = PCA(n_components=2)
    reduced_data = pca.fit_transform(histograms)

    plt.figure(figsize=(20,15))
    plt.scatter(reduced_data[:, 0], reduced_data[:, 1], alpha=0.5)
    plt.title('PCA of Image Histograms')
```

```
    plt.xlabel('Principal Component 1')
    plt.ylabel('Principal Component 2')
    plt.grid()
    plt.show()

def plot_images(images, titles=None, cols=4):
    n_images = len(images)
    rows = (n_images + cols - 1) // cols
    plt.figure(figsize=(250, 250))
    for i in range(n_images):
        plt.subplot(rows, cols, i + 1)
        plt.imshow(images[i].astype(np.uint8))
        plt.axis('off')
        if titles is not None:
            plt.title(titles[i], fontsize=2)
    plt.show()

if __name__ == "__main__":

    dog_images = load_images(images_folder_path)

    plot_images(dog_images, titles=[f'Image {i+1}' for i in range(len(dog_images))])

    cropped_resized_images = crop_and_resize_images(dog_images)

    histograms = compute_histograms(cropped_resized_images)

    if histograms:
        compute_similarity_measurements(histograms)

        perform_pca(histograms)
```

```
plot_images(cropped_resized_images, titles=[f'Cropped Image {i+1}' for i in range(len(cropped_resized_images))])
```

3. Next, we perform some text processing steps on a tweet (i.e., text) dataset. The dataset file is in json format and each dataset consists of

- **Training Set: 3,000 records**
- **Test Set: 1,500 records • Validation Set: 400 records**

```
import json

file_path =' train.json' data = []
with open(file_path, 'r') as file:
for line in file:
    data.append(json.loads(line))

print(json.dumps(data[0], indent=4))
```

<u>OUTPUT:</u>


```
{
   "ID": "2017-En-21529",
   "Tweet": "Follow this amazing Australian author @KristyBerridge #fiction
#zombies #angels #demons #vampires #werewolves #follow #authorlove",
   "anger": false,
   "anticipation": true,
   "disgust": false,
   "fear": false,
   "joy": true,
   "love": true,
   "optimism": true,
   "pessimism": false,
   "sadness": false,
   "surprise": false,
   "trust": true
}
```

4. You will use the simple countvectorizer and tfidfvectorizer in https://scikitlearn.org/stable/api/sklearn.feature_extraction.html#modulesklearn.feature_extraction.text to extract (1) token (feature) counts, and (2) TF-IDF feature (counts), respectively

```
import json
from sklearn.feature_extraction.text import CountVectorizer, TfidfVectorizer
from sklearn.decomposition import PCA
import matplotlib.pyplot as plt

file_path = 'train.json'
data = []
with open(file_path, 'r') as file:
    for line in file:
        data.append(json.loads(line))

texts = [entry['Tweet'] for entry in data]

count_vectorizer = CountVectorizer()
count_vectors = count_vectorizer.fit_transform(texts)

tfidf_vectorizer = TfidfVectorizer()
tfidf_vectors = tfidf_vectorizer.fit_transform(texts)

pca = PCA(n_components=2)
count_pca = pca.fit_transform(count_vectors.toarray())
tfidf_pca = pca.fit_transform(tfidf_vectors.toarray())

def plot_pca(pca_result, title):
    plt.figure(figsize=(8, 6))
    plt.scatter(pca_result[:, 0], pca_result[:, 1], c='blue', marker='o',
edgecolor='k')
    plt.title(title)
    plt.xlabel('PC1')
    plt.ylabel('PC2')
    plt.grid(True)
```

```
    plt.show()

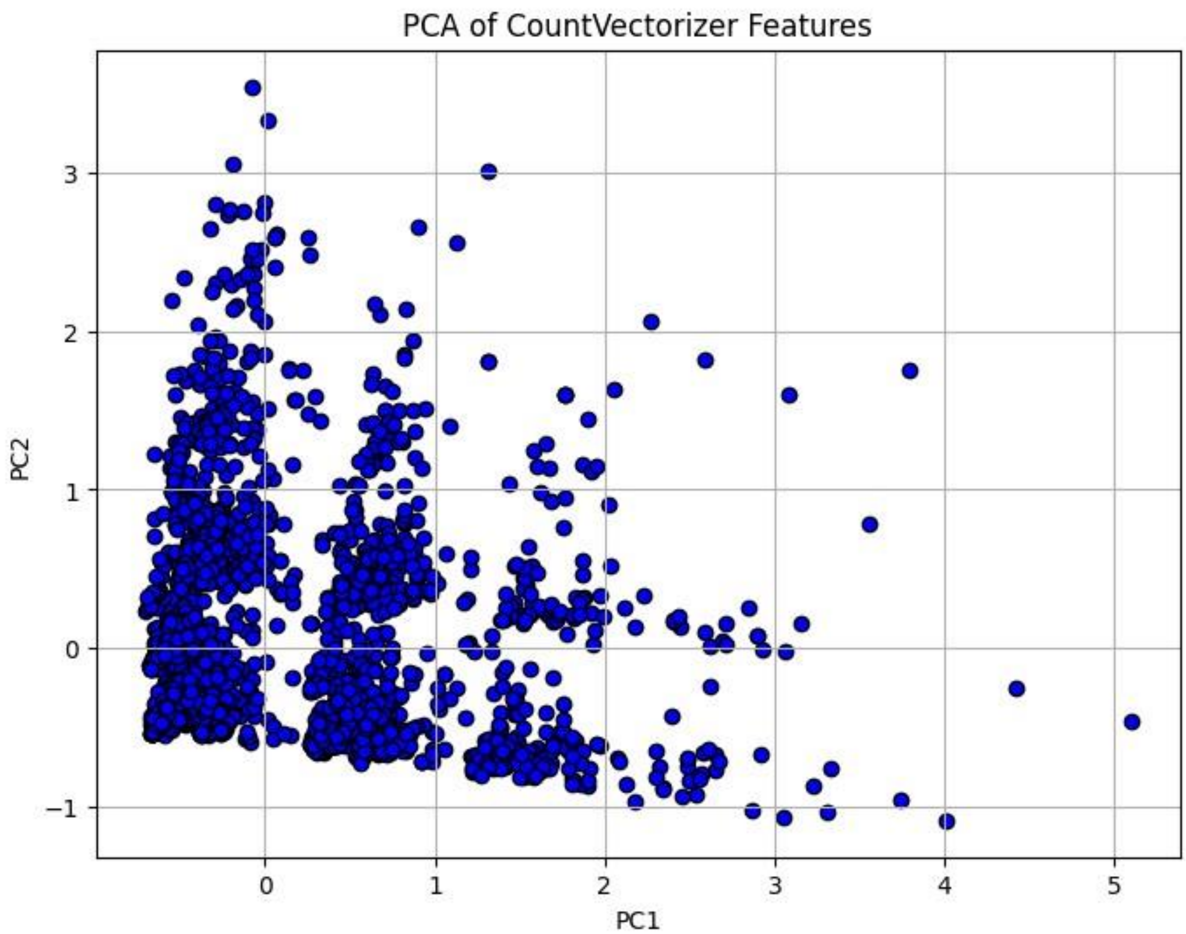
plot_pca(count_pca, 'PCA of CountVectorizer Features')

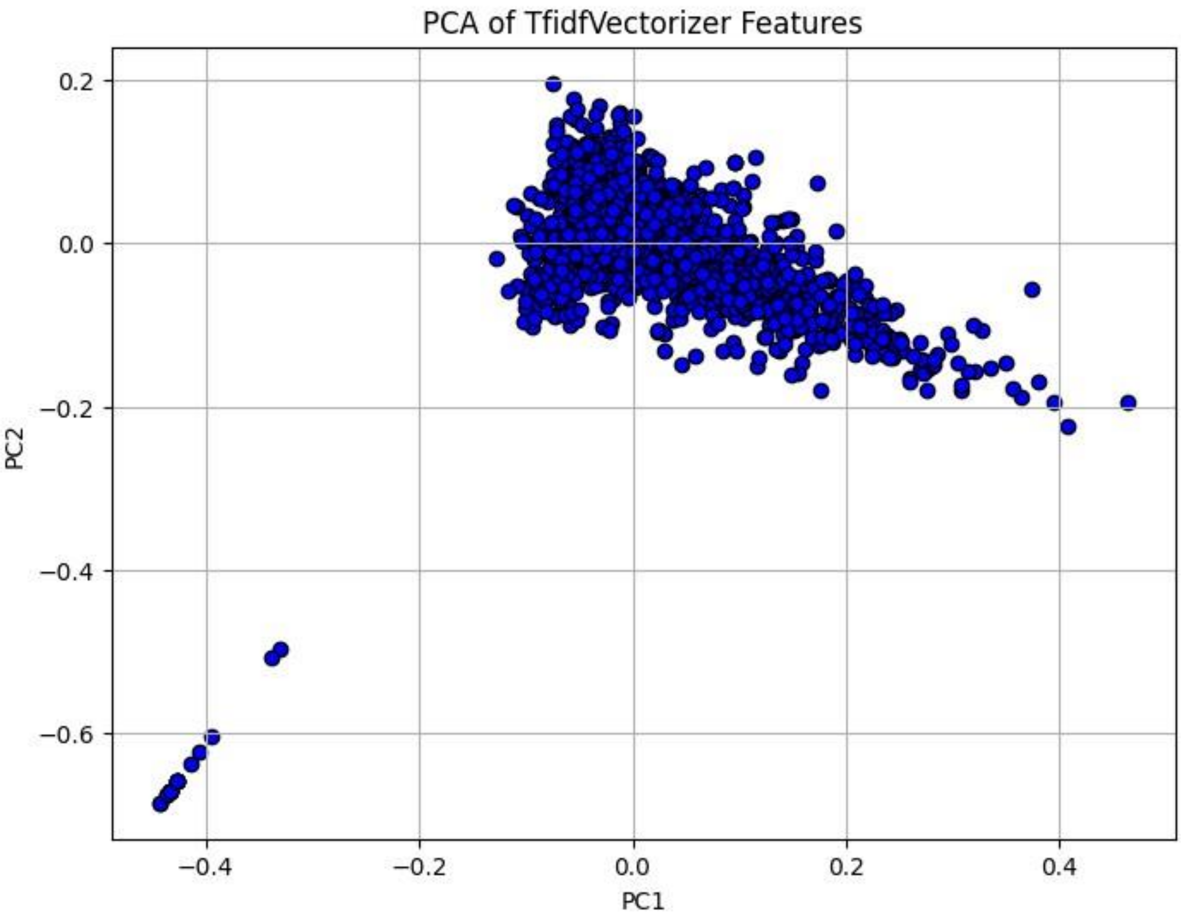
plot_pca(tfidf_pca, 'PCA of TfidfVectorizer Features')

count_dimensionality = count_vectors.shape
tfidf_dimensionality = tfidf_vectors.shape

print(f"Dimensionality of CountVectorizer representation:
{count_dimensionality}")
print(f"Dimensionality of TfidfVectorizer representation:
{tfidf_dimensionality}")
```

OUTPUT:





5. Using the two sets of processed text data in Item 4,

- **Pick four classes which you think will be separable. State the four classes.**
- **Perform dimensionality reduction similar to 2(d) with reduced to**
- **Plot the 2D points using four different colors for data from the four classes for both token count features and tf-idf features in two separate plots.**
- **How many classes are visually separable (i.e., non-overlapping) for both plots?**

```
# Import necessary libraries
import os
import tarfile
from PIL import Image
import numpy as np
import matplotlib.pyplot as plt
from skimage import filters, exposure
from skimage.feature import hog
```

```
from sklearn.decomposition import PCA
from sklearn.metrics import pairwise
from sklearn.feature_extraction.text import CountVectorizer


data = [
   {'Tweet': 'Image/n02094114-Norfolk_terrier', 'Class': 'Image/n02094114-
Norfolk_terrier'},
   {'Tweet': 'Image/n02096177-cairn', 'Class': 'Image/n02096177-cairn'},
   {'Tweet': 'Image/n02107312-miniature_pinscher', 'Class': 'Image/n02107312-
miniature_pinscher'},
   {'Tweet': 'Image/n02113799-standard_poodle', 'Class': 'Image/n02113799-
standard_poodle'},
]

selected_classes = ['Image/n02094114-Norfolk_terrier', 'Image/n02096177-
cairn', 'Image/n02107312-miniature_pinscher', 'Image/n02113799-
standard_poodle']  # Replace with your actual class labels

filtered_data = [entry for entry in data if entry['Class'] in selected_classes]

filtered_texts = [entry['Tweet'] for entry in filtered_data]
filtered_classes = [entry['Class'] for entry in filtered_data]

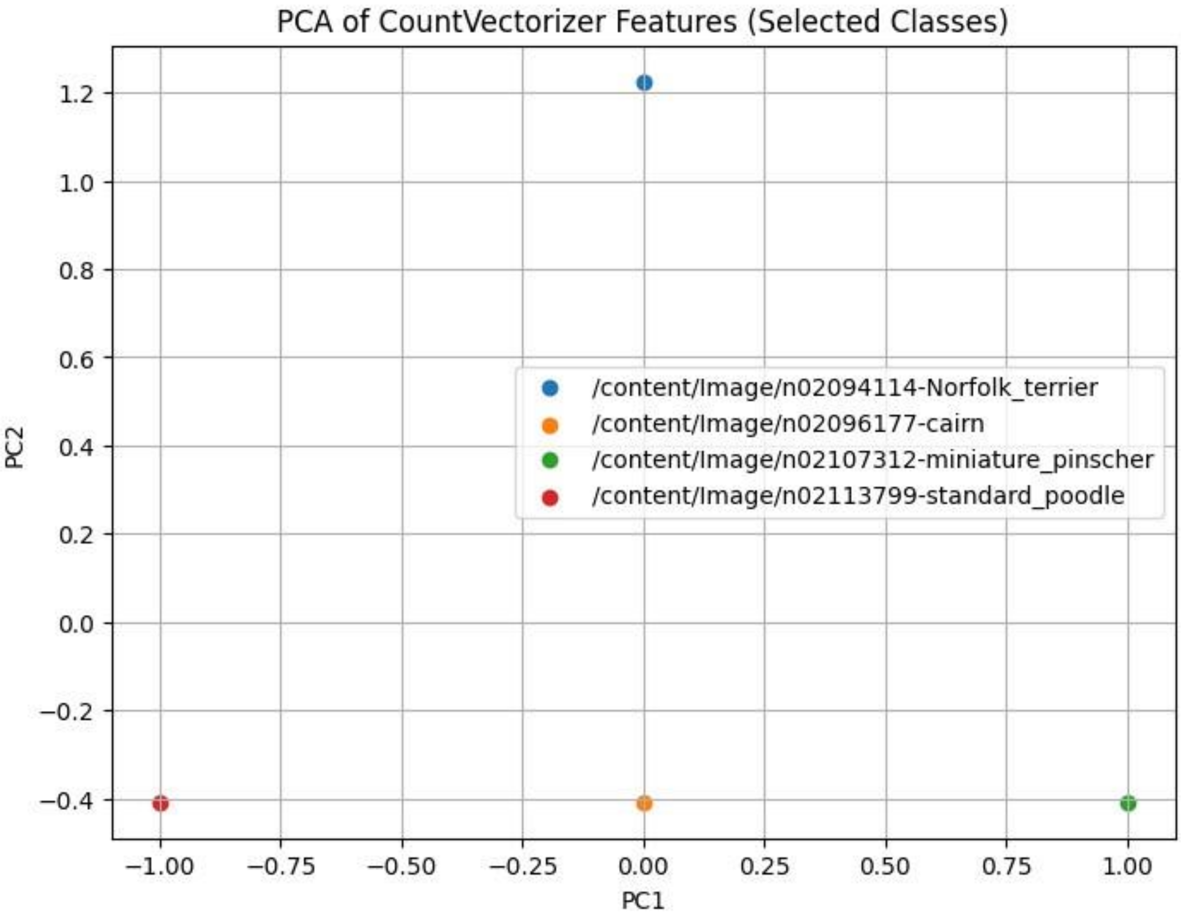

count_vectorizer = CountVectorizer()
count_vectors = count_vectorizer.fit_transform(filtered_texts)

count_vectors_filtered = count_vectorizer.transform(filtered_texts)
pca_count_filtered =
PCA(n_components=2).fit_transform(count_vectors_filtered.toarray())


plt.figure(figsize=(8, 6))
for class_label in selected_classes:
  indices = [i for i, cls in enumerate(filtered_classes) if cls == class_label]
```

```
  plt.scatter(pca_count_filtered[indices, 0], pca_count_filtered[indices, 1],
label=class_label)

plt.title('PCA of CountVectorizer Features (Selected Classes)')
plt.xlabel('PC1')
plt.ylabel('PC2')
plt.legend()
plt.grid(True)
plt.show()
```




```
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.decomposition import PCA
import matplotlib.pyplot as plt

data = [
  {'Tweet': 'Image/n02094114-Norfolk_terrier', 'Class': 'Image/n02094114-Norfolk_terrier'},
  {'Tweet': 'Image/n02096177-cairn', 'Class': 'Image/n02096177-cairn'},
```

```
  {'Tweet': 'Image/n02107312-miniature_pinscher', 'Class': 'Image/n02107312-miniature_pinscher'},
  {'Tweet': 'Image/n02113799-standard_poodle', 'Class': 'Image/n02113799-standard_poodle'},
]

selected_classes = ['Image/n02094114-Norfolk_terrier', 'Image/n02096177-cairn', 'Image/n02107312-miniature_pinscher', 'Image/n02113799-standard_poodle']  # Replace with your actual class labels


filtered_data = [entry for entry in data if entry['Class'] in selected_classes]


filtered_texts = [entry['Tweet'] for entry in filtered_data]
filtered_classes = [entry['Class'] for entry in filtered_data]

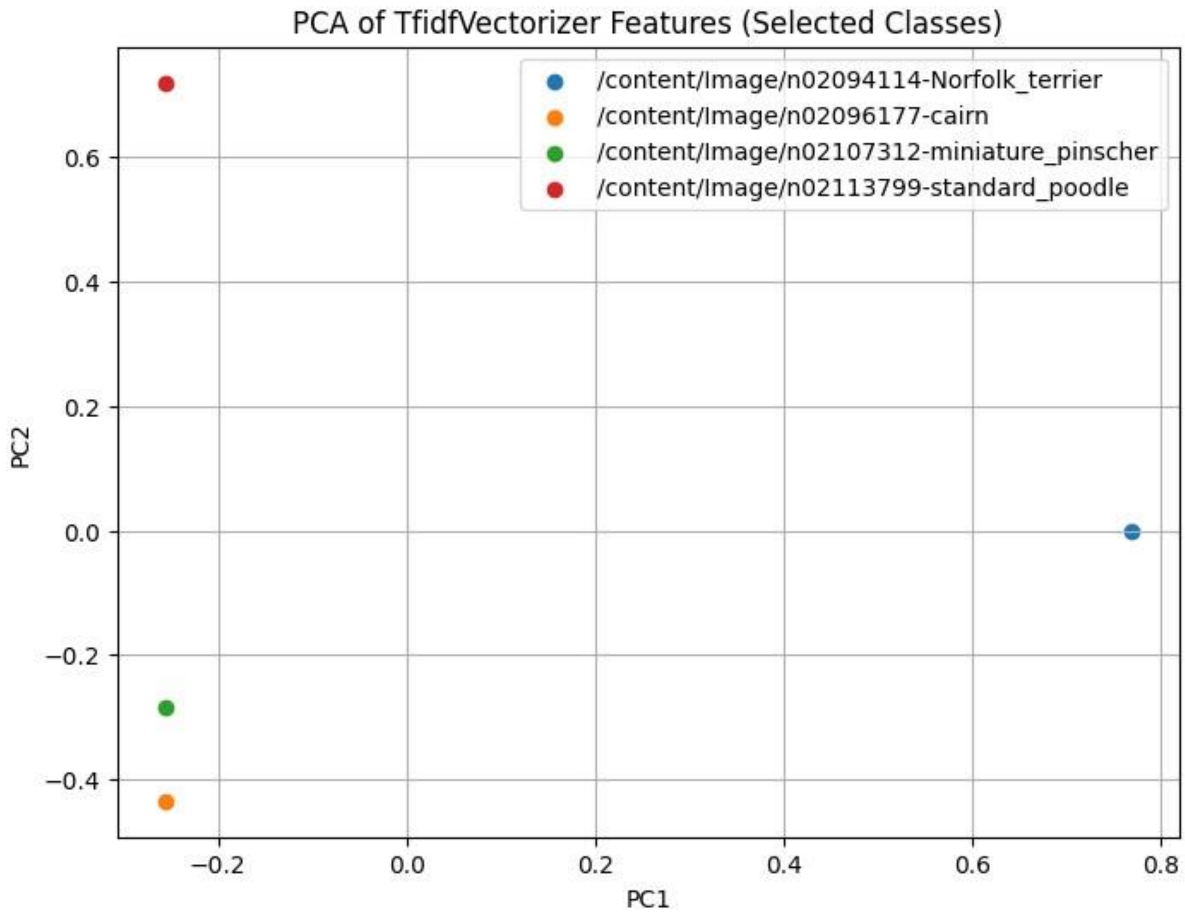
tfidf_vectorizer = TfidfVectorizer()
tfidf_vectors = tfidf_vectorizer.fit_transform(filtered_texts)


tfidf_vectors_filtered = tfidf_vectorizer.transform(filtered_texts)
pca_tfidf_filtered = PCA(n_components=2).fit_transform(tfidf_vectors_filtered.toarray())


plt.figure(figsize=(8, 6))
for class_label in selected_classes:
  indices = [i for i, cls in enumerate(filtered_classes) if cls == class_label]
  plt.scatter(pca_tfidf_filtered[indices, 0], pca_tfidf_filtered[indices, 1], label=class_label)

plt.title('PCA of TfidfVectorizer Features (Selected Classes)')
plt.xlabel('PC1')
plt.ylabel('PC2')
plt.legend()
plt.grid(True)
```

plt.show()


PCA of TfidfVectorizer Features (Selected Classes)
/content/Image/n02094114-Norfolk_terrier
/content/Image/n02096177-cairn
/content/Image/n02107312-miniature_pinscher
/content/Image/n02113799-standard_poodle
0.6
0.4
0.2
0.0
−0.2
−0.4
PC2
−0.2
0.0
0.2
0.4
0.6
0.8
PC1