O

March 30, 2024

1 If any issues arise during execution, utilize parallel GPU processing, considering that the model has been trained and saved using parallel GPU architecture.

[1]:
```
import os
import cv2
import h5py
import pyarrow.parquet as pq
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from tqdm import tqdm
from statistics import mean
from sklearn.metrics import accuracy_score, roc_auc_score
from sklearn.model_selection import StratifiedKFold, train_test_split
from sklearn.preprocessing import StandardScaler

import torch
import torch.nn as nn
import torch.optim as optim
from torch.optim import lr_scheduler
import torchmetrics
from torch.utils.data import DataLoader, TensorDataset
from torch.optim.lr_scheduler import CosineAnnealingLR, StepLR
from torch.utils.data.sampler import SubsetRandomSampler, BatchSampler, Sampler
from torch.optim import Adam, SGD
from torchvision import transforms, models
from torchvision.models import resnet18
from torch.utils.data import Dataset
from torchvision.transforms import Resize, ToTensor
from torch.cuda.amp import autocast, GradScaler
import torch.nn.functional as F
import timm
import albumentations as A
from albumentations.pytorch import ToTensorV2
from PIL import Image
```

```
torch.manual_seed(42)
np.random.seed(42)
torch.cuda.manual_seed(42)
```

[2]:
```
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
```

[3]:
```
gpus = torch.cuda.device_count()

if gpus <= 1:
    device = torch.device("cuda:0" if torch.cuda.is_available() else "cpu")
    print(f'Using {gpus} GPU')
else:
    device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
    print(f'Using {gpus} GPUs')
```

```
Using 2 GPUs
```

[4]:
```
MIX = False
if MIX:
    scaler = GradScaler()
    print('Mixed precision enabled')
else:
    print('Using full precision')
```

```
Using full precision
```

[5]:
```
dfs = []
parquet_file = pq.ParquetFile('/kaggle/input/task-3a/Task_3a/top_gun_opendata_3.
 ↪parquet')
total_rows = parquet_file.metadata.num_rows
chunk_size = 8
for i in range(0,total_rows,chunk_size):
    chunk = parquet_file.read_row_group(i)
    df = chunk.to_pandas()
    condition = (df['m'] > 0) & (df['m'] < 256) & (df['pt'] > 320) & (df['pt']␣
 ↪< 1600) & (df['ieta'] < 80.25)
    filtered_df = df[condition]
    if not filtered_df.empty:
        dfs.append(filtered_df)

dataset = pd.concat(dfs, ignore_index=True)
print('Dataset Length:', len(dataset))
```

```
Dataset Length: 7676
```

[6]:
```
dataset.describe()
```

[6]:

	m	iphi	pt	ieta
count	7676.000000	7676.000000	7676.000000	7676.000000
mean	170.188106	35.123372	699.564382	27.449844
std	49.473223	20.743823	173.854311	8.596656
min	85.339424	0.000000	400.474030	12.000000
25%	127.098766	17.000000	547.183167	20.000000
50%	171.119751	35.000000	701.326172	27.000000
75%	213.003334	53.000000	850.035019	35.000000
max	255.973297	71.000000	999.966858	43.000000

[7]:
```
dataset.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7676 entries, 0 to 7675
Data columns (total 5 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   X_jet   7676 non-null   object
 1   m       7676 non-null   float64
 2   iphi    7676 non-null   float64
 3   pt      7676 non-null   float64
 4   ieta    7676 non-null   float64
dtypes: float64(4), object(1)
memory usage: 300.0+ KB
```

[8]:
```
total_r = dataset["X_jet"].shape[0]
total_r
```

[8]: 7676

[9]:
```
dataset["X_jet"][0].shape
```

[9]: (8,)

[10]:
```
dataset["X_jet"][0][0].shape
```

[10]: (125,)

[11]:
```
dataset["X_jet"][0][0][0].shape
```

[11]: (125,)

[12]:
```
def to_array(data):
    arr = []
    for i in range(0, 4):
        a = np.stack(np.stack(data)[i], axis=-1)
        arr.append(a)
    arr = np.array(arr)
```

```
    arr = arr.reshape((125, 125, 4))
    return arr
```

[13]:
```
dataset["X_jet"] = dataset["X_jet"].apply(to_array)
```

[14]:
```
dataset["X_jet"][0].shape
```

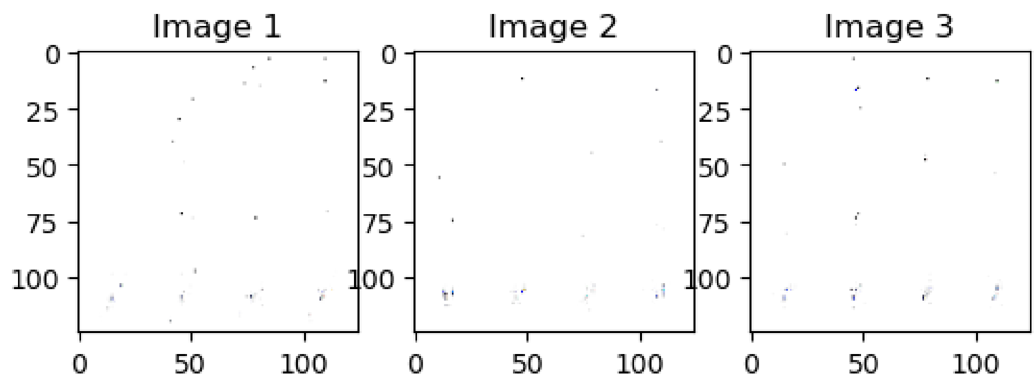
[14]: (125, 125, 4)

[15]:
```
y = dataset["m"]
scaler = StandardScaler()
dataset["m"] = scaler.fit_transform(np.array(y).reshape(-1, 1))

X_jet = np.stack(dataset['X_jet'].apply(np.concatenate).values).
 ↪reshape(-1,125,125,4)
mean = np.mean(X_jet, axis=(0, 1, 2))
std = np.std(X_jet, axis=(0, 1, 2))
X_jet = (X_jet-mean)/std
```

[16]:
```
for i in range(len(X_jet)):
    dataset["X_jet"][i] = X_jet[i]
```

```
/opt/conda/lib/python3.7/site-packages/ipykernel_launcher.py:2:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
```

[17]:
```
fig, axes = plt.subplots(nrows=1, ncols=3)
for i, ax in enumerate(axes.flatten()):
    image = dataset['X_jet'][i][:,:,:]
    ax.imshow(image)
    ax.set_title(f'Image {i+1}')

plt.show()
```



[18]:
```
train_df, val_df = train_test_split(dataset, test_size=0.2, random_state=42)
```

[19]:
```
class CFG:
    model_name = 'resnet18'
    batch_size = 64
    learning_rate = 5e-4
    num_epochs = 25
    random_state = 42
    num_class=3
    weight_decay = 1e-2
```

[20]:
```
class BasicBlock(nn.Module):
    expansion = 1

    def __init__(self, in_planes, planes, stride=1):
        super(BasicBlock, self).__init__()
        self.conv1 = nn.Conv2d(in_planes, planes, kernel_size=3, stride=stride,␣
↪padding=1, bias=False)
        self.bn1 = nn.BatchNorm2d(planes)
        self.conv2 = nn.Conv2d(planes, planes, kernel_size=3, stride=1,␣
↪padding=1, bias=False)
        self.bn2 = nn.BatchNorm2d(planes)

        self.shortcut = nn.Sequential()
        if stride != 1 or in_planes != self.expansion*planes:
            self.shortcut = nn.Sequential(
                nn.Conv2d(in_planes, self.expansion*planes, kernel_size=1,␣
↪stride=stride, bias=False),
                nn.BatchNorm2d(self.expansion*planes)
            )

    def forward(self, x):
```

```
        out = F.relu(self.bn1(self.conv1(x)))
        out = self.bn2(self.conv2(out))
        out += self.shortcut(x)
        out = F.relu(out)
        return out

class CustomResNet18(nn.Module):
    def __init__(self, num_classes=1):
        super(CustomResNet18, self).__init__()

        # Define the convolutional layers
        self.conv1 = nn.Conv2d(4, 64, kernel_size=3, stride=1, padding=1,
 ↪bias=False)
        self.bn1 = nn.BatchNorm2d(64)
        self.relu = nn.ReLU(inplace=True)
        self.maxpool = nn.MaxPool2d(kernel_size=3, stride=2, padding=1)

        self.in_planes = 64

        self.layer1 = self._make_layer(BasicBlock, 64, 2, stride=1)
        self.layer2 = self._make_layer(BasicBlock, 128, 2, stride=2)
        self.layer3 = self._make_layer(BasicBlock, 256, 2, stride=2)

        self.fc1 = nn.Linear(256 * 16 * 16, 512)
        self.fc2 = nn.Linear(512, 256)

        self.fc3 = nn.Linear(256,128)
        self.fc4 = nn.Linear(128, num_classes)

    def _make_layer(self, block, planes, num_blocks, stride):
        strides = [stride] + [1]*(num_blocks-1)
        layers = []
        for stride in strides:
            layers.append(block(self.in_planes, planes, stride))
            self.in_planes = planes * block.expansion
        return nn.Sequential(*layers)

    def forward(self, x):
        x = self.relu(self.bn1(self.conv1(x)))
        x = self.maxpool(x)

        x = self.layer1(x)
        x = self.layer2(x)
        x = self.layer3(x)


        x = torch.flatten(x, 1)
```

```
        x = F.relu(self.fc1(x))
        x = F.relu(self.fc2(x))
        x = F.relu(self.fc3(x))
        x = self.fc4(x)
        return x.squeeze()
```

[21]:
```
model = CustomResNet18().to(device)
if torch.cuda.device_count() > 1:
    model = nn.DataParallel(model)
model = model.to(device)
criterion = nn.MSELoss()
optimizer = optim.Adam(model.parameters(), lr=CFG.learning_rate)
scheduler = CosineAnnealingLR(optimizer, T_max=25, eta_min=1e-7)
```

[22]:
```
X_jets = np.stack(train_df['X_jet'].apply(np.concatenate).values)
X_train = torch.tensor(X_jets, dtype=torch.float32).view(-1, 125,125, 4)
y_train = pd.to_numeric(train_df['m'])
y_train = torch.tensor(y_train.values, dtype=torch.float32)

X_jets = np.stack(val_df['X_jet'].apply(np.concatenate).values)
X_val = torch.tensor(X_jets, dtype=torch.float32).view(-1,125, 125, 4)

y_val = pd.to_numeric(val_df['m'])
y_val = torch.tensor(y_val.values, dtype=torch.float32)


train_dataset = TensorDataset(X_train, y_train)
val_dataset = TensorDataset(X_val, y_val)

train_loader = DataLoader(train_dataset, batch_size=CFG.batch_size,␣
 ↪shuffle=True)
val_loader = DataLoader(val_dataset, batch_size=CFG.batch_size, shuffle=True)
```

[23]:
```
next(iter(train_loader))[0].shape
```

[23]: torch.Size([64, 125, 125, 4])

[24]:
```
train_losses = []
val_losses = []
mae_losses = []
mre_losses = []

best_val_loss = float('inf')
best_mre = float('inf')
best_val_loss_model = None
best_mre_model = None
```

```python
for epoch in range(CFG.num_epochs):
    model.train()
    train_loss = 0.0
    train_preds_list = []

    for inputs, labels in tqdm(train_loader, desc=f'Epoch {epoch + 1}/{CFG.
 ↪num_epochs} (Training)'):
        inputs, labels = inputs.to(device), labels.to(device)
        inputs = inputs.permute(0, 3, 1, 2)

        optimizer.zero_grad()

        outputs = model(inputs)
        loss = criterion(outputs, labels)
        loss.backward()
        optimizer.step()

        train_loss += loss.item()
        train_preds_list.append(outputs.detach().cpu().numpy())

    train_loss /= len(train_loader)
    train_preds = np.concatenate(train_preds_list)

    model.eval()
    val_loss = 0.0
    mae_loss = 0.0
    mre_loss = 0.0
    val_preds_list = []

    for inputs, labels in tqdm(val_loader, desc=f'Epoch {epoch + 1}/{CFG.
 ↪num_epochs} (Validation)'):
        inputs = inputs.permute(0, 3, 1, 2)
        val_inputs, val_labels = inputs.to(device), labels.to(device)
        val_outputs = model(val_inputs)
        val_loss += criterion(val_outputs, val_labels).item()
        val_preds_list.append(val_outputs.detach().cpu().numpy())
        mae_loss += torch.abs(val_outputs - val_labels).sum().item()
        absolute_errors = torch.abs(val_outputs - val_labels)
        mre_loss += (absolute_errors / (torch.abs(val_labels) + 1e-6)).sum().
 ↪item()

    val_loss /= len(val_loader)
    mae_loss /= len(val_loader.dataset)
    mre_loss /= len(val_loader.dataset)

    train_losses.append(train_loss)
    val_losses.append(val_loss)
```

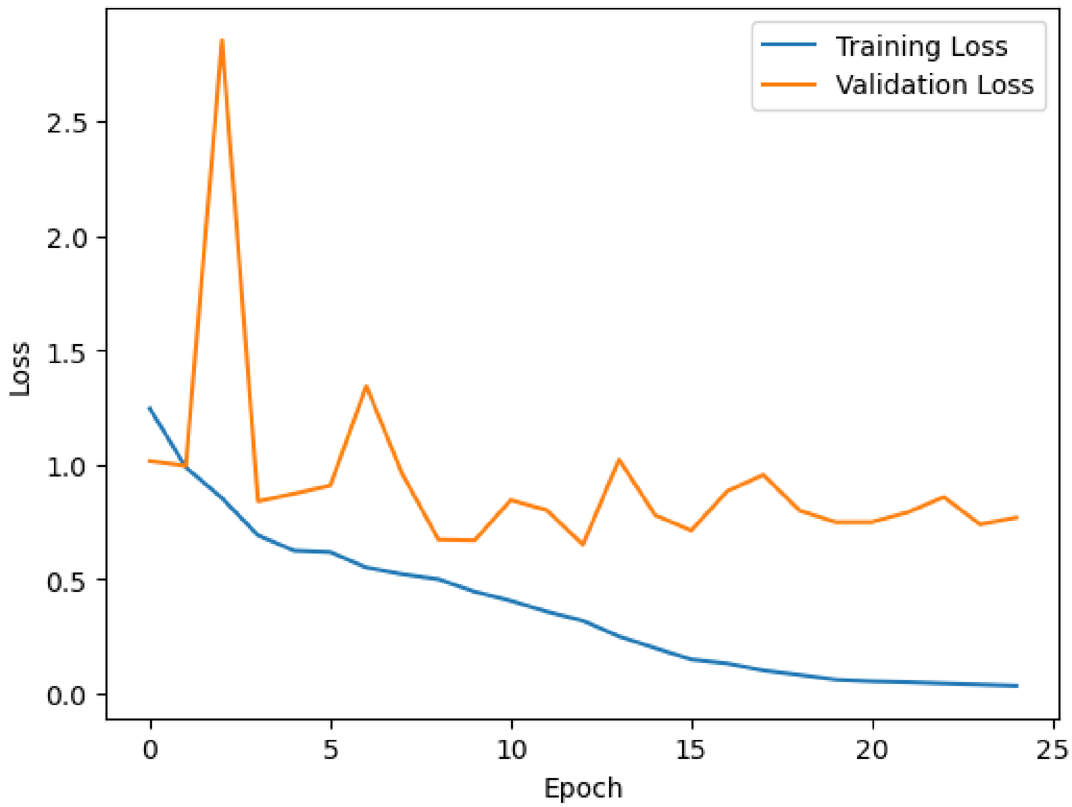
```python
    mae_losses.append(mae_loss)
    mre_losses.append(mre_loss)

    scheduler.step(val_loss)

    if val_loss < best_val_loss:
        best_val_loss = val_loss
        best_val_loss_model = model.state_dict()

    if mre_loss < best_mre:
        best_mre = mre_loss
        best_mre_model = model.state_dict()

    print(f"Epoch {epoch + 1}/{CFG.num_epochs}, Train Loss: {train_loss:.4f}, 
 ↪Val Loss: {val_loss:.4f}, MAE: {mae_loss:.4f}, MRE: {mre_loss:.4f}")

torch.save(best_val_loss_model, 'best_model_val_loss.pth')
torch.save(best_mre_model, 'best_model_mre.pth')
print("Model saved successfully.")
print("Finished training")
```

```
Epoch 1/25 (Training): 100%|      | 96/96 [00:32<00:00,  2.94it/s]
Epoch 1/25 (Validation): 100%|      | 24/24 [00:01<00:00, 17.95it/s]

Epoch 1/25, Train Loss: 1.2456, Val Loss: 1.0159, MAE: 0.8733, MRE: 1.4182

Epoch 2/25 (Training): 100%|      | 96/96 [00:20<00:00,  4.68it/s]
Epoch 2/25 (Validation): 100%|      | 24/24 [00:01<00:00, 17.66it/s]

Epoch 2/25, Train Loss: 0.9879, Val Loss: 0.9946, MAE: 0.8575, MRE: 1.6905

Epoch 3/25 (Training): 100%|      | 96/96 [00:21<00:00,  4.53it/s]
Epoch 3/25 (Validation): 100%|      | 24/24 [00:01<00:00, 17.16it/s]

Epoch 3/25, Train Loss: 0.8541, Val Loss: 2.8539, MAE: 1.4660, MRE: 6.3990

Epoch 4/25 (Training): 100%|      | 96/96 [00:21<00:00,  4.43it/s]
Epoch 4/25 (Validation): 100%|      | 24/24 [00:01<00:00, 17.20it/s]

Epoch 4/25, Train Loss: 0.6909, Val Loss: 0.8401, MAE: 0.7461, MRE: 2.0049

Epoch 5/25 (Training): 100%|      | 96/96 [00:21<00:00,  4.49it/s]
Epoch 5/25 (Validation): 100%|      | 24/24 [00:01<00:00, 17.44it/s]

Epoch 5/25, Train Loss: 0.6243, Val Loss: 0.8731, MAE: 0.7570, MRE: 2.2628

Epoch 6/25 (Training): 100%|      | 96/96 [00:21<00:00,  4.54it/s]
Epoch 6/25 (Validation): 100%|      | 24/24 [00:01<00:00, 17.32it/s]

Epoch 6/25, Train Loss: 0.6179, Val Loss: 0.9086, MAE: 0.7679, MRE: 2.9458

Epoch 7/25 (Training): 100%|      | 96/96 [00:21<00:00,  4.50it/s]
Epoch 7/25 (Validation): 100%|      | 24/24 [00:01<00:00, 17.27it/s]
```

```
Epoch 7/25, Train Loss: 0.5506, Val Loss: 1.3430, MAE: 0.9491, MRE: 3.7623

Epoch 8/25 (Training): 100%|     | 96/96 [00:21<00:00,  4.48it/s]
Epoch 8/25 (Validation): 100%|     | 24/24 [00:01<00:00, 17.28it/s]

Epoch 8/25, Train Loss: 0.5212, Val Loss: 0.9575, MAE: 0.7916, MRE: 3.1592

Epoch 9/25 (Training): 100%|     | 96/96 [00:21<00:00,  4.50it/s]
Epoch 9/25 (Validation): 100%|     | 24/24 [00:01<00:00, 17.29it/s]

Epoch 9/25, Train Loss: 0.4994, Val Loss: 0.6727, MAE: 0.6446, MRE: 2.2153

Epoch 10/25 (Training): 100%|     | 96/96 [00:21<00:00,  4.50it/s]
Epoch 10/25 (Validation): 100%|     | 24/24 [00:01<00:00, 17.19it/s]

Epoch 10/25, Train Loss: 0.4450, Val Loss: 0.6695, MAE: 0.6798, MRE: 2.2099

Epoch 11/25 (Training): 100%|     | 96/96 [00:21<00:00,  4.49it/s]
Epoch 11/25 (Validation): 100%|     | 24/24 [00:01<00:00, 17.26it/s]

Epoch 11/25, Train Loss: 0.4052, Val Loss: 0.8451, MAE: 0.7459, MRE: 2.0842

Epoch 12/25 (Training): 100%|     | 96/96 [00:21<00:00,  4.49it/s]
Epoch 12/25 (Validation): 100%|     | 24/24 [00:01<00:00, 17.22it/s]

Epoch 12/25, Train Loss: 0.3577, Val Loss: 0.8012, MAE: 0.7001, MRE: 2.3503

Epoch 13/25 (Training): 100%|     | 96/96 [00:21<00:00,  4.49it/s]
Epoch 13/25 (Validation): 100%|     | 24/24 [00:01<00:00, 17.20it/s]

Epoch 13/25, Train Loss: 0.3180, Val Loss: 0.6502, MAE: 0.6505, MRE: 2.0864

Epoch 14/25 (Training): 100%|     | 96/96 [00:21<00:00,  4.49it/s]
Epoch 14/25 (Validation): 100%|     | 24/24 [00:01<00:00, 17.17it/s]

Epoch 14/25, Train Loss: 0.2495, Val Loss: 1.0224, MAE: 0.7833, MRE: 3.2172

Epoch 15/25 (Training): 100%|     | 96/96 [00:21<00:00,  4.50it/s]
Epoch 15/25 (Validation): 100%|     | 24/24 [00:01<00:00, 17.28it/s]

Epoch 15/25, Train Loss: 0.1985, Val Loss: 0.7792, MAE: 0.6842, MRE: 2.7696

Epoch 16/25 (Training): 100%|     | 96/96 [00:21<00:00,  4.50it/s]
Epoch 16/25 (Validation): 100%|     | 24/24 [00:01<00:00, 17.25it/s]

Epoch 16/25, Train Loss: 0.1490, Val Loss: 0.7124, MAE: 0.6555, MRE: 2.5821

Epoch 17/25 (Training): 100%|     | 96/96 [00:21<00:00,  4.49it/s]
Epoch 17/25 (Validation): 100%|     | 24/24 [00:01<00:00, 17.32it/s]

Epoch 17/25, Train Loss: 0.1312, Val Loss: 0.8845, MAE: 0.7320, MRE: 3.0572

Epoch 18/25 (Training): 100%|     | 96/96 [00:21<00:00,  4.50it/s]
Epoch 18/25 (Validation): 100%|     | 24/24 [00:01<00:00, 17.28it/s]

Epoch 18/25, Train Loss: 0.1008, Val Loss: 0.9552, MAE: 0.7538, MRE: 3.2224

Epoch 19/25 (Training): 100%|     | 96/96 [00:21<00:00,  4.50it/s]
Epoch 19/25 (Validation): 100%|     | 24/24 [00:01<00:00, 17.26it/s]
```

```
Epoch 19/25, Train Loss: 0.0813, Val Loss: 0.7999, MAE: 0.6936, MRE: 2.7555

Epoch 20/25 (Training): 100%|          | 96/96 [00:21<00:00,  4.51it/s]
Epoch 20/25 (Validation): 100%|          | 24/24 [00:01<00:00, 17.34it/s]

Epoch 20/25, Train Loss: 0.0605, Val Loss: 0.7487, MAE: 0.6774, MRE: 2.3921

Epoch 21/25 (Training): 100%|          | 96/96 [00:21<00:00,  4.50it/s]
Epoch 21/25 (Validation): 100%|          | 24/24 [00:01<00:00, 17.22it/s]

Epoch 21/25, Train Loss: 0.0533, Val Loss: 0.7490, MAE: 0.6755, MRE: 2.4497

Epoch 22/25 (Training): 100%|          | 96/96 [00:21<00:00,  4.50it/s]
Epoch 22/25 (Validation): 100%|          | 24/24 [00:01<00:00, 17.34it/s]

Epoch 22/25, Train Loss: 0.0492, Val Loss: 0.7921, MAE: 0.7042, MRE: 2.5932

Epoch 23/25 (Training): 100%|          | 96/96 [00:21<00:00,  4.49it/s]
Epoch 23/25 (Validation): 100%|          | 24/24 [00:01<00:00, 17.28it/s]

Epoch 23/25, Train Loss: 0.0436, Val Loss: 0.8585, MAE: 0.7320, MRE: 2.4565

Epoch 24/25 (Training): 100%|          | 96/96 [00:21<00:00,  4.50it/s]
Epoch 24/25 (Validation): 100%|          | 24/24 [00:01<00:00, 17.34it/s]

Epoch 24/25, Train Loss: 0.0389, Val Loss: 0.7393, MAE: 0.6741, MRE: 2.4653

Epoch 25/25 (Training): 100%|          | 96/96 [00:21<00:00,  4.51it/s]
Epoch 25/25 (Validation): 100%|          | 24/24 [00:01<00:00, 17.30it/s]

Epoch 25/25, Train Loss: 0.0335, Val Loss: 0.7684, MAE: 0.6859, MRE: 2.5986
Model saved successfully.
Finished training
```

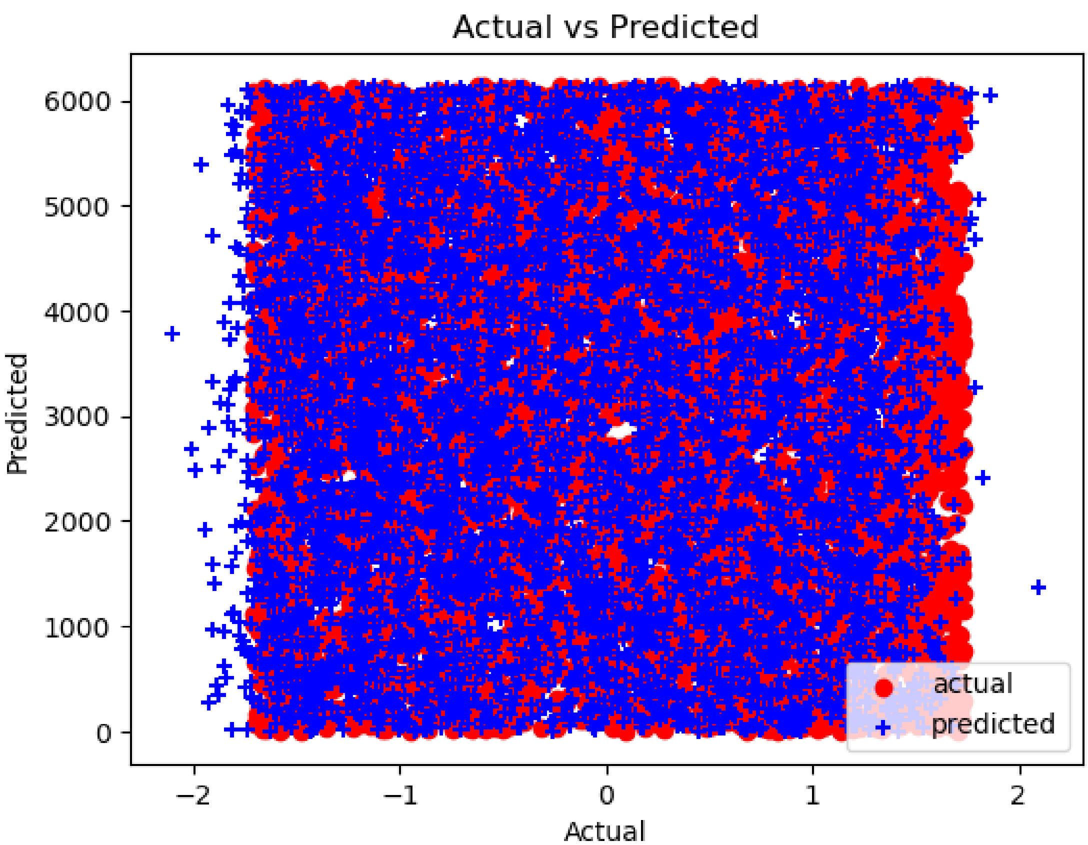
[25]:
```
plt.plot( train_losses, label='Training Loss')
plt.plot( val_losses, label='Validation Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend()
plt.show()
```



[26]:

```
checkpoint = torch.load("/kaggle/working/best_model_val_loss.pth")
model = CustomResNet18()
if torch.cuda.device_count() > 1:
    model = nn.DataParallel(model)
model.load_state_dict(checkpoint)
model = model.to(device)
model.eval()

y_true = []
y_pred = []
losses = []

with torch.no_grad():
    for data, target in train_loader:
        data, target = data.to(device), target.to(device)
        data = data.permute(0, 3, 1, 2)
        output = model(data)
        loss = criterion(output, target)
        losses.append(loss.item())
        y_true.extend(target.cpu().numpy().tolist())
        y_pred.extend(output.cpu().numpy().tolist())
```

```
overall_loss = sum(losses) / len(losses)
plt.scatter(y_true, range(len(train_dataset)), color='red', label='actual')
plt.scatter(y_pred, range(len(train_dataset)), color='blue', marker='+',␣
  ↪label="predicted")
plt.xlabel('Actual')
plt.ylabel('Predicted')
plt.legend()
plt.title('Actual vs Predicted')
plt.show()
```

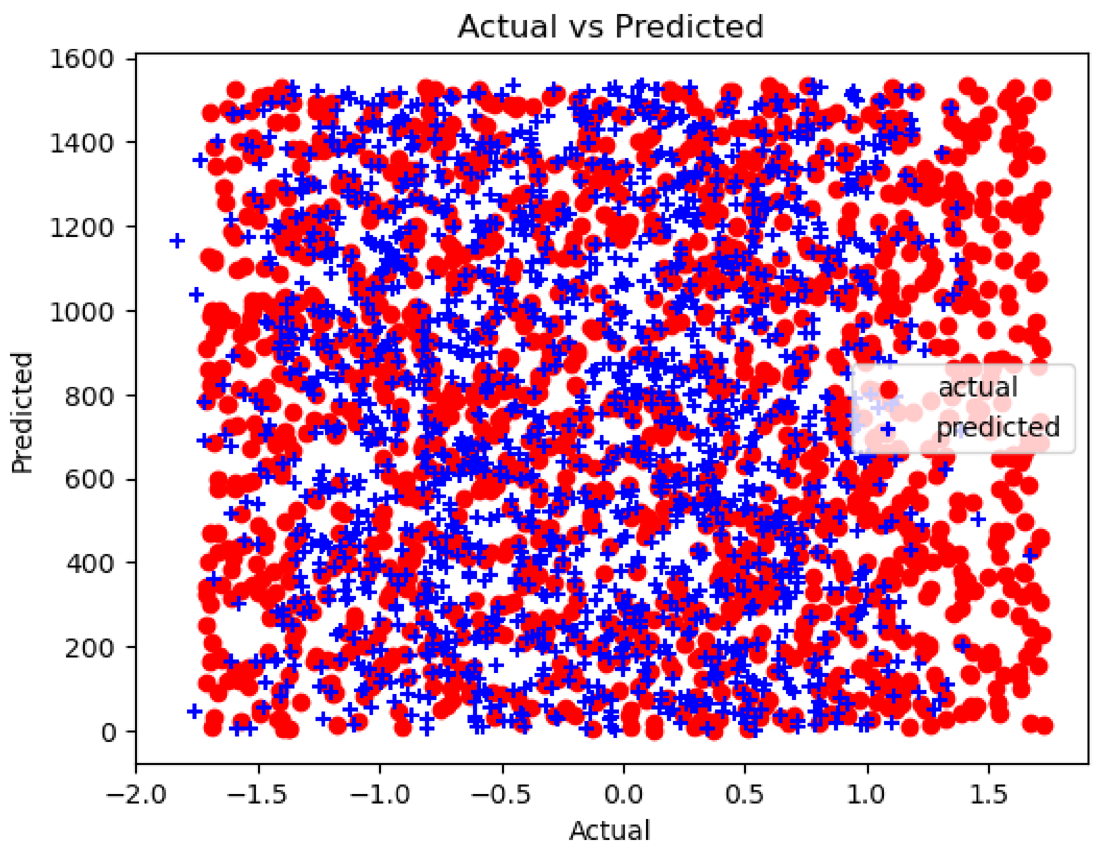


[27]:
```
print("Training Loss on min. Val Loss model:", overall_loss)
```

```
Training Loss on min. Val Loss model: 0.05079690141913792
```

[28]:
```
model.eval()
y_true = []
y_pred = []
losses = []
```

```
with torch.no_grad():
    for batch_idx, (data, target) in enumerate(val_loader):
        data, target = data.to(device), target.to(device)
        data = data.permute(0, 3, 1, 2)
        output = model(data)
        loss = criterion(output, target)
        losses.append(loss.item())
        y_true.extend(target.cpu().numpy().tolist())
        y_pred.extend(output.cpu().numpy().tolist())

overall_loss = sum(losses) / len(losses)
plt.scatter(y_true, range(len(val_dataset)), color='red', label='actual')
plt.scatter(y_pred, range(len(val_dataset)), color='blue', marker='+',␣
 ↪label="predicted")
plt.xlabel('Actual')
plt.ylabel('Predicted')
plt.legend()
plt.title('Actual vs Predicted')
plt.show()
```



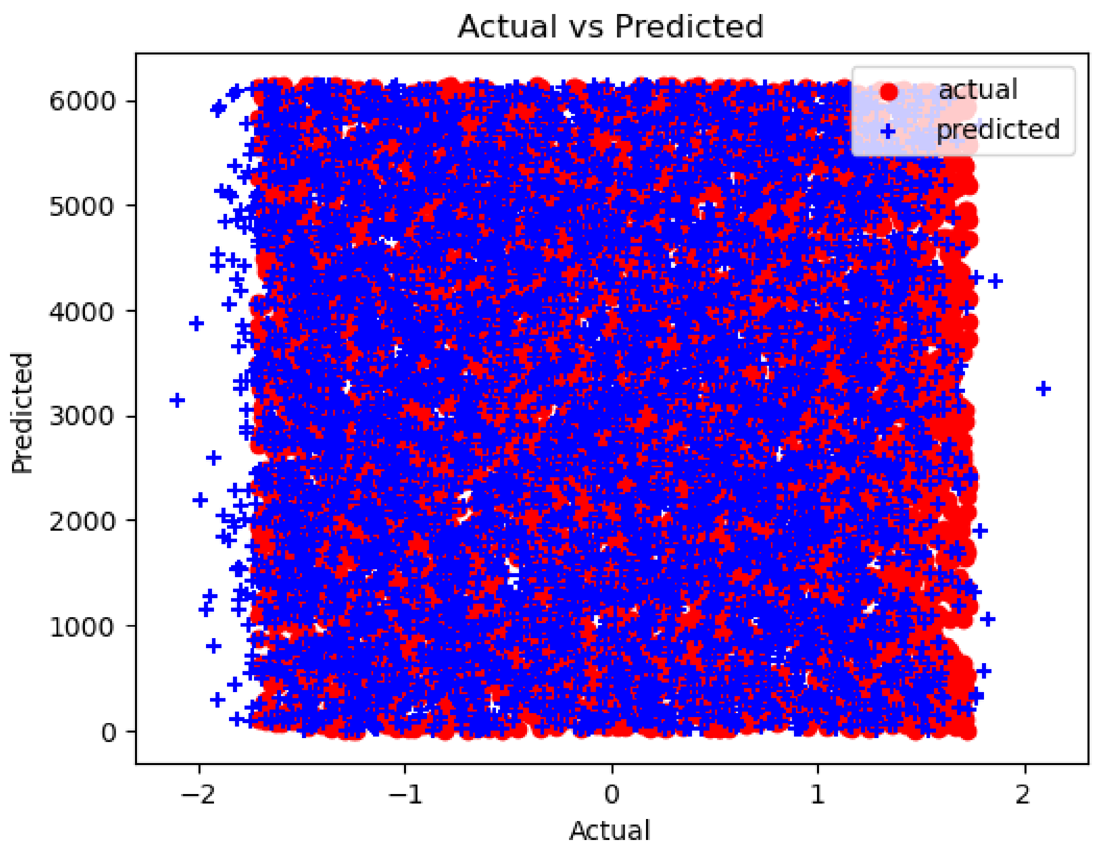
[29]:

```
print("Validation Loss based on min. Val Loss model",overall_loss)
```

```
Validation Loss based on min. Val Loss model 0.7683576780060927
```

[30]:

```
checkpoint = torch.load("/kaggle/working/best_model_mre.pth")
model = CustomResNet18()
if torch.cuda.device_count() > 1:
    model = nn.DataParallel(model)
model.load_state_dict(checkpoint)
model = model.to(device)
model.eval()

y_true = []
y_pred = []
losses = []

with torch.no_grad():
    for data, target in train_loader:
        data, target = data.to(device), target.to(device)
        data = data.permute(0, 3, 1, 2)
        output = model(data)
        loss = criterion(output, target)
        losses.append(loss.item())
        y_true.extend(target.cpu().numpy().tolist())
        y_pred.extend(output.cpu().numpy().tolist())

overall_loss = sum(losses) / len(losses)
plt.scatter(y_true, range(len(train_dataset)), color='red', label='actual')
plt.scatter(y_pred, range(len(train_dataset)), color='blue', marker='+',␣
 ↪label="predicted")
plt.xlabel('Actual')
plt.ylabel('Predicted')
plt.legend()
plt.title('Actual vs Predicted')
plt.show()
```

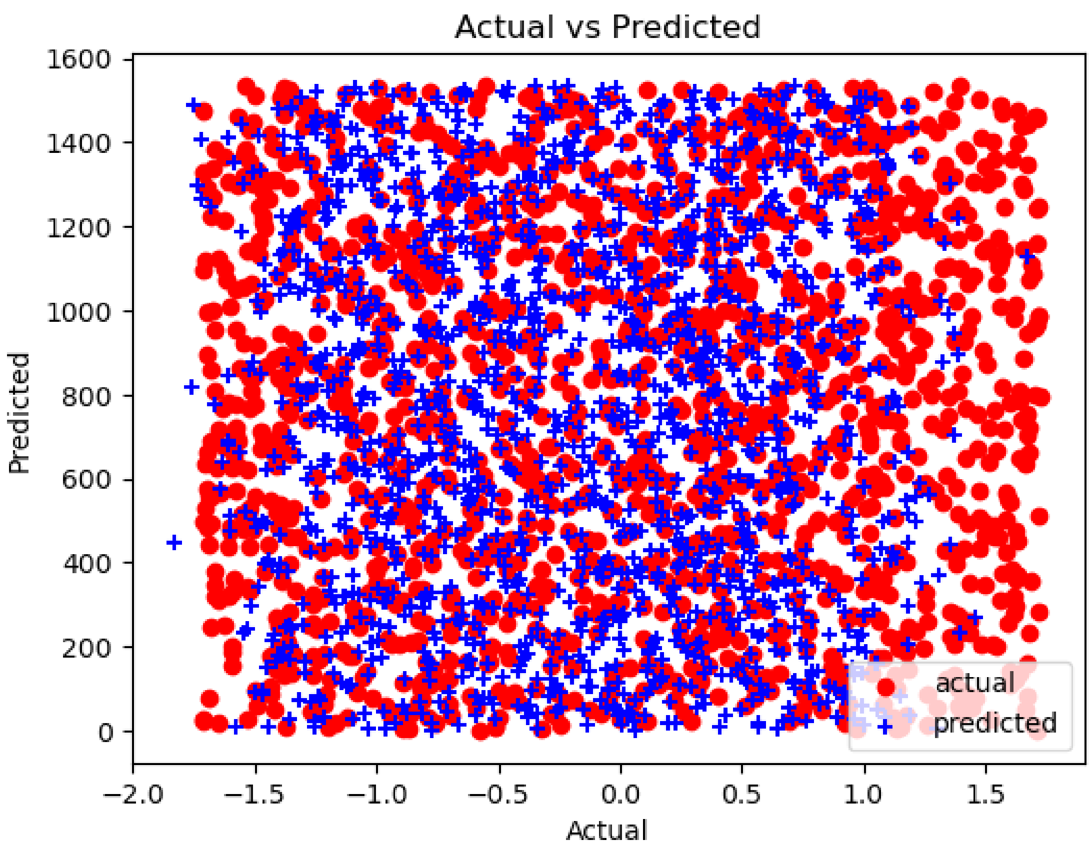


[31]:
```
print("Training Loss on min. MRE model:", overall_loss)
```

Training Loss on min. MRE model: 0.05079110184063514

[32]:
```
model.eval()
y_true = []
y_pred = []
losses = []

with torch.no_grad():
    for batch_idx, (data, target) in enumerate(val_loader):
        data, target = data.to(device), target.to(device)
        data = data.permute(0, 3, 1, 2)
        output = model(data)
        loss = criterion(output, target)
        losses.append(loss.item())
        y_true.extend(target.cpu().numpy().tolist())
        y_pred.extend(output.cpu().numpy().tolist())

overall_loss = sum(losses) / len(losses)
```

```
plt.scatter(y_true, range(len(val_dataset)), color='red', label='actual')
plt.scatter(y_pred, range(len(val_dataset)), color='blue', marker='+',␣
 ↪label="predicted")
plt.xlabel('Actual')
plt.ylabel('Predicted')
plt.legend()
plt.title('Actual vs Predicted')
plt.show()
```



[33]:
```
print("Validation Loss on min. MRE model",overall_loss)
```

```
Validation Loss on min. MRE model 0.7683576693137487
```