

```
1 # IMPORTANT: RUN THIS CELL IN ORDER TO IMPORT YOUR KAGGLE DATA SOURCES,
2 # THEN FEEL FREE TO DELETE THIS CELL.
3 # NOTE: THIS NOTEBOOK ENVIRONMENT DIFFERS FROM KAGGLE'S PYTHON
4 # ENVIRONMENT SO THERE MAY BE MISSING LIBRARIES USED BY YOUR
5 # NOTEBOOK.
6 import kagglehub
7 shubham2703_five_crop_diseases_dataset_path = kagglehub.dataset_download('shubham2703/five-crop-diseases-dataset')
8
9 print('Data source import complete.')
10
```

```
1 !nvidia-smi
```

✓ Installations

```
1 # !pip install split-folders
```

```
Collecting split-folders
  Downloading split_folders-0.5.1-py3-none-any.whl.metadata (6.2 kB)
Downloading split_folders-0.5.1-py3-none-any.whl (8.4 kB)
Installing collected packages: split-folders
Successfully installed split-folders-0.5.1
```

✓ Imports

```
1 import random
2 # import splitfolders
3 import os
4 import json
5 import shutil
6 from pathlib import Path
7 from typing import Optional, List, Union, Tuple, Dict
8
9 import torch
10 import torch.nn as nn
11 import torch.nn.functional as F
12 from torchvision import transforms, datasets, utils
13 import torchvision.models as models
14 from torch.utils.data import DataLoader, Dataset
15 from torch.utils.tensorboard import SummaryWriter
16
17 import numpy as np
18 import pandas as pd
19 import matplotlib.pyplot as plt
20 import seaborn as sns
21 from tqdm import tqdm
22
23 from sklearn.metrics import confusion_matrix, classification_report, precision_recall_fscore_support
```

✓ Set seed for deterministic results

```
1 SEED = 42
2 random.seed(SEED)
3 np.random.seed(SEED)
4 torch.manual_seed(SEED)
5 torch.backends.cudnn.deterministic = True
6
7 if torch.cuda.is_available():
8     torch.cuda.manual_seed(SEED)
9     torch.cuda.manual_seed_all(SEED)
10
```

✓ Dataset Preparation

› Fetching Dataset

↳ 3 cells hidden

> Extract and restructure

↳ 6 cells hidden

> Train-Val-Test Split

↳ 3 cells hidden

> Data Loading and Augmentation

↳ 2 cells hidden

> Defining Model Architecture and Params

↳ 3 cells hidden

> Training

↳ 7 cells hidden

> Training

↳ 1 cell hidden

> Model Evaluation

↳ 2 cells hidden

> Mobilenet

↳ 4 cells hidden

> Efficient Net

↳ 3 cells hidden

✓ Contrastive Learning with Triplet Loss

```
1 import os
2
3 def rename_folders(base_dir):
4     """
5     Renames specific folders within train, val, and test directories
6     by adding a 'Sugarcane_' prefix.
7     """
8     if not os.path.isdir(base_dir):
9         raise ValueError(f"Base directory '{base_dir}' does not exist.")
10
11     # Define the splits (subdirectories) to process
12     splits = ["train", "val", "test"]
13
14     # Define the folder names to be changed
15     folders_to_rename = ["Healthy", "Bacterial Blight", "Red Rot"]
16
17     # Loop through each split (train, val, test)
18     for split in splits:
19         split_path = os.path.join(base_dir, split)
20
21         # Check if the split directory (e.g., 'dataset/train') exists
22         if not os.path.isdir(split_path):
```

```

23         continue
24
25     print(f"Processing directory: {split_path}")
26
27     # Loop through each folder name we want to rename
28     for folder_name in folders_to_rename:
29         old_path = os.path.join(split_path, folder_name)
30         new_name = f"Sugarcane_{folder_name}"
31         new_path = os.path.join(split_path, new_name)
32
33         # Check if the source folder (e.g., 'dataset/train/Health') exists
34         if os.path.isdir(old_path):
35             try:
36                 os.rename(old_path, new_path)
37                 print(f" - Renamed '{folder_name}' to '{new_name}'")
38             except OSError as e:
39                 print(f" - Error renaming '{folder_name}': {e}")
40
41     print("\nRenaming complete.")
42
43 rename_folders('dataset')

```

```

Processing directory: dataset/train
Processing directory: dataset/val
Processing directory: dataset/test

```

Renaming complete.

```

1 class Siamese(nn.Module):
2     def __init__(self, backbone="resnet18", pretrained=True, embedding_dim=128, freeze_backbone=True):
3         super().__init__()
4         if backbone == "resnet18":
5             base = models.resnet18(pretrained=pretrained)
6             in_features = base.fc.in_features
7             base.fc = nn.Identity() # remove final classifier
8         elif backbone == "resnet50":
9             base = models.resnet50(pretrained=pretrained)
10            in_features = base.fc.in_features
11            base.fc = nn.Identity() # remove final classifier
12        else:
13            raise NotImplementedError("Only resnet18 implemented here")
14
15        self.backbone = base
16        self.embedding = nn.Linear(in_features, embedding_dim)
17
18        if freeze_backbone:
19            for param in self.backbone.parameters():
20                param.requires_grad = False
21
22    def forward(self, x):
23        x = self.backbone(x) # features
24        x = self.embedding(x) # project to embedding_dim
25        x = F.normalize(x, p=2, dim=1) # L2 normalize
26        return x

```

```

1 class SiameseTripletDataset(Dataset):
2     def __init__(self, root, transform=None):
3         """
4         root: path to dataset root, structured as ImageFolder
5         e.g. root/ClassName/*.jpg
6         """
7         self.dataset = datasets.ImageFolder(root=root, transform=transform)
8         self.transform = transform
9
10        # Map class -> indices
11        self.class_to_indices = {}
12        for idx, (_, label) in enumerate(self.dataset.samples):
13            cls = self.dataset.classes[label]
14            self.class_to_indices.setdefault(cls, []).append(idx)
15
16        # Separate healthy and disease classes
17        self.healthy_classes = [c for c in self.dataset.classes if "Healthy" in c]
18        self.disease_classes = [c for c in self.dataset.classes if "Healthy" not in c]
19
20        if not self.healthy_classes:
21            raise ValueError("No healthy classes found in dataset!")
22
23    def __len__(self):
24        # length = total number of healthy samples
25        return sum(len(self.class_to_indices[c]) for c in self.healthy_classes)
26

```

```

27     def __getitem__(self, idx):
28         # Pick a healthy class at random
29         healthy_class = random.choice(self.healthy_classes)
30         anchor_idx = random.choice(self.class_to_indices[healthy_class])
31         anchor_img, _ = self.dataset[anchor_idx]
32
33         # Positive (same healthy class)
34         pos_idx = random.choice(self.class_to_indices[healthy_class])
35         pos_img, _ = self.dataset[pos_idx]
36
37         # Negative (any disease class)
38         neg_class = random.choice(self.disease_classes)
39         neg_idx = random.choice(self.class_to_indices[neg_class])
40         neg_img, _ = self.dataset[neg_idx]
41
42         return anchor_img, pos_img, neg_img
43

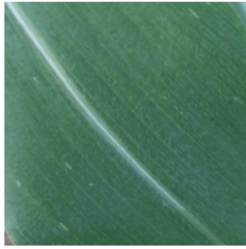
```

```

1 from torchvision import transforms
2 from torch.utils.data import DataLoader
3 import matplotlib.pyplot as plt
4
5 # Define transforms
6 transform = transforms.Compose([
7     transforms.Resize((224,224)),
8     transforms.ToTensor()
9 ])
10
11 # Initialize dataset
12 data_dir = "dataset/train" # path to your dataset
13 triplet_ds = SiameseTripletDataset(root=data_dir, transform=transform)
14
15 # Wrap in DataLoader
16 loader = DataLoader(triplet_ds, batch_size=1, shuffle=True)
17
18 # Visualize a few triplets
19 for i, (a, p, n) in enumerate(loader):
20     fig, axes = plt.subplots(1, 3, figsize=(8, 3))
21     axes[0].imshow(a[0].permute(1,2,0))
22     axes[0].set_title("Anchor")
23     axes[1].imshow(p[0].permute(1,2,0))
24     axes[1].set_title("Positive")
25     axes[2].imshow(n[0].permute(1,2,0))
26     axes[2].set_title("Negative")
27     for ax in axes: ax.axis("off")
28     plt.show()
29     if i == 3: break # show 3 triplets only
30

```

Anchor



Positive



Negative



Anchor



Positive



Negative



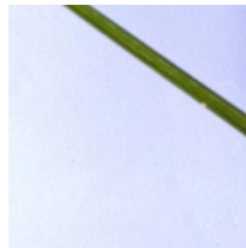
Anchor



Positive



Negative



Anchor



Positive



Negative



```
1 from torch import amp
```

```
1 class SiameseTrainer:
2     def __init__(self, model, device, lr=1e-3, log_interval=20, use_amp=False, checkpoint_dir="siamese_crops_checkpoints")
3         model = model.to(device)
4         if torch.cuda.device_count() > 1:
5             print(f"Using {torch.cuda.device_count()} GPUs with DataParallel")
6             model = nn.DataParallel(model)
7         self.model = model # torch.compile(model)
8         if isinstance(self.model, nn.DataParallel):
9             self.model_to_save = self.model.module
10        else:
11            self.model_to_save = self.model
12
13        self.device = device
14        self.optimizer = torch.optim.Adam(filter(lambda p: p.requires_grad, self.model.parameters()), lr=lr)
15        self.criterion = nn.TripletMarginLoss(margin=1.0, p=2)
16        self.scaler = amp.GradScaler("cuda", enabled=use_amp)
17        self.use_amp = use_amp
18        self.log_interval = log_interval
19
20        self.checkpoint_dir = checkpoint_dir
21        os.makedirs(self.checkpoint_dir, exist_ok=True)
22        self.best_loss = float('inf')
23        self.count_trainable_parameters()
24
25    def count_trainable_parameters(self):
26        """Counts and prints the number of trainable parameters in the model."""
27        num_params = sum(p.numel() for p in self.model.parameters() if p.requires_grad)
28        print(f"Number of trainable parameters: {num_params:,}")
29        return num_params
30
```

```

31 def train(self, train_loader, epochs=5):
32     self.model.train()
33
34     epoch_bar = tqdm(range(epochs), desc="Epochs")
35     for epoch in epoch_bar:
36         total_loss = 0
37
38         batch_bar = tqdm(train_loader, desc=f"Epoch {epoch+1}", leave=False)
39         for batch_idx, (a, p, n) in enumerate(batch_bar):
40             a, p, n = a.to(self.device), p.to(self.device), n.to(self.device)
41
42             with amp.autocast("cuda", enabled=self.use_amp):
43                 emb_a = self.model(a)
44                 emb_p = self.model(p)
45                 emb_n = self.model(n)
46                 loss = self.criterion(emb_a, emb_p, emb_n)
47
48                 self.optimizer.zero_grad(set_to_none=True)
49                 self.scaler.scale(loss).backward()
50                 self.scaler.step(self.optimizer)
51                 self.scaler.update()
52
53                 total_loss += loss.item()
54                 batch_bar.set_postfix(loss=f"{loss.item():.4f}")
55
56         avg_loss = total_loss / len(train_loader)
57         epoch_bar.set_postfix(avg_loss=f"{avg_loss:.4f}")
58
59         last_checkpoint_path = os.path.join(self.checkpoint_dir, "siamese_crops_last_model.pth")
60         self.save_checkpoint(last_checkpoint_path, epoch, avg_loss)
61
62         if avg_loss < self.best_loss:
63             self.best_loss = avg_loss
64             best_checkpoint_path = os.path.join(self.checkpoint_dir, "siamese_crops_best_model.pth")
65             self.save_checkpoint(best_checkpoint_path, epoch, self.best_loss)
66             tqdm.write(f"best model updated: {self.best_loss:.4f} at epoch {epoch+1}")
67
68 def save_checkpoint(self, file_path, epoch, loss):
69     """Saves a checkpoint dictionary to a file (works for single & multi-GPU)."""
70     # unwrap model if DataParallel was used
71     model_to_save = self.model.module if isinstance(self.model, torch.nn.DataParallel) else self.model
72     checkpoint = {
73         'epoch': epoch + 1,
74         'model_state_dict': model_to_save.state_dict(),
75         'optimizer_state_dict': self.optimizer.state_dict(),
76         'scaler_state_dict': self.scaler.state_dict() if hasattr(self, "scaler") else None,
77         'loss': loss,
78     }
79     # save checkpoint (portable)
80     torch.save(checkpoint, file_path)
81
82     print(f"Checkpoint saved at {file_path}")
83
84 def save_embeddings(self, dataloader, save_path="embeddings.pt"):
85     """Extract embeddings for whole dataset"""
86     self.model.eval()
87     embeddings, labels = [], []
88     with torch.no_grad():
89         for imgs, lbls in dataloader:
90             imgs = imgs.to(self.device)
91             emb = self.model(imgs)
92             embeddings.append(emb.cpu())
93             labels.append(lbls)
94     torch.save({"embeddings": torch.cat(embeddings), "labels": torch.cat(labels)}, save_path)
95     print(f"Embeddings saved to {save_path}")

```

data_dir: " dataset/train "

BATCH_SIZE: 512

IMAGE_SIZE: 224

EPOCHS: 20

LR: 1e-5

Show code

```

1 model = Siamese(backbone="resnet18", embedding_dim=128, freeze_backbone=True)
2 model.to(device)
3 trainer = SiameseTrainer(model, device, lr=1e-5, use_amp=True)

```

Using 2 GPUs with DataParallel
Number of trainable parameters: 65,664

```
1 # trainer.train(triplet_loader, epochs=10)
```

```

Epochs: 0%|          | 0/10 [00:00<?, ?it/s]
Epoch 1: 0%|          | 0/7 [00:00<?, ?it/s]
Epoch 1: 0%|          | 0/7 [03:03<?, ?it/s, loss=0.8442]
Epoch 1: 14%|██        | 1/7 [03:03<18:23, 183.87s/it, loss=0.8442]
Epoch 1: 14%|██        | 1/7 [03:19<18:23, 183.87s/it, loss=0.8356]
Epoch 1: 29%|████      | 2/7 [03:19<07:03, 84.63s/it, loss=0.8356]
Epoch 1: 29%|████      | 2/7 [03:25<07:03, 84.63s/it, loss=0.8359]
Epoch 1: 43%|██████    | 3/7 [03:25<03:15, 48.84s/it, loss=0.8359]
Epoch 1: 43%|██████    | 3/7 [03:25<03:15, 48.84s/it, loss=0.8369]
Epoch 1: 57%|████████  | 4/7 [03:25<01:29, 29.76s/it, loss=0.8369]
Epoch 1: 57%|████████  | 4/7 [05:18<01:29, 29.76s/it, loss=0.8301]
Epoch 1: 71%|█████████ | 5/7 [05:18<01:59, 59.78s/it, loss=0.8301]
Epoch 1: 71%|█████████ | 5/7 [05:30<01:59, 59.78s/it, loss=0.8183]
Epoch 1: 86%|██████████| 6/7 [05:30<00:43, 43.42s/it, loss=0.8183]
Epoch 1: 86%|██████████| 6/7 [05:30<00:43, 43.42s/it, loss=0.8274]
Epoch 1: 100%|██████████| 7/7 [05:30<00:00, 29.31s/it, loss=0.8274]
Epochs: 10%|██        | 1/10 [05:30<49:38, 331.00s/it, avg_loss=0.8326]Checkpoint saved at siamese_crops_checkpoints/siamese
Checkpoint saved at siamese_crops_checkpoints/siamese_crops_best_model.pth
best model updated: 0.8326 at epoch 1

```

```

Epoch 2: 0%|          | 0/7 [00:00<?, ?it/s]
Epoch 2: 0%|          | 0/7 [02:58<?, ?it/s, loss=0.8211]
Epoch 2: 14%|██        | 1/7 [02:58<17:49, 178.30s/it, loss=0.8211]
Epoch 2: 14%|██        | 1/7 [03:00<17:49, 178.30s/it, loss=0.8278]
Epoch 2: 29%|████      | 2/7 [03:00<06:14, 74.96s/it, loss=0.8278]
Epoch 2: 29%|████      | 2/7 [03:09<06:14, 74.96s/it, loss=0.8301]
Epoch 2: 43%|██████    | 3/7 [03:09<02:57, 44.46s/it, loss=0.8301]
Epoch 2: 43%|██████    | 3/7 [03:09<02:57, 44.46s/it, loss=0.8358]
Epoch 2: 57%|████████  | 4/7 [03:09<01:21, 27.12s/it, loss=0.8358]
Epoch 2: 57%|████████  | 4/7 [04:56<01:21, 27.12s/it, loss=0.8274]
Epoch 2: 71%|█████████ | 5/7 [04:56<01:51, 55.83s/it, loss=0.8274]
Epoch 2: 71%|█████████ | 5/7 [05:04<01:51, 55.83s/it, loss=0.8221]
Epoch 2: 86%|██████████| 6/7 [05:04<00:39, 39.52s/it, loss=0.8221]
Epoch 2: 86%|██████████| 6/7 [05:04<00:39, 39.52s/it, loss=0.8484]
Epoch 2: 100%|██████████| 7/7 [05:04<00:00, 26.67s/it, loss=0.8484]
Epochs: 20%|██        | 2/10 [10:35<42:05, 315.66s/it, avg_loss=0.8304]Checkpoint saved at siamese_crops_checkpoints/siamese
Checkpoint saved at siamese_crops_checkpoints/siamese_crops_best_model.pth
best model updated: 0.8304 at epoch 2

```

```

Epoch 3: 0%|          | 0/7 [00:00<?, ?it/s]
Epoch 3: 0%|          | 0/7 [03:07<?, ?it/s, loss=0.8184]
Epoch 3: 14%|██        | 1/7 [03:07<18:42, 187.12s/it, loss=0.8184]
Epoch 3: 14%|██        | 1/7 [03:07<18:42, 187.12s/it, loss=0.8314]
Epoch 3: 29%|████      | 2/7 [03:07<06:26, 77.34s/it, loss=0.8314]
Epoch 3: 29%|████      | 2/7 [03:11<06:26, 77.34s/it, loss=0.8089]
Epoch 3: 43%|██████    | 3/7 [03:11<02:55, 43.78s/it, loss=0.8089]
Epoch 3: 43%|██████    | 3/7 [03:11<02:55, 43.78s/it, loss=0.8268]
Epoch 3: 57%|████████  | 4/7 [03:11<01:20, 26.69s/it, loss=0.8268]
Epoch 3: 57%|████████  | 4/7 [05:16<01:20, 26.69s/it, loss=0.8215]
Epoch 3: 71%|█████████ | 5/7 [05:16<02:03, 61.98s/it, loss=0.8215]
Epoch 3: 71%|█████████ | 5/7 [05:16<02:03, 61.98s/it, loss=0.8244]
Epoch 3: 86%|██████████| 6/7 [05:16<00:41, 41.07s/it, loss=0.8244]
Epoch 3: 86%|██████████| 6/7 [05:17<00:41, 41.07s/it, loss=0.8459]
Epoch 3: 100%|██████████| 7/7 [05:17<00:00, 27.71s/it, loss=0.8459]
Epochs: 30%|██        | 3/10 [15:53<36:56, 316.59s/it, avg_loss=0.8254]Checkpoint saved at siamese_crops_checkpoints/siamese
Checkpoint saved at siamese_crops_checkpoints/siamese_crops_best_model.pth
best model updated: 0.8254 at epoch 3

```

```

1 model_to_save = trainer.model.module if isinstance(trainer.model, torch.nn.DataParallel) else trainer.model
2 checkpoint = {
3     'epoch': 1,
4     'model_state_dict': model_to_save.state_dict(),
5     'optimizer_state_dict': trainer.optimizer.state_dict(),
6     'scaler_state_dict': trainer.scaler.state_dict() if hasattr(trainer, "scaler") else None,
7 }
8 # save checkpoint (portable)
9 torch.save(checkpoint, "siamese_crops_first_model.pth")

```

```
1 device = torch.device("cuda:0" if torch.cuda.is_available() else "cpu")
```

```

1 siamese_model = Siamese()
2
3 siamese_model.load_state_dict(
4     torch.load("siamese_crops_first_model.pth", map_location='cpu').get("model_state_dict")

```

```
5 )
6
```

<All keys matched successfully>

```
1 class EmbeddingDataset(Dataset):
2     def __init__(self, image_folder_root, siamese_model, device, transform=None, class_to_idx=None):
3         self.image_folder_dataset = datasets.ImageFolder(root=image_folder_root, transform=transform)
4
5         if class_to_idx:
6             self.image_folder_dataset.class_to_idx = class_to_idx
7             self.image_folder_dataset.samples = [
8                 (s, class_to_idx[c]) for s, c in self.image_folder_dataset.samples if c in class_to_idx
9             ]
10
11         self.siamese_model = siamese_model.eval().to(device)
12         self.device = device
13         self.classes = self.image_folder_dataset.classes
14         self.class_to_idx = self.image_folder_dataset.class_to_idx
15
16     def __len__(self):
17         return len(self.image_folder_dataset)
18
19     def __getitem__(self, idx):
20         img, label = self.image_folder_dataset[idx]
21         with torch.no_grad():
22             embedding = self.siamese_model(img.unsqueeze(0).to(self.device))
23         return embedding.squeeze(0), label
24
```

```
1 class EmbeddingClassifier(nn.Module):
2     """A simple linear classifier on top of embeddings."""
3     def __init__(self, embedding_dim, num_classes):
4         super().__init__()
5         self.fc = nn.Linear(embedding_dim, num_classes)
6
7     def forward(self, x):
8         return self.fc(x)
9
```

```
1 import os
2
3 def train_classifier(train_loader, val_loader, model, device, epochs=10, lr=1e-3, checkpoint_dir="/kaggle/working"):
4     os.makedirs(checkpoint_dir, exist_ok=True)
5
6     if torch.cuda.device_count() > 1:
7         print(f"Using {torch.cuda.device_count()} GPUs for training")
8         model = nn.DataParallel(model)
9
10    model.to(device)
11    criterion = nn.CrossEntropyLoss()
12    optimizer = torch.optim.Adam(model.parameters(), lr=lr)
13    best_val_acc = 0.0
14
15    for epoch in range(epochs):
16        model.train()
17        total_loss, correct, total = 0, 0, 0
18        for emb, labels in train_loader:
19            emb, labels = emb.to(device), labels.to(device)
20            outputs = model(emb)
21            loss = criterion(outputs, labels)
22            optimizer.zero_grad()
23            loss.backward()
24            optimizer.step()
25
26            total_loss += loss.item() * emb.size(0)
27            _, preds = torch.max(outputs, 1)
28            correct += (preds == labels).sum().item()
29            total += labels.size(0)
30
31        train_loss = total_loss / total
32        train_acc = correct / total
33
34        # Validation
35        model.eval()
36        val_correct, val_total = 0, 0
37        val_loss_total = 0
38        with torch.no_grad():
39            for emb, labels in val_loader:
40                emb, labels = emb.to(device), labels.to(device)
```



```

41         outputs = model(emb)
42         loss = criterion(outputs, labels)
43         val_loss_total += loss.item() * emb.size(0)
44         _, preds = torch.max(outputs, 1)
45         val_correct += (preds == labels).sum().item()
46         val_total += labels.size(0)
47
48     val_loss = val_loss_total / val_total
49     val_acc = val_correct / val_total
50
51     print(f"Epoch [{epoch+1}/{epochs}] - "
52           f"Train Loss: {train_loss:.4f}, Train Acc: {train_acc:.4f}, "
53           f"Val Loss: {val_loss:.4f}, Val Acc: {val_acc:.4f}")
54
55     latest_path = os.path.join(checkpoint_dir, "siamese_classifier_last.pth")
56     torch.save({
57         'epoch': epoch + 1,
58         'model_state_dict': model.module.state_dict() if isinstance(model, nn.DataParallel) else model.state_dict(),
59         'optimizer_state_dict': optimizer.state_dict(),
60         'val_loss': val_loss,
61         'val_acc': val_acc
62     }, latest_path)
63
64     if val_acc > best_val_acc:
65         best_val_acc = val_acc
66         best_path = os.path.join(checkpoint_dir, "siamese_classifier_best.pth")
67         torch.save({
68             'epoch': epoch + 1,
69             'model_state_dict': model.module.state_dict() if isinstance(model, nn.DataParallel) else model.state_dict(),
70             'optimizer_state_dict': optimizer.state_dict(),
71             'val_loss': val_loss,
72             'val_acc': val_acc
73         }, best_path)
74         print(f"--> Best model updated (Val Acc: {best_val_acc:.4f}")
75
76     # Unwrap model for final return
77     model_to_save = model.module if isinstance(model, nn.DataParallel) else model

```

```

1 import gc
2 gc.collect()
3 os.environ['CUDA_LAUNCH_BLOCKING']='1'
4 os.environ['TORCH_USE_CUDA_DSA'] = '1'
5 !echo $CUDA_LAUNCH_BLOCKING

```

1

```

1 IMAGE_SIZE = 224
2 BATCH_SIZE = 64
3
4 transform = transforms.Compose([
5     transforms.Resize((IMAGE_SIZE, IMAGE_SIZE)),
6     transforms.ToTensor(),
7     transforms.Normalize(mean=[0.485,0.456,0.406], std=[0.229,0.224,0.225])
8 ])
9
10 train_dataset = EmbeddingDataset("dataset/train", siamese_model, device, transform)
11
12 class_to_idx_map = train_dataset.class_to_idx
13 num_classes = len(train_dataset.classes)
14
15 val_dataset = EmbeddingDataset("dataset/val", siamese_model, device, transform)
16

```