sccrfciwe

December 16, 2024

1 1

[58]:
```python
import os
import numpy as np
import torch
from PIL import Image
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.manifold import TSNE
from transformers import CLIPProcessor, CLIPModel
from torchvision import transforms
```

[59]:
```python
# Load the pre-trained CLIP model and processor
model_name = "openai/clip-vit-base-patch32"
device = "cuda" if torch.cuda.is_available() else "cpu"

model = CLIPModel.from_pretrained(model_name).to(device)
processor = CLIPProcessor.from_pretrained(model_name)
```

1.1 CLIP Model Description: `openai/clip-vit-base-patch32`

1.2 1. Model Architecture

1.2.1 Vision Encoder

- **Backbone**: Vision Transformer (ViT)
  - Splits input images into **fixed-size patches** (32x32 pixels per patch).
  - Each patch is flattened and embedded into a **512-dimensional vector**.
  - The embeddings are passed through a **Transformer encoder**.
- **Number of Layers**: 12 Transformer layers.
- **Self-Attention Mechanism**: Each layer uses **multi-head self-attention**.
  - Each attention head has **Key (K)**, **Query (Q)**, and **Value (V)** matrices.
- **Final Output**: A fixed-size feature vector for the image.

1.2.2 Text Encoder

- **Backbone**: Transformer-based encoder for natural language.
  - Tokenizes the input text and embeds each token into a **512-dimensional vector**.
  - Embeddings are passed through 12 Transformer layers with self-attention.

- **Number of Layers**: 12 Transformer layers.
- **Self-Attention Mechanism**: Similar to the vision encoder, uses multi-head self-attention with K, Q, and V matrices.

1.2.3 Shared Space

- Both the vision and text encoders project their outputs into a **shared embedding space** using a **linear projection layer**.
- The model computes the similarity (dot product) between image and text embeddings in this space.

1.3 2. Parameter Breakdown

The total number of parameters in `clip-vit-base-patch32` is approximately **149M**. Below is a detailed breakdown:

1.3.1 Vision Encoder (ViT):

1. **Embedding Layer**:
   - Converts 32x32 patches into 512-dimensional vectors using a linear layer.
   - **Parameters**: ((32 * 32 * 3) * 512 = 1,572,864).
2. **Transformer Layers (12 Layers)**:
   - Each layer consists of:
     - **Multi-Head Attention** (8 heads):
       * Each head has K, Q, and V matrices of size (512 * 64) (64 = 512 / 8).
       * Total parameters for K, Q, V per layer: (3 * (512 * 64) = 98,304).
       * Output projection matrix: (512 * 512 = 262,144).
       * **Total per attention layer**: (98,304 + 262,144 = 360,448).
     - **Feed-Forward Network**:
       * Two dense layers: (512 $\rightarrow$2048 $\rightarrow$512).
       * **Parameters**: (512 * 2048 + 2048 * 512 = 4,194,304).
     - **Total parameters per Transformer layer**: (360,448 + 4,194,304 = 4,554,752).
   - **Total for 12 layers**: (4,554,752 * 12 = 54,657,024).
3. **Positional Embeddings**:
   - Added to patch embeddings to encode spatial information.
   - **Parameters**: (197 * 512 = 100,864) (197 = 196 patches + 1 CLS token).
4. **Final Linear Projection**:
   - Projects the 512-dimensional vector into the shared embedding space.
   - **Parameters**: (512 * 512 = 262,144).

1.3.2 Text Encoder:

1. **Embedding Layer**:
   - Converts input tokens to 512-dimensional vectors.
   - **Parameters**: (49,152 * 512 = 25,165,824) (Vocabulary size = 49,152).
2. **Transformer Layers (12 Layers)**:

- Similar to the vision encoder.
- **Total for 12 layers**: (54,657,024).

3. **Final Linear Projection**:
   - Projects the 512-dimensional vector into the shared embedding space.
   - **Parameters**: (512 * 512 = 262,144).

1.4 3. What the Parameters Are Doing

1.4.1 Vision Encoder:

- **K, Q, V Matrices**:
  - Capture relationships between different patches in the image using attention.
  - Enable the model to understand global and local patterns in the image.
- **Feed-Forward Network**:
  - Introduces non-linearity and combines features across attention heads.
- **Positional Embeddings**:
  - Provide spatial information about the patches to the model.
- **Final Linear Projection**:
  - Maps the vision features into the shared embedding space for similarity computation.

1.4.2 Text Encoder:

- **K, Q, V Matrices**:
  - Model relationships between words (e.g., syntax, semantics) using self-attention.
- **Feed-Forward Network**:
  - Helps process token-level features and combine contextual information.
- **Final Linear Projection**:
  - Maps the text features into the shared embedding space.

1.5 4. Summary of Parameter Counts

Component	Parameter Count
Vision Encoder (ViT)	~86M
Text Encoder	~63M
Total	~149M

2 2

[60]:
```
categories = ["airplane", "car", "chair", "cup", "dog", "donkey", "duck", "hat"]
conditions = ["realistic", "geons", "silhouettes", "blurred", "features"]
```

[61]:
```
# Function to load an image from the dataset
def load_image(image_path):
    return Image.open(image_path)
```

[62]:

```python
# Function to extract the category from the image filename
def get_category_from_filename(filename):
    # Convert filename to lowercase and check for categories in the name
    filename_lower = filename.lower()
    for category in categories:
        if filename_lower.startswith(category):
            return category
    return None
```

[63]:

```python
# Function to evaluate the model on each image for all categories and conditions
image_paths = []
category_list = []
condition_list = []

def evaluate_model(dataset_path):
    results = {condition: {'correct': 0, 'total': 0} for condition in␣
 ↪conditions}

    for condition in conditions:
        condition_path = os.path.join(dataset_path, condition)

        # Make sure the condition folder exists before proceeding
        if not os.path.exists(condition_path):
            print(f"Warning: {condition_path} does not exist!")
            continue

        for img_name in os.listdir(condition_path):
            img_path = os.path.join(condition_path, img_name)
            if img_path.endswith(('.png', '.jpg', '.jpeg')):
                # Extract category from filename
                extracted_category = get_category_from_filename(img_name)
                print(f'{condition}_{img_name} - {extracted_category}')
                if extracted_category is None:
                    continue  # Skip if category cannot be extracted

                image_paths.append(img_path)
                category_list.append(extracted_category)
                condition_list.append(condition)
                # Load the image
                image = load_image(img_path)

                # Prepare the text labels (one for each category)
                text_inputs = [f"This is a {cat}" for cat in categories]

                # Process the image and text inputs
                inputs = processor(text=text_inputs, images=image,␣
 ↪return_tensors="pt", padding=True).to(device)
```

```python
                # Get model outputs
                outputs = model(**inputs)

                # Compute similarity scores between image and text embeddings
                logits_per_image = outputs.logits_per_image  # Similarity␣
↪scores (image vs text)
                probs = logits_per_image.softmax(dim=1)   # Normalize to␣
↪probabilities

                # Get the index of the highest score (max probability)
                predicted_class_idx = torch.argmax(probs, dim=1).item()

                # Check if the prediction is correct
                if predicted_class_idx == categories.index(extracted_category):
                    results[condition]['correct'] += 1

                # Increment the total count for this condition
                results[condition]['total'] += 1

    return results
```

[64]:
```python
dataset_path = "./image_files/image_files/v0"

# Evaluate the model
evaluation_results = evaluate_model(dataset_path)
```

```
realistic_AirplaneSide_v1.jpg - airplane
realistic_Airplaneside_v2.jpg - airplane
realistic_AirplaneThree-Quarter_v1.jpg - airplane
realistic_AirplaneThree-Quarter_v3.jpg - airplane
realistic_AirplaneThree-Quarter_V4.jpg - airplane
realistic_CarSide_v1.jpg - car
realistic_Carside_v3.jpg - car
realistic_CarSide_v4.jpg - car
realistic_CarThree-Quarter_v1.jpg - car
realistic_CarThree-Quarter_v2.jpg - car
realistic_Chairside_v1.jpg - chair
realistic_Chairside_v2.jpg - chair
realistic_Chairside_v3.jpg - chair
realistic_ChairThree-Quarter_v1.jpg - chair
realistic_ChairThree-Quarter_v4.jpg - chair
realistic_CupSide_v1.jpg - cup
realistic_CupSide_v2.jpg - cup
realistic_CupThreeQuarter_v1.jpg - cup
realistic_CupThreeQuarter_v2.jpg - cup
realistic_CupThreeQuarter_v3.jpg - cup
```

realistic_DogSide_V1.jpg - dog
realistic_DogSide_v2.jpg - dog
realistic_DogSide_v4.jpg - dog
realistic_DogThree-Quarter_v2.jpg - dog
realistic_DogThreeQuarter_v3.jpg - dog
realistic_DogThreeQuarter_v4.jpg - dog
realistic_DonkeySide_v2.jpg - donkey
realistic_DonkeyThreeQuarter_v1.jpg - donkey
realistic_DonkeyThreeQuarter_v2.jpg - donkey
realistic_DonkeyThreeQuarter_v3.jpg - donkey
realistic_DonkeyThreeQuarter_v4.jpg - donkey
realistic_DuckSide_v1.jpg - duck
realistic_DuckSide_v2.jpg - duck
realistic_DuckSide_v4.jpg - duck
realistic_DuckThreeQuarter_v1.jpg - duck
realistic_DuckThreeQuarter_v3.jpg - duck
realistic_Hatside_v1.jpg - hat
realistic_Hatside_v3.jpg - hat
realistic_HatThree-quarter_v1.jpg - hat
geons_AirplaneSide_v1.jpg - airplane
geons_Airplaneside_V3.png - airplane
geons_AirplaneThreeQuarter_4.png - airplane
geons_AirplaneThreeQuarter_v1.jpg - airplane
geons_AirplaneThreeQuarter_V1.png - airplane
geons_AirplaneThreeQuarter_V2.png - airplane
geons_AirplaneThreeQuarter_v3.jpg - airplane
geons_AirplaneThreeQuarter_V4.png - airplane
geons_Carside2.png - car
geons_Carside_V1.png - car
geons_Carside_V3.png - car
geons_Carside_V4.png - car
geons_CarThreeQuarters_V1.png - car
geons_CarThreeQuarters_V2.png - car
geons_CarThreeQuarters_V3.png - car
geons_CarThreeQuarter_V4.png - car
geons_Chairside_V1.png - chair
geons_Chairside_V2.png - chair
geons_ChairSide_v3.jpg - chair
geons_Chairside_V4.png - chair
geons_ChairThreeQuarters_V4.png - chair
geons_ChairThreeQuarter_V1.png - chair
geons_ChairThreeQuarter_v2.jpg - chair
geons_Cupside_V1.png - cup
geons_CupSide_v2.jpg - cup
geons_Cupside_V3.png - cup
geons_CupSide_v4.jpg - cup
geons_cupThree-Quarter_v1.jpg - cup
geons_CupThree-Quarter_v3.jpg - cup

geons_CupThree-Quarter_v4.jpg - cup
geons_CupThreeQuarters_V2.png - cup
geons_Dogside_V1.png - dog
geons_dogSide_v2.jpg - dog
geons_Dogside_V3.png - dog
geons_dogSide_v4.jpg - dog
geons_DogThreeQuarters_V1.png - dog
geons_DogThreeQuarters_V4.png - dog
geons_dogThreeQuarter_v2.jpg - dog
geons_Donkeyside_V1.png - donkey
geons_Donkeyside_V2.png - donkey
geons_donkeySide_v3.jpg - donkey
geons_donkeySide_v4.jpg - donkey
geons_DonkeyThree-Quarter_v1.jpg - donkey
geons_donkeyThree-Quarter_v2.jpg - donkey
geons_donkeyThree-Quarter_v3.jpg - donkey
geons_DuckSideview_2.png - duck
geons_Duckside_V1.png - duck
geons_Duckside_V3.png - duck
geons_Duckside_V4.png - duck
geons_DuckThreeQuarters_V1.png - duck
geons_DuckThreeQuarters_V3.png - duck
geons_DuckThreeQuarter_V4.png - duck
geons_Hatside_V1.png - hat
geons_Hatside_V2.png - hat
geons_hatSide_v3.jpg - hat
geons_hatSide_v4.jpg - hat
geons_hatThree-Quarter_v3.jpg - hat
geons_HatThreeQuarters_V1.png - hat
geons_HatThreeQuarters_V4.png - hat
geons_page 8-3.jpg - None
silhouettes_AirplaneSide_V1.jpg - airplane
silhouettes_Airplaneside_V2.jpg - airplane
silhouettes_AirplaneThreeQuarters_V1.jpg - airplane
silhouettes_AirplaneThreeQuarters_V3.jpg - airplane
silhouettes_AirplaneThreeQuarters_V4.jpg - airplane
silhouettes_Carside_V1.jpg - car
silhouettes_CarSide_V3.jpg - car
silhouettes_Carside_V4.jpg - car
silhouettes_CarThreeQuarters_V1.jpg - car
silhouettes_CarThreeQuarters_V2.jpg - car
silhouettes_Chairside_V1.jpg - chair
silhouettes_chairSide_v2.jpg - chair
silhouettes_Chairside_V3.jpg - chair
silhouettes_ChairThreeQuarter_V1.jpg - chair
silhouettes_ChairThreeQuarter_V4.jpg - chair
silhouettes_CupSide_V1.jpg - cup
silhouettes_Cupside_V2.jpg - cup

silhouettes_CupThreeQuarters_V1.jpg - cup
silhouettes_CupThreeQuarters_V4.jpg - cup
silhouettes_CupThreeQuarter_v2.jpg - cup
silhouettes_CupThreeQuarter_V3.jpg - cup
silhouettes_DogSide_V2.jpg - dog
silhouettes_Dogside_V4.jpg - dog
silhouettes_dogThree-Quarter_v2.jpg - dog
silhouettes_DogThreeQuarters_V4.jpg - dog
silhouettes_DonkeySide_V2.jpg - donkey
silhouettes_DonkeyThreeQuarters_V3.jpg - donkey
silhouettes_DonkeyThreeQuarter_V1.jpg - donkey
silhouettes_DonkeyTHreeQuarter_V2.jpg - donkey
silhouettes_DonkeyTHreeQuarter_V4.jpg - donkey
silhouettes_DuckSide_V1.jpg - duck
silhouettes_Duckside_V2.jpg - duck
silhouettes_Duckside_V4.jpg - duck
silhouettes_DuckThreeQuarters_V1.jpg - duck
silhouettes_DuckThreeQuarters_V3.jpg - duck
silhouettes_Hatside_V1.jpg - hat
silhouettes_hatSide_v3.jpg - hat
silhouettes_Hatside_v4.jpg - hat
silhouettes_HatThreeQuarters_V1.jpg - hat
silhouettes_HatThreequarters_V2.jpg - hat
blurred_AirplaneSide_V1.jpg - airplane
blurred_AirplaneSide_V2.jpg - airplane
blurred_Airplaneside_V3.jpg - airplane
blurred_airplaneThree-Quarter_v3.jpg - airplane
blurred_AirplaneThreeQuarter_V1.jpg - airplane
blurred_airplanethreequarter_V4.jpg - airplane
blurred_carside-v1.jpg - car
blurred_CarSide_V4.jpg - car
blurred_carThree-Quarter_v3.jpg - car
blurred_CarThreequartersV_2.jpg - car
blurred_CarThreeQuarters_v1.jpg - car
blurred_Chairside_V1.jpg - chair
blurred_Chairside_V2.jpg - chair
blurred_Chairside_V3.jpg - chair
blurred_chairSide_v5.jpg - chair
blurred_ChairThreequarters_V1.jpg - chair
blurred_ChairThreequarter_V4.jpg - chair
blurred_Cupside_V1.jpg - cup
blurred_Cupside_V2.jpg - cup
blurred_CupThreeQuarter_V1.jpg - cup
blurred_CupThreequarter_V2.jpg - cup
blurred_CupThreeQuarter_V3.jpg - cup
blurred_DogSide-V4.jpg - dog
blurred_Dogside_V1.jpg - dog
blurred_DogThreequarters_V2.jpg - dog

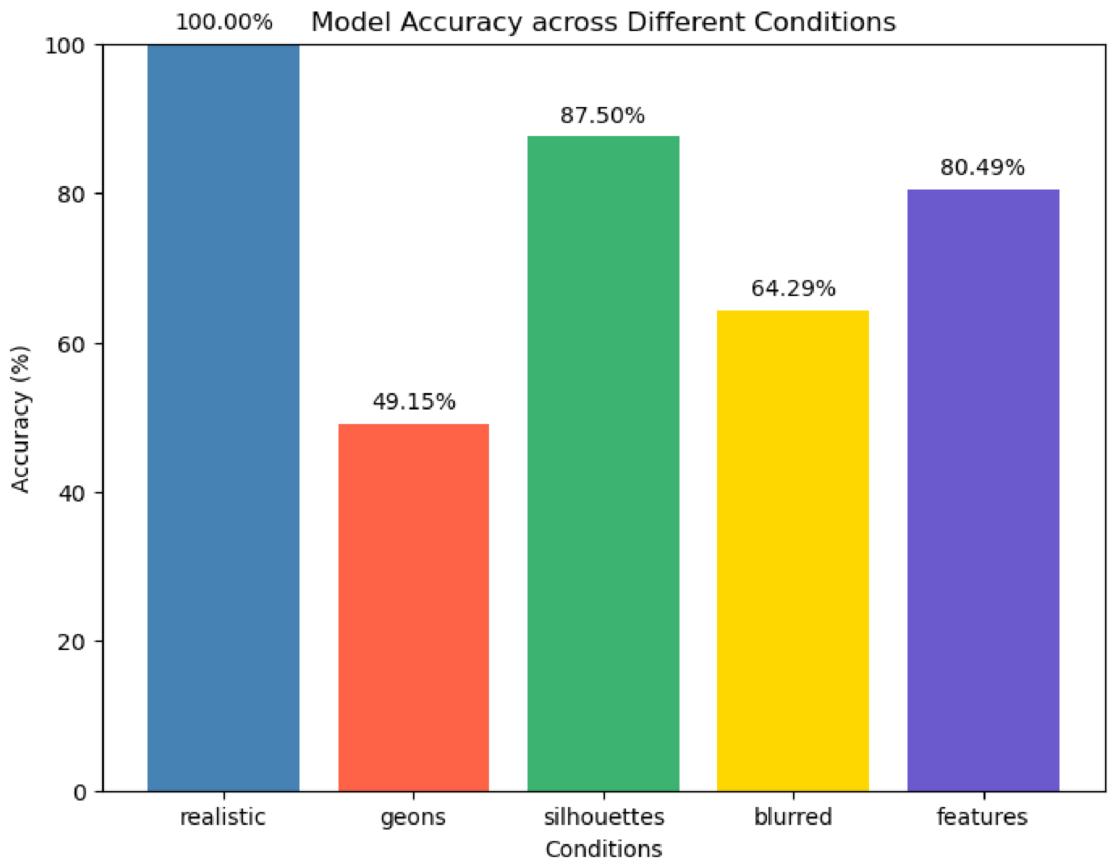
blurred_DogThreequarters_V3.jpg - dog
blurred_DogThreeQuarter_V4.jpg - dog
blurred_Donkeyside_V2.jpg - donkey
blurred_DonkeyThreeQuarters_V2.jpg - donkey
blurred_DonkeyThreequarters_V3.jpg - donkey
blurred_DonkeyThreequarter_V4.jpg - donkey
blurred_Duckside-V2.jpg - duck
blurred_Duckside_V1.jpg - duck
blurred_Duckside_V3.jpg - duck
blurred_Duckside_V4.jpg - duck
blurred_DuckThreeQuarters_V1.jpg - duck
blurred_DuckThreeQuarters_V3.jpg - duck
blurred_Hatside-V4.jpg - hat
blurred_Hatside_V1.jpg - hat
blurred_Hatside_V3.jpg - hat
blurred_HatThreeQuarters_V1.jpg - hat
blurred_HatThreequarters_V2.jpg - hat
features_Airplaneside.V3.jpg - airplane
features_AirplaneSide_V1.jpg - airplane
features_Airplaneside_V2.jpg - airplane
features_airplaneThree-Quarter_v3.jpg - airplane
features_AirplaneThreeQuarters_V1.jpg - airplane
features_AirplaneThreeQuarters_V4.jpg - airplane
features_Carside1.jpg - car
features_Carside_V4.jpg - car
features_carThree-Quarter_v3.jpg - car
features_CarThreeQuarter_V1.jpg - car
features_CarThreeWQauarter_V2.jpg - car
features_Chairside_V1.jpg - chair
features_Chairside_V2.jpg - chair
features_Chairside_V3.jpg - chair
features_chairSide_v5.jpg - chair
features_ChairThreeQuarter_V1.jpg - chair
features_ChariThreeQuarters_V4.jpg - None
features_Cupside_V1.jpg - cup
features_Cupside_V2.jpg - cup
features_Cupthreequarter_V1.jpg - cup
features_CupThreeQuarter_V2.jpg - cup
features_CupThreeQuarter_V3.jpg - cup
features_DogSide_V1.jpg - dog
features_Dogside_V4.jpg - dog
features_DogThreeQuarter_V2.jpg - dog
features_DogThreequarter_V3.jpg - dog
features_DogThreequarter_V4.jpg - dog
features_DonkeySide_V2.jpg - donkey
features_DonkeyThreeQuarters_V4.jpg - donkey
features_DonkeyThreeQuarter_V2.jpg - donkey
features_DonkeyThreeQuarter_V3.jpg - donkey

```
features_Duckside_V1.jpg - duck
features_Duckside_V2.jpg - duck
features_Duckside_V3.jpg - duck
features_DuckSide_V4.jpg - duck
features_DuckThreeQuarters_V1.jpg - duck
features_DuckThreeQuarter_V3.jpg - duck
features_Hatside_V1.jpg - hat
features_Hatside_V3.jpg - hat
features_Hatside_V4.jpg - hat
features_HatThreedQuarter_V1.jpg - hat
features_HatThreequarter_V2.jpg - hat
```

[65]:
```
accuracy_values = []
for condition, result in evaluation_results.items():
    accuracy = result['correct'] / result['total'] * 100 if result['total'] > 0␣
 ↪else 0
    print(f"Accuracy for condition '{condition}': {accuracy:.2f}%")
    accuracy_values.append(accuracy)
```

```
Accuracy for condition 'realistic': 100.00%
Accuracy for condition 'geons': 49.15%
Accuracy for condition 'silhouettes': 87.50%
Accuracy for condition 'blurred': 64.29%
Accuracy for condition 'features': 80.49%
```

[66]:
```
import matplotlib.pyplot as plt

colors = ['#4682B4', '#FF6347', '#3CB371', '#FFD700', '#6A5ACD']
plt.figure(figsize=(8, 6))
plt.bar(conditions, accuracy_values, color=colors)
plt.xlabel('Conditions')
plt.ylabel('Accuracy (%)')
plt.title('Model Accuracy across Different Conditions')
plt.ylim(0, 100)

for i, value in enumerate(accuracy_values):
    plt.text(i, value + 2, f'{value:.2f}%', ha='center', fontsize=10)

plt.show()
```



2.1 openai/clip-vit-base-patch32 Model vs Baby Performance Comparison

Model's Accuracy: - **Realistic:** 100.00% - **Geons:** 49.15% - **Silhouettes:** 87.50% - **Blurred:** 64.29% - **Features:** 80.49%

Baby's Accuracy: - **Realistic:** 84% - **Geons:** 58% - **Silhouettes:** 78% - **Blurred:** 55% - **Features:** 54%

2.1.1 Analysis:

1. Better Performance by the Model:

- **Realistic:** The model outperforms the baby significantly (100.00% vs. 84%).
- **Silhouettes:** The model performs better (87.50% vs. 78%).
- **Blurred:** The model outperforms the baby (64.29% vs. 55%).
- **Features:** The model performs better by a significant margin (80.49% vs. 54%).

2. Worse Performance by the Model:

- **Geons:** The model performs worse than the baby (49.15% vs. 58%).

2.1.2 Summary of Model Performance:

- The model performs **better** than the baby in **Realistic**, **Silhouettes**, **Blurred**, and **Features** conditions.
- The model performs **worse** than the baby only in the **Geons** condition.
- The model outperforms the baby in **Features** by a large margin (80.49% vs. 54%).

2.1.3 Conclusion:

- The **model performs better** than the baby in all conditions except for **Geons**.
- In **Geons**, the **baby performs better** than the model.
- The model's performance in the **Features** condition is particularly strong, showing a **significant advantage** over the baby.

This suggests that the model, particularly with the CLIP architecture, excels in recognizing more structured patterns (like realistic images, silhouettes, and features) but struggles more with abstract or less defined patterns like **Geons**.

3 3

[67]:
```
# Function to extract embeddings from the vision model
def extract_embeddings(image_paths):
    embeddings = []
    loaded_images = []  # List to store loaded images

    for img_path in image_paths:
        try:
            # Load the image
            image = load_image(img_path)
            loaded_images.append(image.convert("RGB").resize((100, 100)))  #␣
↪Store the loaded image

            # Process the image for the model
            inputs = processor(images=image, return_tensors="pt").to(device)

            # Extract embeddings from the vision model
            with torch.no_grad():
                vision_outputs = model.vision_model(**inputs)
                image_embedding = vision_outputs.pooler_output.squeeze().cpu().
↪numpy()

            embeddings.append(image_embedding)

        except Exception as e:
```

```
            print(f"Error processing image {img_path}: {e}")

    return np.array(embeddings), loaded_images
```

[68]:
```
# Extract embeddings
embeddings, loaded_images = extract_embeddings(image_paths)
```

[69]:
```
image_df = pd.DataFrame({
        "Condition" : condition_list,
        "Category" : category_list,
        "Image": loaded_images,
    })
```

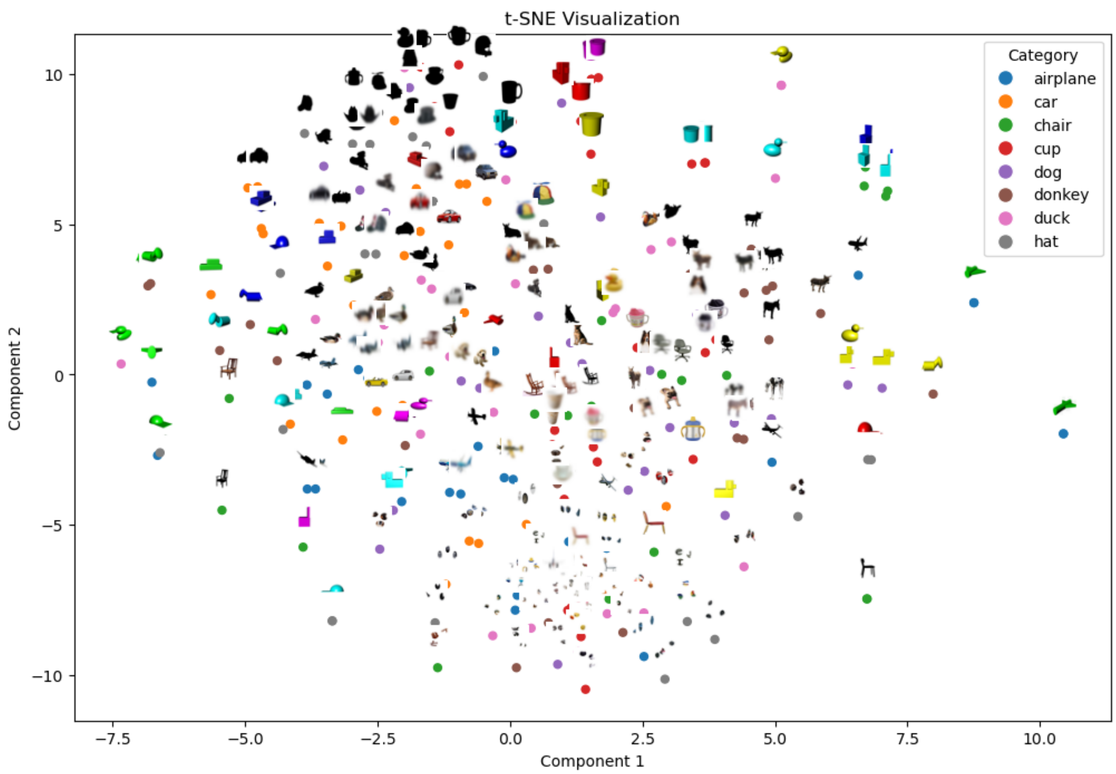
[70]:
```
category_color_map = {
    "airplane": "#1f77b4",  # Blue
    "car": "#ff7f0e",         # Orange
    "chair": "#2ca02c",       # Green
    "cup": "#d62728",         # Red
    "dog": "#9467bd",         # Purple
    "donkey": "#8c564b",      # Brown
    "duck": "#e377c2",        # Pink
    "hat": "#7f7f7f"          # Gray
}

# Map each row's category to its corresponding color
image_df['Color'] = image_df['Category'].map(category_color_map)
```

[71]:
```
image_df['Image_Array'] = image_df['Image'].apply(lambda img: np.array(img).
 ↪flatten())

# Stack all the flattened images into a 2D NumPy array
image_data = np.stack(image_df['Image_Array'].values)

# Normalize the image data (optional but recommended)
image_data = image_data / 255.0
```

[72]:
```
import matplotlib.pyplot as plt
from matplotlib.offsetbox import OffsetImage, AnnotationBbox
from sklearn.manifold import TSNE
from PIL import Image
import numpy as np
import matplotlib.patches as patches
```

[73]:
```
reduced_data_2d_TSNE = TSNE(n_components=2, random_state=42).
 ↪fit_transform(image_data)

fig, ax = plt.subplots(figsize=(12, 8))
```

```python
# Add scatter points
scatter = ax.scatter(
    reduced_data_2d_TSNE[:, 0],
    reduced_data_2d_TSNE[:, 1],
    c=image_df['Color'],
    s=25,
    alpha=1,
)

# Add legend
legend_elements = [
    plt.Line2D([0], [0], marker='o', color='w', label=key, markersize=10,␣
 ↪markerfacecolor=color)
    for key, color in category_color_map.items()
]
ax.legend(handles=legend_elements, title="Category", loc="best")


# Define the vertical offset for the images
vertical_offset = 1  # Adjust this value as needed

# Add images to the scatter plot
for i, row in image_df.iterrows():
    try:
        # Resize the image for visualization
        image = np.array(row['Image'].resize((24, 24)))
        im = OffsetImage(image, zoom=0.65, alpha=1.0)
        # Position the image above the dot
        ab = AnnotationBbox(
            im,
            (reduced_data_2d_TSNE[i, 0], reduced_data_2d_TSNE[i, 1] +␣
 ↪vertical_offset),
            frameon=False
        )
        ax.add_artist(ab)
    except Exception as e:
        print(f"Error adding image for {row['Filename']}: {e}")


# Set axis labels and title
ax.set_xlabel("Component 1")
ax.set_ylabel("Component 2")
ax.set_title(f"t-SNE Visualization")

# Display the plot
plt.show()
```


t-SNE Visualization
Category
airplane
car
chair
cup
dog
donkey
duck
hat
Component 1
Component 2
−7.5
−5.0
−2.5
0.0
2.5
5.0
7.5
10.0
10
5
0
−5
−10