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

```
!pip install einops
!pip install pyspark
```

```
Collecting einops
  Downloading einops-0.6.1-py3-none-any.whl (42 kB)
━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 42.2/42.2 kB 690.1 kB/s eta
0:00:00
WARNING: Running pip as the 'root' user can result in broken
permissions and conflicting behaviour with the system package manager.
It is recommended to use a virtual environment instead:
https://pip.pypa.io/warnings/venv
Collecting pyspark
  Downloading pyspark-3.4.2.tar.gz (311.1 MB)
━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 311.1/311.1 MB 4.0 MB/s eta
0:00:00
etadata (setup.py) ... ent already satisfied: py4j==0.10.9.7 in
/opt/conda/lib/python3.7/site-packages (from pyspark) (0.10.9.7)
Building wheels for collected packages: pyspark
  Building wheel for pyspark (setup.py) ... e=pyspark-3.4.2-py2.py3-
none-any.whl size=311619854
sha256=184c98a748ea501ebcf8917eb2dcffbd0686e6413e159d507fa6d6087bf641a
4
  Stored in directory:
/root/.cache/pip/wheels/c1/1e/45/21d8f2dd514b2c1318a24a9b75427ecbee40e
d9abf91917256
Successfully built pyspark
Installing collected packages: pyspark
Successfully installed pyspark-3.4.2
WARNING: Running pip as the 'root' user can result in broken
permissions and conflicting behaviour with the system package manager.
It is recommended to use a virtual environment instead:
https://pip.pypa.io/warnings/venv
```

```python
import os
import timm
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.utils.data import DataLoader, TensorDataset
from torch.optim.lr_scheduler import CosineAnnealingLR,
StepLR,ExponentialLR
from torchvision.transforms import Resize, ToTensor
from torch.cuda.amp import autocast, GradScaler
import einops
from einops import repeat, rearrange,einsum
from skimage.transform import resize


from einops.layers.torch import Rearrange
from pyspark.sql import SparkSession

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

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

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
```

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

```
Using full precision
```

```
dfs = []
parquet_file =
pq.ParquetFile('/kaggle/input/task-3a/Task_3a/top_gun_opendata_3.parqu
et')
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
```

```
dataset.describe()
```

	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

```
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
```

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

```
7676
```

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

```
(8,)
```

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

```
(125,)
```

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

```
(125,)
```

```
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
```

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

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

```
(125, 125, 4)
```

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

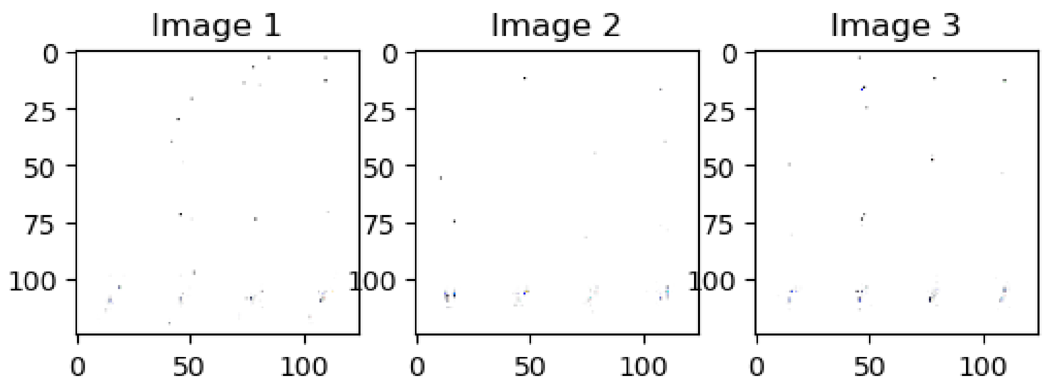
```
X_jet =
np.stack(dataset['X_jet'].apply(np.concatenate).values).reshape(-
1,125,125,4)
mean = np.mean(X_jet, axis=(0, 1, 2))
std = np.std(X_jet, axis=(0, 1, 2))
X_jet = (X_jet-mean)/std
```

```
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
```

```
del X_jet
```

```
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()
```




```
train_df, val_df = train_test_split(dataset, test_size=0.2,
random_state=42)

class CFG:
    model_name = 'DeepVit'
    batch_size = 32
    learning_rate = 1e-3
    num_epochs = 25
    random_state = 42
    weight_decay = 1e-4

class FeedForward(nn.Module):
    def __init__(self, dim, hidden_dim, dropout = 0.4):
        super().__init__()
        self.net = nn.Sequential(
            nn.LayerNorm(dim),
            nn.Linear(dim, hidden_dim),
            nn.GELU(),
            nn.Dropout(dropout),
            nn.Linear(hidden_dim, dim),
            nn.Dropout(dropout)
        )
    def forward(self, x):
        return self.net(x)

class Attention(nn.Module):
    def __init__(self, dim, heads = 8, dim_head = 64, dropout = 0.4):
        super().__init__()
        inner_dim = dim_head *  heads
```

```
        self.heads = heads
        self.scale = dim_head ** -0.5

        self.norm = nn.LayerNorm(dim)
        self.to_qkv = nn.Linear(dim, inner_dim * 3, bias = False)

        self.dropout = nn.Dropout(dropout)

        self.reattn_weights = nn.Parameter(torch.randn(heads, heads))

        self.reattn_norm = nn.Sequential(
            Rearrange('b h i j -> b i j h'),
            nn.LayerNorm(heads),
            Rearrange('b i j h -> b h i j')
        )

        self.to_out = nn.Sequential(
            nn.Linear(inner_dim, dim),
            nn.Dropout(dropout)
        )

    def forward(self, x):
        b, n, _, h = *x.shape, self.heads
        x = self.norm(x)

        qkv = self.to_qkv(x).chunk(3, dim = -1)
        q, k, v = map(lambda t: rearrange(t, 'b n (h d) -> b h n d', h
= h), qkv)

        # attention
        dots = torch.einsum('bhid,bhjd->bhij', q, k) * self.scale
        attn = dots.softmax(dim=-1)

        attn = self.dropout(attn)

        # re-attention
        attn = torch.einsum('bhij,hg->bgij', attn,
self.reattn_weights)

        attn = self.reattn_norm(attn)

        # aggregate and out

        out = torch.einsum('b h i j, b h j d -> b h i d', attn, v)
        out = rearrange(out, 'b h n d -> b n (h d)')
        out =  self.to_out(out)
        return out

class Transformer(nn.Module):
    def __init__(self, dim, depth, heads, dim_head, mlp_dim, dropout =
0.):
```

```
        super().__init__()
        self.layers = nn.ModuleList([])
        for _ in range(depth):
            self.layers.append(nn.ModuleList([
                Attention(dim, heads = heads, dim_head = dim_head,
dropout = dropout),
                FeedForward(dim, mlp_dim, dropout = dropout)
            ]))
    def forward(self, x):
        for attn, ff in self.layers:
            x = attn(x) + x
            x = ff(x) + x
        return x

class DeepViT(nn.Module):
    def __init__(self, *, image_size, patch_size, num_classes, dim,
depth, heads, mlp_dim, pool='cls', channels=4, dim_head=64,
dropout=0., emb_dropout=0.):
        super().__init__()
        assert image_size % patch_size == 0, 'Image dimensions must be
divisible by the patch size.'
        assert channels == 4, 'Number of input channels must be 4 for
the given input format.'

        num_patches = (image_size // patch_size) ** 2
        patch_dim = channels * patch_size ** 2
        assert pool in {'cls', 'mean'}, 'pool type must be either cls
(cls token) or mean (mean pooling)'

        self.to_patch_embedding = nn.Sequential(
            Rearrange('b c (h p1) (w p2) -> b (h w) (p1 p2 c)',
p1=patch_size, p2=patch_size),
            nn.LayerNorm(patch_dim),
            nn.Linear(patch_dim, dim),
            nn.LayerNorm(dim)
        )

        self.pos_embedding = nn.Parameter(torch.randn(1, num_patches +
1, dim))
        self.cls_token = nn.Parameter(torch.randn(1, 1, dim))
        self.dropout = nn.Dropout(emb_dropout)

        self.transformer = Transformer(dim, depth, heads, dim_head,
mlp_dim, dropout)

        self.pool = pool
        self.to_latent = nn.Identity()

        self.mlp_head = nn.Sequential(
            nn.LayerNorm(dim),
```

```
            nn.Linear(dim, num_classes)
        )

    def forward(self, img):
        x = self.to_patch_embedding(img)
        b, n, _ = x.shape

        cls_tokens = repeat(self.cls_token, '() n d -> b n d', b=b)
        x = torch.cat((cls_tokens, x), dim=1)
        x += self.pos_embedding[:, :(n + 1)]
        x = self.dropout(x)

        x = self.transformer(x)

        x = x.mean(dim=1) if self.pool == 'mean' else x[:, 0]

        x = self.to_latent(x)
        return self.mlp_head(x)

model = DeepViT(
    image_size = 125,
    patch_size = 25,
    num_classes = 1,
    dim = 1024,
    depth = 6,
    heads = 8,
    channels = 4,
    mlp_dim = 2048,
    dropout = 0.1,
    emb_dropout = 0.1
)

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,
weight_decay=CFG.weight_decay)
scheduler = ExponentialLR(optimizer, gamma=0.4)

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)

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

```
torch.Size([32, 125, 125, 4])
```

```
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

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.squeeze(), labels.squeeze())
        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)
    mae_losses.append(mae_loss)
    mre_losses.append(mre_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()
    scheduler.step()
    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%|██████████| 192/192 [00:22<00:00, 8.39it/s]
Epoch 1/25 (Validation):   0%|          | 0/48 [00:00<?, ?it/s]/opt/conda/lib/python3.7/site-packages/torch/nn/modules/loss.py:536: UserWarning: Using a target size (torch.Size([32])) that is different to the input size (torch.Size([32, 1])). This will likely lead to incorrect results due to broadcasting. Please ensure they have the same size.
  return F.mse_loss(input, target, reduction=self.reduction)
```

```
Epoch 1/25 (Validation): 100%|██████████| 48/48 [00:01<00:00,
28.18it/s]

Epoch 1/25, Train Loss: 2.2910, Val Loss: 1.0468, MAE: 28.2551, MRE:
53.1900

Epoch 2/25 (Training): 100%|██████████| 192/192 [00:17<00:00,
10.78it/s]
Epoch 2/25 (Validation): 100%|██████████| 48/48 [00:01<00:00,
27.96it/s]

Epoch 2/25, Train Loss: 1.0168, Val Loss: 1.0053, MAE: 27.8867, MRE:
40.5672

Epoch 3/25 (Training): 100%|██████████| 192/192 [00:17<00:00,
10.93it/s]
Epoch 3/25 (Validation): 100%|██████████| 48/48 [00:01<00:00,
28.29it/s]

Epoch 3/25, Train Loss: 0.9926, Val Loss: 1.0094, MAE: 27.8555, MRE:
39.7913

Epoch 4/25 (Training): 100%|██████████| 192/192 [00:17<00:00,
10.86it/s]
Epoch 4/25 (Validation): 100%|██████████| 48/48 [00:01<00:00,
27.69it/s]

Epoch 4/25, Train Loss: 0.9432, Val Loss: 1.0516, MAE: 28.2206, MRE:
50.1168

Epoch 5/25 (Training): 100%|██████████| 192/192 [00:17<00:00,
10.87it/s]
Epoch 5/25 (Validation): 100%|██████████| 48/48 [00:01<00:00,
28.69it/s]

Epoch 5/25, Train Loss: 0.8352, Val Loss: 1.1161, MAE: 28.7988, MRE:
61.0838

Epoch 6/25 (Training): 100%|██████████| 192/192 [00:17<00:00,
10.92it/s]
Epoch 6/25 (Validation): 100%|██████████| 48/48 [00:01<00:00,
27.64it/s]

Epoch 6/25, Train Loss: 0.7214, Val Loss: 1.1602, MAE: 29.1545, MRE:
65.5315

Epoch 7/25 (Training): 100%|██████████| 192/192 [00:18<00:00,
10.63it/s]
Epoch 7/25 (Validation): 100%|██████████| 48/48 [00:01<00:00,
27.80it/s]
```

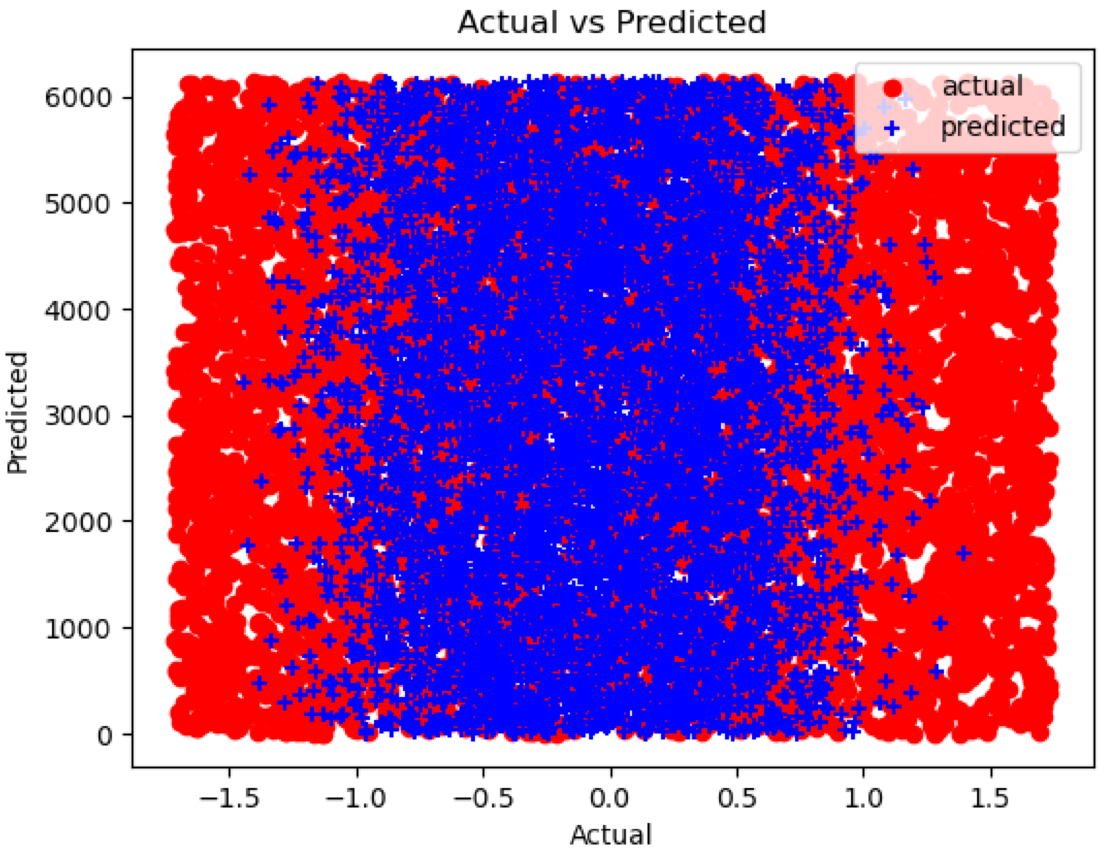
```
Epoch 7/25, Train Loss: 0.6681, Val Loss: 1.1804, MAE: 29.3739, MRE:
67.6969

Epoch 8/25 (Training): 100%|██████████| 192/192 [00:17<00:00,
10.88it/s]
Epoch 8/25 (Validation): 100%|██████████| 48/48 [00:01<00:00,
24.25it/s]

Epoch 8/25, Train Loss: 0.6355, Val Loss: 1.1841, MAE: 29.3788, MRE:
70.1966

Epoch 9/25 (Training): 100%|██████████| 192/192 [00:17<00:00,
10.75it/s]
Epoch 9/25 (Validation): 100%|██████████| 48/48 [00:01<00:00,
28.27it/s]

Epoch 9/25, Train Loss: 0.6284, Val Loss: 1.1927, MAE: 29.4578, MRE:
66.7619

Epoch 10/25 (Training): 100%|██████████| 192/192 [00:17<00:00,
10.84it/s]
Epoch 10/25 (Validation): 100%|██████████| 48/48 [00:01<00:00,
27.92it/s]

Epoch 10/25, Train Loss: 0.6279, Val Loss: 1.1952, MAE: 29.4827, MRE:
68.5710

Epoch 11/25 (Training): 100%|██████████| 192/192 [00:17<00:00,
10.91it/s]
Epoch 11/25 (Validation): 100%|██████████| 48/48 [00:01<00:00,
28.80it/s]

Epoch 11/25, Train Loss: 0.6212, Val Loss: 1.1971, MAE: 29.5317, MRE:
68.6669

Epoch 12/25 (Training): 100%|██████████| 192/192 [00:17<00:00,
10.82it/s]
Epoch 12/25 (Validation): 100%|██████████| 48/48 [00:01<00:00,
28.62it/s]

Epoch 12/25, Train Loss: 0.6217, Val Loss: 1.1946, MAE: 29.4807, MRE:
67.9945

Epoch 13/25 (Training): 100%|██████████| 192/192 [00:17<00:00,
10.89it/s]
Epoch 13/25 (Validation): 100%|██████████| 48/48 [00:01<00:00,
28.73it/s]

Epoch 13/25, Train Loss: 0.6260, Val Loss: 1.2023, MAE: 29.5888, MRE:
69.7192
```

```
Epoch 14/25 (Training): 100%|██████████| 192/192 [00:17<00:00,
10.75it/s]
Epoch 14/25 (Validation): 100%|██████████| 48/48 [00:01<00:00,
28.48it/s]

Epoch 14/25, Train Loss: 0.6217, Val Loss: 1.2009, MAE: 29.5425, MRE:
70.5573

Epoch 15/25 (Training): 100%|██████████| 192/192 [00:17<00:00,
10.81it/s]
Epoch 15/25 (Validation): 100%|██████████| 48/48 [00:01<00:00,
27.95it/s]

Epoch 15/25, Train Loss: 0.6157, Val Loss: 1.2013, MAE: 29.5451, MRE:
71.3579

Epoch 16/25 (Training): 100%|██████████| 192/192 [00:17<00:00,
10.87it/s]
Epoch 16/25 (Validation): 100%|██████████| 48/48 [00:01<00:00,
25.66it/s]

Epoch 16/25, Train Loss: 0.6229, Val Loss: 1.1934, MAE: 29.4546, MRE:
69.8453

Epoch 17/25 (Training): 100%|██████████| 192/192 [00:17<00:00,
10.69it/s]
Epoch 17/25 (Validation): 100%|██████████| 48/48 [00:01<00:00,
28.80it/s]

Epoch 17/25, Train Loss: 0.6210, Val Loss: 1.2000, MAE: 29.5747, MRE:
68.9351

Epoch 18/25 (Training): 100%|██████████| 192/192 [00:17<00:00,
10.78it/s]
Epoch 18/25 (Validation): 100%|██████████| 48/48 [00:01<00:00,
28.05it/s]

Epoch 18/25, Train Loss: 0.6232, Val Loss: 1.1924, MAE: 29.4755, MRE:
71.0570

Epoch 19/25 (Training): 100%|██████████| 192/192 [00:17<00:00,
10.88it/s]
Epoch 19/25 (Validation): 100%|██████████| 48/48 [00:01<00:00,
28.32it/s]

Epoch 19/25, Train Loss: 0.6228, Val Loss: 1.1969, MAE: 29.5328, MRE:
71.6054

Epoch 20/25 (Training): 100%|██████████| 192/192 [00:17<00:00,
10.87it/s]
Epoch 20/25 (Validation): 100%|██████████| 48/48 [00:01<00:00,
27.00it/s]
```

```
Epoch 20/25, Train Loss: 0.6276, Val Loss: 1.1953, MAE: 29.5002, MRE:
68.7393

Epoch 21/25 (Training): 100%|██████████| 192/192 [00:17<00:00,
10.84it/s]
Epoch 21/25 (Validation): 100%|██████████| 48/48 [00:01<00:00,
28.29it/s]

Epoch 21/25, Train Loss: 0.6189, Val Loss: 1.2001, MAE: 29.5660, MRE:
67.1437

Epoch 22/25 (Training): 100%|██████████| 192/192 [00:17<00:00,
10.72it/s]
Epoch 22/25 (Validation): 100%|██████████| 48/48 [00:01<00:00,
28.44it/s]

Epoch 22/25, Train Loss: 0.6202, Val Loss: 1.1977, MAE: 29.5159, MRE:
71.3000

Epoch 23/25 (Training): 100%|██████████| 192/192 [00:17<00:00,
10.86it/s]
Epoch 23/25 (Validation): 100%|██████████| 48/48 [00:01<00:00,
28.19it/s]

Epoch 23/25, Train Loss: 0.6072, Val Loss: 1.1940, MAE: 29.4635, MRE:
70.7605

Epoch 24/25 (Training): 100%|██████████| 192/192 [00:17<00:00,
10.91it/s]
Epoch 24/25 (Validation): 100%|██████████| 48/48 [00:02<00:00,
22.54it/s]

Epoch 24/25, Train Loss: 0.6257, Val Loss: 1.1993, MAE: 29.5373, MRE:
73.3018

Epoch 25/25 (Training): 100%|██████████| 192/192 [00:17<00:00,
10.90it/s]
Epoch 25/25 (Validation): 100%|██████████| 48/48 [00:01<00:00,
27.53it/s]

Epoch 25/25, Train Loss: 0.6159, Val Loss: 1.1982, MAE: 29.4879, MRE:
69.7402
Model saved successfully.
Finished training
```

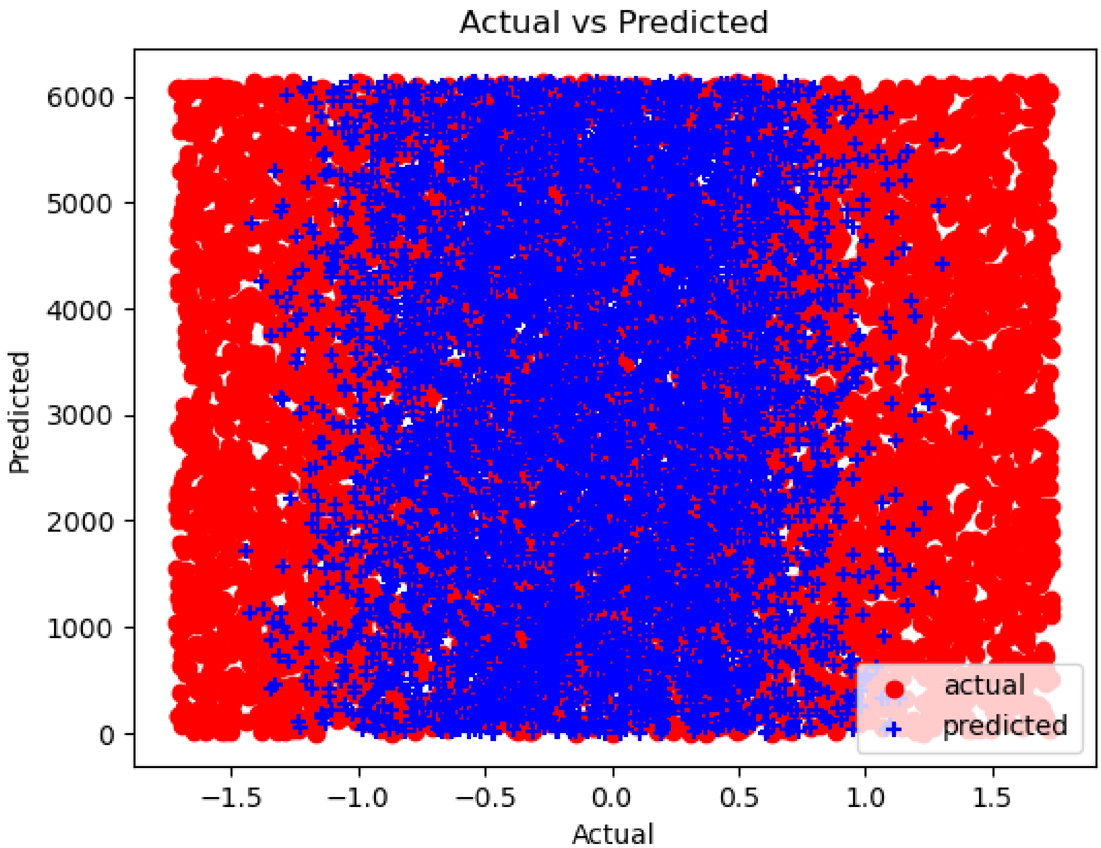
```
checkpoint = torch.load("/kaggle/working/best_model_val_loss.pth")
model = DeepViT(
    image_size = 125,
    patch_size = 25,
    num_classes = 1,
    dim = 1024,
    depth = 6,
```

```
    heads = 8,
    channels = 4,
    mlp_dim = 2048,
    dropout = 0.1,
    emb_dropout = 0.1
)

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 = []

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)
        y_true.extend(target.cpu().numpy().tolist())
        y_pred.extend(output.cpu().numpy().tolist())

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()
```




```
criterion(torch.tensor(y_pred),torch.tensor(y_true))

/opt/conda/lib/python3.7/site-packages/torch/nn/modules/loss.py:536:
UserWarning: Using a target size (torch.Size([6140])) that is
different to the input size (torch.Size([6140, 1])). This will likely
lead to incorrect results due to broadcasting. Please ensure they have
the same size.
  return F.mse_loss(input, target, reduction=self.reduction)

tensor(1.2714)

checkpoint = torch.load("/kaggle/working/best_model_mre.pth")
modell = DeepViT(
    image_size = 125,
    patch_size = 25,
    num_classes = 1,
    dim = 1024,
    depth = 6,
    heads = 8,
    channels = 4,
    mlp_dim = 2048,
    dropout = 0.1,
    emb_dropout = 0.1
)
```

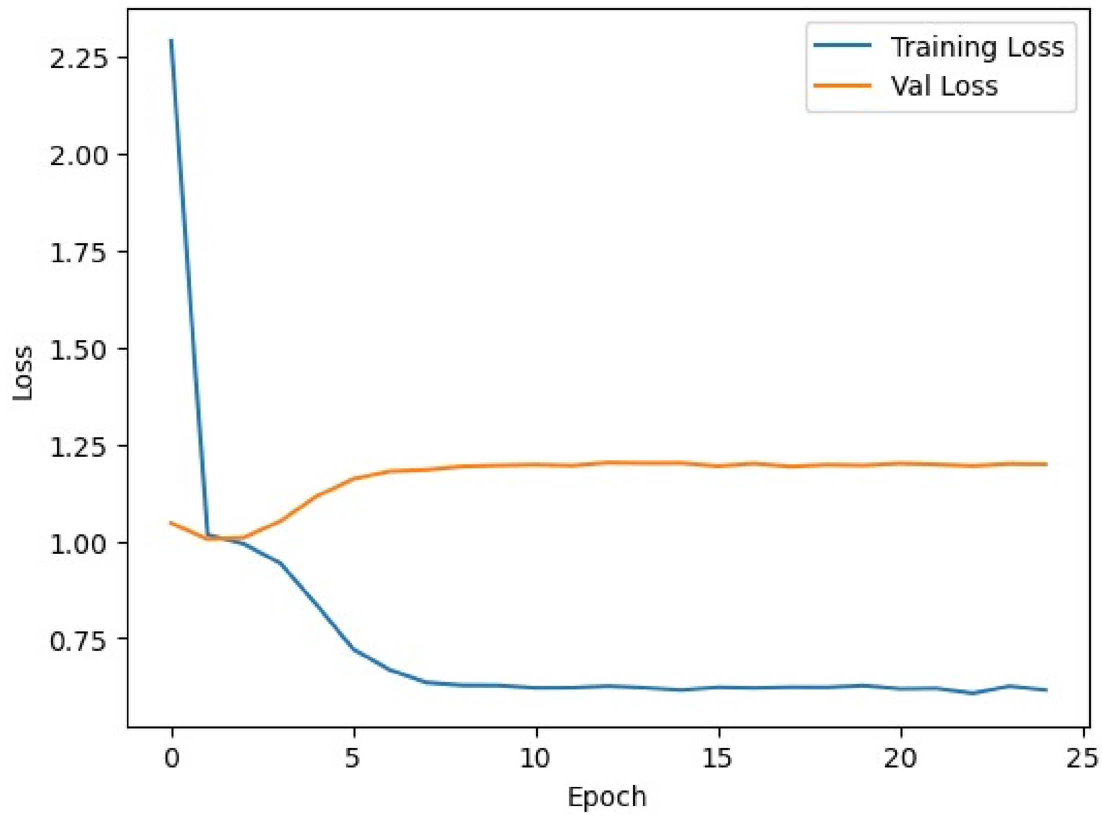
```python
if torch.cuda.device_count() > 1:
    modell = nn.DataParallel(modell)
modell.load_state_dict(checkpoint)
modell = modell.to(device)
modell.eval()

y_true = []
y_pred = []

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 = modell(data)
        y_true.extend(target.cpu().numpy().tolist())
        y_pred.extend(output.cpu().numpy().tolist())

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()
```



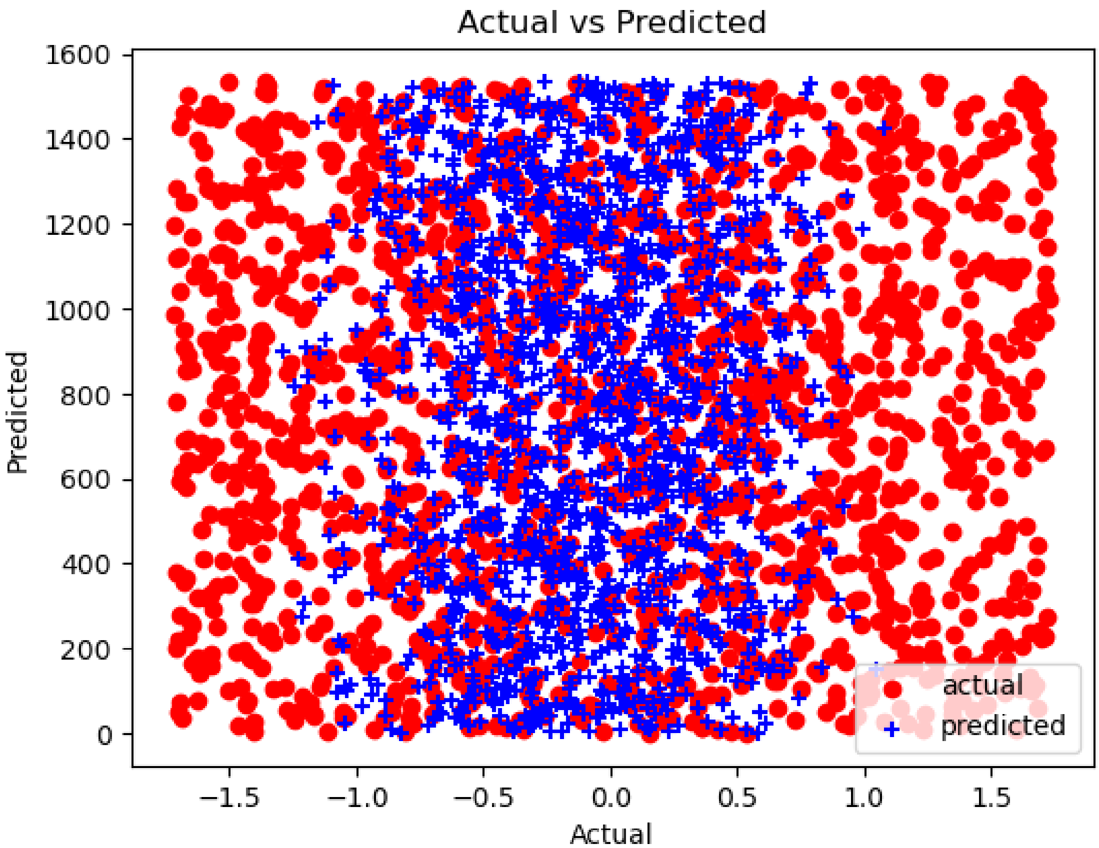

```
criterion(torch.tensor(y_pred),torch.tensor(y_true))
```

```
tensor(1.2714)
```

```
plt.plot( train_losses, label='Training Loss')
plt.plot( val_losses, label='Val Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend()
plt.show()
```




```
model.eval()
y_true = []
y_pred = []

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)

        y_true.extend(target.cpu().numpy().tolist())
        y_pred.extend(output.cpu().numpy().tolist())

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()
```




```
criterion(torch.tensor(y_pred),torch.tensor(y_true))
```

```
/opt/conda/lib/python3.7/site-packages/torch/nn/modules/loss.py:536:
UserWarning: Using a target size (torch.Size([1536])) that is
different to the input size (torch.Size([1536, 1])). This will likely
lead to incorrect results due to broadcasting. Please ensure they have
the same size.
  return F.mse_loss(input, target, reduction=self.reduction)

tensor(1.2054)
```