```
%load_ext autoreload
In [ ]: |
         %autoreload 2
        import cv2
In [ ]: |
         import numpy as np
         import matplotlib.pyplot as plt
         from tqdm.notebook import tqdm
         import torch
         from torch.utils.data import DataLoader, Dataset
         from torchvision import models, transforms
         device = "cuda" if torch.cuda.is_available() else 'cpu'
         print(device)
         import wandb
         import torch.nn as nn
        cuda
In [ ]: | wandb.login()
        Failed to detect the name of this notebook, you can set it manually with the WANDB_NOTEBOOK_NAME
        environment variable to enable code saving.
        wandb: Currently logged in as: sup3rm. Use `wandb login --relogin` to force relogin
        True
Out[]:
        from data utils import load dataset, LESION TYPE
```

CLIP Zero-Shot Classification

```
In [ ]: import clip
        clip_model, clip_preprocess = clip.load("ViT-B/32", device=device)
In [ ]:
        ham_train, ham_test = load_dataset("HAM10000", transform=clip_preprocess)
In [ ]:
        print(f"Train size: {len(ham_train)}")
        print(f"Test size: {len(ham_test)}")
        print(ham_train)
        print(ham_test)
        Loading HAM10000 dataset...
        Train size: 9013
        Test size: 1002
        <torch.utils.data.dataset.Subset object at 0x000002144EAB63D0>
        <torch.utils.data.dataset.Subset object at 0x000002144EAB6390>
In [ ]: BATCH_SIZE = 128
In [ ]: def clip_zero_shot(data_set, classes):
            # https://colab.research.google.com/drive/1IqJfoqZdC61dqE4BDQILCJS-zUiphD4y?authuser=2#scrol
            data_loader = DataLoader(data_set, batch_size=BATCH_SIZE, shuffle=True, num_workers=2)
            # Encode text features here
            text_inputs = torch.cat([clip.tokenize(f"a photo of a {c}, a type of skin lesion.") for c in
            with torch.no_grad():
                text_features = clip_model.encode_text(text_inputs)
            text_features /= text_features.norm(dim=-1, keepdim=True)
            # Encode image features here
            correct = 0
```

```
total = 0
for image, label in tqdm(data_loader):
    image, label = image.to(device), label.to(device)
    with torch.no_grad():
        image_features = clip_model.encode_image(image)
    image_features /= image_features.norm(dim=-1, keepdim=True)
    similarity = (100.0 * image_features @ text_features.T).softmax(dim=-1)
    _, pred = similarity.max(dim=-1)
    correct += (pred == label).sum().item()
    total += len(label)

return correct / total
```

Testing HAM10000 dataset with CLIP zero-shot classification

```
lesion_classes = LESION_TYPE.values() # This was probably only because the class labels were number
In [ ]:
        accuracy = clip_zero_shot(data_set=ham_train, classes=lesion_classes)
In [ ]:
         print(f"\nAccuracy = {100*accuracy:.3f}%")
                        | 0/71 [00:00<?, ?it/s]
        Accuracy = 21.147\%
        Testing NIH dataset with CLIP zero-shot classification w/ NIH labels
In [ ]: from data_utils import NIH_CLASS_TYPES
         nih_train, nih_test = load_dataset("NIH", transform=clip_preprocess)
         print(f"Train size: {len(nih_train)}")
         print(f"Test size: {len(nih_test)}")
         # NIH_CLASS_TYPES
         nih_classes = list(NIH_CLASS_TYPES) # From the data_utils.py file
        Loading NIH dataset...
        Train size: 100908
        Test size: 11212
In [ ]: BATCH_SIZE = 64
         accuracy = clip_zero_shot(data_set=nih_train, classes=nih_classes)
         print(f"\nAccuracy = {100*accuracy:.3f}%")
                        | 0/1577 [00:00<?, ?it/s]
        Accuracy = 0.572\%
```

CLIP Linear-Probe Classification

Logistic Regression

```
In []: from sklearn.linear_model import LogisticRegression

In []: def get_features(data_set):
    all_features = []
    all_labels = []

with torch.no_grad():
    for images, labels in tqdm(DataLoader(data_set, batch_size=BATCH_SIZE)):
        features = clip_model.encode_image(images.to(device))
        all_features.append(features)
```

```
all_labels.append(labels)
            return torch.cat(all_features).cpu().numpy(), torch.cat(all_labels).cpu().numpy()
        HAM10000 dataset with CLIP Logistic Regression
In [ ]: # Calculate the image features
        train_features, train_labels = get_features(ham_train)
        test_features, test_labels = get_features(ham_test)
          0%|
                       | 0/71 [00:00<?, ?it/s]
          0%|
                       | 0/8 [00:00<?, ?it/s]
In [ ]: # Perform logistic regression
        classifier = LogisticRegression(random_state=0, C=0.316, max_iter=10000, verbose=1, n_jobs=-1)
        classifier.fit(train features, train labels)
        # Evaluate using the logistic regression classifier
        predictions = classifier.predict(test_features)
        accuracy = np.mean((test labels == predictions).astype(float))
        print(f"\nAccuracy = {100*accuracy:.3f}%")
        [Parallel(n_jobs=-1)]: Using backend LokyBackend with 16 concurrent workers.
        [Parallel(n_jobs=-1)]: Done 1 out of 1 | elapsed:
                                                               20.8s finished
        Accuracy = 81.737\%
        NIH dataset with CLIP Logistic Regression w/ NIH labels
In [ ]: # calculate the image features
        train_features, train_labels = get_features(nih_train)
        test_features, test_labels = get_features(nih test)
                       | 1577/1577 [22:23<00:00, 1.17it/s]
        100%
              | 176/176 [02:29<00:00, 1.18it/s]
In [ ]: # Perform logistic regression
        classifier = LogisticRegression(random_state=0, C=0.316, max_iter=10000, verbose=1, n_jobs=-1)
        classifier.fit(train_features, train_labels)
        # Evaluate using the logistic regression classifier
        predictions = classifier.predict(test_features)
        accuracy = np.mean((test_labels == predictions).astype(float))
        print(f"\nAccuracy = {100*accuracy:.3f}%")
        [Parallel(n_jobs=-1)]: Using backend LokyBackend with 16 concurrent workers.
        [Parallel(n_jobs=-1)]: Done 1 out of 1 | elapsed: 8.5min finished
        Accuracy = 56.894\%
        SVM
In [ ]: from sklearn import svm
        HAM10000 dataset with CLIP SVM classification
In [ ]: # Perform Logistic regression
        classifier = svm.SVC(random_state=0, C=0.316, max_iter=5000, verbose=1)
        classifier.fit(train_features, train_labels)
        # Evaluate using the logistic regression classifier
        predictions = classifier.predict(test_features)
```

```
accuracy = np.mean((test_labels == predictions).astype(float))
        print(f"\nAccuracy = {100*accuracy:.3f}%")
        [LibSVM]
        Accuracy = 71.457\%
        NIH dataset with CLIP SVM classification w/ NIH labels
In [ ]: # Perform Logistic regression
        classifier = svm.SVC(random_state=0, C=0.316, max_iter=5000, verbose=1)
        classifier.fit(train_features, train_labels)
        # Evaluate using the logistic regression classifier
        predictions = classifier.predict(test_features)
        accuracy = np.mean((test_labels == predictions).astype(float))
        print(f"\nAccuracy = {100*accuracy:.3f}%")
        [LibSVM]
        c:\Users\mario\anaconda3\Lib\site-packages\sklearn\svm\_base.py:297: ConvergenceWarning: Solver
        terminated early (max_iter=5000). Consider pre-processing your data with StandardScaler or MinM
        axScaler.
          warnings.warn(
        Accuracy = 54.210\%
        K-Means Clusteriungfrom scipy import stats
In [ ]: from scipy import stats
In [ ]: def knn(x_train, y_train, x_test, y_test, K=5):
            # Needs code here
            test_pred = []
            for i in tqdm(range(len(x_test))):
                distance = np.linalg.norm(x_train - x_test[i], axis=-1)
                indices = np.argsort(distance)[:K]
                neighbors_labels = y_train[indices]
                test_pred.append(stats.mode(neighbors_labels).mode[0])
            correct = (test_pred == y_test).sum()
            total = len(y_test)
            return correct / total
```

```
In [ ]: accuracy = knn(train_features, train_labels, test_features, test_labels, K=1)
    print(f"\nAccuracy = {100*accuracy:.3f}%")
```

0% | 0/1002 [00:00<?, ?it/s]

C:\Users\mario\AppData\Local\Temp\ipykernel_12396\3497779333.py:8: FutureWarning: Unlike other r eduction functions (e.g. `skew`, `kurtosis`), the default behavior of `mode` typically preserves the axis it acts along. In SciPy 1.11.0, this behavior will change: the default value of `keepdi ms` will become False, the `axis` over which the statistic is taken will be eliminated, and the value None will no longer be accepted. Set `keepdims` to True or False to avoid this warning. test_pred.append(stats.mode(neighbors_labels).mode[0])

Accuracy = 76.347%

```
In [ ]: from sklearn.cluster import KMeans
```

```
In [ ]: # Perform Logistic regression
    classifier = KMeans(n_clusters=7)
    classifier.fit(train_features, train_labels)
# Evaluate using the Logistic regression classifier
```

```
predictions = classifier.predict(test_features)
        accuracy = np.mean((test_labels == predictions).astype(float))
        print(f"\nAccuracy = {100*accuracy:.3f}%")
        c:\Users\mario\anaconda3\Lib\site-packages\sklearn\cluster\_kmeans.py:1412: FutureWarning: The d
        efault value of `n_init` will change from 10 to 'auto' in 1.4. Set the value of `n_init` explici
        tly to suppress the warning
          super()._check_params_vs_input(X, default_n_init=10)
        Accuracy = 19.561\%
        NIH dataset with CLIP K-Means clustering w/ NIH labels
In [ ]: from scipy import stats
        def knn(x_train, y_train, x_test, y_test, K=5):
            # Needs code here
            test_pred = []
            for i in tqdm(range(len(x_test))):
                distance = np.linalg.norm(x_train - x_test[i], axis=-1)
                indices = np.argsort(distance)[:K]
                neighbors_labels = y_train[indices]
                test_pred.append(stats.mode(neighbors_labels).mode[0])
            correct = (test_pred == y_test).sum()
            total = len(y_test)
            return correct / total
        accuracy = knn(train_features, train_labels, test_features, test_labels, K=1)
        print(f"\nNIH CLIP scipy Accuracy = {100*accuracy:.3f}%")
          0%
                        | 0/11212 [00:00<?, ?it/s]C:\Users\mario\AppData\Local\Temp\ipykernel_9832\588109
        221.py:9: FutureWarning: Unlike other reduction functions (e.g. `skew`, `kurtosis`), the default
        behavior of `mode` typically preserves the axis it acts along. In SciPy 1.11.0, this behavior wi
        ll change: the default value of `keepdims` will become False, the `axis` over which the statisti
        c is taken will be eliminated, and the value None will no longer be accepted. Set `keepdims` to
        True or False to avoid this warning.
          test_pred.append(stats.mode(neighbors_labels).mode[0])
                 11212/11212 [1:57:28<00:00, 1.59it/s]
        NIH CLIP scipy Accuracy = 40.885%
In [ ]: from sklearn.cluster import KMeans
In [ ]: # Perform Logistic regression
        classifier = KMeans(n_clusters=7)
        classifier.fit(train_features, train_labels)
        # Evaluate using the logistic regression classifier
        predictions = classifier.predict(test_features)
         accuracy = np.mean((test_labels == predictions).astype(float))
        print(f"\nNIH CLIP sklearn.KMeans Accuracy = {100*accuracy:.3f}%")
        c:\Users\mario\anaconda3\Lib\site-packages\sklearn\cluster\_kmeans.py:1412: FutureWarning: The d
        efault value of `n_init` will change from 10 to 'auto' in 1.4. Set the value of `n_init` explici
        tly to suppress the warning
          super()._check_params_vs_input(X, default_n_init=10)
        NIH CLIP sklearn.KMeans Accuracy = 1.677%
```

Random Forest

In []: from sklearn.ensemble import RandomForestClassifier

```
In [ ]: # Perform logistic regression
        classifier = RandomForestClassifier(random_state=0, verbose=1, n_jobs=-1)
        classifier.fit(train_features, train_labels)
        # Evaluate using the logistic regression classifier
        predictions = classifier.predict(test_features)
        accuracy = np.mean((test_labels == predictions).astype(float))
        print(f"\nAccuracy = {100*accuracy:.3f}%")
        [Parallel(n_jobs=-1)]: Using backend ThreadingBackend with 16 concurrent workers.
        [Parallel(n_jobs=-1)]: Done 18 tasks
                                                  elapsed:
        Accuracy = 71.457\%
        [Parallel(n_jobs=-1)]: Done 100 out of 100 | elapsed:
                                                                 3.3s finished
        [Parallel(n_jobs=16)]: Using backend ThreadingBackend with 16 concurrent workers.
        [Parallel(n_jobs=16)]: Done 18 tasks
                                                   | elapsed:
                                                                 0.0s
        [Parallel(n_jobs=16)]: Done 100 out of 100 | elapsed:
                                                                 0.0s finished
        NIH dataset with CLIP Random Forest classification w/ NIH labels
In [ ]: from sklearn.ensemble import RandomForestClassifier
        # Perform Logistic regression
        classifier = RandomForestClassifier(random_state=0, verbose=1, n_jobs=-1)
        classifier.fit(train_features, train_labels)
        # Evaluate using the logistic regression classifier
        predictions = classifier.predict(test_features)
        accuracy = np.mean((test_labels == predictions).astype(float))
        print(f"\n NIH CLIP sklearn.RandomForestClassifier Accuracy = {100*accuracy:.3f}%")
        [Parallel(n_jobs=-1)]: Using backend ThreadingBackend with 16 concurrent workers.
        [Parallel(n_jobs=-1)]: Done 18 tasks
                                                  elapsed:
         NIH CLIP sklearn.RandomForestClassifier Accuracy = 55.137%
        [Parallel(n_jobs=-1)]: Done 100 out of 100 | elapsed:
                                                                48.3s finished
        [Parallel(n_jobs=16)]: Using backend ThreadingBackend with 16 concurrent workers.
        [Parallel(n_jobs=16)]: Done 18 tasks
                                                  elapsed:
                                                                 0.0s
        [Parallel(n_jobs=16)]: Done 100 out of 100 | elapsed:
                                                                 0.0s finished
        ResNet 50
In [ ]: resnet_preprocess = models.ResNet50_Weights.IMAGENET1K_V2.transforms()
        weights = models.ResNet50 Weights.IMAGENET1K V2
        resnet50 = models.resnet50(weights=weights)
        # Change Last Layer
        num_features = resnet50.fc.in_features
        resnet50.fc = nn.Linear(num_features, len(LESION_TYPE))
        resnet50.to(device);
```

```
num_correct = 0
total = 0
for images, labels in tqdm(dataloader, desc="Evaluating", position=2, leave=False):
    num_correct += torch.sum(labels.to(device) == torch.argmax(model(images.to(device)),
    total += labels.size(0)
return num_correct / total
```

```
In [ ]: def train(model, optim, loss_fn, train_data, test_data, config):
            Train a PyTorch model using the provided parameters.
             :param model: PyTorch model to train
             :param optim: Optimizer to use for training
            :param loss_fn: Loss function to use for training
             :param train_data: Training dataset
             :param test_data: Test dataset
             :param num epochs: Number of epochs to train for (default is 100)
            :param batch_size: Batch size to use for data loading (default is 32)
            model.train()
            run = wandb.init(
            # Set the project where this run will be logged
            project="vision-project-resnet",
            # Track hyperparameters and run metadata
            config=config)
            num_epochs = config['epochs']
            batch_size = config['batch_size']
            # Create data Loaders
            train_loader = DataLoader(train_data, batch_size=batch_size, shuffle=True, num_workers=2)
            test_loader = DataLoader(test_data, batch_size=batch_size, shuffle=False, num_workers=2)
            for epoch in tqdm(range(num_epochs), desc="Epochs", position=0, leave=True):
                train_loss = 0.0
                correct train = 0
                total_train = 0
                for inputs, targets in tqdm(train_loader, desc="Training", position=1, leave=False):
                     # Forward pass
                     targets = targets.to(device)
                     outputs = model(inputs.to(device))
                     loss = loss_fn(outputs, targets)
                     # Backward pass and optimization
                     optim.zero_grad()
                     loss.backward()
                     optim.step()
                     # Calculate train loss
                     train_loss += loss.item()
                     predicted = torch.argmax(outputs, 1)
                     total_train += targets.size(0)
                     correct_train += (predicted == targets).sum().item()
                 if (epoch+1) % 2 == 0 or epoch == num_epochs - 1:
                     train_loss /= len(train_loader)
                     train_accuracy = correct_train / total_train
                     test_accuracy = evaluate(model, test_loader)
                     model.train()
                     # , Test Loss: {test_loss:.4f}
                     # print(f"Epoch {epoch+1}/{num_epochs}, Train Loss: {train_loss:.4f}, Train Accuracy
```

```
"epoch": epoch+1,
                         "train_loss": train_loss,
                         "train_accuracy": train_accuracy,
                         "test_accuracy": test_accuracy
                    })
In [ ]:
        config = {
            "learning_rate":1e-5,
            "batch_size":64,
            "epochs":50,
            "weight_decay":1e-5,
        Zero-Shot Resnet
        HAM10000 Dataset
In [ ]:
        HAM_test_loader = DataLoader(HAM_test_data, batch_size=64, shuffle=False, num_workers=2)
In [ ]: print(evaluate(resnet50, HAM_test_loader))
        Evaluating:
                      0%
                                    | 0/16 [00:00<?, ?it/s]
        0.312375249500998
        NIH Chest X-Ray Dataset
In [ ]:
        NIH_test_loader = DataLoader(NIH_test_data, batch_size=64, shuffle=False, num_workers=2)
In [ ]: print(evaluate(resnet50, NIH_test_loader))
                                    | 0/176 [00:00<?, ?it/s]
        Evaluating:
                      0%|
        0.02167320727791652
        Fine-Tuned Resnet
In [ ]: optim = Adam(resnet50.parameters(), lr=config['learning_rate'], weight_decay=config['weight_deca
        loss = nn.CrossEntropyLoss()
        HAM10000 Dataset
        train(resnet50, optim, loss, HAM_train_data, HAM_test_data, config)
In [ ]:
       wandb version 0.16.1 is available! To upgrade, please run: $ pip install wandb --upgrade
       Tracking run with wandb version 0.16.0
       Run data is saved locally in c:\GitHub\Evaluating-CLIP-Features-for-Medical-Image-
       Classification\wandb\run-20231210_000108-mmoyd7kv
       Syncing run grateful-grass-4 to Weights & Biases (docs)
       View project at https://wandb.ai/sup3rm/vision-project-resnet
       View run at https://wandb.ai/sup3rm/vision-project-resnet/runs/mmoyd7kv
        Epochs:
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Log metrics to wandb

wandb.log({

Training:

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        Evaluating:
                       0%
        Training:
                    0%
                                  | 0/141 [00:00<?, ?it/s]
                                  | 0/141 [00:00<?, ?it/s]
        Training:
                     0%
        Evaluating: 0%
                                    | 0/16 [00:00<?, ?it/s]
        Training: 0%
                                  | 0/141 [00:00<?, ?it/s]
        Training:
                     0%
                                  | 0/141 [00:00<?, ?it/s]
        Evaluating:
                      0%|
                                    | 0/16 [00:00<?, ?it/s]
In [ ]: print(evaluate(resnet50, HAM_test_loader))
                                    | 0/16 [00:00<?, ?it/s]
        Evaluating:
                       0%|
        0.8562874251497006
        NIH Chest X-Ray Dataset
In [ ]:
        train(resnet50, optim, loss, NIH_train_data, NIH_test_data, config)
         print(evaluate(resnet50, NIH_test_loader))
        wandb version 0.16.1 is available! To upgrade, please run: $ pip install wandb --upgrade
        Tracking run with wandb version 0.16.0
        Run data is saved locally in c:\GitHub\Evaluating-CLIP-Features-for-Medical-Image-
        Classification\wandb\run-20231211 004851-w9toyvdz
        Syncing run worldly-deluge-7 to Weights & Biases (docs)
        View project at https://wandb.ai/sup3rm/vision-project-resnet
        View run at https://wandb.ai/sup3rm/vision-project-resnet/runs/w9toyvdz
        Epochs:
                   0%|
                                | 0/50 [00:07<?, ?it/s]
```

```
RuntimeError
                                                  Traceback (most recent call last)
        Cell In[53], line 1
        ----> 1 train(resnet50, optim, loss, NIH train data, NIH test data, config)
              2 print(evaluate(resnet50, NIH_test_loader))
        Cell In[48], line 35, in train(model, optim, loss_fn, train_data, test_data, config)
             33 targets = targets.to(device)
             34 outputs = model(inputs.to(device))
        ---> 35 loss = loss_fn(outputs, targets)
             37 # Backward pass and optimization
             38 optim.zero_grad()
        File c:\Users\mario\anaconda3\Lib\site-packages\torch\nn\modules\module.py:1518, in Module._wrap
        ped_call_impl(self, *args, **kwargs)
                    return self._compiled_call_impl(*args, **kwargs) # type: ignore[misc]
           1517 else:
        -> 1518
                   return self._call_impl(*args, **kwargs)
        File c:\Users\mario\anaconda3\Lib\site-packages\torch\nn\modules.py:1527, in Module._call
        _impl(self, *args, **kwargs)
           1522 # If we don't have any hooks, we want to skip the rest of the logic in
           1523 # this function, and just call forward.
           1524 if not (self._backward_hooks or self._backward_pre_hooks or self._forward_hooks or self.
        _forward_pre_hooks
           1525
                        or _global_backward_pre_hooks or _global_backward_hooks
           1526
                        or _global_forward_hooks or _global_forward_pre_hooks):
        -> 1527
                   return forward_call(*args, **kwargs)
           1529 try:
           1530
                   result = None
        File c:\Users\mario\anaconda3\Lib\site-packages\torch\nn\modules\loss.py:1179, in CrossEntropyLo
        ss.forward(self, input, target)
           1178 def forward(self, input: Tensor, target: Tensor) -> Tensor:
        -> 1179
                    return F.cross_entropy(input, target, weight=self.weight,
                                           ignore_index=self.ignore_index, reduction=self.reduction,
           1180
           1181
                                           label_smoothing=self.label_smoothing)
        File c:\Users\mario\anaconda3\Lib\site-packages\torch\nn\functional.py:3053, in cross_entropy(in
        put, target, weight, size_average, ignore_index, reduce, reduction, label_smoothing)
           3051 if size_average is not None or reduce is not None:
                    reduction = _Reduction.legacy_get_string(size_average, reduce)
        -> 3053 return torch._C._nn.cross_entropy_loss(input, target, weight, _Reduction.get_enum(reduct
        ion), ignore_index, label_smoothing)
        RuntimeError: "nll_loss_forward_reduce_cuda_kernel_2d_index" not implemented for 'Char'
In [ ]: | import os
        print(os.getcwd())
        c:\GitHub\Evaluating-CLIP-Features-for-Medical-Image-Classification
```

Implement a zero-shot function for medclip

```
import torch
import torchvision
from transformers import AutoTokenizer
from torch.utils.data import DataLoader
from tqdm import tqdm
```

```
from medclip import MedCLIPModel, MedCLIPVisionModelViT
        from medclip.modeling_medclip import MedCLIPVisionModel
        from medclip import MedCLIPProcessor
        # debuggin
        from PIL import Image
        # prepare for the demo image and texts
        from build.lib.medclip.constants import BERT_TYPE, IMG_MEAN, IMG_STD, IMG_SIZE
        device = torch.device('cuda' if torch.cuda.is available() else 'cpu')
        from data_utils import load_dataset, LESION_TYPE, load_ham10000_dataset
        BATCH_SIZE = 64
In [ ]: def medclip_zero_shot(model, test_dataset, classes, batch_size=BATCH_SIZE):
            # Data Loader for the dataset
            data_loader = DataLoader(test_dataset, batch_size=batch_size, shuffle=True, num_workers=4)
            # Prepare text prompts
            text_prompts = [f"a photo of a {c}, a type of Chest x ray." for c in classes]
            # Initialize the tokenizer
            tokenizer = AutoTokenizer.from_pretrained(BERT_TYPE)
            device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')
            print(f"Device: {device}")
            # Tokenize text prompts and convert to tensors
            text_tokens = [tokenizer(text, return_tensors='pt', padding=True, truncation=False, add_spec
            # Encode text prompts using MedClip's text model
            # Inside the medclip zero shot function
            text_features = [
                model.encode_text(
                    input_ids=tokens['input_ids'].to(device),
                    attention mask=tokens['attention mask'].to(device)
                for tokens in text_tokens
            ]
            # Initialize variables for accuracy calculation
            correct = 0
            total = 0
            for images, labels in tqdm(data loader):
                images, labels = images.to(device), labels.to(device)
                # Encode images using MedClip's vision model
                # with torch.no_grad():
                image_features = model.encode_image(images)
                # Flatten text_features into a single 2D tensor
                text_features_tensor = torch.cat(text_features, dim=0)
                # Calculate similarity and make predictions
                similarity = torch.matmul(image_features, text_features_tensor.t())
                _, predictions = similarity.max(dim=-1)
                # Update correct and total counts
                correct += (predictions == labels).sum().item()
                total += len(labels)
            return correct / total
```

Device configuration

Load HAM10000 dataset and test MedClip's zero-shot capabilities

MedCLIP ResNet50 model

```
In [ ]: # Load MedCLIP-ResNet50
MedCLIP_ResNet50_model = MedCLIPModel(vision_cls=MedCLIPVisionModel).to(device)
accuracy = medclip_zero_shot(MedCLIP_ResNet50_model, ham_train, classes)
print(f"\nAccuracy = {100*accuracy:.3f}%")
```

Some weights of the model checkpoint at emilyalsentzer/Bio_ClinicalBERT were not used when initi alizing BertModel: ['cls.predictions.transform.dense.bias', 'cls.seq_relationship.bias', 'cls.predictions.transform.LayerNorm.weight', 'cls.predictions.transform.LayerNorm.bias', 'cls.predictions.transform.dense.weight', 'cls.seq_relationship.weight', 'cls.predictions.bias', 'cls.predictions.decoder.weight']

- This IS expected if you are initializing BertModel from the checkpoint of a model trained on a nother task or with another architecture (e.g. initializing a BertForSequenceClassification model from a BertForPreTraining model).
- This IS NOT expected if you are initializing BertModel from the checkpoint of a model that you expect to be exactly identical (initializing a BertForSequenceClassification model from a BertForSequenceClassification model).

Device: cuda

```
100%| 141/141 [00:23<00:00, 6.11it/s]
Accuracy = 22.346%
```

MedCLIP_ViT_model

```
In []: # Load MedCLIP-ViT
MedCLIP_ViT_model = MedCLIPModel(vision_cls=MedCLIPVisionModelViT).to(device)
accuracy = medclip_zero_shot(MedCLIP_ViT_model, ham_train, classes)
print(f"\nAccuracy = {100*accuracy:.3f}%")
```

Some weights of the model checkpoint at microsoft/swin-tiny-patch4-window7-224 were not used whe n initializing SwinModel: ['classifier.bias', 'classifier.weight']

- This IS expected if you are initializing SwinModel from the checkpoint of a model trained on a nother task or with another architecture (e.g. initializing a BertForSequenceClassification model from a BertForPreTraining model).
- This IS NOT expected if you are initializing SwinModel from the checkpoint of a model that you expect to be exactly identical (initializing a BertForSequenceClassification model from a BertForSequenceClassification model).

Some weights of the model checkpoint at emilyalsentzer/Bio_ClinicalBERT were not used when initi alizing BertModel: ['cls.predictions.transform.dense.bias', 'cls.seq_relationship.bias', 'cls.predictions.transform.LayerNorm.weight', 'cls.predictions.transform.LayerNorm.bias', 'cls.predictions.transform.dense.weight', 'cls.seq_relationship.weight', 'cls.predictions.bias', 'cls.predictions.decoder.weight']

- This IS expected if you are initializing BertModel from the checkpoint of a model trained on a nother task or with another architecture (e.g. initializing a BertForSequenceClassification model from a BertForPreTraining model).
- This IS NOT expected if you are initializing BertModel from the checkpoint of a model that you expect to be exactly identical (initializing a BertForSequenceClassification model from a BertForSequenceClassification model).

```
Device: cuda

100%| 141/141 [00:25<00:00, 5.63it/s]

Accuracy = 27.593%
```

Load NIH Chest X-ray dataset

```
In [ ]: import os
        # os.chdir('../')
        print(os.getcwd())
        c:\GitHub\Evaluating-CLIP-Features-for-Medical-Image-Classification
        import torch
In [ ]: |
        import torchvision
        import torch.nn.functional as F
        from tqdm import tqdm
        from transformers import AutoTokenizer
        from torch.utils.data import DataLoader
        # Device configuration
        from data_utils import load_nih_dataset_split, NIH_CLASS_TYPES, load_dataset
        from medclip import MedCLIPModel, MedCLIPVisionModelViT, MedCLIPVisionModel
        from build.lib.medclip.constants import BERT_TYPE, IMG_MEAN, IMG_STD, IMG_SIZE
        # debuggin
        from PIL import Image
        BATCH_SIZE = 128
        transform = torchvision.transforms.Compose([
            torchvision.transforms.Resize((IMG_SIZE, IMG_SIZE)),
            torchvision.transforms.ToTensor(),
            torchvision.transforms.Normalize(mean=[IMG_MEAN], std=[IMG_STD])
        ])
        device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')
        # NIH_CLASS_TYPES
        classes = list(NIH_CLASS_TYPES) # From the data_utils.py file
        classes
        # nih_train, nih_test = load_nih_dataset_split(transform=transform)
        nih_train, nih_test = load_dataset("NIH", transform=transform, data_dir='data/nih/')
```

Loading NIH dataset...

```
In []: def medclip_zero_shot(model, test_dataset, classes, batch_size=BATCH_SIZE):
            # Data Loader for the dataset
            data_loader = DataLoader(test_dataset, batch_size=batch_size, shuffle=True, num_workers=2)
            # Prepare text prompts
            text_prompts = [f"a photo of a {c}, a type of Chest x ray." for c in classes]
            # Initialize the tokenizer
            tokenizer = AutoTokenizer.from_pretrained(BERT_TYPE)
            device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')
            print(f"Device: {device}")
            # Tokenize text prompts and convert to tensors
            text_tokens = [tokenizer(text, return_tensors='pt', padding=True, truncation=False, add_spec
            # print('text_tokens', text_prompts)
            # Encode text prompts using MedClip's text model
            # Inside the medclip_zero_shot function
            text features = [
                model.encode text(
                    input_ids=tokens['input_ids'].to(device),
                    attention_mask=tokens['attention_mask'].to(device)
                for tokens in text_tokens
            # Initialize variables for accuracy calculation
            correct = 0
            total = 0
            # print('text_features', text_features)
            for images, labels in tqdm(data_loader):
                images, labels = images.to(device), labels.to(device)
                # Encode images using MedClip's vision model
                # with torch.no_grad():
                image features = model.encode image(images)
                # Flatten text_features into a single 2D tensor
                text_features_tensor = torch.cat(text_features, dim=0)
                # Calculate similarity and make predictions
                similarity = torch.matmul(image_features, text_features_tensor.t())
                _, predictions = similarity.max(dim=-1)
                # Update correct and total counts
                correct += (predictions == labels).sum().item()
                total += len(labels)
            return correct / total
```

Load MedCLIP-ResNet50

```
In [ ]: MedCLIP_ResNet50_model = MedCLIPModel(vision_cls=MedCLIPVisionModel).to(device)
    MedCLIP_ResNet50_model
    accuracy = medclip_zero_shot(MedCLIP_ResNet50_model, nih_train, classes)
    print(f"\nAccuracy = {100*accuracy:.3f}%")
```

c:\Users\mario\anaconda3\Lib\site-packages\torchvision\models_utils.py:208: UserWarning: The pa rameter 'pretrained' is deprecated since 0.13 and may be removed in the future, please use 'weig hts' instead.

warnings.warn(

c:\Users\mario\anaconda3\Lib\site-packages\torchvision\models_utils.py:223: UserWarning: Argume
nts other than a weight enum or `None` for 'weights' are deprecated since 0.13 and may be remove
d in the future. The current behavior is equivalent to passing `weights=ResNet50_Weights.IMAGENE
T1K_V1`. You can also use `weights=ResNet50_Weights.DEFAULT` to get the most up-to-date weights.
 warnings.warn(msg)

Some weights of the model checkpoint at emilyalsentzer/Bio_ClinicalBERT were not used when initi alizing BertModel: ['cls.predictions.transform.dense.bias', 'cls.predictions.transform.LayerNorm.weight', 'cls.predictions.transform.LayerNorm.bias', 'cls.predictions.decoder.weight', 'cls.predictions.transform.dense.weight', 'cls.seq_relationship.bias', 'cls.seq_relationship.weight', 'cls.predictions.bias']

- This IS expected if you are initializing BertModel from the checkpoint of a model trained on a nother task or with another architecture (e.g. initializing a BertForSequenceClassification model from a BertForPreTraining model).
- This IS NOT expected if you are initializing BertModel from the checkpoint of a model that you expect to be exactly identical (initializing a BertForSequenceClassification model from a BertForSequenceClassification model).

Device: cuda

```
100% | 789/789 [04:57<00:00, 2.66it/s]
```

Accuracy = 53.138%

Load MedCLIP-ViT

```
In [ ]: MedCLIP_ViT_model = MedCLIPModel(vision_cls=MedCLIPVisionModelViT).to(device)
    accuracy = medclip_zero_shot(MedCLIP_ViT_model, nih_train, classes)
    print(f"\nAccuracy = {100*accuracy:.3f}%")
```

c:\Users\mario\anaconda3\Lib\site-packages\torch\functional.py:504: UserWarning: torch.meshgrid:
in an upcoming release, it will be required to pass the indexing argument. (Triggered internally
at C:\cb\pytorch_1000000000000\work\aten\src\ATen\native\TensorShape.cpp:3527.)

return _VF.meshgrid(tensors, **kwargs) # type: ignore[attr-defined]

Some weights of the model checkpoint at microsoft/swin-tiny-patch4-window7-224 were not used whe n initializing SwinModel: ['classifier.weight', 'classifier.bias']

- This IS expected if you are initializing SwinModel from the checkpoint of a model trained on a nother task or with another architecture (e.g. initializing a BertForSequenceClassification model from a BertForPreTraining model).
- This IS NOT expected if you are initializing SwinModel from the checkpoint of a model that you expect to be exactly identical (initializing a BertForSequenceClassification model from a BertForSequenceClassification model).

Some weights of the model checkpoint at emilyalsentzer/Bio_ClinicalBERT were not used when initi alizing BertModel: ['cls.predictions.transform.LayerNorm.bias', 'cls.seq_relationship.bias', 'cl s.predictions.transform.dense.bias', 'cls.predictions.bias', 'cls.predictions.transform.LayerNorm.weight', 'cls.seq_relationship.weight', 'cls.predictions.transform.dense.weight', 'cls.predictions.decoder.weight']

- This IS expected if you are initializing BertModel from the checkpoint of a model trained on a nother task or with another architecture (e.g. initializing a BertForSequenceClassification model from a BertForPreTraining model).
- This IS NOT expected if you are initializing BertModel from the checkpoint of a model that you expect to be exactly identical (initializing a BertForSequenceClassification model from a BertForSequenceClassification model).

Device: cuda

```
100%| 789/789 [3:36:49<00:00, 16.49s/it]
```

Accuracy = 16.531%

```
import numpy as np
def get_features(data_set, model):
    all_features = []
    all_labels = []
```

```
for images, labels in tqdm(DataLoader(data set, batch size=BATCH SIZE)):
                    features = model.encode_image(images.to(device))
                    all features.append(features)
                    all_labels.append(labels)
            return torch.cat(all_features).cpu().numpy(), torch.cat(all_labels).cpu().numpy()
In [ ]: MedCLIP_ResNet50_model = MedCLIPModel(vision_cls=MedCLIPVisionModel).to(device)
        # Calculate the image features
        train features, train labels = get features(nih train, MedCLIP ResNet50 model)
        test_features, test_labels = get_features(nih_test, MedCLIP_ResNet50_model)
        c:\Users\mario\anaconda3\Lib\site-packages\torchvision\models\_utils.py:208: UserWarning: The pa
        rameter 'pretrained' is deprecated since 0.13 and may be removed in the future, please use 'weig
        hts' instead.
          warnings.warn(
        c:\Users\mario\anaconda3\Lib\site-packages\torchvision\models\_utils.py:223: UserWarning: Argume
        nts other than a weight enum or `None` for 'weights' are deprecated since 0.13 and may be remove
        d in the future. The current behavior is equivalent to passing `weights=ResNet50_Weights.IMAGENE
        T1K_V1`. You can also use `weights=ResNet50_Weights.DEFAULT` to get the most up-to-date weights.
          warnings.warn(msg)
        Some weights of the model checkpoint at emilyalsentzer/Bio_ClinicalBERT were not used when initi
        alizing BertModel: ['cls.predictions.transform.LayerNorm.bias', 'cls.seq_relationship.bias', 'cl
        s.predictions.transform.dense.bias', 'cls.predictions.bias', 'cls.predictions.transform.LayerNor
        m.weight', 'cls.seq relationship.weight', 'cls.predictions.transform.dense.weight', 'cls.predict
        ions.decoder.weight']
        - This IS expected if you are initializing BertModel from the checkpoint of a model trained on a
        nother task or with another architecture (e.g. initializing a BertForSequenceClassification mode
        1 from a BertForPreTraining model).
        - This IS NOT expected if you are initializing BertModel from the checkpoint of a model that you
        expect to be exactly identical (initializing a BertForSequenceClassification model from a BertFo
        rSequenceClassification model).
        100%
                789/789 [20:23<00:00, 1.55s/it]
        100%
                       | 88/88 [02:14<00:00, 1.52s/it]
In [ ]: from sklearn.linear_model import LogisticRegression
        # Perform Logistic regression
        classifier = LogisticRegression(random_state=0, C=0.316, max_iter=10000, verbose=1, n_jobs=-1)
        classifier.fit(train_features, train_labels)
        # Evaluate using the logistic regression classifier
        predictions = classifier.predict(test features)
        accuracy = np.mean((test_labels == predictions).astype(float))
        print(f"\n MedClip ResNet50 NIH Image Features Accuracy = {100*accuracy:.3f}%")
        [Parallel(n_jobs=-1)]: Using backend LokyBackend with 16 concurrent workers.
        [Parallel(n_jobs=-1)]: Done 1 out of 1 | elapsed: 1.5min finished
         MedClip ResNet50 NIH Image Features Accuracy = 54.995%
In [ ]: # same thing for ViT
        MedCLIP_ViT_model = MedCLIPModel(vision_cls=MedCLIPVisionModelViT).to(device)
        # Calculate the image features
        train_features, train_labels = get_features(nih_train, MedCLIP_ViT_model)
        test_features, test_labels = get_features(nih_test, MedCLIP_ViT_model)
```

with torch.no_grad():

Some weights of the model checkpoint at microsoft/swin-tiny-patch4-window7-224 were not used whe n initializing SwinModel: ['classifier.weight', 'classifier.bias']

- This IS expected if you are initializing SwinModel from the checkpoint of a model trained on a nother task or with another architecture (e.g. initializing a BertForSequenceClassification model from a BertForPreTraining model).
- This IS NOT expected if you are initializing SwinModel from the checkpoint of a model that you expect to be exactly identical (initializing a BertForSequenceClassification model from a BertForSequenceClassification model).

Some weights of the model checkpoint at emilyalsentzer/Bio_ClinicalBERT were not used when initi alizing BertModel: ['cls.predictions.transform.LayerNorm.bias', 'cls.seq_relationship.bias', 'cl s.predictions.transform.dense.bias', 'cls.predictions.transform.LayerNorm.weight', 'cls.seq_relationship.weight', 'cls.predictions.transform.dense.weight', 'cls.predictions.decoder.weight']

- This IS expected if you are initializing BertModel from the checkpoint of a model trained on a nother task or with another architecture (e.g. initializing a BertForSequenceClassification model from a BertForPreTraining model).
- This IS NOT expected if you are initializing BertModel from the checkpoint of a model that you expect to be exactly identical (initializing a BertForSequenceClassification model from a BertForSequenceClassification model).

```
100%| 789/789 [26:12<00:00, 1.99s/it]
100%| 88/88 [02:53<00:00, 1.97s/it]
```

MedClip ViT NIH Image Features Accuracy = 55.342%

```
In [ ]: from sklearn.linear_model import LogisticRegression
    # Perform Logistic regression
    classifier = LogisticRegression(random_state=0, C=0.316, max_iter=10000, verbose=1, n_jobs=-1)
    classifier.fit(train_features, train_labels)

# Evaluate using the Logistic regression classifier
    predictions = classifier.predict(test_features)
    accuracy = np.mean((test_labels == predictions).astype(float))
    print(f"\n MedClip ViT NIH Image Features Accuracy = {100*accuracy:.3f}%")

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 16 concurrent workers.
[Parallel(n_jobs=-1)]: Done    1 out of    1 | elapsed: 1.6min finished
```

```
In []: # now for HAM10000
MedCLIP_ResNet50_model = MedCLIPModel(vision_cls=MedCLIPVisionModel).to(device)

# Calculate the image features
train_features, train_labels = get_features(ham_train, MedCLIP_ResNet50_model)
test_features, test_labels = get_features(ham_test, MedCLIP_ResNet50_model)
```

```
rameter 'pretrained' is deprecated since 0.13 and may be removed in the future, please use 'weig
        hts' instead.
          warnings.warn(
        c:\Users\mario\anaconda3\Lib\site-packages\torchvision\models\_utils.py:223: UserWarning: Argume
        nts other than a weight enum or `None` for 'weights' are deprecated since 0.13 and may be remove
        d in the future. The current behavior is equivalent to passing `weights=ResNet50_Weights.IMAGENE
        T1K_V1`. You can also use `weights=ResNet50_Weights.DEFAULT` to get the most up-to-date weights.
          warnings.warn(msg)
        Some weights of the model checkpoint at emilyalsentzer/Bio_ClinicalBERT were not used when initi
        alizing BertModel: ['cls.predictions.transform.LayerNorm.bias', 'cls.seq_relationship.bias', 'cl
        s.predictions.transform.dense.bias', 'cls.predictions.bias', 'cls.predictions.transform.LayerNor
        m.weight', 'cls.seq_relationship.weight', 'cls.predictions.transform.dense.weight', 'cls.predict
        ions.decoder.weight']
        - This IS expected if you are initializing BertModel from the checkpoint of a model trained on a
        nother task or with another architecture (e.g. initializing a BertForSequenceClassification mode
        1 from a BertForPreTraining model).
        - This IS NOT expected if you are initializing BertModel from the checkpoint of a model that you
        expect to be exactly identical (initializing a BertForSequenceClassification model from a BertFo
        rSequenceClassification model).
                       | 141/141 [01:31<00:00, 1.54it/s]
        100%
        100%
                       | 16/16 [00:06<00:00, 2.33it/s]
        from sklearn.linear model import LogisticRegression
In [ ]:
        # Perform logistic regression
        classifier = LogisticRegression(random_state=0, C=0.316, max_iter=10000, verbose=1, n_jobs=-1)
        classifier.fit(train_features, train_labels)
        # Evaluate using the logistic regression classifier
        predictions = classifier.predict(test_features)
         accuracy = np.mean((test_labels == predictions).astype(float))
        print(f"\n MedClip ResNet50 HAM1000 Image Features Accuracy = {100*accuracy:.3f}%")
        [Parallel(n_jobs=-1)]: Using backend LokyBackend with 16 concurrent workers.
        [Parallel(n_jobs=-1)]: Done  1 out of  1 | elapsed:
                                                                 2.4s finished
         MedClip ResNet50 HAM1000 Image Features Accuracy = 73.054%
In [ ]: # same thing for ViT
        MedCLIP_ViT_model = MedCLIPModel(vision_cls=MedCLIPVisionModelViT).to(device)
        # Calculate the image features
        train_features, train_labels = get_features(ham_train, MedCLIP_ViT_model)
        test_features, test_labels = get_features(ham_test, MedCLIP_ViT_model)
        from sklearn.linear model import LogisticRegression
        # Perform Logistic regression
        classifier = LogisticRegression(random_state=0, C=0.316, max_iter=10000, verbose=1, n jobs=-1)
        classifier.fit(train_features, train_labels)
        # Evaluate using the logistic regression classifier
        predictions = classifier.predict(test_features)
        accuracy = np.mean((test_labels == predictions).astype(float))
        print(f"\n MedClip ViT HAM1000 Image Features Accuracy = {100*accuracy:.3f}%")
```

c:\Users\mario\anaconda3\Lib\site-packages\torchvision\models_utils.py:208: UserWarning: The pa

Some weights of the model checkpoint at microsoft/swin-tiny-patch4-window7-224 were not used whe n initializing SwinModel: ['classifier.weight', 'classifier.bias']

- This IS expected if you are initializing SwinModel from the checkpoint of a model trained on a nother task or with another architecture (e.g. initializing a BertForSequenceClassification model from a BertForPreTraining model).
- This IS NOT expected if you are initializing SwinModel from the checkpoint of a model that you expect to be exactly identical (initializing a BertForSequenceClassification model from a BertForSequenceClassification model).

Some weights of the model checkpoint at emilyalsentzer/Bio_ClinicalBERT were not used when initi alizing BertModel: ['cls.predictions.transform.LayerNorm.bias', 'cls.seq_relationship.bias', 'cl s.predictions.transform.dense.bias', 'cls.predictions.transform.LayerNorm.weight', 'cls.seq_relationship.weight', 'cls.predictions.transform.dense.weight', 'cls.predictions.decoder.weight']

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```
100%| 141/141 [04:20<00:00, 1.85s/it]
100%| 16/16 [00:19<00:00, 1.24s/it]
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 16 concurrent workers.
[Parallel(n_jobs=-1)]: Done 1 out of 1 | elapsed: 1.7s finished
```

MedClip ViT HAM1000 Image Features Accuracy = 74.152%

SVM testing for MedCLIP-ResNet50 and MedCLIP-ViT

```
In [ ]: import torch
        from torch.utils.data import DataLoader
        from tqdm import tqdm
        # Device configuration
        from medclip import MedCLIPModel, MedCLIPVisionModelViT
        from medclip.modeling_medclip import MedCLIPVisionModel
        import numpy as np
        def get_features(data_set, model):
            all_features = []
            all_labels = []
            with torch.no_grad():
                for images, labels in tqdm(DataLoader(data_set, batch_size=BATCH_SIZE)):
                    features = model.encode_image(images.to(device))
                    all_features.append(features)
                    all_labels.append(labels)
            return torch.cat(all_features).cpu().numpy(), torch.cat(all_labels).cpu().numpy()
```

ResNet50

```
In []: # ResNet50
MedCLIP_ResNet50_model = MedCLIPModel(vision_cls=MedCLIPVisionModel).to(device)

# HAM10000
MedCLIP_ResNet50_model_HAM_train_features, MedCLIP_ResNet50_model_HAM_train_labels = get_feature
MedCLIP_ResNet50_model_HAM_test_features, MedCLIP_ResNet50_model_HAM_test_labels = get_features(
# NIH
```

MedCLIP_ResNet50_model_NIH_train_features, MedCLIP_ResNet50_model_NIH_train_labels = get_feature
MedCLIP_ResNet50_model_NIH_test_features, MedCLIP_ResNet50_model_NIH_test_labels = get_features(

Some weights of the model checkpoint at emilyalsentzer/Bio_ClinicalBERT were not used when initi alizing BertModel: ['cls.predictions.transform.LayerNorm.bias', 'cls.predictions.bias', 'cls.predictions.transform.dense.weight', 'cls.predictions.transform.LayerNorm.weight', 'cls.prediction s.decoder.weight', 'cls.seq_relationship.bias', 'cls.seq_relationship.weight', 'cls.predictions.transform.dense.bias']

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- This IS NOT expected if you are initializing BertModel from the checkpoint of a model that you expect to be exactly identical (initializing a BertForSequenceClassification model from a BertForSequenceClassification model).

```
100% | 141/141 [01:04<00:00, 2.19it/s]

100% | 16/16 [00:07<00:00, 2.28it/s]

100% | 1577/1577 [22:22<00:00, 1.17it/s]

100% | 176/176 [02:30<00:00, 1.17it/s]
```

ViT

In []: # ViT
MedCLIP_ViT_model = MedCLIPModel(vision_cls=MedCLIPVisionModelViT).to(device)

HAM10000
MedCLIP_ViT_model_HAM_train_features, MedCLIP_ViT_model_HAM_train_labels = get_features(ham_train_MedCLIP_ViT_model_HAM_test_features, MedCLIP_ViT_model_HAM_test_labels = get_features(ham_test, MedCLIP_ViT_model_NIH_train_labels = get_features(nih_train_MedCLIP_ViT_model_NIH_train_labels = get_features(nih_train_MedCLIP_ViT_model_NIH_test_labels = get_features(nih_test, MedCLIP_ViT_model_NIH_test_labels = get_features(nih_test, MedCLIP_ViT_model_NIH_test_labels)

c:\Users\mario\anaconda3\Lib\site-packages\torch\functional.py:504: UserWarning: torch.meshgrid:
in an upcoming release, it will be required to pass the indexing argument. (Triggered internally
at C:\cb\pytorch_1000000000000\work\aten\src\ATen\native\TensorShape.cpp:3527.)

return _VF.meshgrid(tensors, **kwargs) # type: ignore[attr-defined]

Some weights of the model checkpoint at microsoft/swin-tiny-patch4-window7-224 were not used whe n initializing SwinModel: ['classifier.weight', 'classifier.bias']

- This IS expected if you are initializing SwinModel from the checkpoint of a model trained on a nother task or with another architecture (e.g. initializing a BertForSequenceClassification model from a BertForPreTraining model).
- This IS NOT expected if you are initializing SwinModel from the checkpoint of a model that you expect to be exactly identical (initializing a BertForSequenceClassification model from a BertForSequenceClassification model).

Some weights of the model checkpoint at emilyalsentzer/Bio_ClinicalBERT were not used when initi alizing BertModel: ['cls.predictions.transform.LayerNorm.bias', 'cls.predictions.bias', 'cls.predictions.transform.dense.weight', 'cls.predictions.transform.LayerNorm.weight', 'cls.prediction s.decoder.weight', 'cls.seq_relationship.bias', 'cls.seq_relationship.weight', 'cls.predictions.transform.dense.bias']

- This IS expected if you are initializing BertModel from the checkpoint of a model trained on a nother task or with another architecture (e.g. initializing a BertForSequenceClassification model from a BertForPreTraining model).
- This IS NOT expected if you are initializing BertModel from the checkpoint of a model that you expect to be exactly identical (initializing a BertForSequenceClassification model from a BertForSequenceClassification model).

```
100% | 141/141 [01:13<00:00, 1.93it/s]
100% | 16/16 [00:08<00:00, 1.97it/s]
100% | 1577/1577 [24:34<00:00, 1.07it/s]
100% | 176/176 [02:36<00:00, 1.13it/s]
```

```
In [ ]: from sklearn import svm
    from sklearn.preprocessing import StandardScaler
    import numpy as np
```

```
# Data preprocessing with StandardScaler
         scaler = StandardScaler()
In [ ]: # ResNet50 and ViT Models
         # HAM10000
         scaler.fit(MedCLIP ResNet50 model HAM train features)
        MedCLIP_ResNet50_model_HAM_train_features = scaler.transform(MedCLIP_ResNet50_model_HAM_train_fe
        MedCLIP_ResNet50_model_HAM_test_features = scaler.transform(MedCLIP_ResNet50_model_HAM_test_features)
         scaler.fit(MedCLIP_ViT_model_HAM_train_features)
        MedCLIP_ViT_model_HAM_train_features = scaler.transform(MedCLIP_ViT_model_HAM_train_features)
        MedCLIP_ViT_model_HAM_test_features = scaler.transform(MedCLIP_ViT_model_HAM_test_features)
         # NIH
         scaler.fit(MedCLIP_ResNet50_model_NIH_train_features)
        MedCLIP_ResNet50_model_NIH_train_features = scaler.transform(MedCLIP_ResNet50_model_NIH_train_fe
        MedCLIP_ResNet50_model_NIH_test_features = scaler.transform(MedCLIP_ResNet50_model_NIH_test_feat
         scaler.fit(MedCLIP ViT model NIH train features)
        MedCLIP_ViT_model_NIH_train_features = scaler.transform(MedCLIP_ViT_model_NIH_train_features)
        MedCLIP_ViT_model_NIH_test_features = scaler.transform(MedCLIP_ViT_model_NIH_test_features)
```

classifier = svm.SVC(random state=0, C=0.316, max iter=1000, verbose=1)

HAM10000

Perform SVM regression

```
In [ ]: # HAM10000 ResNet50
        classifier.fit(MedCLIP_ResNet50_model_HAM_train_features, MedCLIP_ResNet50_model_HAM_train_label
        predictions = classifier.predict(MedCLIP_ResNet50_model_HAM_test_features)
        accuracy = np.mean((MedCLIP_ResNet50_model_HAM_test_labels == predictions).astype(float))
        print(f"\n MedClip ResNet50 HAM1000 SVM Image Features Accuracy = {100*accuracy:.3f}%")
        [LibSVM]
        c:\Users\mario\anaconda3\Lib\site-packages\sklearn\svm\_base.py:297: ConvergenceWarning: Solver
        terminated early (max_iter=1000). Consider pre-processing your data with StandardScaler or MinM
        axScaler.
          warnings.warn(
         MedClip ResNet50 HAM1000 SVM Image Features Accuracy = 75.948%
In [ ]: # HAM10000 ViT
        classifier.fit(MedCLIP_ViT_model_HAM_train_features, MedCLIP_ViT_model_HAM_train_labels)
        predictions = classifier.predict(MedCLIP_ViT_model_HAM_test_features)
        accuracy = np.mean((MedCLIP_ViT_model_HAM_test_labels == predictions).astype(float))
        print(f"\n MedClip ViT HAM1000 SVM Image Features Accuracy = {100*accuracy:.3f}%")
        [LibSVM]
```

c:\Users\mario\anaconda3\Lib\site-packages\sklearn\svm_base.py:297: ConvergenceWarning: Solver terminated early (max_iter=1000). Consider pre-processing your data with StandardScaler or MinM

NIH Chest X-ray dataset

MedClip ViT HAM1000 SVM Image Features Accuracy = 76.946%

axScaler.

[LibSVM]

warnings.warn(

```
In []: # NIH ResNet50
classifier.fit(MedCLIP_ResNet50_model_NIH_train_features, MedCLIP_ResNet50_model_NIH_train_label
predictions = classifier.predict(MedCLIP_ResNet50_model_NIH_test_features)
accuracy = np.mean((MedCLIP_ResNet50_model_NIH_test_labels == predictions).astype(float))
print(f"\n MedClip ResNet50 NIH SVM Image Features Accuracy = {100*accuracy:.3f}%")
```

```
warnings.warn(
    MedClip ResNet50 NIH SVM Image Features Accuracy = 33.518%

In []: # NIH ViT
    classifier.fit(MedCLIP_ViT_model_NIH_train_features, MedCLIP_ViT_model_NIH_train_labels)
    predictions = classifier.predict(MedCLIP_ViT_model_NIH_test_features)
    accuracy = np.mean((MedCLIP_ViT_model_NIH_test_labels == predictions).astype(float))
    print(f"\n MedClip ViT NIH SVM Image Features Accuracy = {100*accuracy:.3f}%")

[LibSVM]
    c:\Users\mario\anaconda3\Lib\site-packages\sklearn\svm\_base.py:297: ConvergenceWarning: Solver terminated early (max_iter=1000). Consider pre-processing your data with StandardScaler or MinM axScaler.
    warnings.warn(
    MedClip ViT NIH SVM Image Features Accuracy = 34.748%
```

c:\Users\mario\anaconda3\Lib\site-packages\sklearn\svm_base.py:297: ConvergenceWarning: Solver terminated early (max_iter=1000). Consider pre-processing your data with StandardScaler or MinM

K-Means testing for MedCLIP-ResNet50 and MedCLIP-ViT

```
In []: # Perform KNN regression
from scipy import stats
def knn(x_train, y_train, x_test, y_test, K=5):
    # Needs code here
    test_pred = []
    for i in tqdm(range(len(x_test))):
        distance = np.linalg.norm(x_train - x_test[i], axis=-1)
        indices = np.argsort(distance)[:K]
        neighbors_labels = y_train[indices]
        test_pred.append(stats.mode(neighbors_labels).mode[0])

correct = (test_pred == y_test).sum()
    total = len(y_test)

return correct / total
```

HAM10000 Dataset

```
In [ ]: # Perform KNN regression for ViT HAM10000
    accuracy = knn(MedCLIP_ViT_model_HAM_train_features, MedCLIP_ViT_model_HAM_train_labels, MedCLIP_
    print(f"\n MedClip ViT HAM1000 Image Features Accuracy = {100*accuracy:.3f}%")
```

```
0%| | 0/1002 [00:00<?, ?it/s]C:\Users\mario\AppData\Local\Temp\ipykernel_20616\355302 4242.py:10: FutureWarning: Unlike other reduction functions (e.g. `skew`, `kurtosis`), the defau lt behavior of `mode` typically preserves the axis it acts along. In SciPy 1.11.0, this behavior will change: the default value of `keepdims` will become False, the `axis` over which the statis tic is taken will be eliminated, and the value None will no longer be accepted. Set `keepdims` to True or False to avoid this warning.

test_pred.append(stats.mode(neighbors_labels).mode[0])

100%| 1002/1002 [00:06<00:00, 153.57it/s]

MedClip ViT HAM1000 Image Features Accuracy = 76.447%
```

NIH Chest X-ray dataset

```
In [ ]: # Perform KNN regression for ResNet50 NIH
        accuracy = knn(MedCLIP_ResNet50_model_NIH_train_features, MedCLIP_ResNet50_model_NIH_train_label
        print(f"\n MedClip ResNet50 NIH Image Features Accuracy = {100*accuracy:.3f}%")
                       0/11212 [00:00<?, ?it/s]C:\Users\mario\AppData\Local\Temp\ipykernel_20616\35530
        24242.py:10: FutureWarning: Unlike other reduction functions (e.g. `skew`, `kurtosis`), the defa
        ult behavior of `mode` typically preserves the axis it acts along. In SciPy 1.11.0, this behavio
        r will change: the default value of `keepdims` will become False, the `axis` over which the stat
        istic is taken will be eliminated, and the value None will no longer be accepted. Set `keepdims`
        to True or False to avoid this warning.
          test_pred.append(stats.mode(neighbors_labels).mode[0])
                | 11212/11212 [18:25<00:00, 10.14it/s]
         MedClip ResNet50 NIH Image Features Accuracy = 41.322%
In [ ]: # Perform KNN regression for ViT NIH
        accuracy = knn(MedCLIP_ViT_model_NIH_train_features, MedCLIP_ViT_model_NIH_train_labels, MedCLIP
        print(f"\n MedClip ViT NIH Image Features Accuracy = {100*accuracy:.3f}%")
                       0/11212 [00:00<?, ?it/s]C:\Users\mario\AppData\Local\Temp\ipykernel_20616\35530
        24242.py:10: FutureWarning: Unlike other reduction functions (e.g. `skew`, `kurtosis`), the defa
        ult behavior of `mode` typically preserves the axis it acts along. In SciPy 1.11.0, this behavio
        r will change: the default value of `keepdims` will become False, the `axis` over which the stat
        istic is taken will be eliminated, and the value None will no longer be accepted. Set `keepdims`
        to True or False to avoid this warning.
          test pred.append(stats.mode(neighbors labels).mode[0])
                 11212/11212 [18:33<00:00, 10.07it/s]
         MedClip ViT NIH Image Features Accuracy = 42.133%
```

Random Forest testing for MedCLIP-ResNet50 and MedCLIP-ViT

HAM10000 dataset

[Parallel(n_jobs=-1)]: Done 18 tasks

```
In []: # Perform Random Forest regression for ResNet50 HAM10000
    from sklearn.ensemble import RandomForestClassifier
    classifier = RandomForestClassifier(random_state=0, verbose=1, n_jobs=-1)
    classifier.fit(MedCLIP_ResNet50_model_HAM_train_features, MedCLIP_ResNet50_model_HAM_train_label

# Evaluate using the logistic regression classifier for ResNet50 HAM10000
    predictions = classifier.predict(MedCLIP_ResNet50_model_HAM_test_features)
    accuracy = np.mean((MedCLIP_ResNet50_model_HAM_test_labels == predictions).astype(float))
    print(f"\n MedClip ResNet50 HAM1000 Image Features Accuracy = {100*accuracy:.3f}%")

[Parallel(n_jobs=-1)]: Using backend ThreadingBackend with 16 concurrent workers.
```

| elapsed:

```
MedClip ResNet50 HAM1000 Image Features Accuracy = 68.463%
         [Parallel(n_jobs=-1)]: Done 100 out of 100 | elapsed:
                                                                 3.7s finished
        [Parallel(n_jobs=16)]: Using backend ThreadingBackend with 16 concurrent workers.
        [Parallel(n_jobs=16)]: Done 18 tasks
                                                                 0.0s
                                                    elapsed:
        [Parallel(n_jobs=16)]: Done 100 out of 100 | elapsed:
                                                                 0.0s finished
In [ ]: # Perform Random Forest regression for ViT HAM10000
        from sklearn.ensemble import RandomForestClassifier
        classifier = RandomForestClassifier(random_state=0, verbose=1, n_jobs=-1)
        classifier.fit(MedCLIP_ViT_model_HAM_train_features, MedCLIP_ViT_model_HAM_train_labels)
        # Evaluate using the logistic regression classifier for ViT HAM10000
        predictions = classifier.predict(MedCLIP ViT model HAM test features)
        accuracy = np.mean((MedCLIP_ViT_model_HAM_test_labels == predictions).astype(float))
        print(f"\n MedClip ViT HAM1000 Image Features Accuracy = {100*accuracy:.3f}%")
         [Parallel(n_jobs=-1)]: Using backend ThreadingBackend with 16 concurrent workers.
        [Parallel(n_jobs=-1)]: Done 18 tasks
         MedClip ViT HAM1000 Image Features Accuracy = 70.060%
         [Parallel(n_jobs=-1)]: Done 100 out of 100 | elapsed:
                                                                 4.4s finished
        [Parallel(n_jobs=16)]: Using backend ThreadingBackend with 16 concurrent workers.
        [Parallel(n_jobs=16)]: Done 18 tasks
                                                   | elapsed:
        [Parallel(n_jobs=16)]: Done 100 out of 100 | elapsed:
                                                                 0.0s finished
        NIH Chest X-ray dataset
In [ ]: # Perform Random Forest regression for ResNet50 NIH
        from sklearn.ensemble import RandomForestClassifier
        classifier = RandomForestClassifier(random_state=0, verbose=1, n_jobs=-1)
        classifier.fit(MedCLIP_ResNet50_model_NIH_train_features, MedCLIP_ResNet50_model_NIH_train_label
        # Evaluate using the logistic regression classifier for ResNet50 NIH
        predictions = classifier.predict(MedCLIP ResNet50 model NIH test features)
         accuracy = np.mean((MedCLIP_ResNet50_model_NIH_test_labels == predictions).astype(float))
        print(f"\n MedClip ResNet50 NIH Image Features Accuracy = {100*accuracy:.3f}%")
         [Parallel(n_jobs=-1)]: Using backend ThreadingBackend with 16 concurrent workers.
        [Parallel(n_jobs=-1)]: Done 18 tasks
         MedClip ResNet50 NIH Image Features Accuracy = 53.951%
```

```
[Parallel(n_jobs=-1)]: Done 100 out of 100 | elapsed: 1.0min finished
        [Parallel(n_jobs=16)]: Using backend ThreadingBackend with 16 concurrent workers.
        [Parallel(n jobs=16)]: Done 18 tasks
                                                                 0.0s
        [Parallel(n_jobs=16)]: Done 100 out of 100 | elapsed:
                                                                 0.0s finished
In [ ]: # Perform Random Forest regression for ViT NIH
        from sklearn.ensemble import RandomForestClassifier
        classifier = RandomForestClassifier(random_state=0, verbose=1, n_jobs=-1)
        classifier.fit(MedCLIP_ViT_model_NIH_train_features, MedCLIP_ViT_model_NIH_train_labels)
        # Evaluate using the logistic regression classifier for ViT NIH
        predictions = classifier.predict(MedCLIP_ViT_model_NIH_test_features)
        accuracy = np.mean((MedCLIP_ViT_model_NIH_test_labels == predictions).astype(float))
        print(f"\n MedClip ViT NIH Image Features Accuracy = {100*accuracy:.3f}%")
        [Parallel(n jobs=-1)]: Using backend ThreadingBackend with 16 concurrent workers.
        [Parallel(n_jobs=-1)]: Done 18 tasks
                                                  elapsed:
         MedClip ViT NIH Image Features Accuracy = 54.772%
```

[Parallel(n_jobs=-1)]: Done 100 out of 100 | elapsed: 1.1min finished

[Parallel(n_jobs=16)]: Done 18 tasks

[Parallel(n_jobs=16)]: Done 100 out of 100 | elapsed:

[Parallel(n_jobs=16)]: Using backend ThreadingBackend with 16 concurrent workers.

elapsed:

0.0s finished