CSCI 5922 - 001 Neural Networks and Deep Learning
Lab Assignment 3

Challenge: To Design the best multi-modal visual question answering architecture

Dataset : VizWiz - It provides the visual and textual inputs for the models

It contains,
Training samples - 20523
Validation samples - 4319
Test samples - 8000

Each sample contains a single image, a text question and a binary label in which '0' indicates the question is not answerable and '1' indicates the question is answerable and '10' text answers to the posted questions.

Data Processing:

Preprocessing for Binary Classification Challenge & Answer Prediction Challenge:

The goal here is to classify whether the given question image pair is answerable or not.

- For doing this task, I created a balanced and consistent subset from the original dataset to effectively train and evaluate. This process will eliminate the class imbalance issue which exists while pulling random data from the whole dataset.

  Here I took,
  1500 training samples[Training set 1]: 750 of class '0' and 750 of class '1'
  3000 training samples[Training set 2]: 1500 of each class
  300 validation samples: 150 samples from each class
  100 test samples - here I took the first 100 samples (I didn't do class balancing here)

- Image Preprocessing
  Here I converted the image to RGB using the PIL
  Resized the image to 128 x 128
  Transformed the image using 'transforms.compose' where I did 'resize', 'converted to tensor' and 'normalize' operations.

- Text Processing
  Here I did text processing for the questions, I used NLP steps using NLTK and Glove Word2Vec Embeddings.
  I used tokenization using nltk.tokenize.word_tokenize
  I used lemmatization using nltk.stem.WordNetLemmatizer

I used stop words removal approach using nltk.corpus.stopwords

I used 50 dimensional Glove Word2Vec Embeddings where the 'get_text_embedding' generates the average of all the words present in the glove vocabulary.
If there is no valid words found then a zero vector [50,] will be returned.

Then we saved all the question embeddings as tensors.pt files

For the answer prediction challenge,

- We didn't do class balancing and all, there I took the first 3500 samples for training, 300 for validation and in testing I took first 100 samples for making the predictions.

- And for image processing,
  I did standard image transformation techniques such as resize, RandomHorizontalflip, ColorJitter, Normalization and converted those to Tensors.

- Here for the text processing, i wrote a function get_text_embedding which mainly utilizes the Glove Word2Vec model, where lowercasing question, tokenizing the words, removing stopwords and non alpha numeric tokens, lemmatization of the remaining words and fetching Glove Embeddings for all the valid words.
  Then I averaged all of the words and produced a single (50,) embedding if no words then a zero vector of (50,0) is returned as a result.
  Then loaded all the image and text to store all of those as tensors.

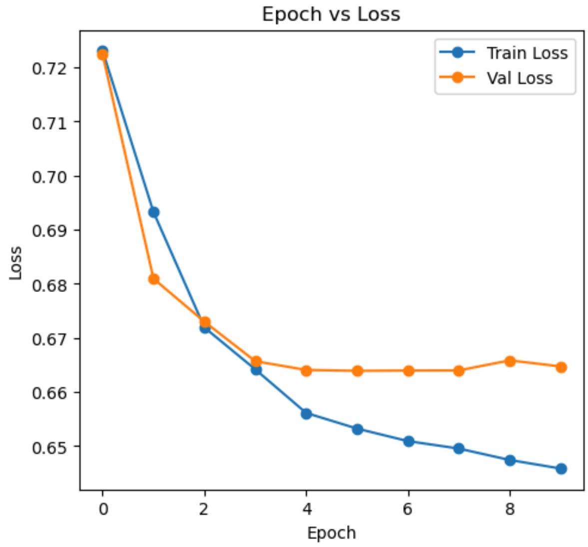
- Then I chose to do the Top N answer selection, for that from the training data I extracted the most common answers from 10 human responses then counted all the frequencies using the Counter. Then I retained the top 500 answers as the valid prediction classes.
- I did label mapping by creating two dictionaries
  1. 'category_name2id which maps the string to the class index
  2. 'category_id2name' which maps the class index to string

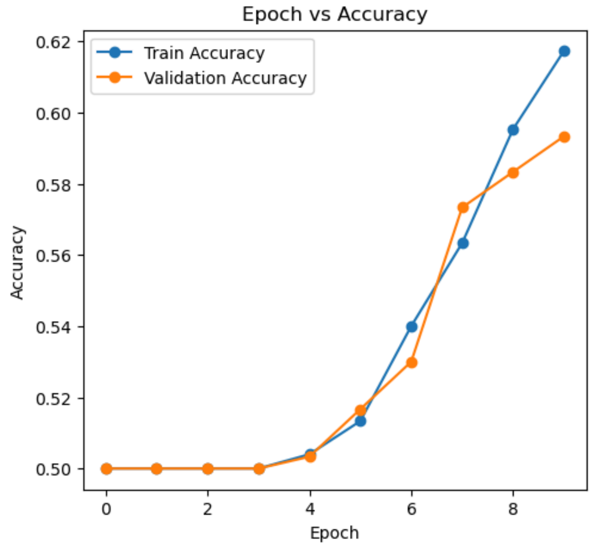
  Then assigned an extra class for all 'other/unseen' answers.

- I did target creation, where I processed the answers to tensors.

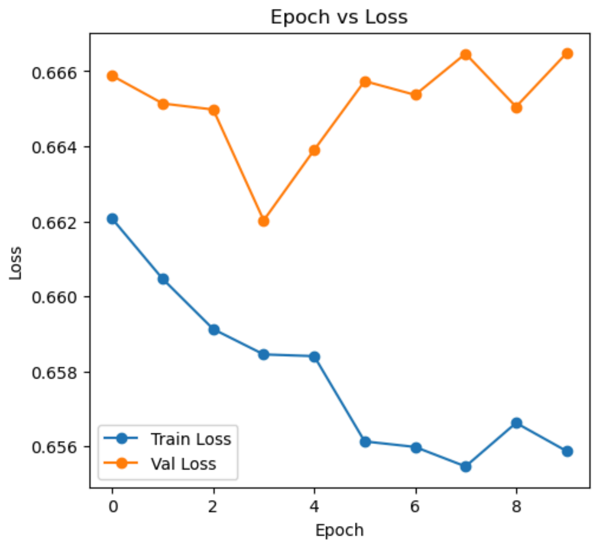
Clarification on usage of 3000 training Samples:

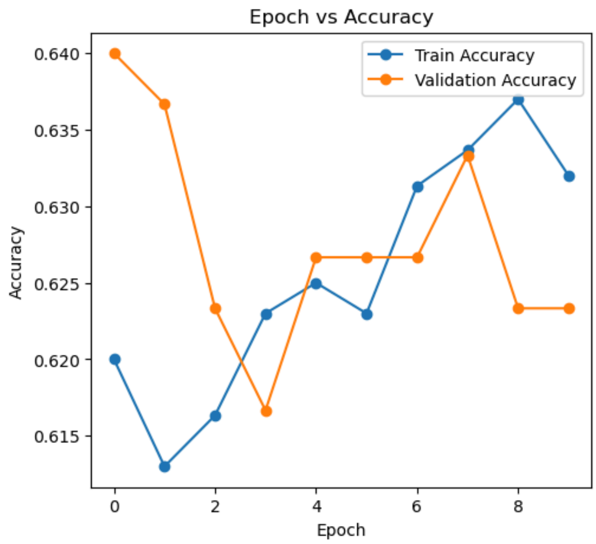
I took two training sampled tests and tested the model with both the training samples, With 1500 training samples:





With 3000 training samples:





Here these graphs will have a clear representation indicating,Using 3000 training samples got a better validation accuracy and generalization this made to prefer 3000 samples.

Details of MultiModal Architectures:

Architecture for Challenge 1:

The VQA model which I created for processing both the images and text helps in determining the answerability of a question for a given image. The model consists of mainly two components: convolution neural network(for extracting features from the image) and fully connected layers (for text preprocessing). The CNN has 4 Convolutional layers, followed by

Batch Normalization layers and ReLU activation function which helps in capturing the features and patterns in an image. The extracted features then flattened and passed through FC layers to generate the visual embeddings. At the same time, the text input ‘Word2Vec’ embeddings is processed through a series of FC layers and map it to a higher dimensional space so that it will be compatible with the image features.

Inorder to merge these two modalities, I used a cross attention mechanism using the multi head attention layers. This mechanism helps in aligning features from both the image and text which ensures that the model focuses on important visual areas based on the context of the question. If we allow the image and text influence on each other, then the attention layer will enhance the model’s ability to determine the answerability of the model more accurately.

After the fusion step, the Fully Connected layers further refine the combined features which leads to the final classification. The output layer activates with a sigmoid activation function which produces a probability score which indicates whether the question is answerable or not, this makes this as a binary classification problem.

This architecture integrates both the visual and text information, by means of CNN (image representations) and attention mechanism (for context aware learning). The Binary Cross Entropy loss is used for the training, optimizing and differentiating between answerable and the unanswerable questions.

Architecture for Challenge 2:

Here the ImprovedVQA model solves the challenge 2, it combines CNNS for extracting features from the image, with FC layers and attention based transformer layers for text processing. For processing image, the architecture uses ResNet34 its a pretrained deep learning model, inorder to avoid the overfitting and generalize the early layers of the ResNet34 are frozen and the layers at the end are only finetuned. The final FC layers of ResNet is replaced by hidden dimensional projection layer, which ensures that the image features are mapped to the same space as the textual embeddings. For processing the text, a Fully connected network with layer normalization, ReLU activations and dropout layers are employed which extracts the semantic features from the 50D Word2Vec embeddings.

Inorder to merge both the modalities, the model uses a bi directional cross attention mechanism using the multi head attention layers. This helps the model to refine the image representations dynamically based on the text and text based on images, which ensures the model correctly captures the contextual relationships between the visual in the image and the question. Layer normalization is applied to stabilize the training and a gated fusion layer mechanism is added to regulate the contribution of both the image and text features. The fusion process helps in balancing the need of each modality, which allows the model to make accurate predictions.

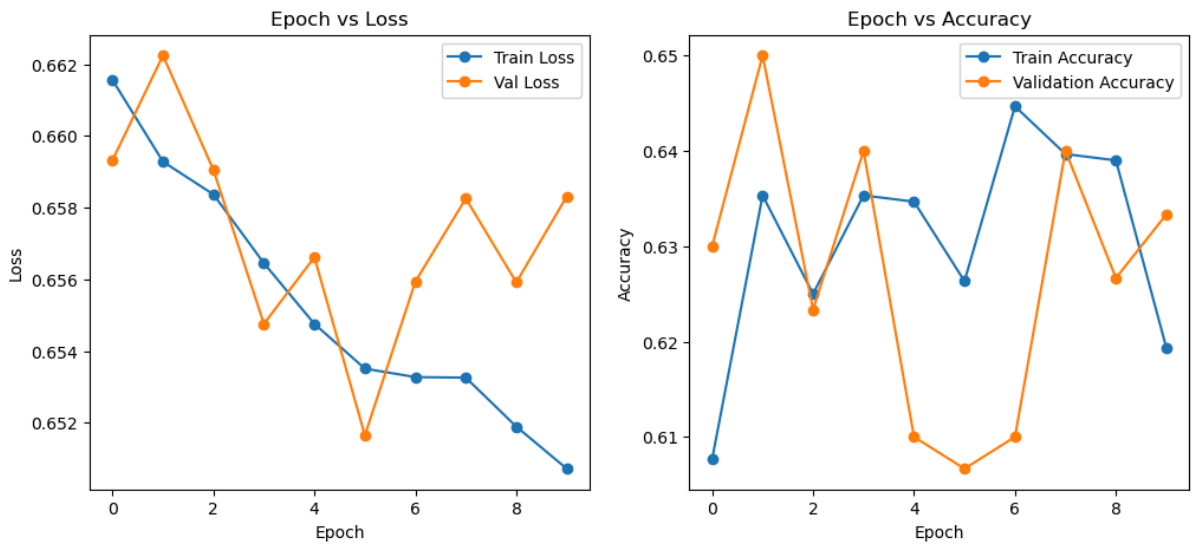
For the output layer, the model uses a multi class attention classification head which makes suitable for predicting one of the 500+ answer categories which we took while preprocessing. The classification module consists of a 3 layered FC network with ReLU activation and dropout for regularization. The final output that we will get is a probability distribution of all the possible answer categories. This ensures that the model effectively incorporates both the visual and textual data, aligns them with attention and it produces a interpretable and structured output for this challenge.

Model Adjustment and Hyperparameter Tuning using Validation set:

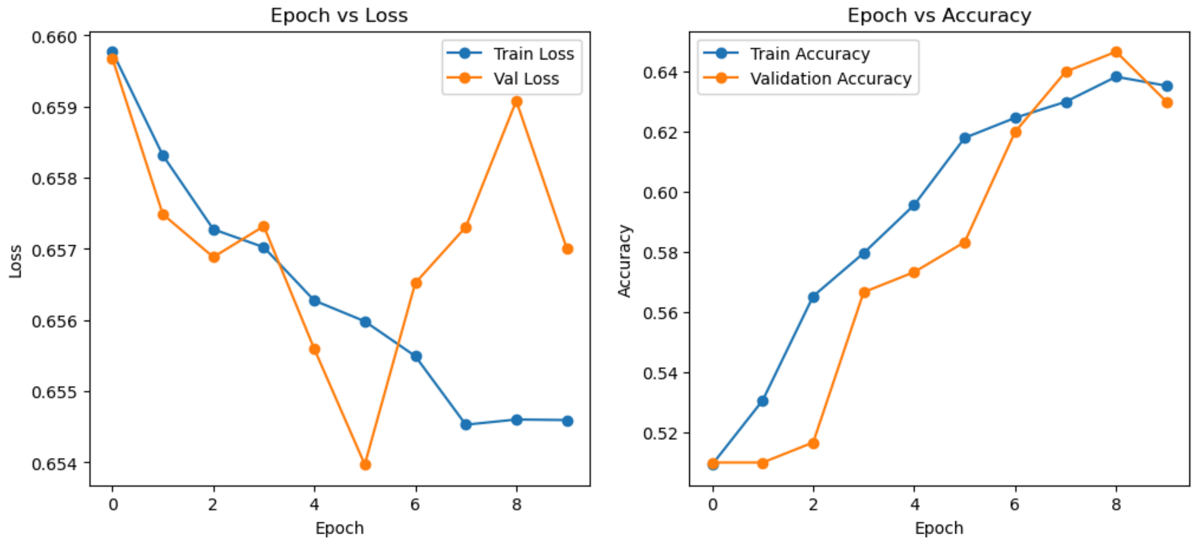
Challenge 1:

Hyper parameter tuning:

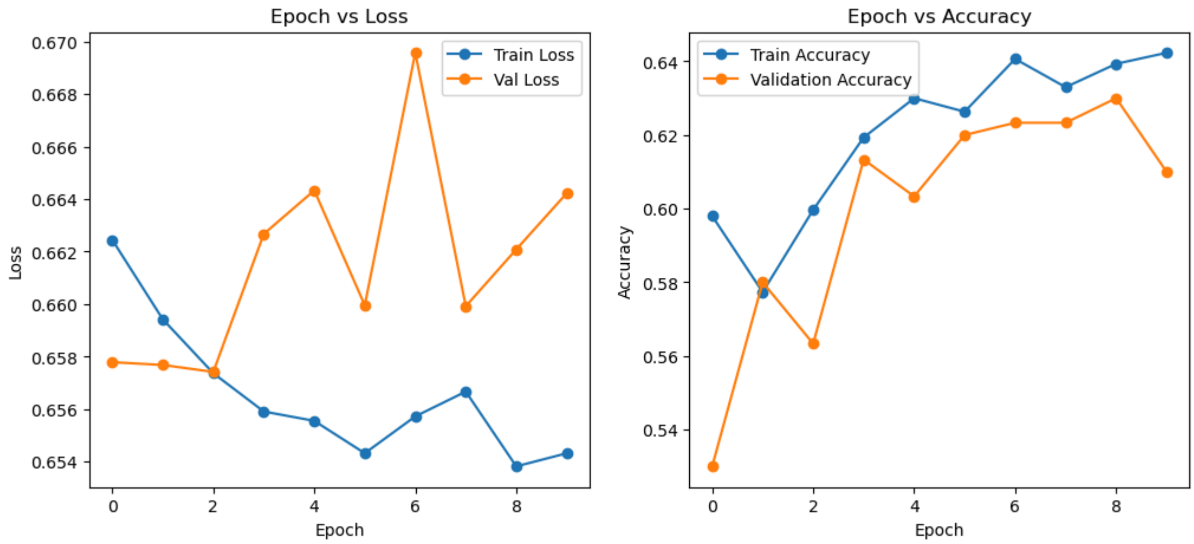
i) learning rate: 0.001, weight_decay = 1e-4, batch_size = 32, epochs = 10, optimizer = 'Adam'



ii) learning rate: 0.003, weight_decay = 1e-3, batch_size = 32, epochs = 10, optimizer = 'SGD'



iii) learning rate: 0.0007, weight_decay = 5e-5, batch_size = 32, epochs = 10, optimizer = ‘AdamW’



The best model here is learning rate: 0.003, weight_decay = 1e-3, batch_size = 32, epochs = 10, optimizer = ‘SGD’. This particular setup achieved the highest val accuracy of 0.64 while also maintaining the steady upward trend both during the validation and training performances. These plots shows a very minimal overfitting with the validation accuracy closely tracking the training accuracy, which indicates a good generalization of the model. The training process is also stable and the convergence here was very smooth compared to the other hyper parameter sets which is sometimes showing noise in the val loss or there is a slight divergence in the trend.

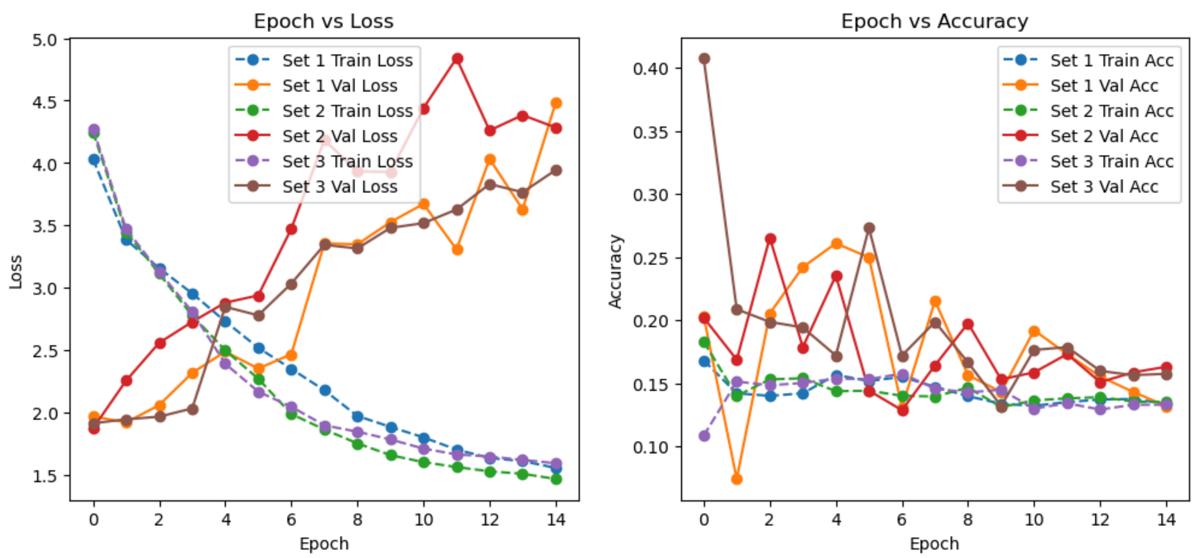
Throughout the model development and training, some of the key trends are observed. Learning rate has the most significant impact ie. too high value results in an unstabled learning, too low value might cause slower convergence while reaching the global minima. Moderate learning rate like ‘0.0003’ will correctly struck in the right balance. Weight decay also plays a crucial role in the generalization, higher values like ‘1e-3’ helps in prevention of the overfitting without delaying the learning. Here the optimizers AdamW which contributes to faster and more stable updates, performs really well but eventhough an optimizer like SGD with the right set of other parameters performing well. These hyperparameter tuning helped in ending up with the best model parameters which helps in solving this particular challenge.

Challenge 2:

Set 1: learning rate: 0.0002, weight_decay = 1e-5, batch_size = 16, epochs = 15, optimizer = ‘AdamW’

Set 2: learning rate: 0.0001, weight_decay = 5e-5, batch_size = 32, epochs = 15, optimizer = ‘AdamW’

Set 3: learning rate: 0.0005, weight_decay = 1e-6, batch_size = 32, epochs = 15, optimizer = ‘AdamW’



During the model adjustment and hyper parameter tuning for the challenge 2, three different hyper parameter sets were tested by different learning rates, weight decay and the batch size. The validation set here is used to track the human answer accuracy ie min(no.of human answered/3,1) which helps in identifying the most effective setup. Among the different hyper parameters tested, the set 3 with learning rate: 0.0005, weight_decay = 1e-6, batch_size = 32, epochs = 15, optimizer = ‘AdamW’ achieved the highest val accuracy of 0.4078 in the first epoch and this model is saved as best model as a pytorch file. While this performance decreases over time, it significantly outperformed the other configurations in the early learning periods.

These results clearly shows that the learning rate and weight decay are the most sensitive hyperparameters. Set 1 and Set 2 with a smaller learning rate showed a gradual improvement at first but then struggled with the overfitting/slower convergence. Despite similar training losses the validation accuracy patterns seems different across different hyperparameter sets which suggests that the model architecture benefits from the aggressive learning at the start which is possibly due to the pretrained ResNet backbone and the multi head attention layers as those are the ones which needed faster updates initially. Based on this I chose set 3 because of it's high val accuracy with the validation set and its generalization capability.

The final prediction results are also submitted with this file, including one .pkl file and one .json file.

```python
import torch
import numpy as np
import torchvision.transforms as transforms
from torch.utils.data import Dataset, DataLoader
import requests
from PIL import Image
import json
import random
import nltk
import os
from io import BytesIO
import re
from transformers import BertTokenizer
import gensim
from gensim.models import Word2Vec

nltk.download('punkt')

device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
print(f"Using device: {device}")
```

```
c:\Users\yoges\anaconda3\Lib\site-packages\paramiko\transport.py:219:
CryptographyDeprecationWarning: Blowfish has been deprecated and will
be removed in a future release
  "class": algorithms.Blowfish,

Using device: cuda

[nltk_data] Downloading package punkt to
[nltk_data]     C:\Users\yoges\AppData\Roaming\nltk_data...
[nltk_data]   Package punkt is already up-to-date!
```

```python
IMG_DIR = "https://vizwiz.cs.colorado.edu/VizWiz_visualization_img/"


ANN_DIR =
"https://vizwiz.cs.colorado.edu/VizWiz_final/vqa_data/Annotations/"
TRAIN_ANNOTATION_PATH = f"{ANN_DIR}train.json"
VAL_ANNOTATION_PATH = f"{ANN_DIR}val.json"
TEST_ANNOTATION_PATH = f"{ANN_DIR}test.json"


train_data = requests.get(TRAIN_ANNOTATION_PATH).json()
val_data = requests.get(VAL_ANNOTATION_PATH).json()
test_data = requests.get(TEST_ANNOTATION_PATH).json()


print("Total Train Set Size:", len(train_data))
print("Total Validation Set Size:", len(val_data))
print("Total Test Set Size:", len(test_data))
```

```
Total Train Set Size: 20523
Total Validation Set Size: 4319
Total Test Set Size: 8000
```

```
def balance_and_sample(data, sample_size, is_test=False):
    """Ensure class balance while selecting a subset of the dataset.

    If `is_test=True`, random sampling is used instead of class
balancing.
    """
    if is_test:
        return random.sample(data, sample_size)

    class_1 = [sample for sample in data if sample.get('answerable', -
1) == 1]
    class_0 = [sample for sample in data if sample.get('answerable', -
1) == 0]


    size_per_class = sample_size // 2

    balanced_samples = random.sample(class_1, min(size_per_class,
len(class_1))) + \
                       random.sample(class_0, min(size_per_class,
len(class_0)))


    random.shuffle(balanced_samples)
    return balanced_samples


TRAIN_SIZE_1 = 1500
TRAIN_SIZE_2 = 3000
VAL_SIZE = 300



train_samples_1500 = balance_and_sample(train_data, TRAIN_SIZE_1)
train_samples_3000 = balance_and_sample(train_data, TRAIN_SIZE_2)
val_samples = balance_and_sample(val_data, VAL_SIZE)
test_samples = test_data[:100]


train_1500_class_1 = sum(1 for sample in train_samples_1500 if
sample.get('answerable', -1) == 1)
train_1500_class_0 = sum(1 for sample in train_samples_1500 if
sample.get('answerable', -1) == 0)

train_3000_class_1 = sum(1 for sample in train_samples_3000 if
sample.get('answerable', -1) == 1)
train_3000_class_0 = sum(1 for sample in train_samples_3000 if
```

```
sample.get('answerable', -1) == 0)

print(f"Train Set (1500 samples) -> Class 1: {train_1500_class_1},
Class 0: {train_1500_class_0}")
print(f"Train Set (3000 samples) -> Class 1: {train_3000_class_1},
Class 0: {train_3000_class_0}")
print(f"Balanced Validation Set Size: {len(val_samples)}")
print(f"Randomly Sampled Test Set Size: {len(test_samples)}")
```

```
Train Set (1500 samples) -> Class 1: 750, Class 0: 750
Train Set (3000 samples) -> Class 1: 1500, Class 0: 1500
Balanced Validation Set Size: 300
Randomly Sampled Test Set Size: 100
```

```
transform = transforms.Compose([
    transforms.Resize((128, 128)),
    transforms.ToTensor(),
    transforms.Normalize(mean=[0.485, 0.456, 0.406], std=[0.229,
0.224, 0.225])  # Normalize
])

print("Image preprocessing defined.")
```

```
Image preprocessing defined.
```

```
def image_tensors(dataset, dataset_name,
save_path="preprocessed_tensors"):
    """Convert images to tensors, process on GPU, and save for future
use."""

    os.makedirs(save_path, exist_ok=True)
    image_tensors = []

    for sample in dataset:
        image_url = IMG_DIR + sample['image']
        response = requests.get(image_url)
        img = Image.open(BytesIO(response.content)).convert("RGB")


        img_tensor = transform(img).to(device, non_blocking=True)
        image_tensors.append(img_tensor)


    image_tensors = torch.stack(image_tensors, dim=0)


    save_file = os.path.join(save_path,
f"{dataset_name}_image_tensors.pt")
    torch.save(image_tensors, save_file)
```

```
    print(f"Saved {dataset_name} image tensors to {save_file} on
{device}")

    return image_tensors



train_image_tensors1 = image_tensors(train_samples_1500, "train_1500")
train_image_tensors2 = image_tensors(train_samples_3000, "train_3000")
val_image_tensors = image_tensors(val_samples, "val")
test_image_tensors = image_tensors(test_samples, "test")

print("All image tensors saved successfully!")

def image_tensors(dataset, dataset_name,
save_path="preprocessed_tensors"):
    """Convert images to tensors, process on GPU, and save for future
use."""

    os.makedirs(save_path, exist_ok=True)
    image_tensors = []

    for sample in dataset:
        image_url = IMG_DIR + sample['image']
        response = requests.get(image_url)
        img = Image.open(BytesIO(response.content)).convert("RGB")


        img_tensor = transform(img).to(device, non_blocking=True)
        image_tensors.append(img_tensor)


    image_tensors = torch.stack(image_tensors, dim=0)


    save_file = os.path.join(save_path,
f"{dataset_name}_image_tensors.pt")
    torch.save(image_tensors, save_file)

    print(f"Saved {dataset_name} image tensors to {save_file} on
{device}")

    return image_tensors

test_image_tensors = image_tensors(test_samples, "test")
```

```
Saved train_1500 image tensors to preprocessed_tensors\
train_1500_image_tensors.pt on cuda
Saved train_3000 image tensors to preprocessed_tensors\
```

```
train_3000_image_tensors.pt on cuda
Saved val image tensors to preprocessed_tensors\val_image_tensors.pt
on cuda
Saved test image tensors to preprocessed_tensors\test_image_tensors.pt
on cuda
All image tensors saved successfully!
```

```python
def load_image_tensors(dataset_name,
save_path="preprocessed_tensors"):
    """Load saved image tensors from disk."""
    load_file = os.path.join(save_path,
f"{dataset_name}_image_tensors.pt")
    image_tensors = torch.load(load_file).to(device)
    print(f"Loaded {dataset_name} image tensors from {load_file}")
    return image_tensors


train_image_tensors1 = load_image_tensors("train_1500")
train_image_tensors2 = load_image_tensors("train_3000")
val_image_tensors = load_image_tensors("val")
test_image_tensors = load_image_tensors("test")

print("Image tensors successfully loaded and ready for use!")
```

```
C:\Users\yoges\AppData\Local\Temp\ipykernel_35360\2116569202.py:4:
FutureWarning: You are using `torch.load` with `weights_only=False`
(the current default value), which uses the default pickle module
implicitly. It is possible to construct malicious pickle data which
will execute arbitrary code during unpickling (See
https://github.com/pytorch/pytorch/blob/main/SECURITY.md#untrusted-
models for more details). In a future release, the default value for
`weights_only` will be flipped to `True`. This limits the functions
that could be executed during unpickling. Arbitrary objects will no
longer be allowed to be loaded via this mode unless they are
explicitly allowlisted by the user via
`torch.serialization.add_safe_globals`. We recommend you start setting
`weights_only=True` for any use case where you don't have full control
of the loaded file. Please open an issue on GitHub for any issues
related to this experimental feature.
  image_tensors = torch.load(load_file).to(device)

Loaded train_1500 image tensors from preprocessed_tensors\
train_1500_image_tensors.pt
Loaded train_3000 image tensors from preprocessed_tensors\
train_3000_image_tensors.pt
Loaded val image tensors from preprocessed_tensors\
val_image_tensors.pt
Loaded test image tensors from preprocessed_tensors\
test_image_tensors.pt
Image tensors successfully loaded and ready for use!
```

TEXT PREPROCESSING

```
import os
import numpy as np
import torch
import gensim.downloader as api
import nltk
from nltk.tokenize import word_tokenize
from nltk.corpus import stopwords
from nltk.stem import WordNetLemmatizer


nltk.download('punkt')
nltk.download('stopwords')
nltk.download('wordnet')


print("Loading GloVe Word2Vec model...")
word2vec_model = api.load("glove-wiki-gigaword-50")
print("Word2Vec model loaded successfully!")


stop_words = set(stopwords.words("english"))
lemmatizer = WordNetLemmatizer()

def get_text_embedding(text):
    """Converts input text into a 50D Word2Vec vector after 
preprocessing."""
    words = word_tokenize(text.lower())
    words = [lemmatizer.lemmatize(word) for word in words if 
word.isalnum() and word not in stop_words]
    word_vectors = [word2vec_model[w] for w in words if w in 
word2vec_model]

    return np.mean(word_vectors, axis=0) if word_vectors else 
np.zeros(50)


save_path = "preprocessed_tensors"
os.makedirs(save_path, exist_ok=True)

train_1500_question_embeddings = 
[get_text_embedding(sample['question']) for sample in 
train_samples_1500]
train_3000_question_embeddings = 
[get_text_embedding(sample['question']) for sample in 
train_samples_3000]
val_question_embeddings = [get_text_embedding(sample['question']) for 
sample in val_samples]
test_question_embeddings = [get_text_embedding(sample['question']) for 
sample in test_samples]
```

```
train_1500_question_tensors =
torch.tensor(train_1500_question_embeddings,
dtype=torch.float32).to(device)
train_3000_question_tensors =
torch.tensor(train_3000_question_embeddings,
dtype=torch.float32).to(device)
val_question_tensors = torch.tensor(val_question_embeddings,
dtype=torch.float32).to(device)
test_question_tensors = torch.tensor(test_question_embeddings,
dtype=torch.float32).to(device)


torch.save(train_1500_question_tensors, os.path.join(save_path,
"train_1500_question_tensors.pt"))
torch.save(train_3000_question_tensors, os.path.join(save_path,
"train_3000_question_tensors.pt"))
torch.save(val_question_tensors, os.path.join(save_path,
"val_question_tensors.pt"))
torch.save(test_question_tensors, os.path.join(save_path,
"test_question_tensors.pt"))
```

```
[nltk_data] Downloading package punkt to
[nltk_data]     C:\Users\yoges\AppData\Roaming\nltk_data...
[nltk_data]   Package punkt is already up-to-date!
[nltk_data] Downloading package stopwords to
[nltk_data]     C:\Users\yoges\AppData\Roaming\nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
[nltk_data] Downloading package wordnet to
[nltk_data]     C:\Users\yoges\AppData\Roaming\nltk_data...
[nltk_data]   Package wordnet is already up-to-date!

Loading GloVe Word2Vec model...
Word2Vec model loaded successfully!
```

CHALLENGE 1

```
import torch
import torch.nn as nn
import torch.nn.functional as F
from torch.optim import AdamW
from torch.utils.data import DataLoader, TensorDataset


device = torch.device("cuda" if torch.cuda.is_available() else "cpu")

class CrossAttention(nn.Module):
    def __init__(self, embed_dim, num_heads):
        super(CrossAttention, self).__init__()
```

```
        self.multihead_attn =
nn.MultiheadAttention(embed_dim=embed_dim, num_heads=num_heads,
batch_first=True)

    def forward(self, query, key, value):
        attn_output, _ = self.multihead_attn(query, key, value)
        return attn_output

class VQAModel(nn.Module):
    def __init__(self, image_size=(128, 128), hidden_dim=32,
num_classes=1, num_heads=4):
        super(VQAModel, self).__init__()


        self.conv1 = nn.Conv2d(in_channels=3, out_channels=16,
kernel_size=3, stride=1, padding=1)
        self.bn1 = nn.BatchNorm2d(16)
        self.conv2 = nn.Conv2d(in_channels=16, out_channels=32,
kernel_size=3, stride=1, padding=1)
        self.bn2 = nn.BatchNorm2d(32)
        self.conv3 = nn.Conv2d(in_channels=32, out_channels=64,
kernel_size=3, stride=1, padding=1)
        self.conv4 = nn.Conv2d(in_channels=64, out_channels=64,
kernel_size=3, stride=1, padding=1)

        H, W = image_size
        feature_size = H * W * 64
        self.fc_image1 = nn.Linear(feature_size, hidden_dim * 2)
        self.bn3 = nn.BatchNorm1d(hidden_dim * 2)
        self.fc_image2 = nn.Linear(hidden_dim * 2, hidden_dim)


        self.fc_text1 = nn.Linear(50, hidden_dim * 2)
        self.fc_text2 = nn.Linear(hidden_dim * 2, hidden_dim)


        self.cross_attention = CrossAttention(embed_dim=hidden_dim,
num_heads=num_heads)


        self.fc_fusion = nn.Linear(hidden_dim, hidden_dim)
        self.fc_hidden1 = nn.Linear(hidden_dim, hidden_dim * 2)
        self.fc_output = nn.Linear(hidden_dim * 2, num_classes)

    def forward(self, image, text):

        x_image = F.relu(self.bn1(self.conv1(image)))
        x_image = F.relu(self.bn2(self.conv2(x_image)))
        x_image = F.relu(self.conv3(x_image))
        x_image = F.relu(self.conv4(x_image))
```

```
        x_image = x_image.view(x_image.size(0), -1)
        x_image = F.relu(self.bn3(self.fc_image1(x_image)))
        x_image = F.relu(self.fc_image2(x_image))


        x_text = F.relu(self.fc_text1(text))
        x_text = F.relu(self.fc_text2(x_text))


        x_image = x_image.unsqueeze(1)
        x_text = x_text.unsqueeze(1)


        x_fused = self.cross_attention(query=x_image, key=x_text,
value=x_text)
        x_fused = x_fused.squeeze(1)


        x_fused = F.relu(self.fc_fusion(x_fused))
        x_fused = F.relu(self.fc_hidden1(x_fused))


        output = torch.sigmoid(self.fc_output(x_fused)).squeeze(1)
        return output


model = VQAModel().to(device)

import os
import torch.optim as optim
import matplotlib.pyplot as plt
from torch.utils.data import DataLoader, TensorDataset


hyperparams = {
    'lr': 0.0005,
    'weight_decay': 1e-5,
    'batch_size': 32,
    'epochs': 10,
    'optimizer': 'AdamW'
}


submission_dir = "submission"
os.makedirs(submission_dir, exist_ok=True)
best_model_path = os.path.join(submission_dir, "best_model.pth")  #
Path to save best model


train_image_tensors1 =
torch.load("preprocessed_tensors/train_1500_image_tensors.pt").to(devi
```

```
ce)
train_image_tensors2 =
torch.load("preprocessed_tensors/train_3000_image_tensors.pt").to(devi
ce)
train_text_tensors1 =
torch.load("preprocessed_tensors/train_1500_question_tensors.pt").to(d
evice)
train_text_tensors2 =
torch.load("preprocessed_tensors/train_3000_question_tensors.pt").to(d
evice)
val_image_tensors =
torch.load("preprocessed_tensors/val_image_tensors.pt").to(device)
val_text_tensors =
torch.load("preprocessed_tensors/val_question_tensors.pt").to(device)


train_labels1 = torch.tensor([sample['answerable'] for sample in
train_samples_1500], dtype=torch.float32).to(device)
train_labels2 = torch.tensor([sample['answerable'] for sample in
train_samples_3000], dtype=torch.float32).to(device)
val_labels = torch.tensor([sample['answerable'] for sample in
val_samples], dtype=torch.float32).to(device)


train_dataset1 = TensorDataset(train_image_tensors1,
train_text_tensors1, train_labels1)
train_dataset2 = TensorDataset(train_image_tensors2,
train_text_tensors2, train_labels2)
val_dataset = TensorDataset(val_image_tensors, val_text_tensors,
val_labels)

train_loader1 = DataLoader(train_dataset1,
batch_size=hyperparams['batch_size'], shuffle=True)
train_loader2 = DataLoader(train_dataset2,
batch_size=hyperparams['batch_size'], shuffle=True)
val_loader = DataLoader(val_dataset,
batch_size=hyperparams['batch_size'], shuffle=False)


def train_model(model, train_loader, val_loader, hyperparams,
save_best=True):
    optimizer = optim.AdamW(model.parameters(), lr=hyperparams['lr'],
weight_decay=hyperparams['weight_decay'])
    criterion = nn.BCEWithLogitsLoss()

    train_losses, val_losses, train_accs, val_accs = [], [], [], []
    best_val_acc = 0

    for epoch in range(hyperparams['epochs']):
        model.train()
```

```
        total_loss, correct, total = 0, 0, 0

        for images, text, labels in train_loader:
            images, text, labels = images.to(device), text.to(device),
labels.to(device)

            optimizer.zero_grad()
            outputs = model(images, text).squeeze()
            loss = criterion(outputs, labels)
            loss.backward()
            optimizer.step()

            total_loss += loss.item()
            predicted = (torch.sigmoid(outputs) > 0.5).float()
            correct += (predicted == labels).sum().item()
            total += labels.size(0)

        train_loss = total_loss / len(train_loader)
        train_acc = correct / total

        model.eval()
        total_loss, correct, total = 0, 0, 0
        with torch.no_grad():
            for images, text, labels in val_loader:
                images, text, labels = images.to(device),
text.to(device), labels.to(device)

                outputs = model(images, text).squeeze()
                loss = criterion(outputs, labels)
                total_loss += loss.item()
                predicted = (torch.sigmoid(outputs) > 0.5).float()
                correct += (predicted == labels).sum().item()
                total += labels.size(0)

        val_loss = total_loss / len(val_loader)
        val_acc = correct / total

        train_losses.append(train_loss)
        val_losses.append(val_loss)
        train_accs.append(train_acc)
        val_accs.append(val_acc)

        print(f"Epoch [{epoch+1}/{hyperparams['epochs']}]: Train
Loss={train_loss:.4f}, Val Loss={val_loss:.4f}, Train
Acc={train_acc:.4f}, Val Acc={val_acc:.4f}")


        if save_best and val_acc > best_val_acc:
            best_val_acc = val_acc
            torch.save(model.state_dict(), best_model_path)
```

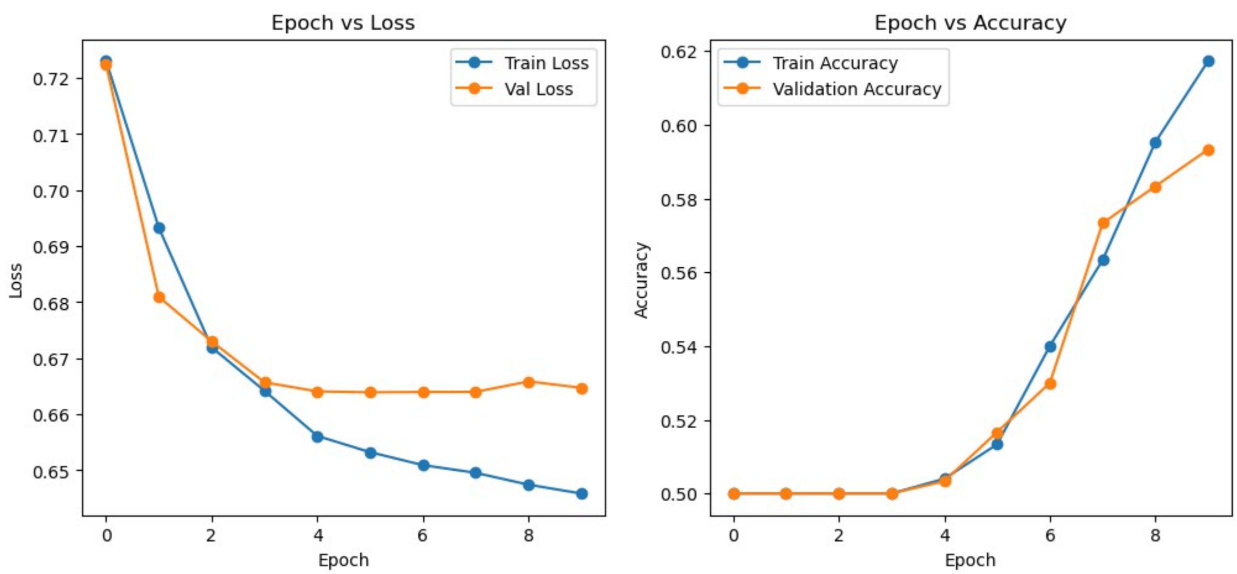
```
            print(f"Saved best model with Val Acc: {val_acc:.4f}")


    plt.figure(figsize=(12, 5))


    plt.subplot(1, 2, 1)
    plt.plot(train_losses, label='Train Loss', marker='o')
    plt.plot(val_losses, label='Val Loss', marker='o')
    plt.legend()
    plt.xlabel('Epoch')
    plt.ylabel('Loss')
    plt.title('Epoch vs Loss')


    plt.subplot(1, 2, 2)
    plt.plot(train_accs, label='Train Accuracy', marker='o')
    plt.plot(val_accs, label='Validation Accuracy', marker='o')
    plt.legend()
    plt.xlabel('Epoch')
    plt.ylabel('Accuracy')
    plt.title('Epoch vs Accuracy')

    plt.show()


model = VQAModel().to(device)
train_model(model, train_loader1, val_loader, hyperparams)
train_model(model, train_loader2, val_loader, hyperparams)

print(f" Best model saved at: {best_model_path}")
```

```
C:\Users\yoges\AppData\Local\Temp\ipykernel_35360\4280651903.py:21:
FutureWarning: You are using `torch.load` with `weights_only=False`
(the current default value), which uses the default pickle module
implicitly. It is possible to construct malicious pickle data which
will execute arbitrary code during unpickling (See
https://github.com/pytorch/pytorch/blob/main/SECURITY.md#untrusted-
models for more details). In a future release, the default value for
`weights_only` will be flipped to `True`. This limits the functions
that could be executed during unpickling. Arbitrary objects will no
longer be allowed to be loaded via this mode unless they are
explicitly allowlisted by the user via
`torch.serialization.add_safe_globals`. We recommend you start setting
`weights_only=True` for any use case where you don't have full control
of the loaded file. Please open an issue on GitHub for any issues
related to this experimental feature.
  train_image_tensors1 =
torch.load("preprocessed_tensors/train_1500_image_tensors.pt").to(devi
ce)
```

```
C:\Users\yoges\AppData\Local\Temp\ipykernel_35360\4280651903.py:22:
FutureWarning: You are using `torch.load` with `weights_only=False`
(the current default value), which uses the default pickle module
implicitly. It is possible to construct malicious pickle data which
will execute arbitrary code during unpickling (See
https://github.com/pytorch/pytorch/blob/main/SECURITY.md#untrusted-
models for more details). In a future release, the default value for
`weights_only` will be flipped to `True`. This limits the functions
that could be executed during unpickling. Arbitrary objects will no
longer be allowed to be loaded via this mode unless they are
explicitly allowlisted by the user via
`torch.serialization.add_safe_globals`. We recommend you start setting
`weights_only=True` for any use case where you don't have full control
of the loaded file. Please open an issue on GitHub for any issues
related to this experimental feature.
  train_image_tensors2 =
torch.load("preprocessed_tensors/train_3000_image_tensors.pt").to(devi
ce)
C:\Users\yoges\AppData\Local\Temp\ipykernel_35360\4280651903.py:23:
FutureWarning: You are using `torch.load` with `weights_only=False`
(the current default value), which uses the default pickle module
implicitly. It is possible to construct malicious pickle data which
will execute arbitrary code during unpickling (See
https://github.com/pytorch/pytorch/blob/main/SECURITY.md#untrusted-
models for more details). In a future release, the default value for
`weights_only` will be flipped to `True`. This limits the functions
that could be executed during unpickling. Arbitrary objects will no
longer be allowed to be loaded via this mode unless they are
explicitly allowlisted by the user via
`torch.serialization.add_safe_globals`. We recommend you start setting
`weights_only=True` for any use case where you don't have full control
of the loaded file. Please open an issue on GitHub for any issues
related to this experimental feature.
  train_text_tensors1 =
torch.load("preprocessed_tensors/train_1500_question_tensors.pt").to(d
evice)
C:\Users\yoges\AppData\Local\Temp\ipykernel_35360\4280651903.py:24:
FutureWarning: You are using `torch.load` with `weights_only=False`
(the current default value), which uses the default pickle module
implicitly. It is possible to construct malicious pickle data which
will execute arbitrary code during unpickling (See
https://github.com/pytorch/pytorch/blob/main/SECURITY.md#untrusted-
models for more details). In a future release, the default value for
`weights_only` will be flipped to `True`. This limits the functions
that could be executed during unpickling. Arbitrary objects will no
longer be allowed to be loaded via this mode unless they are
explicitly allowlisted by the user via
`torch.serialization.add_safe_globals`. We recommend you start setting
`weights_only=True` for any use case where you don't have full control
```

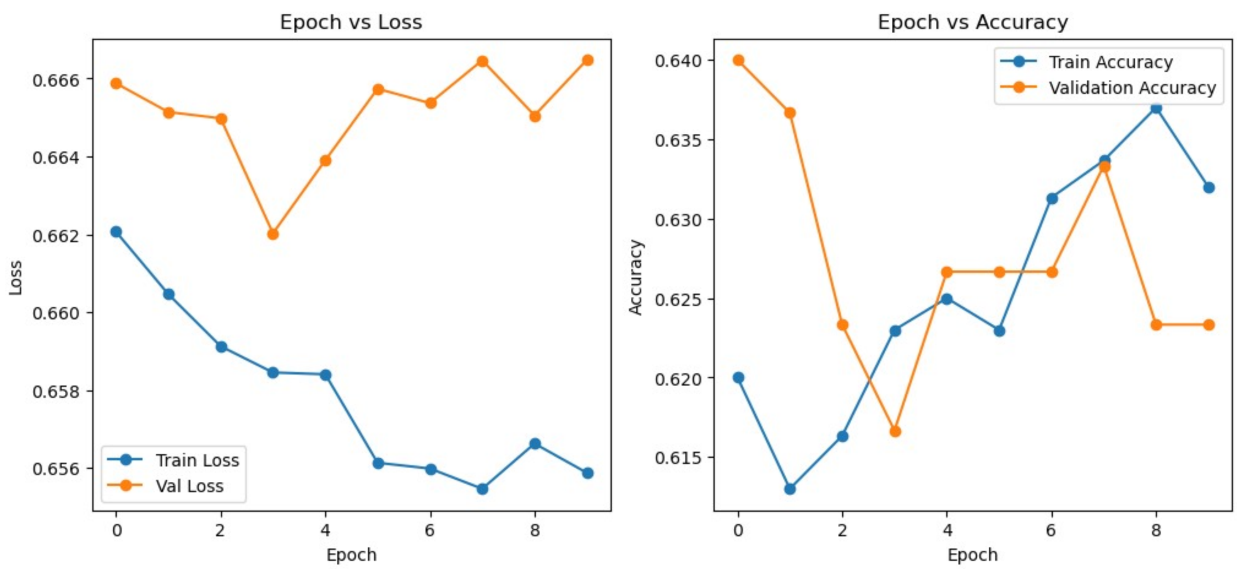
```
of the loaded file. Please open an issue on GitHub for any issues
related to this experimental feature.
  train_text_tensors2 =
torch.load("preprocessed_tensors/train_3000_question_tensors.pt").to(d
evice)
C:\Users\yoges\AppData\Local\Temp\ipykernel_35360\4280651903.py:25:
FutureWarning: You are using `torch.load` with `weights_only=False`
(the current default value), which uses the default pickle module
implicitly. It is possible to construct malicious pickle data which
will execute arbitrary code during unpickling (See
https://github.com/pytorch/pytorch/blob/main/SECURITY.md#untrusted-
models for more details). In a future release, the default value for
`weights_only` will be flipped to `True`. This limits the functions
that could be executed during unpickling. Arbitrary objects will no
longer be allowed to be loaded via this mode unless they are
explicitly allowlisted by the user via
`torch.serialization.add_safe_globals`. We recommend you start setting
`weights_only=True` for any use case where you don't have full control
of the loaded file. Please open an issue on GitHub for any issues
related to this experimental feature.
  val_image_tensors =
torch.load("preprocessed_tensors/val_image_tensors.pt").to(device)
C:\Users\yoges\AppData\Local\Temp\ipykernel_35360\4280651903.py:26:
FutureWarning: You are using `torch.load` with `weights_only=False`
(the current default value), which uses the default pickle module
implicitly. It is possible to construct malicious pickle data which
will execute arbitrary code during unpickling (See
https://github.com/pytorch/pytorch/blob/main/SECURITY.md#untrusted-
models for more details). In a future release, the default value for
`weights_only` will be flipped to `True`. This limits the functions
that could be executed during unpickling. Arbitrary objects will no
longer be allowed to be loaded via this mode unless they are
explicitly allowlisted by the user via
`torch.serialization.add_safe_globals`. We recommend you start setting
`weights_only=True` for any use case where you don't have full control
of the loaded file. Please open an issue on GitHub for any issues
related to this experimental feature.
  val_text_tensors =
torch.load("preprocessed_tensors/val_question_tensors.pt").to(device)

Epoch [1/10]: Train Loss=0.7231, Val Loss=0.7224, Train Acc=0.5000,
Val Acc=0.5000
 Saved best model with Val Acc: 0.5000
Epoch [2/10]: Train Loss=0.6932, Val Loss=0.6809, Train Acc=0.5000,
Val Acc=0.5000
Epoch [3/10]: Train Loss=0.6719, Val Loss=0.6730, Train Acc=0.5000,
Val Acc=0.5000
Epoch [4/10]: Train Loss=0.6642, Val Loss=0.6657, Train Acc=0.5000,
Val Acc=0.5000
Epoch [5/10]: Train Loss=0.6561, Val Loss=0.6641, Train Acc=0.5040,
```

```
Val Acc=0.5033
 Saved best model with Val Acc: 0.5033
Epoch [6/10]: Train Loss=0.6532, Val Loss=0.6639, Train Acc=0.5133,
Val Acc=0.5167
 Saved best model with Val Acc: 0.5167
Epoch [7/10]: Train Loss=0.6509, Val Loss=0.6640, Train Acc=0.5400,
Val Acc=0.5300
 Saved best model with Val Acc: 0.5300
Epoch [8/10]: Train Loss=0.6495, Val Loss=0.6640, Train Acc=0.5633,
Val Acc=0.5733
 Saved best model with Val Acc: 0.5733
Epoch [9/10]: Train Loss=0.6474, Val Loss=0.6658, Train Acc=0.5953,
Val Acc=0.5833
 Saved best model with Val Acc: 0.5833
Epoch [10/10]: Train Loss=0.6458, Val Loss=0.6647, Train Acc=0.6173,
Val Acc=0.5933
 Saved best model with Val Acc: 0.5933
```




```
Epoch [1/10]: Train Loss=0.6621, Val Loss=0.6659, Train Acc=0.6200,
Val Acc=0.6400
 Saved best model with Val Acc: 0.6400
Epoch [2/10]: Train Loss=0.6605, Val Loss=0.6651, Train Acc=0.6130,
Val Acc=0.6367
Epoch [3/10]: Train Loss=0.6591, Val Loss=0.6650, Train Acc=0.6163,
Val Acc=0.6233
Epoch [4/10]: Train Loss=0.6585, Val Loss=0.6620, Train Acc=0.6230,
Val Acc=0.6167
Epoch [5/10]: Train Loss=0.6584, Val Loss=0.6639, Train Acc=0.6250,
Val Acc=0.6267
Epoch [6/10]: Train Loss=0.6561, Val Loss=0.6657, Train Acc=0.6230,
Val Acc=0.6267
```

```
Epoch [7/10]: Train Loss=0.6560, Val Loss=0.6654, Train Acc=0.6313,
Val Acc=0.6267
Epoch [8/10]: Train Loss=0.6555, Val Loss=0.6665, Train Acc=0.6337,
Val Acc=0.6333
Epoch [9/10]: Train Loss=0.6566, Val Loss=0.6651, Train Acc=0.6370,
Val Acc=0.6233
Epoch [10/10]: Train Loss=0.6559, Val Loss=0.6665, Train Acc=0.6320,
Val Acc=0.6233
```




```
 Best model saved at: submission\best_model.pth

import torch.optim as optim
import matplotlib.pyplot as plt
from torch.utils.data import DataLoader, TensorDataset


hyperparams = {
    'lr': 0.001,
    'weight_decay': 1e-4,
    'batch_size': 32,
    'epochs': 10,
    'optimizer': 'Adam'
}


train_image_tensors1 =
torch.load("preprocessed_tensors/train_1500_image_tensors.pt").to(devi
ce)
train_image_tensors2 =
torch.load("preprocessed_tensors/train_3000_image_tensors.pt").to(devi
ce)
train_text_tensors1 =
```

```
torch.load("preprocessed_tensors/train_1500_question_tensors.pt").to(d
evice)
train_text_tensors2 =
torch.load("preprocessed_tensors/train_3000_question_tensors.pt").to(d
evice)
val_image_tensors =
torch.load("preprocessed_tensors/val_image_tensors.pt").to(device)
val_text_tensors =
torch.load("preprocessed_tensors/val_question_tensors.pt").to(device)


train_labels1 = torch.tensor([sample['answerable'] for sample in
train_samples_1500], dtype=torch.float32).to(device)
train_labels2 = torch.tensor([sample['answerable'] for sample in
train_samples_3000], dtype=torch.float32).to(device)
val_labels = torch.tensor([sample['answerable'] for sample in
val_samples], dtype=torch.float32).to(device)


train_dataset1 = TensorDataset(train_image_tensors1,
train_text_tensors1, train_labels1)
train_dataset2 = TensorDataset(train_image_tensors2,
train_text_tensors2, train_labels2)
val_dataset = TensorDataset(val_image_tensors, val_text_tensors,
val_labels)

train_loader1 = DataLoader(train_dataset1,
batch_size=hyperparams['batch_size'], shuffle=True)
train_loader2 = DataLoader(train_dataset2,
batch_size=hyperparams['batch_size'], shuffle=True)
val_loader = DataLoader(val_dataset,
batch_size=hyperparams['batch_size'], shuffle=False)


def train_model(model, train_loader, val_loader, hyperparams):
    optimizer = optim.AdamW(model.parameters(), lr=hyperparams['lr'],
weight_decay=hyperparams['weight_decay'])
    criterion = nn.BCEWithLogitsLoss()

    train_losses, val_losses, train_accs, val_accs = [], [], [], []

    for epoch in range(hyperparams['epochs']):
        model.train()
        total_loss, correct, total = 0, 0, 0

        for images, text, labels in train_loader:
            images, text, labels = images.to(device), text.to(device),
labels.to(device)

            optimizer.zero_grad()
```

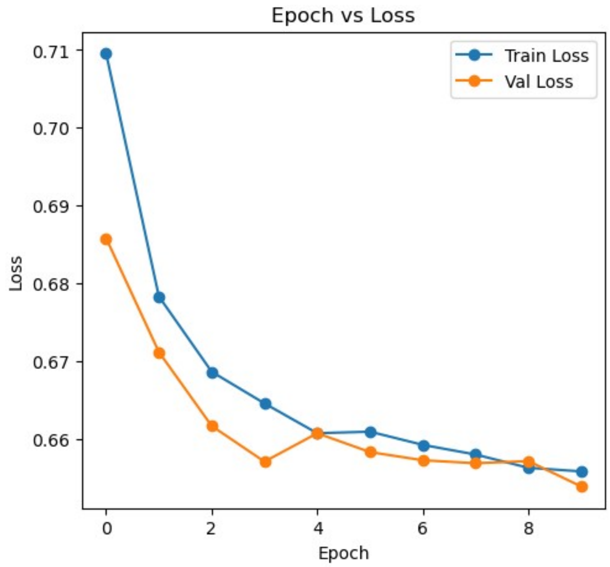
```
            outputs = model(images, text).squeeze()
            loss = criterion(outputs, labels)
            loss.backward()
            optimizer.step()

            total_loss += loss.item()
            predicted = (torch.sigmoid(outputs) > 0.5).float()  #
Convert logits to binary predictions
            correct += (predicted == labels).sum().item()
            total += labels.size(0)

        train_loss = total_loss / len(train_loader)
        train_acc = correct / total


        model.eval()
        total_loss, correct, total = 0, 0, 0
        with torch.no_grad():
            for images, text, labels in val_loader:
                images, text, labels = images.to(device),
text.to(device), labels.to(device)

                outputs = model(images, text).squeeze()
                loss = criterion(outputs, labels)
                total_loss += loss.item()
                predicted = (torch.sigmoid(outputs) > 0.5).float()
                correct += (predicted == labels).sum().item()
                total += labels.size(0)

        val_loss = total_loss / len(val_loader)
        val_acc = correct / total

        train_losses.append(train_loss)
        val_losses.append(val_loss)
        train_accs.append(train_acc)
        val_accs.append(val_acc)

        print(f"Epoch [{epoch+1}/{hyperparams['epochs']}]: Train
Loss={train_loss:.4f}, Val Loss={val_loss:.4f}, Train
Acc={train_acc:.4f}, Val Acc={val_acc:.4f}")


    plt.figure(figsize=(12, 5))

    # Loss Plot
    plt.subplot(1, 2, 1)
    plt.plot(train_losses, label='Train Loss', marker='o')
    plt.plot(val_losses, label='Val Loss', marker='o')
    plt.legend()
    plt.xlabel('Epoch')
```

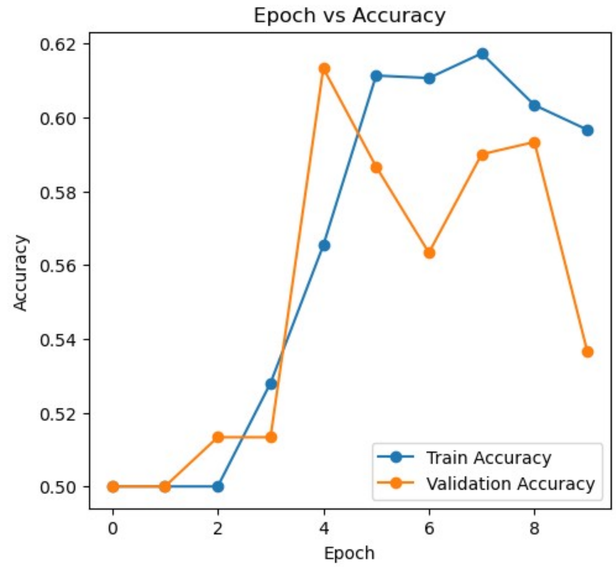
```python
    plt.ylabel('Loss')
    plt.title('Epoch vs Loss')


    plt.subplot(1, 2, 2)
    plt.plot(train_accs, label='Train Accuracy', marker='o')
    plt.plot(val_accs, label='Validation Accuracy', marker='o')
    plt.legend()
    plt.xlabel('Epoch')
    plt.ylabel('Accuracy')
    plt.title('Epoch vs Accuracy')

    plt.show()


model = VQAModel().to(device)
train_model(model, train_loader1, val_loader, hyperparams)  # Training
with 1500 samples
train_model(model, train_loader2, val_loader, hyperparams)  # Training
with 3000 samples
```

```
C:\Users\yoges\AppData\Local\Temp\ipykernel_23232\525851763.py:15:
FutureWarning: You are using `torch.load` with `weights_only=False`
(the current default value), which uses the default pickle module
implicitly. It is possible to construct malicious pickle data which
will execute arbitrary code during unpickling (See
https://github.com/pytorch/pytorch/blob/main/SECURITY.md#untrusted-
models for more details). In a future release, the default value for
`weights_only` will be flipped to `True`. This limits the functions
that could be executed during unpickling. Arbitrary objects will no
longer be allowed to be loaded via this mode unless they are
explicitly allowlisted by the user via
`torch.serialization.add_safe_globals`. We recommend you start setting
`weights_only=True` for any use case where you don't have full control
of the loaded file. Please open an issue on GitHub for any issues
related to this experimental feature.
  train_image_tensors1 =
torch.load("preprocessed_tensors/train_1500_image_tensors.pt").to(devi
ce)
C:\Users\yoges\AppData\Local\Temp\ipykernel_23232\525851763.py:16:
FutureWarning: You are using `torch.load` with `weights_only=False`
(the current default value), which uses the default pickle module
implicitly. It is possible to construct malicious pickle data which
will execute arbitrary code during unpickling (See
https://github.com/pytorch/pytorch/blob/main/SECURITY.md#untrusted-
models for more details). In a future release, the default value for
`weights_only` will be flipped to `True`. This limits the functions
that could be executed during unpickling. Arbitrary objects will no
longer be allowed to be loaded via this mode unless they are
explicitly allowlisted by the user via
```

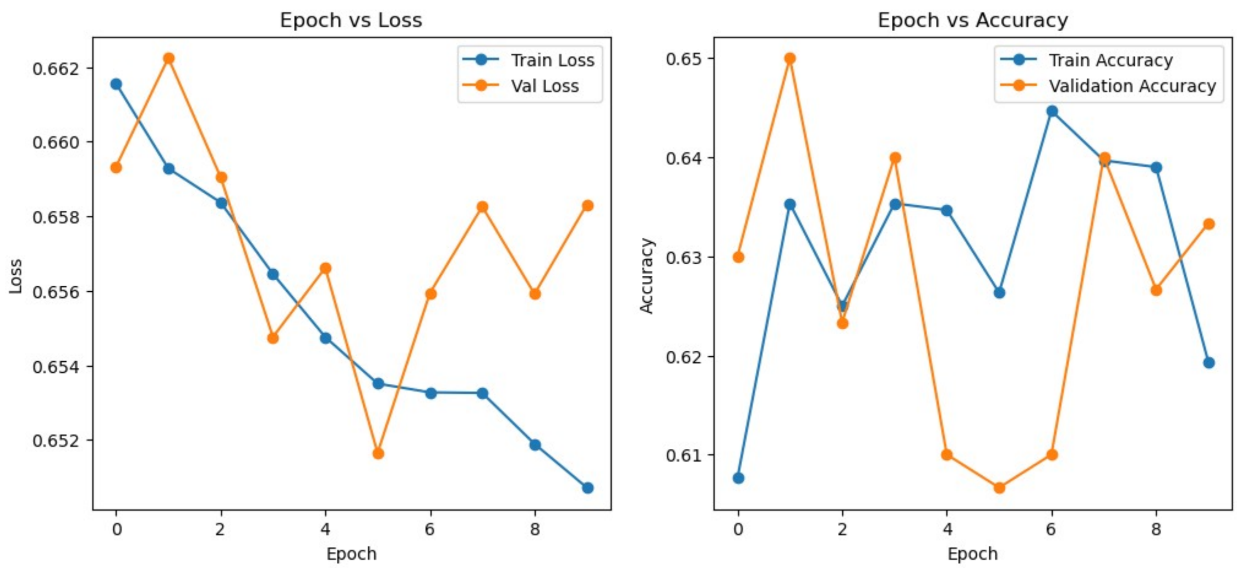
```
`torch.serialization.add_safe_globals`. We recommend you start setting
`weights_only=True` for any use case where you don't have full control
of the loaded file. Please open an issue on GitHub for any issues
related to this experimental feature.
  train_image_tensors2 =
torch.load("preprocessed_tensors/train_3000_image_tensors.pt").to(devi
ce)
C:\Users\yoges\AppData\Local\Temp\ipykernel_23232\525851763.py:17:
FutureWarning: You are using `torch.load` with `weights_only=False`
(the current default value), which uses the default pickle module
implicitly. It is possible to construct malicious pickle data which
will execute arbitrary code during unpickling (See
https://github.com/pytorch/pytorch/blob/main/SECURITY.md#untrusted-
models for more details). In a future release, the default value for
`weights_only` will be flipped to `True`. This limits the functions
that could be executed during unpickling. Arbitrary objects will no
longer be allowed to be loaded via this mode unless they are
explicitly allowlisted by the user via
`torch.serialization.add_safe_globals`. We recommend you start setting
`weights_only=True` for any use case where you don't have full control
of the loaded file. Please open an issue on GitHub for any issues
related to this experimental feature.
  train_text_tensors1 =
torch.load("preprocessed_tensors/train_1500_question_tensors.pt").to(d
evice)
C:\Users\yoges\AppData\Local\Temp\ipykernel_23232\525851763.py:18:
FutureWarning: You are using `torch.load` with `weights_only=False`
(the current default value), which uses the default pickle module
implicitly. It is possible to construct malicious pickle data which
will execute arbitrary code during unpickling (See
https://github.com/pytorch/pytorch/blob/main/SECURITY.md#untrusted-
models for more details). In a future release, the default value for
`weights_only` will be flipped to `True`. This limits the functions
that could be executed during unpickling. Arbitrary objects will no
longer be allowed to be loaded via this mode unless they are
explicitly allowlisted by the user via
`torch.serialization.add_safe_globals`. We recommend you start setting
`weights_only=True` for any use case where you don't have full control
of the loaded file. Please open an issue on GitHub for any issues
related to this experimental feature.
  train_text_tensors2 =
torch.load("preprocessed_tensors/train_3000_question_tensors.pt").to(d
evice)
C:\Users\yoges\AppData\Local\Temp\ipykernel_23232\525851763.py:19:
FutureWarning: You are using `torch.load` with `weights_only=False`
(the current default value), which uses the default pickle module
implicitly. It is possible to construct malicious pickle data which
will execute arbitrary code during unpickling (See
https://github.com/pytorch/pytorch/blob/main/SECURITY.md#untrusted-
```

```
models for more details). In a future release, the default value for
`weights_only` will be flipped to `True`. This limits the functions
that could be executed during unpickling. Arbitrary objects will no
longer be allowed to be loaded via this mode unless they are
explicitly allowlisted by the user via
`torch.serialization.add_safe_globals`. We recommend you start setting
`weights_only=True` for any use case where you don't have full control
of the loaded file. Please open an issue on GitHub for any issues
related to this experimental feature.
  val_image_tensors =
torch.load("preprocessed_tensors/val_image_tensors.pt").to(device)
C:\Users\yoges\AppData\Local\Temp\ipykernel_23232\525851763.py:20:
FutureWarning: You are using `torch.load` with `weights_only=False`
(the current default value), which uses the default pickle module
implicitly. It is possible to construct malicious pickle data which
will execute arbitrary code during unpickling (See
https://github.com/pytorch/pytorch/blob/main/SECURITY.md#untrusted-
models for more details). In a future release, the default value for
`weights_only` will be flipped to `True`. This limits the functions
that could be executed during unpickling. Arbitrary objects will no
longer be allowed to be loaded via this mode unless they are
explicitly allowlisted by the user via
`torch.serialization.add_safe_globals`. We recommend you start setting
`weights_only=True` for any use case where you don't have full control
of the loaded file. Please open an issue on GitHub for any issues
related to this experimental feature.
  val_text_tensors =
torch.load("preprocessed_tensors/val_question_tensors.pt").to(device)

Epoch [1/10]: Train Loss=0.7095, Val Loss=0.6858, Train Acc=0.5000,
Val Acc=0.5000
Epoch [2/10]: Train Loss=0.6783, Val Loss=0.6712, Train Acc=0.5000,
Val Acc=0.5000
Epoch [3/10]: Train Loss=0.6687, Val Loss=0.6617, Train Acc=0.5000,
Val Acc=0.5133
Epoch [4/10]: Train Loss=0.6646, Val Loss=0.6571, Train Acc=0.5280,
Val Acc=0.5133
Epoch [5/10]: Train Loss=0.6608, Val Loss=0.6608, Train Acc=0.5653,
Val Acc=0.6133
Epoch [6/10]: Train Loss=0.6610, Val Loss=0.6583, Train Acc=0.6113,
Val Acc=0.5867
Epoch [7/10]: Train Loss=0.6593, Val Loss=0.6573, Train Acc=0.6107,
Val Acc=0.5633
Epoch [8/10]: Train Loss=0.6580, Val Loss=0.6569, Train Acc=0.6173,
Val Acc=0.5900
Epoch [9/10]: Train Loss=0.6563, Val Loss=0.6572, Train Acc=0.6033,
Val Acc=0.5933
Epoch [10/10]: Train Loss=0.6559, Val Loss=0.6539, Train Acc=0.5967,
Val Acc=0.5367
```






```
Epoch [1/10]: Train Loss=0.6616, Val Loss=0.6593, Train Acc=0.6077,
Val Acc=0.6300
Epoch [2/10]: Train Loss=0.6593, Val Loss=0.6622, Train Acc=0.6353,
Val Acc=0.6500
Epoch [3/10]: Train Loss=0.6584, Val Loss=0.6590, Train Acc=0.6250,
Val Acc=0.6233
Epoch [4/10]: Train Loss=0.6565, Val Loss=0.6548, Train Acc=0.6353,
Val Acc=0.6400
Epoch [5/10]: Train Loss=0.6548, Val Loss=0.6566, Train Acc=0.6347,
Val Acc=0.6100
Epoch [6/10]: Train Loss=0.6535, Val Loss=0.6516, Train Acc=0.6263,
Val Acc=0.6067
Epoch [7/10]: Train Loss=0.6533, Val Loss=0.6559, Train Acc=0.6447,
Val Acc=0.6100
Epoch [8/10]: Train Loss=0.6533, Val Loss=0.6583, Train Acc=0.6397,
Val Acc=0.6400
Epoch [9/10]: Train Loss=0.6519, Val Loss=0.6559, Train Acc=0.6390,
Val Acc=0.6267
Epoch [10/10]: Train Loss=0.6507, Val Loss=0.6583, Train Acc=0.6193,
Val Acc=0.6333
```




```
import torch.optim as optim
import matplotlib.pyplot as plt
from torch.utils.data import DataLoader, TensorDataset


hyperparams = {
    'lr': 0.0003,
    'weight_decay': 1e-3,
    'batch_size': 32,
    'epochs': 10,
    'optimizer': 'SGD'
}


train_image_tensors1 =
torch.load("preprocessed_tensors/train_1500_image_tensors.pt").to(devi
ce)
train_image_tensors2 =
torch.load("preprocessed_tensors/train_3000_image_tensors.pt").to(devi
ce)
train_text_tensors1 =
torch.load("preprocessed_tensors/train_1500_question_tensors.pt").to(d
evice)
train_text_tensors2 =
torch.load("preprocessed_tensors/train_3000_question_tensors.pt").to(d
evice)
val_image_tensors =
torch.load("preprocessed_tensors/val_image_tensors.pt").to(device)
val_text_tensors =
torch.load("preprocessed_tensors/val_question_tensors.pt").to(device)
```

```
train_labels1 = torch.tensor([sample['answerable'] for sample in
train_samples_1500], dtype=torch.float32).to(device)
train_labels2 = torch.tensor([sample['answerable'] for sample in
train_samples_3000], dtype=torch.float32).to(device)
val_labels = torch.tensor([sample['answerable'] for sample in
val_samples], dtype=torch.float32).to(device)


train_dataset1 = TensorDataset(train_image_tensors1,
train_text_tensors1, train_labels1)
train_dataset2 = TensorDataset(train_image_tensors2,
train_text_tensors2, train_labels2)
val_dataset = TensorDataset(val_image_tensors, val_text_tensors,
val_labels)

train_loader1 = DataLoader(train_dataset1,
batch_size=hyperparams['batch_size'], shuffle=True)
train_loader2 = DataLoader(train_dataset2,
batch_size=hyperparams['batch_size'], shuffle=True)
val_loader = DataLoader(val_dataset,
batch_size=hyperparams['batch_size'], shuffle=False)


def train_model(model, train_loader, val_loader, hyperparams):
    optimizer = optim.AdamW(model.parameters(), lr=hyperparams['lr'],
weight_decay=hyperparams['weight_decay'])
    criterion = nn.BCEWithLogitsLoss()

    train_losses, val_losses, train_accs, val_accs = [], [], [], []

    for epoch in range(hyperparams['epochs']):
        model.train()
        total_loss, correct, total = 0, 0, 0

        for images, text, labels in train_loader:
            images, text, labels = images.to(device), text.to(device),
labels.to(device)

            optimizer.zero_grad()
            outputs = model(images, text).squeeze()
            loss = criterion(outputs, labels)
            loss.backward()
            optimizer.step()

            total_loss += loss.item()
            predicted = (torch.sigmoid(outputs) > 0.5).float()
            correct += (predicted == labels).sum().item()
            total += labels.size(0)

        train_loss = total_loss / len(train_loader)
```

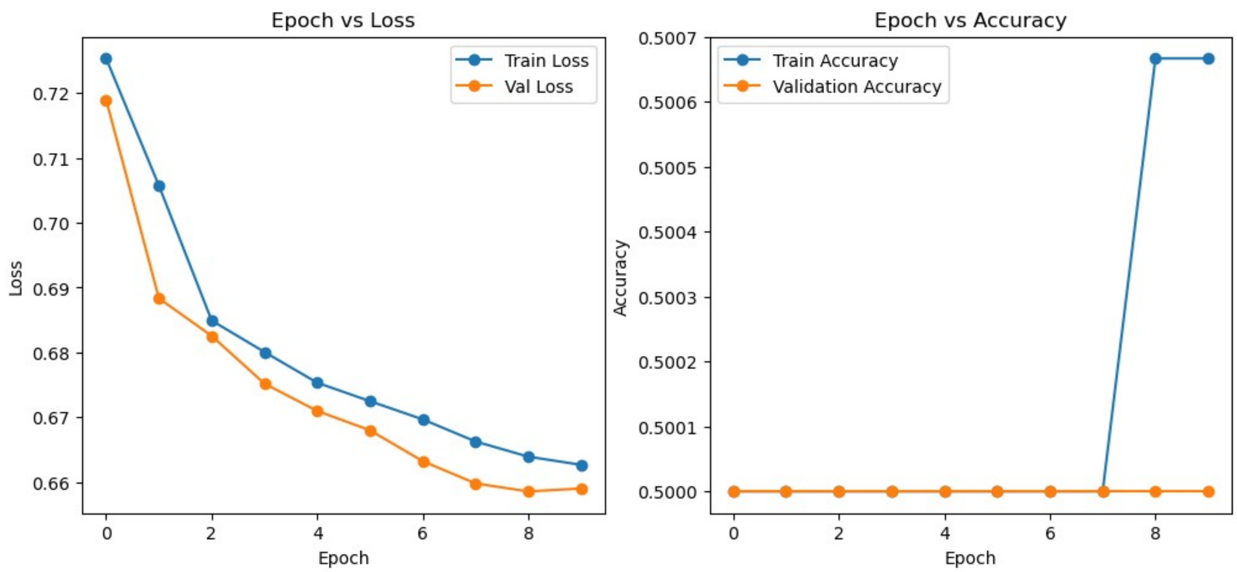
```
        train_acc = correct / total


        model.eval()
        total_loss, correct, total = 0, 0, 0
        with torch.no_grad():
            for images, text, labels in val_loader:
                images, text, labels = images.to(device),
text.to(device), labels.to(device)

                outputs = model(images, text).squeeze()
                loss = criterion(outputs, labels)
                total_loss += loss.item()
                predicted = (torch.sigmoid(outputs) > 0.5).float()
                correct += (predicted == labels).sum().item()
                total += labels.size(0)

        val_loss = total_loss / len(val_loader)
        val_acc = correct / total

        train_losses.append(train_loss)
        val_losses.append(val_loss)
        train_accs.append(train_acc)
        val_accs.append(val_acc)

        print(f"Epoch [{epoch+1}/{hyperparams['epochs']}]: Train
Loss={train_loss:.4f}, Val Loss={val_loss:.4f}, Train
Acc={train_acc:.4f}, Val Acc={val_acc:.4f}")


    plt.figure(figsize=(12, 5))

    # Loss Plot
    plt.subplot(1, 2, 1)
    plt.plot(train_losses, label='Train Loss', marker='o')
    plt.plot(val_losses, label='Val Loss', marker='o')
    plt.legend()
    plt.xlabel('Epoch')
    plt.ylabel('Loss')
    plt.title('Epoch vs Loss')


    plt.subplot(1, 2, 2)
    plt.plot(train_accs, label='Train Accuracy', marker='o')
    plt.plot(val_accs, label='Validation Accuracy', marker='o')
    plt.legend()
    plt.xlabel('Epoch')
    plt.ylabel('Accuracy')
    plt.title('Epoch vs Accuracy')
```

```
    plt.show()


model = VQAModel().to(device)
train_model(model, train_loader1, val_loader, hyperparams)
train_model(model, train_loader2, val_loader, hyperparams)
```

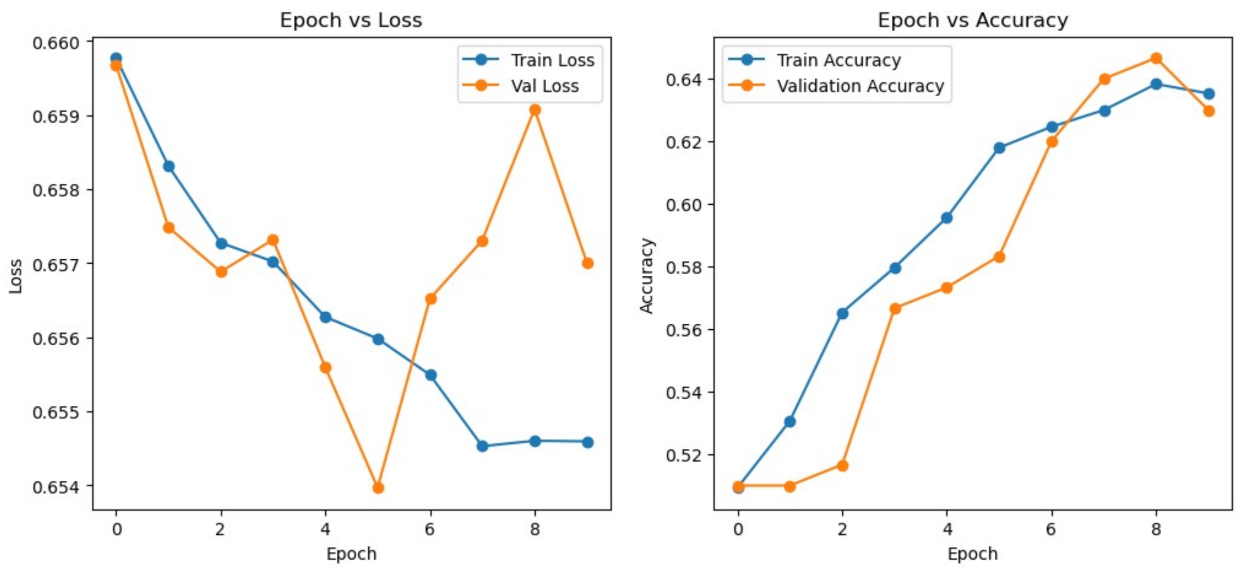
```
C:\Users\yoges\AppData\Local\Temp\ipykernel_23232\1745073582.py:15:
FutureWarning: You are using `torch.load` with `weights_only=False`
(the current default value), which uses the default pickle module
implicitly. It is possible to construct malicious pickle data which
will execute arbitrary code during unpickling (See
https://github.com/pytorch/pytorch/blob/main/SECURITY.md#untrusted-
models for more details). In a future release, the default value for
`weights_only` will be flipped to `True`. This limits the functions
that could be executed during unpickling. Arbitrary objects will no
longer be allowed to be loaded via this mode unless they are
explicitly allowlisted by the user via
`torch.serialization.add_safe_globals`. We recommend you start setting
`weights_only=True` for any use case where you don't have full control
of the loaded file. Please open an issue on GitHub for any issues
related to this experimental feature.
  train_image_tensors1 =
torch.load("preprocessed_tensors/train_1500_image_tensors.pt").to(devi
ce)
C:\Users\yoges\AppData\Local\Temp\ipykernel_23232\1745073582.py:16:
FutureWarning: You are using `torch.load` with `weights_only=False`
(the current default value), which uses the default pickle module
implicitly. It is possible to construct malicious pickle data which
will execute arbitrary code during unpickling (See
https://github.com/pytorch/pytorch/blob/main/SECURITY.md#untrusted-
models for more details). In a future release, the default value for
`weights_only` will be flipped to `True`. This limits the functions
that could be executed during unpickling. Arbitrary objects will no
longer be allowed to be loaded via this mode unless they are
explicitly allowlisted by the user via
`torch.serialization.add_safe_globals`. We recommend you start setting
`weights_only=True` for any use case where you don't have full control
of the loaded file. Please open an issue on GitHub for any issues
related to this experimental feature.
  train_image_tensors2 =
torch.load("preprocessed_tensors/train_3000_image_tensors.pt").to(devi
ce)
C:\Users\yoges\AppData\Local\Temp\ipykernel_23232\1745073582.py:17:
FutureWarning: You are using `torch.load` with `weights_only=False`
(the current default value), which uses the default pickle module
implicitly. It is possible to construct malicious pickle data which
will execute arbitrary code during unpickling (See
https://github.com/pytorch/pytorch/blob/main/SECURITY.md#untrusted-
models for more details). In a future release, the default value for
```

```
`weights_only` will be flipped to `True`. This limits the functions
that could be executed during unpickling. Arbitrary objects will no
longer be allowed to be loaded via this mode unless they are
explicitly allowlisted by the user via
`torch.serialization.add_safe_globals`. We recommend you start setting
`weights_only=True` for any use case where you don't have full control
of the loaded file. Please open an issue on GitHub for any issues
related to this experimental feature.
  train_text_tensors1 =
torch.load("preprocessed_tensors/train_1500_question_tensors.pt").to(d
evice)
C:\Users\yoges\AppData\Local\Temp\ipykernel_23232\1745073582.py:18:
FutureWarning: You are using `torch.load` with `weights_only=False`
(the current default value), which uses the default pickle module
implicitly. It is possible to construct malicious pickle data which
will execute arbitrary code during unpickling (See
https://github.com/pytorch/pytorch/blob/main/SECURITY.md#untrusted-
models for more details). In a future release, the default value for
`weights_only` will be flipped to `True`. This limits the functions
that could be executed during unpickling. Arbitrary objects will no
longer be allowed to be loaded via this mode unless they are
explicitly allowlisted by the user via
`torch.serialization.add_safe_globals`. We recommend you start setting
`weights_only=True` for any use case where you don't have full control
of the loaded file. Please open an issue on GitHub for any issues
related to this experimental feature.
  train_text_tensors2 =
torch.load("preprocessed_tensors/train_3000_question_tensors.pt").to(d
evice)
C:\Users\yoges\AppData\Local\Temp\ipykernel_23232\1745073582.py:19:
FutureWarning: You are using `torch.load` with `weights_only=False`
(the current default value), which uses the default pickle module
implicitly. It is possible to construct malicious pickle data which
will execute arbitrary code during unpickling (See
https://github.com/pytorch/pytorch/blob/main/SECURITY.md#untrusted-
models for more details). In a future release, the default value for
`weights_only` will be flipped to `True`. This limits the functions
that could be executed during unpickling. Arbitrary objects will no
longer be allowed to be loaded via this mode unless they are
explicitly allowlisted by the user via
`torch.serialization.add_safe_globals`. We recommend you start setting
`weights_only=True` for any use case where you don't have full control
of the loaded file. Please open an issue on GitHub for any issues
related to this experimental feature.
  val_image_tensors =
torch.load("preprocessed_tensors/val_image_tensors.pt").to(device)
C:\Users\yoges\AppData\Local\Temp\ipykernel_23232\1745073582.py:20:
FutureWarning: You are using `torch.load` with `weights_only=False`
(the current default value), which uses the default pickle module
```

```
implicitly. It is possible to construct malicious pickle data which
will execute arbitrary code during unpickling (See
https://github.com/pytorch/pytorch/blob/main/SECURITY.md#untrusted-
models for more details). In a future release, the default value for
`weights_only` will be flipped to `True`. This limits the functions
that could be executed during unpickling. Arbitrary objects will no
longer be allowed to be loaded via this mode unless they are
explicitly allowlisted by the user via
`torch.serialization.add_safe_globals`. We recommend you start setting
`weights_only=True` for any use case where you don't have full control
of the loaded file. Please open an issue on GitHub for any issues
related to this experimental feature.
  val_text_tensors =
torch.load("preprocessed_tensors/val_question_tensors.pt").to(device)

Epoch [1/10]: Train Loss=0.7253, Val Loss=0.7190, Train Acc=0.5000,
Val Acc=0.5000
Epoch [2/10]: Train Loss=0.7057, Val Loss=0.6883, Train Acc=0.5000,
Val Acc=0.5000
Epoch [3/10]: Train Loss=0.6849, Val Loss=0.6826, Train Acc=0.5000,
Val Acc=0.5000
Epoch [4/10]: Train Loss=0.6801, Val Loss=0.6752, Train Acc=0.5000,
Val Acc=0.5000
Epoch [5/10]: Train Loss=0.6753, Val Loss=0.6710, Train Acc=0.5000,
Val Acc=0.5000
Epoch [6/10]: Train Loss=0.6725, Val Loss=0.6680, Train Acc=0.5000,
Val Acc=0.5000
Epoch [7/10]: Train Loss=0.6697, Val Loss=0.6632, Train Acc=0.5000,
Val Acc=0.5000
Epoch [8/10]: Train Loss=0.6663, Val Loss=0.6598, Train Acc=0.5000,
Val Acc=0.5000
Epoch [9/10]: Train Loss=0.6639, Val Loss=0.6586, Train Acc=0.5007,
Val Acc=0.5000
Epoch [10/10]: Train Loss=0.6627, Val Loss=0.6590, Train Acc=0.5007,
Val Acc=0.5000
```




```
Epoch [1/10]: Train Loss=0.6598, Val Loss=0.6597, Train Acc=0.5093,
Val Acc=0.5100
Epoch [2/10]: Train Loss=0.6583, Val Loss=0.6575, Train Acc=0.5307,
Val Acc=0.5100
Epoch [3/10]: Train Loss=0.6573, Val Loss=0.6569, Train Acc=0.5653,
Val Acc=0.5167
Epoch [4/10]: Train Loss=0.6570, Val Loss=0.6573, Train Acc=0.5797,
Val Acc=0.5667
Epoch [5/10]: Train Loss=0.6563, Val Loss=0.6556, Train Acc=0.5957,
Val Acc=0.5733
Epoch [6/10]: Train Loss=0.6560, Val Loss=0.6540, Train Acc=0.6180,
Val Acc=0.5833
Epoch [7/10]: Train Loss=0.6555, Val Loss=0.6565, Train Acc=0.6247,
Val Acc=0.6200
Epoch [8/10]: Train Loss=0.6545, Val Loss=0.6573, Train Acc=0.6300,
Val Acc=0.6400
Epoch [9/10]: Train Loss=0.6546, Val Loss=0.6591, Train Acc=0.6383,
Val Acc=0.6467
Epoch [10/10]: Train Loss=0.6546, Val Loss=0.6570, Train Acc=0.6353,
Val Acc=0.6300
```




```
import torch.optim as optim
import matplotlib.pyplot as plt
from torch.utils.data import DataLoader, TensorDataset


hyperparams = {
    'lr': 0.0007,
    'weight_decay': 5e-5,
    'batch_size': 32,
    'epochs': 10,
    'optimizer': 'AdamW'
}


train_image_tensors1 =
torch.load("preprocessed_tensors/train_1500_image_tensors.pt").to(devi
ce)
train_image_tensors2 =
torch.load("preprocessed_tensors/train_3000_image_tensors.pt").to(devi
ce)
train_text_tensors1 =
torch.load("preprocessed_tensors/train_1500_question_tensors.pt").to(d
evice)
train_text_tensors2 =
torch.load("preprocessed_tensors/train_3000_question_tensors.pt").to(d
evice)
val_image_tensors =
torch.load("preprocessed_tensors/val_image_tensors.pt").to(device)
val_text_tensors =
torch.load("preprocessed_tensors/val_question_tensors.pt").to(device)
```

```
train_labels1 = torch.tensor([sample['answerable'] for sample in
train_samples_1500], dtype=torch.float32).to(device)
train_labels2 = torch.tensor([sample['answerable'] for sample in
train_samples_3000], dtype=torch.float32).to(device)
val_labels = torch.tensor([sample['answerable'] for sample in
val_samples], dtype=torch.float32).to(device)

train_dataset1 = TensorDataset(train_image_tensors1,
train_text_tensors1, train_labels1)
train_dataset2 = TensorDataset(train_image_tensors2,
train_text_tensors2, train_labels2)
val_dataset = TensorDataset(val_image_tensors, val_text_tensors,
val_labels)

train_loader1 = DataLoader(train_dataset1,
batch_size=hyperparams['batch_size'], shuffle=True)
train_loader2 = DataLoader(train_dataset2,
batch_size=hyperparams['batch_size'], shuffle=True)
val_loader = DataLoader(val_dataset,
batch_size=hyperparams['batch_size'], shuffle=False)


def train_model(model, train_loader, val_loader, hyperparams):
    optimizer = optim.AdamW(model.parameters(), lr=hyperparams['lr'],
weight_decay=hyperparams['weight_decay'])
    criterion = nn.BCEWithLogitsLoss()

    train_losses, val_losses, train_accs, val_accs = [], [], [], []

    for epoch in range(hyperparams['epochs']):
        model.train()
        total_loss, correct, total = 0, 0, 0

        for images, text, labels in train_loader:
            images, text, labels = images.to(device), text.to(device),
labels.to(device)

            optimizer.zero_grad()
            outputs = model(images, text).squeeze()
            loss = criterion(outputs, labels)
            loss.backward()
            optimizer.step()

            total_loss += loss.item()
            predicted = (torch.sigmoid(outputs) > 0.5).float()
            correct += (predicted == labels).sum().item()
            total += labels.size(0)

        train_loss = total_loss / len(train_loader)
        train_acc = correct / total
```

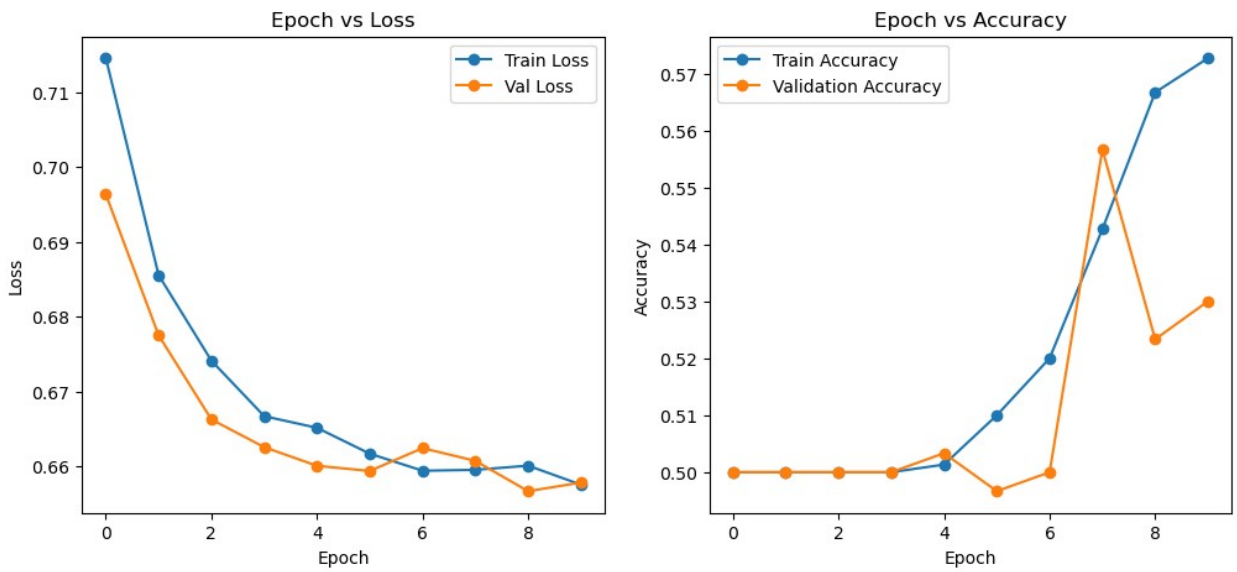
```
        model.eval()
        total_loss, correct, total = 0, 0, 0
        with torch.no_grad():
            for images, text, labels in val_loader:
                images, text, labels = images.to(device),
text.to(device), labels.to(device)

                outputs = model(images, text).squeeze()
                loss = criterion(outputs, labels)
                total_loss += loss.item()
                predicted = (torch.sigmoid(outputs) > 0.5).float()
                correct += (predicted == labels).sum().item()
                total += labels.size(0)

        val_loss = total_loss / len(val_loader)
        val_acc = correct / total

        train_losses.append(train_loss)
        val_losses.append(val_loss)
        train_accs.append(train_acc)
        val_accs.append(val_acc)

        print(f"Epoch [{epoch+1}/{hyperparams['epochs']}]: Train
Loss={train_loss:.4f}, Val Loss={val_loss:.4f}, Train
Acc={train_acc:.4f}, Val Acc={val_acc:.4f}")


    plt.figure(figsize=(12, 5))


    plt.subplot(1, 2, 1)
    plt.plot(train_losses, label='Train Loss', marker='o')
    plt.plot(val_losses, label='Val Loss', marker='o')
    plt.legend()
    plt.xlabel('Epoch')
    plt.ylabel('Loss')
    plt.title('Epoch vs Loss')


    plt.subplot(1, 2, 2)
    plt.plot(train_accs, label='Train Accuracy', marker='o')
    plt.plot(val_accs, label='Validation Accuracy', marker='o')
    plt.legend()
    plt.xlabel('Epoch')
    plt.ylabel('Accuracy')
    plt.title('Epoch vs Accuracy')

    plt.show()
```

```
model = VQAModel().to(device)
train_model(model, train_loader1, val_loader, hyperparams)
train_model(model, train_loader2, val_loader, hyperparams)
```

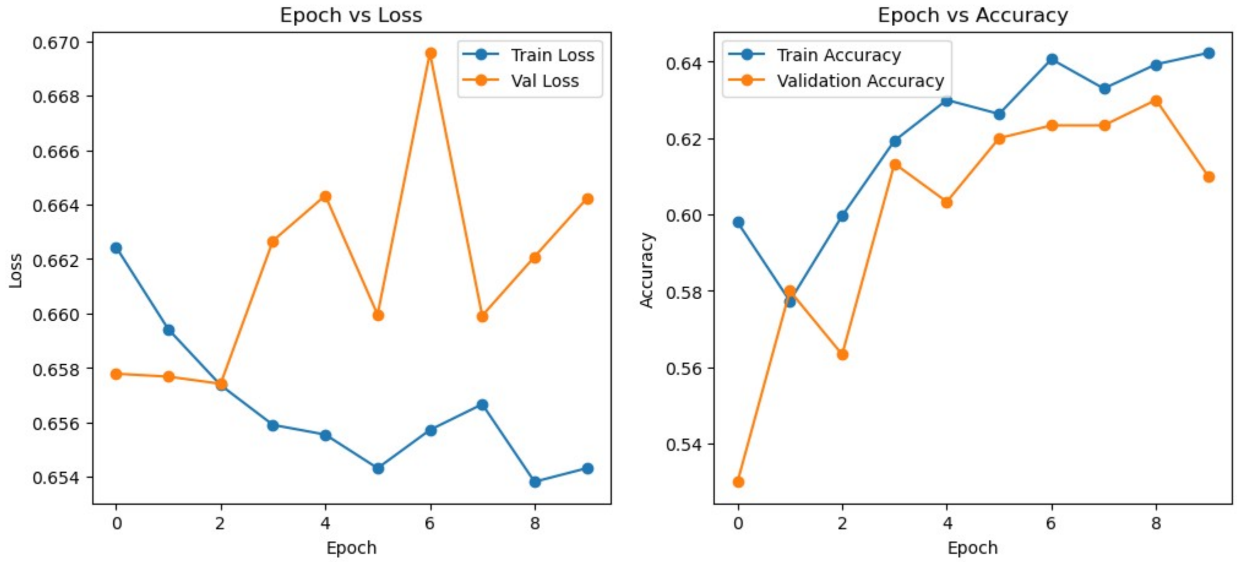
```
C:\Users\yoges\AppData\Local\Temp\ipykernel_23232\1765454162.py:15:
FutureWarning: You are using `torch.load` with `weights_only=False`
(the current default value), which uses the default pickle module
implicitly. It is possible to construct malicious pickle data which
will execute arbitrary code during unpickling (See
https://github.com/pytorch/pytorch/blob/main/SECURITY.md#untrusted-
models for more details). In a future release, the default value for
`weights_only` will be flipped to `True`. This limits the functions
that could be executed during unpickling. Arbitrary objects will no
longer be allowed to be loaded via this mode unless they are
explicitly allowlisted by the user via
`torch.serialization.add_safe_globals`. We recommend you start setting
`weights_only=True` for any use case where you don't have full control
of the loaded file. Please open an issue on GitHub for any issues
related to this experimental feature.
  train_image_tensors1 =
torch.load("preprocessed_tensors/train_1500_image_tensors.pt").to(devi
ce)
C:\Users\yoges\AppData\Local\Temp\ipykernel_23232\1765454162.py:16:
FutureWarning: You are using `torch.load` with `weights_only=False`
(the current default value), which uses the default pickle module
implicitly. It is possible to construct malicious pickle data which
will execute arbitrary code during unpickling (See
https://github.com/pytorch/pytorch/blob/main/SECURITY.md#untrusted-
models for more details). In a future release, the default value for
`weights_only` will be flipped to `True`. This limits the functions
that could be executed during unpickling. Arbitrary objects will no
longer be allowed to be loaded via this mode unless they are
explicitly allowlisted by the user via
`torch.serialization.add_safe_globals`. We recommend you start setting
`weights_only=True` for any use case where you don't have full control
of the loaded file. Please open an issue on GitHub for any issues
related to this experimental feature.
  train_image_tensors2 =
torch.load("preprocessed_tensors/train_3000_image_tensors.pt").to(devi
ce)
C:\Users\yoges\AppData\Local\Temp\ipykernel_23232\1765454162.py:17:
FutureWarning: You are using `torch.load` with `weights_only=False`
(the current default value), which uses the default pickle module
implicitly. It is possible to construct malicious pickle data which
will execute arbitrary code during unpickling (See
https://github.com/pytorch/pytorch/blob/main/SECURITY.md#untrusted-
models for more details). In a future release, the default value for
`weights_only` will be flipped to `True`. This limits the functions
```

```
that could be executed during unpickling. Arbitrary objects will no
longer be allowed to be loaded via this mode unless they are
explicitly allowlisted by the user via
`torch.serialization.add_safe_globals`. We recommend you start setting
`weights_only=True` for any use case where you don't have full control
of the loaded file. Please open an issue on GitHub for any issues
related to this experimental feature.
  train_text_tensors1 =
torch.load("preprocessed_tensors/train_1500_question_tensors.pt").to(d
evice)
C:\Users\yoges\AppData\Local\Temp\ipykernel_23232\1765454162.py:18:
FutureWarning: You are using `torch.load` with `weights_only=False`
(the current default value), which uses the default pickle module
implicitly. It is possible to construct malicious pickle data which
will execute arbitrary code during unpickling (See
https://github.com/pytorch/pytorch/blob/main/SECURITY.md#untrusted-
models for more details). In a future release, the default value for
`weights_only` will be flipped to `True`. This limits the functions
that could be executed during unpickling. Arbitrary objects will no
longer be allowed to be loaded via this mode unless they are
explicitly allowlisted by the user via
`torch.serialization.add_safe_globals`. We recommend you start setting
`weights_only=True` for any use case where you don't have full control
of the loaded file. Please open an issue on GitHub for any issues
related to this experimental feature.
  train_text_tensors2 =
torch.load("preprocessed_tensors/train_3000_question_tensors.pt").to(d
evice)
C:\Users\yoges\AppData\Local\Temp\ipykernel_23232\1765454162.py:19:
FutureWarning: You are using `torch.load` with `weights_only=False`
(the current default value), which uses the default pickle module
implicitly. It is possible to construct malicious pickle data which
will execute arbitrary code during unpickling (See
https://github.com/pytorch/pytorch/blob/main/SECURITY.md#untrusted-
models for more details). In a future release, the default value for
`weights_only` will be flipped to `True`. This limits the functions
that could be executed during unpickling. Arbitrary objects will no
longer be allowed to be loaded via this mode unless they are
explicitly allowlisted by the user via
`torch.serialization.add_safe_globals`. We recommend you start setting
`weights_only=True` for any use case where you don't have full control
of the loaded file. Please open an issue on GitHub for any issues
related to this experimental feature.
  val_image_tensors =
torch.load("preprocessed_tensors/val_image_tensors.pt").to(device)
C:\Users\yoges\AppData\Local\Temp\ipykernel_23232\1765454162.py:20:
FutureWarning: You are using `torch.load` with `weights_only=False`
(the current default value), which uses the default pickle module
implicitly. It is possible to construct malicious pickle data which
```

```
will execute arbitrary code during unpickling (See
https://github.com/pytorch/pytorch/blob/main/SECURITY.md#untrusted-
models for more details). In a future release, the default value for
`weights_only` will be flipped to `True`. This limits the functions
that could be executed during unpickling. Arbitrary objects will no
longer be allowed to be loaded via this mode unless they are
explicitly allowlisted by the user via
`torch.serialization.add_safe_globals`. We recommend you start setting
`weights_only=True` for any use case where you don't have full control
of the loaded file. Please open an issue on GitHub for any issues
related to this experimental feature.
  val_text_tensors =
torch.load("preprocessed_tensors/val_question_tensors.pt").to(device)

Epoch [1/10]: Train Loss=0.7145, Val Loss=0.6963, Train Acc=0.5000,
Val Acc=0.5000
Epoch [2/10]: Train Loss=0.6855, Val Loss=0.6775, Train Acc=0.5000,
Val Acc=0.5000
Epoch [3/10]: Train Loss=0.6741, Val Loss=0.6663, Train Acc=0.5000,
Val Acc=0.5000
Epoch [4/10]: Train Loss=0.6667, Val Loss=0.6626, Train Acc=0.5000,
Val Acc=0.5000
Epoch [5/10]: Train Loss=0.6651, Val Loss=0.6601, Train Acc=0.5013,
Val Acc=0.5033
Epoch [6/10]: Train Loss=0.6617, Val Loss=0.6594, Train Acc=0.5100,
Val Acc=0.4967
Epoch [7/10]: Train Loss=0.6594, Val Loss=0.6624, Train Acc=0.5200,
Val Acc=0.5000
Epoch [8/10]: Train Loss=0.6595, Val Loss=0.6607, Train Acc=0.5427,
Val Acc=0.5567
Epoch [9/10]: Train Loss=0.6601, Val Loss=0.6567, Train Acc=0.5667,
Val Acc=0.5233
Epoch [10/10]: Train Loss=0.6575, Val Loss=0.6578, Train Acc=0.5727,
Val Acc=0.5300
```




```
Epoch [1/10]: Train Loss=0.6624, Val Loss=0.6578, Train Acc=0.5980,
Val Acc=0.5300
Epoch [2/10]: Train Loss=0.6594, Val Loss=0.6577, Train Acc=0.5773,
Val Acc=0.5800
Epoch [3/10]: Train Loss=0.6574, Val Loss=0.6574, Train Acc=0.5997,
Val Acc=0.5633
Epoch [4/10]: Train Loss=0.6559, Val Loss=0.6627, Train Acc=0.6193,
Val Acc=0.6133
Epoch [5/10]: Train Loss=0.6556, Val Loss=0.6643, Train Acc=0.6300,
Val Acc=0.6033
Epoch [6/10]: Train Loss=0.6543, Val Loss=0.6600, Train Acc=0.6263,
Val Acc=0.6200
Epoch [7/10]: Train Loss=0.6557, Val Loss=0.6696, Train Acc=0.6407,
Val Acc=0.6233
Epoch [8/10]: Train Loss=0.6567, Val Loss=0.6599, Train Acc=0.6330,
Val Acc=0.6233
Epoch [9/10]: Train Loss=0.6538, Val Loss=0.6621, Train Acc=0.6393,
Val Acc=0.6300
Epoch [10/10]: Train Loss=0.6543, Val Loss=0.6642, Train Acc=0.6423,
Val Acc=0.6100
```




```
model = VQAModel().to(device)
model.load_state_dict(torch.load(best_model_path))
model.eval()


test_image_tensors =
torch.load("preprocessed_tensors/test_image_tensors.pt").to(device)
test_text_tensors =
torch.load("preprocessed_tensors/test_question_tensors.pt").to(device)

with torch.no_grad():
    outputs = model(test_image_tensors, test_text_tensors).squeeze()
    predictions = (torch.sigmoid(outputs) > 0.5).float()


print("Model Predictions for Test Samples (First 100):")
print(predictions.tolist())


submission_file = os.path.join(submission_dir,
"HarishNandhan_Shanmugam_challenge1.pkl")
torch.save(predictions.cpu(), submission_file)
print(f"Test predictions saved to {submission_file}")
```

```
C:\Users\yoges\AppData\Local\Temp\ipykernel_35360\2133034373.py:3:
FutureWarning: You are using `torch.load` with `weights_only=False`
(the current default value), which uses the default pickle module
implicitly. It is possible to construct malicious pickle data which
will execute arbitrary code during unpickling (See
https://github.com/pytorch/pytorch/blob/main/SECURITY.md#untrusted-
models for more details). In a future release, the default value for
`weights_only` will be flipped to `True`. This limits the functions
```

```
that could be executed during unpickling. Arbitrary objects will no
longer be allowed to be loaded via this mode unless they are
explicitly allowlisted by the user via
`torch.serialization.add_safe_globals`. We recommend you start setting
`weights_only=True` for any use case where you don't have full control
of the loaded file. Please open an issue on GitHub for any issues
related to this experimental feature.
  model.load_state_dict(torch.load(best_model_path))
C:\Users\yoges\AppData\Local\Temp\ipykernel_35360\2133034373.py:7:
FutureWarning: You are using `torch.load` with `weights_only=False`
(the current default value), which uses the default pickle module
implicitly. It is possible to construct malicious pickle data which
will execute arbitrary code during unpickling (See
https://github.com/pytorch/pytorch/blob/main/SECURITY.md#untrusted-
models for more details). In a future release, the default value for
`weights_only` will be flipped to `True`. This limits the functions
that could be executed during unpickling. Arbitrary objects will no
longer be allowed to be loaded via this mode unless they are
explicitly allowlisted by the user via
`torch.serialization.add_safe_globals`. We recommend you start setting
`weights_only=True` for any use case where you don't have full control
of the loaded file. Please open an issue on GitHub for any issues
related to this experimental feature.
  test_image_tensors =
torch.load("preprocessed_tensors/test_image_tensors.pt").to(device)
C:\Users\yoges\AppData\Local\Temp\ipykernel_35360\2133034373.py:8:
FutureWarning: You are using `torch.load` with `weights_only=False`
(the current default value), which uses the default pickle module
implicitly. It is possible to construct malicious pickle data which
will execute arbitrary code during unpickling (See
https://github.com/pytorch/pytorch/blob/main/SECURITY.md#untrusted-
models for more details). In a future release, the default value for
`weights_only` will be flipped to `True`. This limits the functions
that could be executed during unpickling. Arbitrary objects will no
longer be allowed to be loaded via this mode unless they are
explicitly allowlisted by the user via
`torch.serialization.add_safe_globals`. We recommend you start setting
`weights_only=True` for any use case where you don't have full control
of the loaded file. Please open an issue on GitHub for any issues
related to this experimental feature.
  test_text_tensors =
torch.load("preprocessed_tensors/test_question_tensors.pt").to(device)

Model Predictions for Test Samples (First 100):
[1.0, 1.0, 0.0, 1.0, 1.0, 0.0, 0.0, 1.0, 1.0, 1.0, 0.0, 1.0, 0.0, 0.0,
0.0, 1.0, 1.0, 0.0, 0.0, 1.0, 0.0, 0.0, 1.0, 0.0, 0.0, 0.0, 0.0, 1.0,
0.0, 0.0, 1.0, 1.0, 0.0, 0.0, 0.0, 1.0, 0.0, 1.0, 0.0, 0.0, 0.0, 0.0,
0.0, 1.0, 0.0, 0.0, 0.0, 0.0, 1.0, 1.0, 1.0, 1.0, 0.0, 1.0, 0.0, 1.0,
1.0, 1.0, 1.0, 0.0, 0.0, 0.0, 0.0, 1.0, 1.0, 1.0, 1.0, 0.0, 0.0, 0.0,
0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 1.0, 1.0, 0.0, 1.0, 0.0,
```

```
0.0, 1.0, 0.0, 0.0, 0.0, 1.0, 1.0, 1.0, 0.0, 1.0, 0.0, 1.0, 1.0, 1.0,
1.0, 1.0]
Test predictions saved to submission\
HarishNandhan_Shanmugam_challenge1.pkl
```

CHALLENGE 2

```
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
print(f"Using device: {device}")
```

```
Using device: cuda
```

```
import os
import numpy as np
import torch
import requests
from PIL import Image
from io import BytesIO
from torchvision import transforms
import gensim.downloader as api
import nltk
from nltk.tokenize import word_tokenize
from nltk.corpus import stopwords
from nltk.stem import WordNetLemmatizer
import json
from collections import Counter


nltk.download('punkt')
nltk.download('stopwords')
nltk.download('wordnet')


print("Loading GloVe Word2Vec model...")
word2vec_model = api.load("glove-wiki-gigaword-50")
print("Word2Vec model loaded successfully!")


stop_words = set(stopwords.words("english"))
lemmatizer = WordNetLemmatizer()

def get_text_embedding(text):
    """Converts input text into a 50D Word2Vec vector after
preprocessing."""
    words = word_tokenize(text.lower())
    words = [lemmatizer.lemmatize(word) for word in words if
word.isalnum() and word not in stop_words]
    word_vectors = [word2vec_model[w] for w in words if w in
word2vec_model]
    return np.mean(word_vectors, axis=0) if word_vectors else
```

```
np.zeros(50)


transform = transforms.Compose([
    transforms.Resize((128, 128)),
    transforms.RandomHorizontalFlip(p=0.5),
    transforms.ColorJitter(brightness=0.2, contrast=0.2,
saturation=0.2),
    transforms.ToTensor(),
    transforms.Normalize(mean=[0.485, 0.456, 0.406], std=[0.229,
0.224, 0.225]),
])


IMG_DIR = "https://vizwiz.cs.colorado.edu/VizWiz_visualization_img/"


ANN_DIR =
"https://vizwiz.cs.colorado.edu/VizWiz_final/vqa_data/Annotations/"
TRAIN_ANNOTATION_PATH = f"{ANN_DIR}train.json"
VAL_ANNOTATION_PATH = f"{ANN_DIR}val.json"
TEST_ANNOTATION_PATH = f"{ANN_DIR}test.json"


train_data = requests.get(TRAIN_ANNOTATION_PATH).json()
val_data = requests.get(VAL_ANNOTATION_PATH).json()
test_data = requests.get(TEST_ANNOTATION_PATH).json()


train_subset = train_data[:3500]
val_subset = val_data[:300]
test_subset = test_data[:100]

print(f"Train Set Size: {len(train_subset)}, Val Set Size:
{len(val_subset)}, Test Set Size: {len(test_subset)}")


def load_images_and_texts(dataset):
    """Loads images from URLs and processes text embeddings."""
    image_tensors = []
    question_embeddings = []

    for sample in dataset:
        image_url = IMG_DIR + sample['image']
        response = requests.get(image_url)
        img = Image.open(BytesIO(response.content)).convert("RGB")
        img_tensor = transform(img)
        image_tensors.append(img_tensor)

question_embeddings.append(get_text_embedding(sample['question']))
```

```
    image_tensors = torch.stack(image_tensors).to(device)
    question_tensors = torch.tensor(question_embeddings,
dtype=torch.float32).to(device)
    return image_tensors, question_tensors

print("Processing Train Data...")
train_image_tensors, train_question_tensors =
load_images_and_texts(train_subset)
print("Processing Validation Data...")
val_image_tensors, val_question_tensors =
load_images_and_texts(val_subset)
print("Processing Test Data...")
test_image_tensors, test_question_tensors =
load_images_and_texts(test_subset)


preprocessed_dir = "preprocessed_tensors1"
os.makedirs(preprocessed_dir, exist_ok=True)

torch.save(train_image_tensors, os.path.join(preprocessed_dir,
"train_image_tensors.pt"))
torch.save(train_question_tensors, os.path.join(preprocessed_dir,
"train_question_tensors.pt"))
torch.save(val_image_tensors, os.path.join(preprocessed_dir,
"val_image_tensors.pt"))
torch.save(val_question_tensors, os.path.join(preprocessed_dir,
"val_question_tensors.pt"))
torch.save(test_image_tensors, os.path.join(preprocessed_dir,
"test_image_tensors.pt"))
torch.save(test_question_tensors, os.path.join(preprocessed_dir,
"test_question_tensors.pt"))

print(f"All Tensors Saved Successfully in `{preprocessed_dir}`")
```

```
[nltk_data] Downloading package punkt to
[nltk_data]     C:\Users\yoges\AppData\Roaming\nltk_data...
[nltk_data]   Package punkt is already up-to-date!
[nltk_data] Downloading package stopwords to
[nltk_data]     C:\Users\yoges\AppData\Roaming\nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
[nltk_data] Downloading package wordnet to
[nltk_data]     C:\Users\yoges\AppData\Roaming\nltk_data...
[nltk_data]   Package wordnet is already up-to-date!
```

```
Loading GloVe Word2Vec model...
Word2Vec model loaded successfully!
Train Set Size: 3500, Val Set Size: 300, Test Set Size: 100
Processing Train Data...
```

```
C:\Users\yoges\AppData\Local\Temp\ipykernel_26116\2841783741.py:82:
UserWarning: Creating a tensor from a list of numpy.ndarrays is
extremely slow. Please consider converting the list to a single
numpy.ndarray with numpy.array() before converting to a tensor.
(Triggered internally at C:\actions-runner\_work\pytorch\pytorch\
builder\windows\pytorch\torch\csrc\utils\tensor_new.cpp:281.)
  question_tensors = torch.tensor(question_embeddings,
dtype=torch.float32).to(device)

Processing Validation Data...
Processing Test Data...
All Tensors Saved Successfully in `preprocessed_tensors1`
```

```
from collections import Counter

chosen_answers = []
top_n = 500


for sample in train_subset:
    answers = [entry['answer'] for entry in sample['answers']]
    answer_counts = Counter(answers)
    top_answer, _ = answer_counts.most_common(1)[0]
    chosen_answers.append(top_answer)


answer_counts = Counter(chosen_answers)
top_answers = answer_counts.most_common(top_n)
print(top_answers)


category_name2id = {answer:ind for ind, (answer, _) in
enumerate(top_answers)}
category_id2name = {ind:answer for ind, (answer, _) in
enumerate(top_answers)}
category_id2name[top_n] = 'other_categories'

output_classes = top_n + 1
```

```
[('unanswerable', 693), ('unsuitable', 522), ('no', 96), ('yes', 75),
('white', 51), ('grey', 51), ('black', 42), ('red', 40), ('blue', 30),
('pink', 16), ('dog', 13), ('keyboard', 13), ('brown', 13), ('coca
cola', 12), ('green', 12), ('remote', 11), ('lotion', 10), ('cell
phone', 9), ('phone', 9), ('shampoo', 9), ('cup', 9), ('soup', 9),
('wine', 9), ('tv', 8), ('purple', 8), ('pepsi', 7), ('laptop', 7),
('dr pepper', 6), ('bottle', 6), ('water bottle', 6), ('corn', 6),
('black white', 6), ('pen', 6), ('black beans', 6), ('yellow', 6),
('green beans', 6), ('coffee', 6), ('chair', 6), ('tomatoes', 5),
('beer', 5), ('tan', 5), ('water', 5), ('cookies', 5), ('nothing', 5),
('computer', 5), ('orange', 4), ('dark', 4), ('ketchup', 4), ('door',
4), ('strawberry', 4), ('sunglasses', 4), ('flowers', 4), ('apple',
```

```
4), ('couch', 4), ('beige', 4), ('soda', 4), ('cat', 4), ('apple
juice', 4), ('foot', 3), ('mustard', 3), ('entertainment center', 3),
('chips', 3), ('candy', 3), ('shirt', 3), ('shaving cream', 3),
('iphone', 3), ('diet coke', 3), ('kona blend', 3), ('remote control',
3), ('bedroom', 3), ('chicken', 3), ('cloudy', 3), ('picture', 3),
('radio', 3), ('chicken broth', 3), ('cereal', 3), ('blanket', 3),
('tomato sauce', 3), ('money', 3), ('snickers', 3), ('can', 3), ('75',
3), ('mints', 3), ('beans', 3), ('38.5', 3), ('ginger ale', 3),
('ground beef', 3), ('car', 3), ('watch', 3), ('toothpaste', 3),
('crumbed fillet fish', 3), ('room', 3), ('cigarettes', 3), ('2', 3),
('carrots', 3), ('light', 3), ('rice', 3), ('1 dollar', 3), ('window',
3), ('1', 3), ('8 minutes', 3), ('chocolate', 3), ('book', 3),
('vanilla', 2), ('manwich', 2), ('100', 2), ('ipad', 2), ('melatonin',
2), ('tissues', 2), ('battery', 2), ('20 dollar bill', 2), ('lever
2000', 2), ('finger', 2), ('on', 2), ('raspberry', 2), ('windows', 2),
('gin', 2), ('cappuccino', 2), ('mixed nuts', 2), ('microsoft
corporation', 2), ('hand', 2), ('gift card', 2), ('right', 2), ('73',
2), ('macaroni cheese', 2), ('granola bars', 2), ('8', 2), ('bed', 2),
('medicine', 2), ('white chocolate', 2), ('spray bottle', 2),
('decaffeinated', 2), ('soda can', 2), ('clear', 2), ('cleaner', 2),
('dark chocolate', 2), ('paper', 2), ('fish tank', 2), ('backpack',
2), ('sage', 2), ('heater', 2), ('golden retriever', 2), ('white
fluffy', 2), ('crackers', 2), ('10', 2), ('coupon', 2), ('5 dollar
bill', 2), ('phone case', 2), ('potatoes', 2), ('drink', 2),
('computer mouse', 2), ('stove', 2), ('milk', 2), ('floor', 2),
('neosporin', 2), ('5', 2), ('9:40', 2), ('pineapple', 2), ('glass',
2), ('40', 2), ('acidophilus', 2), ('coors light', 2), ('id give up
chocolate but im not quitter', 2), ('red white', 2), ('sink', 2),
('pudding', 2), ('ravioli', 2), ('mucinex', 2), ('upside down', 2),
('carpet', 2), ('painting', 2), ('meatloaf', 2), ('hazelnut', 2),
('spinach', 2), ('kahlua', 2), ('bug', 2), ('peanut butter', 2),
('clock', 2), ('aquafina', 2), ('cream mushroom soup', 2), ('sprite',
2), ('tree', 2), ('74', 2), ('pillow', 2), ('28', 2), ('soap', 2),
('corned beef', 2), ('coffee cup', 2), ('rug', 2), ('fan', 2),
('ranch', 2), ('pizza', 2), ('3', 2), ('salt', 2), ('speaker', 2),
('oatmeal', 2), ('dr pepper 10', 2), ('refrigerator', 2), ('peaches',
2), ('ibuprofen', 2), ('tissue box', 2), ('tomato paste', 2), ('20',
2), ('olives', 2), ('tomato soup', 2), ('sea salt', 2), ('chicken
noodle soup', 2), ('tea', 2), ('kitchen', 2), ('cranberry', 2),
('409', 2), ('cheerios', 2), ('potato chips', 2), ('sunkist', 2),
('laundry detergent', 2), ('ear training', 2), ('tablet', 2), ('video
game', 2), ('vitamins', 2), ('500', 2), ('kidney beans', 2), ('healthy
choice', 2), ('78', 2), ('banana', 2), ('low', 2), ('cream mushroom',
2), ('kleenex', 2), ('sunny', 2), ('orange juice', 2), ('legs', 2),
('lean cuisine', 2), ('telephone', 2), ('desk', 2), ('silver', 2),
('sparkling cider', 2), ('blue white', 2), ('terrier', 2), ('stapler',
2), ('ipod', 2), ('microsoft', 2), ('gummy vitamins', 2), ('toshiba',
2), ('gum', 2), ('negative', 2), ('hot apple cider', 2), ('350', 2),
('basil leaves', 1), ('t36m', 1), ('solar garden light', 1), ('shoes',
```

```
1), ('mouthwash', 1), ('monitor cleaning kit', 1), ('80 cents', 1),
('grand theft auto vice city', 1), ('light red kidney beans', 1),
('brides maids', 1), ('raiz el evento', 1), ('toad training', 1),
('brown yes', 1), ('open', 1), ('homestyle italian', 1), ('eq02713',
1), ('jack links', 1), ('apple pie spice', 1), ('sweet sour chicken',
1), ('hulk toy', 1), ('sirloin steaks', 1), ('wands upside down', 1),
('beavis', 1), ('floral green', 1), ('winnie pooh', 1), ('blue corn
tortilla chips', 1), ('books photos speaker', 1), ('frequency', 1),
('cough drops', 1), ('minute maid coolers', 1), ('coffee maker', 1),
('oak', 1), ('clorox', 1), ('text', 1), ('steak seasoning', 1),
('mug', 1), ('house blend', 1), ('unsalted', 1), ('pink green white',
1), ('mailbox', 1), ('bottom right', 1), ('tale 2 cities', 1),
('sugar', 1), ('herbs', 1), ('goldenseal', 1), ('earl grey', 1),
('bath salts', 1), ('folic acid', 1), ('no picture', 1), ('2:03
timex', 1), ('green mountain coffee extra bold', 1), ('anti
diarrheal', 1), ('cats claw', 1), ('green apple', 1), ('gourmet cookie
dough', 1), ('suez walnut', 1), ('fiber', 1), ('low fat evaporated
milk', 1), ('ice cream maker', 1), ('ef18 88', 1), ('color
conditioning treatment', 1), ('closet', 1), ('apples', 1), ('cream
corn', 1), ('dietary supplements', 1), ('hot chocolate', 1),
('magenta', 1), ('flip flop', 1), ('3.48', 1), ('mac', 1), ('chores to
do', 1), ('103', 1), ('white pink', 1), ('7', 1), ('pear', 1),
('nokia', 1), ('snack pack pudding', 1), ('language', 1), ('shepherds
pie', 1), ('tuna helper', 1), ('t mobile store', 1), ('oct 27 2011',
1), ('oct 10', 1), ('krackel', 1), ('pasta sauce', 1), ('us twenty
dollar bill', 1), ('welcome home', 1), ('biotin', 1), ('decoration',
1), ('mango chipotle', 1), ('cereal almonds', 1), ('can food', 1),
('tan white', 1), ('scissors', 1), ('pork sausage', 1), ('chewy', 1),
('this my sun devil shirt', 1), ('butterscotch schnapps', 1), ('drying
rack', 1), ('flat iron spray', 1), ('maroon pink grey', 1), ('off',
1), ('tiger woods pga tour 10', 1), ('trail mix', 1), ('store', 1),
('carling lager', 1), ('feb 08 13', 1), ('saxa', 1), ('kp26m1xpm', 1),
('courtesy notice tax reminder 2nd half 2011 taxes due may 10 2012',
1), ('toy', 1), ('slightly right middle', 1), ('stove top stuffing',
1), ('star', 1), ('headphones', 1), ('hawaiian punch', 1),
('moisturizing conditioner', 1), ('grandpas teeth', 1), ('white
yellow', 1), ('christmas story', 1), ('mini cinnamon', 1), ('wine
glass', 1), ('11 26 2013', 1), ('popcorn', 1), ('white button down',
1), ('candy bars', 1), ('juice', 1), ('target ad', 1), ('halloween
pumpkins spiders', 1), ('calcium magnesium', 1), ('olive oil', 1),
('bag in front cigarettes', 1), ('cross necklace', 1), ('tall horse',
1), ('pimentos', 1), ('door carpet luggage nightstand', 1),
('chopper', 1), ('on bed', 1), ('stripes in red blue black', 1),
('storm clouds', 1), ('avatar', 1), ('white charger rectangle for
iphone ipod', 1), ('winston', 1), ('squash', 1), ('1 dollar bill', 1),
('shea body butter', 1), ('diet snapple', 1), ('this app rocks', 1),
('curve', 1), ('sweet bourbon glazed chicken', 1), ('this side up
caution extremely hot', 1), ('miller lite', 1), ('very clear', 1),
('76', 1), ('television', 1), ('left', 1), ('orange lemon lime', 1),
```

```
('toilet paper', 1), ('dont know', 1), ('10 pounds', 1), ('hair', 1),
('disc repair kit', 1), ('cookie cutters', 1), ('press ctrl alt delete
to begin', 1), ('financial planners bible', 1), ('beef dinner', 1),
('french onion soup', 1), ('pool float', 1), ('original', 1), ('phone
charger', 1), ('old spice deodorant', 1), ('nescafe', 1), ('madison
taylor women', 1), ('beef stroganoff', 1), ('dresser', 1),
('whittard', 1), ('sky blue', 1), ('train set', 1), ('pie filling',
1), ('weather', 1), ('click finish', 1), ('fish', 1), ('whole
oysters', 1), ('intel pentium', 1), ('sun block', 1), ('salt vinegar',
1), ('vanilla biscotti', 1), ('corona light', 1), ('fudge
marshmallow', 1), ('fiber 1 cereal', 1), ('lemon lime', 1), ('triple
antibiotic ointment', 1), ('almond crunch', 1), ('parking lot', 1),
('window wash', 1), ('sterling cabernet sauvignon', 1), ('italian meat
trio', 1), ('65', 1), ('our account', 1), ('red no text', 1), ('coffee
pot', 1), ('fanta', 1), ('chili seasoning mix', 1), ('capri sun', 1),
('fiber capsules', 1), ('people', 1), ('perfect granite', 1),
('display', 1), ('sku 247432', 1), ('salisbury steaks', 1),
('monitor', 1), ('beagle', 1), ('conditioner shampoo lotion', 1),
('bakewell tart', 1), ('peach apple carrot fruitsations', 1), ('soup
shanks', 1), ('purse', 1), ('roasted sweet potato chunks', 1), ('819',
1), ('creamy 4 cheese', 1), ('chick fil bowl', 1), ('onion sea salt',
1), ('blue screen', 1), ('white tea', 1), ('on table', 1), ('dark
chocolate truffle', 1), ('stairs', 1), ('out africa', 1),
('underwear', 1), ('multicolored', 1), ('burgers', 1), ('yers finger
better', 1), ('aarp', 1), ('ford blue', 1), ('big print address book',
1), ('rash', 1), ('air vent', 1), ('chicken tortilla', 1), ('3 cheese
tortellini', 1), ('nutrition facts', 1), ('brownie pan', 1), ('songs
south', 1), ('free smartrecord', 1), ('mexican express', 1),
('snyder', 1), ('celestial sleepytime herbal tea', 1), ('diced
tomatoes', 1), ('pepsi max', 1), ('chunky soup', 1), ('laptop apple',
1), ('blue buffalo', 1), ('red yo yo', 1), ('campbells tomato soup',
1), ('jay z kanye west gotta have blue', 1)]
```

```python
targets = []

for ans in chosen_answers:
    if ans in category_name2id.keys():
        targets.append(category_name2id[ans])
    else:
        targets.append(top_n)

targets_tensor = torch.tensor(targets)
print('Target size:', targets_tensor.shape)
```

```
Target size: torch.Size([3500])
```

```python
val_chosen_answers = []
for sample in val_subset:
    answers = [entry['answer'] for entry in sample['answers']]
```

```
    answer_counts = Counter(answers)
    top_answer, _ = answer_counts.most_common(1)[0]
    val_chosen_answers.append(top_answer)

val_targets = [category_name2id.get(ans, top_n) for ans in
val_chosen_answers]
val_targets_tensor = torch.tensor(val_targets)


test_targets = torch.zeros(len(test_subset), dtype=torch.long)


torch.save(targets_tensor, os.path.join(preprocessed_dir,
"train_targets.pt"))
torch.save(val_targets_tensor, os.path.join(preprocessed_dir,
"val_targets.pt"))
torch.save(test_targets, os.path.join(preprocessed_dir,
"test_targets.pt"))

print("Labels processed and saved.")
```

```
Labels processed and saved.
```

```
import torch.nn as nn
import torchvision.models as models

class ImprovedVQAModel(nn.Module):
    def __init__(self, hidden_dim=256, num_classes=output_classes,
num_heads=8, dropout_rate=0.2):
        super(ImprovedVQAModel, self).__init__()


        self.cnn = models.resnet34(pretrained=True)
        for param in list(self.cnn.parameters())[:-8]:
            param.requires_grad = False
        self.cnn.fc = nn.Linear(self.cnn.fc.in_features, hidden_dim)


        self.text_embedding = nn.Sequential(
            nn.Linear(50, hidden_dim * 2),
            nn.LayerNorm(hidden_dim * 2),
            nn.ReLU(),
            nn.Dropout(dropout_rate),
            nn.Linear(hidden_dim * 2, hidden_dim),
            nn.LayerNorm(hidden_dim),
            nn.ReLU(),
            nn.Dropout(dropout_rate)
        )


        self.img_to_text_attention =
```

```
nn.MultiheadAttention(embed_dim=hidden_dim, num_heads=num_heads,
batch_first=True)
        self.text_to_img_attention =
nn.MultiheadAttention(embed_dim=hidden_dim, num_heads=num_heads,
batch_first=True)


        self.norm1 = nn.LayerNorm(hidden_dim)
        self.norm2 = nn.LayerNorm(hidden_dim)


        self.gate = nn.Sequential(
            nn.Linear(hidden_dim * 2, hidden_dim),
            nn.Sigmoid()
        )


        self.classifier = nn.Sequential(
            nn.Linear(hidden_dim, hidden_dim),
            nn.ReLU(),
            nn.Dropout(dropout_rate),
            nn.Linear(hidden_dim, hidden_dim // 2),
            nn.ReLU(),
            nn.Dropout(dropout_rate),
            nn.Linear(hidden_dim // 2, num_classes)
        )

    def forward(self, image, text):

        img_features = self.cnn(image)
        text_features = self.text_embedding(text)


        img_features_attn = img_features.unsqueeze(1)
        text_features_attn = text_features.unsqueeze(1)


        img_attended_text, _ =
self.img_to_text_attention(img_features_attn, text_features_attn,
text_features_attn)
        text_attended_img, _ =
self.text_to_img_attention(text_features_attn, img_features_attn,
img_features_attn)


        img_attended_text = self.norm1(img_attended_text).squeeze(1)
        text_attended_img = self.norm2(text_attended_img).squeeze(1)


        concat_features = torch.cat([img_attended_text,
```

```
text_attended_img], dim=1)
        gate_value = self.gate(concat_features)
        fused_features = gate_value * img_attended_text + (1 -
gate_value) * text_attended_img


        logits = self.classifier(fused_features)
        return logits
```

```
from torch.utils.data import Dataset, DataLoader

class VQADataset(Dataset):
    def __init__(self, images, questions, targets):
        self.images = images
        self.questions = questions
        self.targets = targets

    def __len__(self):
        return len(self.targets)

    def __getitem__(self, idx):
        return self.images[idx], self.questions[idx],
self.targets[idx]


train_targets = torch.load(os.path.join(preprocessed_dir,
"train_targets.pt"))
val_targets = torch.load(os.path.join(preprocessed_dir,
"val_targets.pt"))


train_dataset = VQADataset(train_image_tensors,
train_question_tensors, train_targets)
val_dataset = VQADataset(val_image_tensors, val_question_tensors,
val_targets)


batch_size = 16
train_loader = DataLoader(train_dataset, batch_size=batch_size,
shuffle=True)
val_loader = DataLoader(val_dataset, batch_size=batch_size,
shuffle=False)
```

```
C:\Users\yoges\AppData\Local\Temp\ipykernel_26116\1237128094.py:16:
FutureWarning: You are using `torch.load` with `weights_only=False`
(the current default value), which uses the default pickle module
implicitly. It is possible to construct malicious pickle data which
will execute arbitrary code during unpickling (See
https://github.com/pytorch/pytorch/blob/main/SECURITY.md#untrusted-
models for more details). In a future release, the default value for
`weights_only` will be flipped to `True`. This limits the functions
```

```
that could be executed during unpickling. Arbitrary objects will no
longer be allowed to be loaded via this mode unless they are
explicitly allowlisted by the user via
`torch.serialization.add_safe_globals`. We recommend you start setting
`weights_only=True` for any use case where you don't have full control
of the loaded file. Please open an issue on GitHub for any issues
related to this experimental feature.
  train_targets = torch.load(os.path.join(preprocessed_dir,
"train_targets.pt"))
C:\Users\yoges\AppData\Local\Temp\ipykernel_26116\1237128094.py:17:
FutureWarning: You are using `torch.load` with `weights_only=False`
(the current default value), which uses the default pickle module
implicitly. It is possible to construct malicious pickle data which
will execute arbitrary code during unpickling (See
https://github.com/pytorch/pytorch/blob/main/SECURITY.md#untrusted-
models for more details). In a future release, the default value for
`weights_only` will be flipped to `True`. This limits the functions
that could be executed during unpickling. Arbitrary objects will no
longer be allowed to be loaded via this mode unless they are
explicitly allowlisted by the user via
`torch.serialization.add_safe_globals`. We recommend you start setting
`weights_only=True` for any use case where you don't have full control
of the loaded file. Please open an issue on GitHub for any issues
related to this experimental feature.
  val_targets = torch.load(os.path.join(preprocessed_dir,
"val_targets.pt"))

from collections import Counter

def calculate_human_accuracy(pred_answer, human_answers):
    """Apply human agreement VQA accuracy logic"""
    pred_answer = pred_answer.lower()
    human_answers = [a['answer'].lower() for a in human_answers]
    count = Counter(human_answers)
    agree_count = count.get(pred_answer, 0)
    return min(agree_count / 3, 1.0)

import torch
import torch.nn as nn
import torch.optim as optim
from torch.nn.utils import clip_grad_norm_
import matplotlib.pyplot as plt
from collections import Counter


def calculate_human_accuracy(pred_answer, human_answers):
    pred_answer = pred_answer.lower()
    human_answers = [a['answer'].lower() for a in human_answers]
    agree_count = Counter(human_answers).get(pred_answer, 0)
    return min(agree_count / 3, 1.0)
```

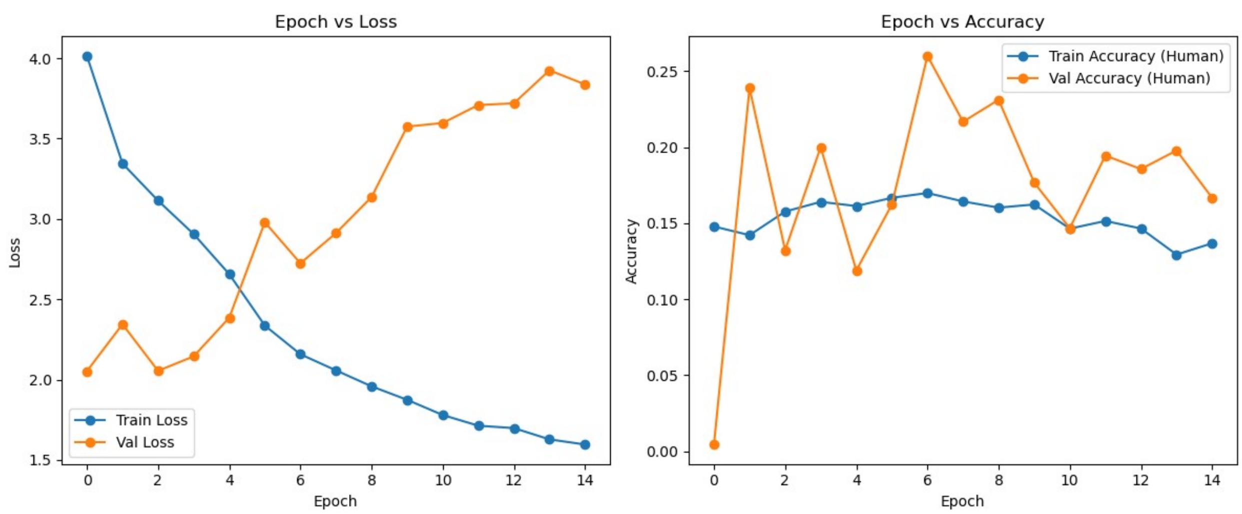
```python
def train_improved_model(model, train_loader, val_loader, val_subset,
category_id2name,
                         train_subset, num_epochs=15, device="cuda"):
    criterion = nn.CrossEntropyLoss()
    optimizer = optim.AdamW(model.parameters(), lr=2e-4,
weight_decay=1e-5)
    scheduler = optim.lr_scheduler.ReduceLROnPlateau(optimizer,
mode='max', factor=0.5, patience=2)

    best_val_acc = 0.0
    train_losses, val_losses, train_accs, val_accs = [], [], [], []

    for epoch in range(num_epochs):

        model.train()
        correct, total, train_loss, train_score = 0, 0, 0.0, 0.0

        for i, (images, questions, targets) in
enumerate(train_loader):
            images, questions, targets = images.to(device),
questions.to(device), targets.to(device)

            optimizer.zero_grad()
            outputs = model(images, questions)
            loss = criterion(outputs, targets)
            loss.backward()
            clip_grad_norm_(model.parameters(), max_norm=1.0)
            optimizer.step()

            train_loss += loss.item()
            _, predicted = torch.max(outputs, 1)
            correct += (predicted == targets).sum().item()
            total += targets.size(0)


            predicted = predicted.cpu().numpy()
            batch_answers = [category_id2name[p] for p in predicted]
            for idx_in_batch, pred_ans in enumerate(batch_answers):
                sample_index = i * train_loader.batch_size +
idx_in_batch
                if sample_index >= len(train_subset):
                    continue
                human_answers = train_subset[sample_index]['answers']
                train_score += calculate_human_accuracy(pred_ans,
human_answers)

        train_loss /= len(train_loader)
        train_acc = train_score / total
```

```
        train_losses.append(train_loss)
        train_accs.append(train_acc)


        model.eval()
        val_loss, val_score, val_total = 0.0, 0.0, 0

        with torch.no_grad():
            for i, (images, questions, targets) in
enumerate(val_loader):
                images, questions, targets = images.to(device),
questions.to(device), targets.to(device)
                outputs = model(images, questions)
                loss = criterion(outputs, targets)
                val_loss += loss.item()

                _, predicted = torch.max(outputs, 1)
                predicted = predicted.cpu().numpy()
                batch_answers = [category_id2name[p] for p in
predicted]

                for idx_in_batch, pred_ans in
enumerate(batch_answers):
                    sample_index = i * val_loader.batch_size +
idx_in_batch
                    if sample_index >= len(val_subset):
                        continue
                    human_answers = val_subset[sample_index]
['answers']
                    val_score += calculate_human_accuracy(pred_ans,
human_answers)

                val_total += len(batch_answers)

        val_loss /= len(val_loader)
        val_acc = val_score / val_total
        val_losses.append(val_loss)
        val_accs.append(val_acc)

        print(f"Epoch [{epoch+1}/{num_epochs}] -> Train Loss:
{train_loss:.4f}, Train Acc (Human): {train_acc:.4f}, "
              f"Val Loss: {val_loss:.4f}, Val Acc (Human):
{val_acc:.4f}")

        scheduler.step(val_acc)

        if val_acc > best_val_acc:
            best_val_acc = val_acc
            best_model_path = "submission/best_model_challenge2.pt"
            torch.save(model.state_dict(), best_model_path)
```

```
            print(f"  New best model saved at {best_model_path} with
Val Acc: {val_acc:.4f}")


    plt.figure(figsize=(12, 5))

    plt.subplot(1, 2, 1)
    plt.plot(train_losses, label='Train Loss', marker='o')
    plt.plot(val_losses, label='Val Loss', marker='o')
    plt.legend()
    plt.xlabel('Epoch')
    plt.ylabel('Loss')
    plt.title('Epoch vs Loss')

    plt.subplot(1, 2, 2)
    plt.plot(train_accs, label='Train Accuracy (Human)', marker='o')
    plt.plot(val_accs, label='Val Accuracy (Human)', marker='o')
    plt.legend()
    plt.xlabel('Epoch')
    plt.ylabel('Accuracy')
    plt.title('Epoch vs Accuracy')

    plt.tight_layout()
    plt.show()

    return model

model = ImprovedVQAModel().to(device)
trained_model = train_improved_model(
    model,
    train_loader,
    val_loader,
    val_subset=val_subset,
    category_id2name=category_id2name,
    train_subset=train_subset,
    num_epochs=15,
    device=device
)
```

```
Epoch [1/15] -> Train Loss: 4.0148, Train Acc (Human): 0.1478, Val
Loss: 2.0523, Val Acc (Human): 0.0044
  New best model saved at submission/best_model_challenge2.pt with Val
Acc: 0.0044
Epoch [2/15] -> Train Loss: 3.3448, Train Acc (Human): 0.1421, Val
Loss: 2.3446, Val Acc (Human): 0.2389
  New best model saved at submission/best_model_challenge2.pt with Val
Acc: 0.2389
Epoch [3/15] -> Train Loss: 3.1136, Train Acc (Human): 0.1576, Val
Loss: 2.0544, Val Acc (Human): 0.1322
```

```
Epoch [4/15] -> Train Loss: 2.9057, Train Acc (Human): 0.1640, Val
Loss: 2.1445, Val Acc (Human): 0.2000
Epoch [5/15] -> Train Loss: 2.6563, Train Acc (Human): 0.1612, Val
Loss: 2.3847, Val Acc (Human): 0.1189
Epoch [6/15] -> Train Loss: 2.3364, Train Acc (Human): 0.1667, Val
Loss: 2.9797, Val Acc (Human): 0.1622
Epoch [7/15] -> Train Loss: 2.1575, Train Acc (Human): 0.1698, Val
Loss: 2.7237, Val Acc (Human): 0.2600
  New best model saved at submission/best_model_challenge2.pt with Val
Acc: 0.2600
Epoch [8/15] -> Train Loss: 2.0572, Train Acc (Human): 0.1643, Val
Loss: 2.9119, Val Acc (Human): 0.2167
Epoch [9/15] -> Train Loss: 1.9578, Train Acc (Human): 0.1602, Val
Loss: 3.1358, Val Acc (Human): 0.2311
Epoch [10/15] -> Train Loss: 1.8741, Train Acc (Human): 0.1623, Val
Loss: 3.5745, Val Acc (Human): 0.1767
Epoch [11/15] -> Train Loss: 1.7794, Train Acc (Human): 0.1464, Val
Loss: 3.5969, Val Acc (Human): 0.1467
Epoch [12/15] -> Train Loss: 1.7129, Train Acc (Human): 0.1514, Val
Loss: 3.7087, Val Acc (Human): 0.1944
Epoch [13/15] -> Train Loss: 1.6980, Train Acc (Human): 0.1465, Val
Loss: 3.7194, Val Acc (Human): 0.1856
Epoch [14/15] -> Train Loss: 1.6278, Train Acc (Human): 0.1293, Val
Loss: 3.9249, Val Acc (Human): 0.1978
Epoch [15/15] -> Train Loss: 1.5958, Train Acc (Human): 0.1368, Val
Loss: 3.8371, Val Acc (Human): 0.1667
```




```
import torch.optim as optim
import matplotlib.pyplot as plt
import os
from torch.utils.data import DataLoader
from collections import Counter
```

```
hyperparameter_sets = [
    {"lr": 2e-4, "weight_decay": 1e-5, "batch_size": 16, "num_epochs":
15, "optimizer": "AdamW"},
    {"lr": 1e-4, "weight_decay": 5e-5, "batch_size": 32, "num_epochs":
15, "optimizer": "AdamW"},
    {"lr": 5e-4, "weight_decay": 1e-6, "batch_size": 32, "num_epochs":
15, "optimizer": "AdamW"}
]


best_val_acc = 0.0
best_hyperparams = None
best_model_path = "submission/best_model_challenge2.pt"
history = {}


val_loader = DataLoader(val_dataset, batch_size=16, shuffle=False)


def calculate_human_accuracy(pred_answer, human_answers):
    pred_answer = pred_answer.lower()
    human_answers = [a['answer'].lower() for a in human_answers]
    agree_count = Counter(human_answers).get(pred_answer, 0)
    return min(agree_count / 3, 1.0)


if os.path.exists(best_model_path):
    best_model = ImprovedVQAModel().to(device)
    best_model.load_state_dict(torch.load(best_model_path))
    best_model.eval()

    val_score, val_total = 0.0, 0
    with torch.no_grad():
        for i, (images, questions, targets) in enumerate(val_loader):
            images, questions, targets = images.to(device),
questions.to(device), targets.to(device)
            outputs = best_model(images, questions)
            _, predicted = torch.max(outputs, 1)
            predicted = predicted.cpu().numpy()
            batch_answers = [category_id2name[p] for p in predicted]

            for idx_in_batch, pred_ans in enumerate(batch_answers):
                sample_index = i * val_loader.batch_size +
idx_in_batch
                if sample_index >= len(val_subset):
                    continue
                human_answers = val_subset[sample_index]['answers']
                val_score += calculate_human_accuracy(pred_ans,
human_answers)
```

```
            val_total += len(batch_answers)

    best_val_acc = val_score / val_total
    print(f" Previous Best Validation Accuracy (Human):
{best_val_acc:.4f}")
```

```
C:\Users\yoges\AppData\Local\Temp\ipykernel_26116\4282781157.py:33:
FutureWarning: You are using `torch.load` with `weights_only=False`
(the current default value), which uses the default pickle module
implicitly. It is possible to construct malicious pickle data which
will execute arbitrary code during unpickling (See
https://github.com/pytorch/pytorch/blob/main/SECURITY.md#untrusted-
models for more details). In a future release, the default value for
`weights_only` will be flipped to `True`. This limits the functions
that could be executed during unpickling. Arbitrary objects will no
longer be allowed to be loaded via this mode unless they are
explicitly allowlisted by the user via
`torch.serialization.add_safe_globals`. We recommend you start setting
`weights_only=True` for any use case where you don't have full control
of the loaded file. Please open an issue on GitHub for any issues
related to this experimental feature.
  best_model.load_state_dict(torch.load(best_model_path))

 Previous Best Validation Accuracy (Human): 0.2600
```

```
import torch
import torch.nn as nn
import torch.optim as optim
from torch.nn.utils import clip_grad_norm_
import matplotlib.pyplot as plt
from collections import Counter
import os
from torch.utils.data import DataLoader


def calculate_human_accuracy(pred_answer, human_answers):
    pred_answer = pred_answer.lower()
    human_answers = [a['answer'].lower() for a in human_answers]
    agree_count = Counter(human_answers).get(pred_answer, 0)
    return min(agree_count / 3, 1.0)


def train_improved_model(model, train_loader, val_loader, val_subset,
category_id2name,
                         train_subset, num_epochs=15, device="cuda"):
    criterion = nn.CrossEntropyLoss()
    optimizer = optim.AdamW(model.parameters(), lr=2e-4,
weight_decay=1e-5)
    scheduler = optim.lr_scheduler.ReduceLROnPlateau(optimizer,
mode='max', factor=0.5, patience=2)
```

```
    best_val_acc = 0.0
    train_losses, val_losses, train_accs, val_accs = [], [], [], []

    for epoch in range(num_epochs):
        model.train()
        correct, total, train_loss, train_score = 0, 0, 0.0, 0.0

        for i, (images, questions, targets) in
enumerate(train_loader):
            images, questions, targets = images.to(device),
questions.to(device), targets.to(device)
            optimizer.zero_grad()
            outputs = model(images, questions)
            loss = criterion(outputs, targets)
            loss.backward()
            clip_grad_norm_(model.parameters(), max_norm=1.0)
            optimizer.step()

            train_loss += loss.item()
            _, predicted = torch.max(outputs, 1)
            correct += (predicted == targets).sum().item()
            total += targets.size(0)

            predicted = predicted.cpu().numpy()
            batch_answers = [category_id2name[p] for p in predicted]
            for idx_in_batch, pred_ans in enumerate(batch_answers):
                sample_index = i * train_loader.batch_size +
idx_in_batch
                if sample_index >= len(train_subset):
                    continue
                human_answers = train_subset[sample_index]['answers']
                train_score += calculate_human_accuracy(pred_ans,
human_answers)

        train_loss /= len(train_loader)
        train_acc = train_score / total
        train_losses.append(train_loss)
        train_accs.append(train_acc)

        model.eval()
        val_loss, val_score, val_total = 0.0, 0.0, 0

        with torch.no_grad():
            for i, (images, questions, targets) in
enumerate(val_loader):
                images, questions, targets = images.to(device),
questions.to(device), targets.to(device)
                outputs = model(images, questions)
                loss = criterion(outputs, targets)
```

```
                val_loss += loss.item()

                _, predicted = torch.max(outputs, 1)
                predicted = predicted.cpu().numpy()
                batch_answers = [category_id2name[p] for p in
predicted]

                for idx_in_batch, pred_ans in
enumerate(batch_answers):
                    sample_index = i * val_loader.batch_size +
idx_in_batch
                    if sample_index >= len(val_subset):
                        continue
                    human_answers = val_subset[sample_index]
['answers']
                    val_score += calculate_human_accuracy(pred_ans,
human_answers)

                val_total += len(batch_answers)

        val_loss /= len(val_loader)
        val_acc = val_score / val_total
        val_losses.append(val_loss)
        val_accs.append(val_acc)

        print(f"Epoch [{epoch+1}/{num_epochs}] -> Train Loss:
{train_loss:.4f}, Train Acc (Human): {train_acc:.4f}, "
              f"Val Loss: {val_loss:.4f}, Val Acc (Human):
{val_acc:.4f}")

        scheduler.step(val_acc)

        if val_acc > best_val_acc:
            best_val_acc = val_acc
            best_model_path = "submission/best_model_challenge2.pt"
            torch.save(model.state_dict(), best_model_path)
            print(f" New best model saved at {best_model_path} with
Val Acc: {val_acc:.4f}")

    return train_losses, val_losses, train_accs, val_accs


hyperparameter_sets = [
    {"lr": 2e-4, "weight_decay": 1e-5, "batch_size": 16, "num_epochs":
15},
    {"lr": 1e-4, "weight_decay": 5e-5, "batch_size": 32, "num_epochs":
15},
    {"lr": 5e-4, "weight_decay": 1e-6, "batch_size": 32, "num_epochs":
15}
]
```

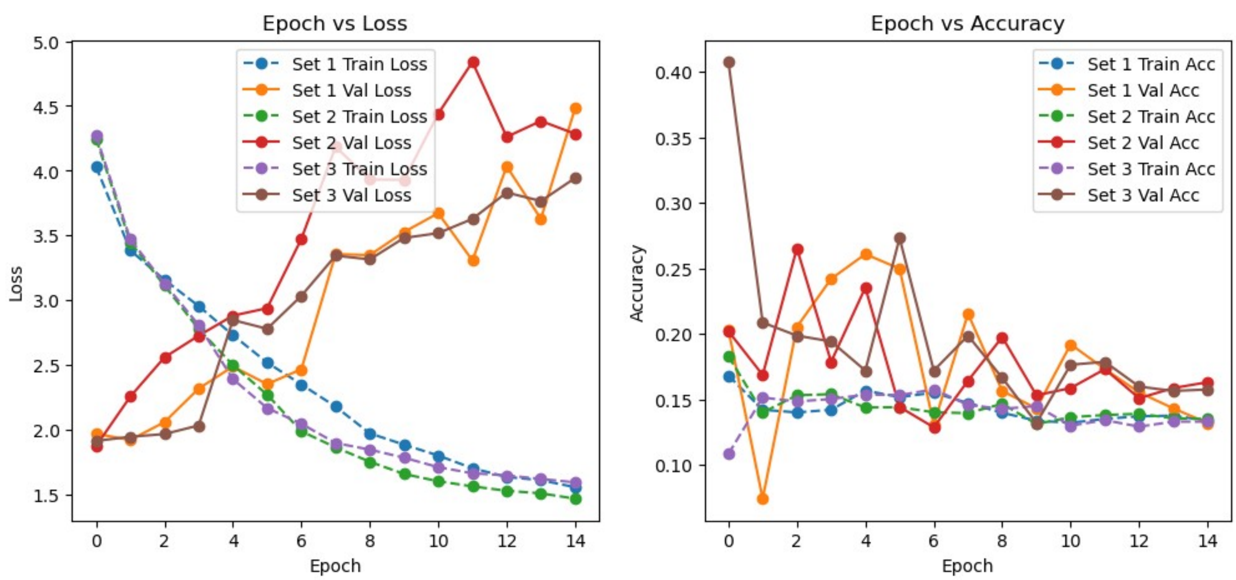
```python
history = {}
best_val_acc = 0.0

for i, hyperparams in enumerate(hyperparameter_sets):
    print(f"\n Training with Hyperparameter Set {i+1}: {hyperparams}\
n")

    train_loader = DataLoader(train_dataset,
batch_size=hyperparams["batch_size"], shuffle=True)
    model = ImprovedVQAModel().to(device)

    train_losses, val_losses, train_accs, val_accs =
train_improved_model(
        model, train_loader, val_loader, val_subset, category_id2name,
train_subset,
        num_epochs=hyperparams["num_epochs"], device=device
    )

    history[f"Set {i+1}"] = {
        "train_loss": train_losses,
        "val_loss": val_losses,
        "train_acc": train_accs,
        "val_acc": val_accs
    }

    if val_accs[-1] > best_val_acc:
        best_val_acc = val_accs[-1]
        print(f" Set {i+1} is currently the best with Val Acc:
{best_val_acc:.4f}")
```

```
 Training with Hyperparameter Set 1: {'lr': 0.0002, 'weight_decay':
1e-05, 'batch_size': 16, 'num_epochs': 15}

Epoch [1/15] -> Train Loss: 4.0319, Train Acc (Human): 0.1684, Val
Loss: 1.9711, Val Acc (Human): 0.2033
 New best model saved at submission/best_model_challenge2.pt with Val
Acc: 0.2033
Epoch [2/15] -> Train Loss: 3.3868, Train Acc (Human): 0.1423, Val
Loss: 1.9229, Val Acc (Human): 0.0744
Epoch [3/15] -> Train Loss: 3.1584, Train Acc (Human): 0.1403, Val
Loss: 2.0609, Val Acc (Human): 0.2056
 New best model saved at submission/best_model_challenge2.pt with Val
Acc: 0.2056
Epoch [4/15] -> Train Loss: 2.9560, Train Acc (Human): 0.1423, Val
Loss: 2.3195, Val Acc (Human): 0.2422
 New best model saved at submission/best_model_challenge2.pt with Val
Acc: 0.2422
Epoch [5/15] -> Train Loss: 2.7323, Train Acc (Human): 0.1570, Val
```

```
Loss: 2.4896, Val Acc (Human): 0.2611
 New best model saved at submission/best_model_challenge2.pt with Val
Acc: 0.2611
Epoch [6/15] -> Train Loss: 2.5205, Train Acc (Human): 0.1520, Val
Loss: 2.3543, Val Acc (Human): 0.2500
Epoch [7/15] -> Train Loss: 2.3518, Train Acc (Human): 0.1553, Val
Loss: 2.4685, Val Acc (Human): 0.1311
Epoch [8/15] -> Train Loss: 2.1804, Train Acc (Human): 0.1474, Val
Loss: 3.3568, Val Acc (Human): 0.2156
Epoch [9/15] -> Train Loss: 1.9744, Train Acc (Human): 0.1400, Val
Loss: 3.3491, Val Acc (Human): 0.1567
Epoch [10/15] -> Train Loss: 1.8871, Train Acc (Human): 0.1340, Val
Loss: 3.5270, Val Acc (Human): 0.1433
Epoch [11/15] -> Train Loss: 1.8032, Train Acc (Human): 0.1324, Val
Loss: 3.6724, Val Acc (Human): 0.1922
Epoch [12/15] -> Train Loss: 1.7052, Train Acc (Human): 0.1353, Val
Loss: 3.3082, Val Acc (Human): 0.1733
Epoch [13/15] -> Train Loss: 1.6383, Train Acc (Human): 0.1373, Val
Loss: 4.0332, Val Acc (Human): 0.1556
Epoch [14/15] -> Train Loss: 1.6130, Train Acc (Human): 0.1378, Val
Loss: 3.6290, Val Acc (Human): 0.1433
Epoch [15/15] -> Train Loss: 1.5590, Train Acc (Human): 0.1340, Val
Loss: 4.4823, Val Acc (Human): 0.1322
 Set 1 is currently the best with Val Acc: 0.1322

 Training with Hyperparameter Set 2: {'lr': 0.0001, 'weight_decay':
5e-05, 'batch_size': 32, 'num_epochs': 15}

Epoch [1/15] -> Train Loss: 4.2492, Train Acc (Human): 0.1832, Val
Loss: 1.8755, Val Acc (Human): 0.2022
 New best model saved at submission/best_model_challenge2.pt with Val
Acc: 0.2022
Epoch [2/15] -> Train Loss: 3.4497, Train Acc (Human): 0.1402, Val
Loss: 2.2571, Val Acc (Human): 0.1689
Epoch [3/15] -> Train Loss: 3.1141, Train Acc (Human): 0.1533, Val
Loss: 2.5602, Val Acc (Human): 0.2656
 New best model saved at submission/best_model_challenge2.pt with Val
Acc: 0.2656
Epoch [4/15] -> Train Loss: 2.7791, Train Acc (Human): 0.1542, Val
Loss: 2.7278, Val Acc (Human): 0.1789
Epoch [5/15] -> Train Loss: 2.5011, Train Acc (Human): 0.1440, Val
Loss: 2.8819, Val Acc (Human): 0.2356
Epoch [6/15] -> Train Loss: 2.2725, Train Acc (Human): 0.1443, Val
Loss: 2.9399, Val Acc (Human): 0.1444
Epoch [7/15] -> Train Loss: 1.9903, Train Acc (Human): 0.1404, Val
Loss: 3.4738, Val Acc (Human): 0.1289
Epoch [8/15] -> Train Loss: 1.8662, Train Acc (Human): 0.1397, Val
Loss: 4.1840, Val Acc (Human): 0.1644
Epoch [9/15] -> Train Loss: 1.7553, Train Acc (Human): 0.1469, Val
```

```
Loss: 3.9329, Val Acc (Human): 0.1978
Epoch [10/15] -> Train Loss: 1.6611, Train Acc (Human): 0.1314, Val
Loss: 3.9297, Val Acc (Human): 0.1533
Epoch [11/15] -> Train Loss: 1.6047, Train Acc (Human): 0.1367, Val
Loss: 4.4399, Val Acc (Human): 0.1589
Epoch [12/15] -> Train Loss: 1.5653, Train Acc (Human): 0.1383, Val
Loss: 4.8391, Val Acc (Human): 0.1733
Epoch [13/15] -> Train Loss: 1.5314, Train Acc (Human): 0.1392, Val
Loss: 4.2610, Val Acc (Human): 0.1511
Epoch [14/15] -> Train Loss: 1.5118, Train Acc (Human): 0.1358, Val
Loss: 4.3837, Val Acc (Human): 0.1589
Epoch [15/15] -> Train Loss: 1.4704, Train Acc (Human): 0.1352, Val
Loss: 4.2846, Val Acc (Human): 0.1633
 Set 2 is currently the best with Val Acc: 0.1633

 Training with Hyperparameter Set 3: {'lr': 0.0005, 'weight_decay':
1e-06, 'batch_size': 32, 'num_epochs': 15}

Epoch [1/15] -> Train Loss: 4.2734, Train Acc (Human): 0.1087, Val
Loss: 1.9160, Val Acc (Human): 0.4078
 New best model saved at submission/best_model_challenge2.pt with Val
Acc: 0.4078
Epoch [2/15] -> Train Loss: 3.4723, Train Acc (Human): 0.1516, Val
Loss: 1.9479, Val Acc (Human): 0.2089
Epoch [3/15] -> Train Loss: 3.1295, Train Acc (Human): 0.1487, Val
Loss: 1.9688, Val Acc (Human): 0.1989
Epoch [4/15] -> Train Loss: 2.8091, Train Acc (Human): 0.1505, Val
Loss: 2.0351, Val Acc (Human): 0.1944
Epoch [5/15] -> Train Loss: 2.3930, Train Acc (Human): 0.1539, Val
Loss: 2.8484, Val Acc (Human): 0.1722
Epoch [6/15] -> Train Loss: 2.1694, Train Acc (Human): 0.1534, Val
Loss: 2.7806, Val Acc (Human): 0.2733
Epoch [7/15] -> Train Loss: 2.0484, Train Acc (Human): 0.1579, Val
Loss: 3.0348, Val Acc (Human): 0.1722
Epoch [8/15] -> Train Loss: 1.8998, Train Acc (Human): 0.1460, Val
Loss: 3.3448, Val Acc (Human): 0.1989
Epoch [9/15] -> Train Loss: 1.8486, Train Acc (Human): 0.1430, Val
Loss: 3.3162, Val Acc (Human): 0.1667
Epoch [10/15] -> Train Loss: 1.7866, Train Acc (Human): 0.1451, Val
Loss: 3.4812, Val Acc (Human): 0.1322
Epoch [11/15] -> Train Loss: 1.7134, Train Acc (Human): 0.1302, Val
Loss: 3.5186, Val Acc (Human): 0.1767
Epoch [12/15] -> Train Loss: 1.6665, Train Acc (Human): 0.1344, Val
Loss: 3.6282, Val Acc (Human): 0.1789
Epoch [13/15] -> Train Loss: 1.6500, Train Acc (Human): 0.1294, Val
Loss: 3.8320, Val Acc (Human): 0.1600
Epoch [14/15] -> Train Loss: 1.6228, Train Acc (Human): 0.1332, Val
Loss: 3.7660, Val Acc (Human): 0.1567
```

```
Epoch [15/15] -> Train Loss: 1.5960, Train Acc (Human): 0.1332, Val
Loss: 3.9437, Val Acc (Human): 0.1578

plt.figure(figsize=(12, 5))

# Loss Plot
plt.subplot(1, 2, 1)
for key, values in history.items():
    plt.plot(values["train_loss"], label=f'{key} Train Loss',
linestyle='--', marker='o')
    plt.plot(values["val_loss"], label=f'{key} Val Loss', marker='o')

plt.legend()
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.title('Epoch vs Loss')


plt.subplot(1, 2, 2)
for key, values in history.items():
    plt.plot(values["train_acc"], label=f'{key} Train Acc',
linestyle='--', marker='o')
    plt.plot(values["val_acc"], label=f'{key} Val Acc', marker='o')

plt.legend()
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.title('Epoch vs Accuracy')

plt.show()
```



```
import torch
import json
import os


best_model_path = "submission/best_model_challenge2.pt"
output_json_file =
"submission/HarishNandhan_Shanmugam_challenge2.json"


device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
model = ImprovedVQAModel().to(device)
model.load_state_dict(torch.load(best_model_path))
model.eval()

print(f" Loaded Best Model from {best_model_path}")
```

```
 Loaded Best Model from submission/best_model_challenge2.pt

C:\Users\yoges\AppData\Local\Temp\ipykernel_26116\3175956843.py:12:
FutureWarning: You are using `torch.load` with `weights_only=False`
(the current default value), which uses the default pickle module
implicitly. It is possible to construct malicious pickle data which
will execute arbitrary code during unpickling (See
https://github.com/pytorch/pytorch/blob/main/SECURITY.md#untrusted-
models for more details). In a future release, the default value for
`weights_only` will be flipped to `True`. This limits the functions
that could be executed during unpickling. Arbitrary objects will no
longer be allowed to be loaded via this mode unless they are
explicitly allowlisted by the user via
`torch.serialization.add_safe_globals`. We recommend you start setting
`weights_only=True` for any use case where you don't have full control
of the loaded file. Please open an issue on GitHub for any issues
related to this experimental feature.
  model.load_state_dict(torch.load(best_model_path))
```

```
test_image_tensors =
torch.load("preprocessed_tensors1/test_image_tensors.pt").to(device)
test_text_tensors =
torch.load("preprocessed_tensors1/test_question_tensors.pt").to(device
)


test_subset = test_data[:100]
print(f" Loaded {len(test_subset)} test samples")
```

```
 Loaded 100 test samples

C:\Users\yoges\AppData\Local\Temp\ipykernel_26116\220327878.py:2:
FutureWarning: You are using `torch.load` with `weights_only=False`
```

```
(the current default value), which uses the default pickle module
implicitly. It is possible to construct malicious pickle data which
will execute arbitrary code during unpickling (See
https://github.com/pytorch/pytorch/blob/main/SECURITY.md#untrusted-
models for more details). In a future release, the default value for
`weights_only` will be flipped to `True`. This limits the functions
that could be executed during unpickling. Arbitrary objects will no
longer be allowed to be loaded via this mode unless they are
explicitly allowlisted by the user via
`torch.serialization.add_safe_globals`. We recommend you start setting
`weights_only=True` for any use case where you don't have full control
of the loaded file. Please open an issue on GitHub for any issues
related to this experimental feature.
  test_image_tensors =
torch.load("preprocessed_tensors1/test_image_tensors.pt").to(device)
C:\Users\yoges\AppData\Local\Temp\ipykernel_26116\220327878.py:3:
FutureWarning: You are using `torch.load` with `weights_only=False`
(the current default value), which uses the default pickle module
implicitly. It is possible to construct malicious pickle data which
will execute arbitrary code during unpickling (See
https://github.com/pytorch/pytorch/blob/main/SECURITY.md#untrusted-
models for more details). In a future release, the default value for
`weights_only` will be flipped to `True`. This limits the functions
that could be executed during unpickling. Arbitrary objects will no
longer be allowed to be loaded via this mode unless they are
explicitly allowlisted by the user via
`torch.serialization.add_safe_globals`. We recommend you start setting
`weights_only=True` for any use case where you don't have full control
of the loaded file. Please open an issue on GitHub for any issues
related to this experimental feature.
  test_text_tensors =
torch.load("preprocessed_tensors1/test_question_tensors.pt").to(device
)
```

```
model.eval()
with torch.no_grad():
    outputs = model(test_image_tensors, test_text_tensors)
    _, predicted = torch.max(outputs, 1)


predictions = [category_id2name[idx.item()] for idx in
predicted.cpu()]


for i in range(100):
    print(f"Image: {test_subset[i]['image']} : Answer:
{predictions[i]}")
```

```
Image: VizWiz_test_00000000.jpg : Answer: unanswerable
Image: VizWiz_test_00000001.jpg : Answer: unanswerable
Image: VizWiz_test_00000002.jpg : Answer: unanswerable
Image: VizWiz_test_00000003.jpg : Answer: other_categories
Image: VizWiz_test_00000004.jpg : Answer: other_categories
Image: VizWiz_test_00000005.jpg : Answer: unanswerable
Image: VizWiz_test_00000006.jpg : Answer: unanswerable
Image: VizWiz_test_00000007.jpg : Answer: other_categories
Image: VizWiz_test_00000008.jpg : Answer: other_categories
Image: VizWiz_test_00000009.jpg : Answer: other_categories
Image: VizWiz_test_00000010.jpg : Answer: unanswerable
Image: VizWiz_test_00000011.jpg : Answer: other_categories
Image: VizWiz_test_00000012.jpg : Answer: unanswerable
Image: VizWiz_test_00000013.jpg : Answer: unanswerable
Image: VizWiz_test_00000014.jpg : Answer: other_categories
Image: VizWiz_test_00000015.jpg : Answer: unanswerable
Image: VizWiz_test_00000016.jpg : Answer: other_categories
Image: VizWiz_test_00000017.jpg : Answer: other_categories
Image: VizWiz_test_00000018.jpg : Answer: other_categories
Image: VizWiz_test_00000019.jpg : Answer: unanswerable
Image: VizWiz_test_00000020.jpg : Answer: other_categories
Image: VizWiz_test_00000021.jpg : Answer: unanswerable
Image: VizWiz_test_00000022.jpg : Answer: unanswerable
Image: VizWiz_test_00000023.jpg : Answer: other_categories
Image: VizWiz_test_00000024.jpg : Answer: unanswerable
Image: VizWiz_test_00000025.jpg : Answer: unanswerable
Image: VizWiz_test_00000026.jpg : Answer: unanswerable
Image: VizWiz_test_00000027.jpg : Answer: unanswerable
Image: VizWiz_test_00000028.jpg : Answer: unanswerable
Image: VizWiz_test_00000029.jpg : Answer: other_categories
Image: VizWiz_test_00000030.jpg : Answer: unanswerable
Image: VizWiz_test_00000031.jpg : Answer: unanswerable
Image: VizWiz_test_00000032.jpg : Answer: other_categories
Image: VizWiz_test_00000033.jpg : Answer: other_categories
Image: VizWiz_test_00000034.jpg : Answer: other_categories
Image: VizWiz_test_00000035.jpg : Answer: other_categories
Image: VizWiz_test_00000036.jpg : Answer: other_categories
Image: VizWiz_test_00000037.jpg : Answer: other_categories
Image: VizWiz_test_00000038.jpg : Answer: unanswerable
Image: VizWiz_test_00000039.jpg : Answer: unanswerable
Image: VizWiz_test_00000040.jpg : Answer: other_categories
Image: VizWiz_test_00000041.jpg : Answer: unanswerable
Image: VizWiz_test_00000042.jpg : Answer: other_categories
Image: VizWiz_test_00000043.jpg : Answer: other_categories
Image: VizWiz_test_00000044.jpg : Answer: unanswerable
Image: VizWiz_test_00000045.jpg : Answer: unanswerable
Image: VizWiz_test_00000046.jpg : Answer: other_categories
Image: VizWiz_test_00000047.jpg : Answer: unanswerable
Image: VizWiz_test_00000048.jpg : Answer: other_categories
Image: VizWiz_test_00000049.jpg : Answer: other_categories
```

```
Image: VizWiz_test_00000050.jpg : Answer: unanswerable
Image: VizWiz_test_00000051.jpg : Answer: other_categories
Image: VizWiz_test_00000052.jpg : Answer: unanswerable
Image: VizWiz_test_00000053.jpg : Answer: unanswerable
Image: VizWiz_test_00000054.jpg : Answer: unanswerable
Image: VizWiz_test_00000055.jpg : Answer: other_categories
Image: VizWiz_test_00000056.jpg : Answer: unanswerable
Image: VizWiz_test_00000057.jpg : Answer: other_categories
Image: VizWiz_test_00000058.jpg : Answer: unanswerable
Image: VizWiz_test_00000059.jpg : Answer: other_categories
Image: VizWiz_test_00000060.jpg : Answer: unanswerable
Image: VizWiz_test_00000061.jpg : Answer: other_categories
Image: VizWiz_test_00000062.jpg : Answer: other_categories
Image: VizWiz_test_00000063.jpg : Answer: other_categories
Image: VizWiz_test_00000064.jpg : Answer: unanswerable
Image: VizWiz_test_00000065.jpg : Answer: unanswerable
Image: VizWiz_test_00000066.jpg : Answer: other_categories
Image: VizWiz_test_00000067.jpg : Answer: other_categories
Image: VizWiz_test_00000068.jpg : Answer: unanswerable
Image: VizWiz_test_00000069.jpg : Answer: other_categories
Image: VizWiz_test_00000070.jpg : Answer: other_categories
Image: VizWiz_test_00000071.jpg : Answer: unanswerable
Image: VizWiz_test_00000072.jpg : Answer: other_categories
Image: VizWiz_test_00000073.jpg : Answer: unanswerable
Image: VizWiz_test_00000074.jpg : Answer: unanswerable
Image: VizWiz_test_00000075.jpg : Answer: unanswerable
Image: VizWiz_test_00000076.jpg : Answer: other_categories
Image: VizWiz_test_00000077.jpg : Answer: unanswerable
Image: VizWiz_test_00000078.jpg : Answer: other_categories
Image: VizWiz_test_00000079.jpg : Answer: other_categories
Image: VizWiz_test_00000080.jpg : Answer: unanswerable
Image: VizWiz_test_00000081.jpg : Answer: other_categories
Image: VizWiz_test_00000082.jpg : Answer: unanswerable
Image: VizWiz_test_00000083.jpg : Answer: unanswerable
Image: VizWiz_test_00000084.jpg : Answer: unanswerable
Image: VizWiz_test_00000085.jpg : Answer: other_categories
Image: VizWiz_test_00000086.jpg : Answer: unanswerable
Image: VizWiz_test_00000087.jpg : Answer: unanswerable
Image: VizWiz_test_00000088.jpg : Answer: other_categories
Image: VizWiz_test_00000089.jpg : Answer: unanswerable
Image: VizWiz_test_00000090.jpg : Answer: unanswerable
Image: VizWiz_test_00000091.jpg : Answer: other_categories
Image: VizWiz_test_00000092.jpg : Answer: other_categories
Image: VizWiz_test_00000093.jpg : Answer: other_categories
Image: VizWiz_test_00000094.jpg : Answer: unanswerable
Image: VizWiz_test_00000095.jpg : Answer: other_categories
Image: VizWiz_test_00000096.jpg : Answer: other_categories
Image: VizWiz_test_00000097.jpg : Answer: unanswerable
```

```
Image: VizWiz_test_00000098.jpg : Answer: other_categories
Image: VizWiz_test_00000099.jpg : Answer: unanswerable
```

```
results = [{"image": test_subset[i]['image'], "answer":
predictions[i]} for i in range(len(test_subset))]


os.makedirs("submission", exist_ok=True)
with open(output_json_file, 'w') as f:
    json.dump(results, f)

print(f" Predictions saved successfully to {output_json_file}")
```

```
 Predictions saved successfully to
submission/HarishNandhan_Shanmugam_challenge2.json
```