Imports

```
import os
import warnings
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from PIL import Image

import torch
import torch.nn as nn
import torch.optim as optim
from torch.utils.data import Dataset, DataLoader
from torchvision import transforms

from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from tqdm import tqdm

```

```
warnings.filterwarnings("ignore")
```

Configuration & Reproducibility

```
SEED = 42
BASE_PATH = "/kaggle/input/csiro-biomass"

IMG_SIZE = 224
BATCH_SIZE = 16
NUM_EPOCHS = 50

LEARNING_RATE = 1e-3
WEIGHT_DECAY = 1e-4

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

np.random.seed(SEED)
torch.manual_seed(SEED)
torch.cuda.manual_seed_all(SEED)
torch.backends.cudnn.deterministic = True
torch.backends.cudnn.benchmark = False

```

Load & Reshape Training Data

```
train_csv = pd.read_csv(f"{BASE_PATH}/train.csv")

train_df = train_csv.pivot_table(
    index="image_path",
    columns="target_name",
    values="target"
).reset_index()

train_df.fillna(0, inplace=True)

```

```
TARGET_COLUMNS = [
    'Dry_Green_g',
    'Dry_Dead_g',
    'Dry_Clover_g',
    'GDM_g',
    'Dry_Total_g'
```

```
]

```

Train / Validation Split & Target Scaling

```
train_df, val_df = train_test_split(
    train_df, test_size=0.2, random_state=SEED, shuffle=True
)

```

```
target_scaler = StandardScaler()
target_scaler.fit(train_df[TARGET_COLUMNS].values)

```

▾ StandardScaler

```
StandardScaler()
```

Dataset Definition

```
class BiomassDataset(Dataset):
    def __init__(self, dataframe, image_dir, transform, scaler=None):
        self.df = dataframe.copy()
        self.df["image_path"] = self.df["image_path"].apply(os.path.basename)
        self.samples = list(self.df.itertuples(index=False))
        self.image_dir = image_dir
        self.transform = transform
        self.scaler = scaler

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

    def __getitem__(self, idx):
        row = self.samples[idx]

        image = Image.open(
            os.path.join(self.image_dir, row.image_path)
        ).convert("RGB")
        image = self.transform(image)

        targets = np.array(
            [getattr(row, c) for c in TARGET_COLUMNS],
            dtype=np.float32
        )

        if self.scaler:
            targets = self.scaler.transform(targets.reshape(1, -1))[0]

        return image, torch.tensor(targets)

```

Transforms & DataLoaders

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

```

```

```

```
train_loader = DataLoader(
    BiomassDataset(train_df, f"{BASE_PATH}/train", image_transforms, target_scaler),
    batch_size=BATCH_SIZE, shuffle=True, num_workers=2
)

val_loader = DataLoader(
    BiomassDataset(val_df, f"{BASE_PATH}/train", image_transforms, target_scaler),
    batch_size=BATCH_SIZE, shuffle=False, num_workers=2
)

```

CNN Regression Model

```
class BiomassCNN(nn.Module):
    def __init__(self):
        super().__init__()

        self.features = nn.Sequential(
            nn.Conv2d(3, 32, 3, padding=1),
            nn.ReLU(),
            nn.MaxPool2d(2),

            nn.Conv2d(32, 64, 3, padding=1),
            nn.ReLU(),
            nn.MaxPool2d(2),

            nn.Conv2d(64, 128, 3, padding=1),
            nn.ReLU(),
            nn.AdaptiveAvgPool2d(1)
        )

        self.regressor = nn.Linear(128, len(TARGET_COLUMNS))

    def forward(self, x):
        x = self.features(x)
        return self.regressor(x.flatten(1))

```

```
model = BiomassCNN().to(DEVICE)

```

Loss Function, Optimizer & Metric

```
TARGET_WEIGHTS = torch.tensor(
    [0.1, 0.1, 0.1, 0.2, 0.5],
    device=DEVICE
)

```

```
class WeightedMSELoss(nn.Module):
    def __init__(self, weights):
        super().__init__()
        self.register_buffer("weights", weights)

    def forward(self, predictions, targets):
        return ((predictions - targets) ** 2 * self.weights).mean()

```

```
criterion = WeightedMSELoss(TARGET_WEIGHTS)
optimizer = optim.Adam(
    model.parameters(),
    lr=LEARNING_RATE,
    weight_decay=WEIGHT_DECAY
)

```

```python
def weighted_r2_score(y_true, y_pred, weights):
    mean_y = y_true.mean(0, keepdim=True)
    ss_res = ((y_true - y_pred) ** 2).sum(0)
    ss_tot = ((y_true - mean_y) ** 2).sum(0)
    r2 = 1 - (weights * ss_res).sum() / ((weights * ss_tot).sum() + 1e-8)
    return r2.item()

```

Training / Validation Epoch Function

```python
def run_epoch(model, dataloader, optimizer=None):
    training = optimizer is not None
    model.train() if training else model.eval()

    total_loss, total_r2, count = 0.0, 0.0, 0

    with torch.set_grad_enabled(training):
        for images, targets in dataloader:
            images = images.to(DEVICE)
            targets = targets.to(DEVICE)

            predictions = model(images)
            loss = criterion(predictions, targets)

            if training:
                optimizer.zero_grad()
                loss.backward()
                optimizer.step()

            batch_size = images.size(0)
            total_loss += loss.item() * batch_size
            total_r2 += weighted_r2_score(targets, predictions, TARGET_WEIGHTS) * batch_size
            count += batch_size

    return total_loss / count, total_r2 / count

```

Training Loop with History Tracking

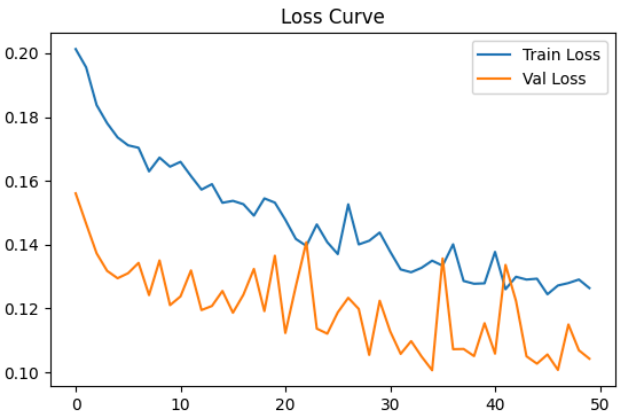
```python
train_losses, val_losses = [], []
train_r2s, val_r2s = [], []

best_val_r2 = -1e9

for epoch in range(NUM_EPOCHS):
    train_loss, train_r2 = run_epoch(model, train_loader, optimizer)
    val_loss, val_r2 = run_epoch(model, val_loader)

    train_losses.append(train_loss)
    val_losses.append(val_loss)
    train_r2s.append(train_r2)
    val_r2s.append(val_r2)

    if val_r2 > best_val_r2:
        best_val_r2 = val_r2
        torch.save(model.state_dict(), "best_model.pth")

    print(
        f"Epoch {epoch+1}/{NUM_EPOCHS} | "
        f"Train Loss: {train_loss:.4f}, R²: {train_r2:.4f} | "
        f"Val Loss: {val_loss:.4f}, R²: {val_r2:.4f}"
    )

```

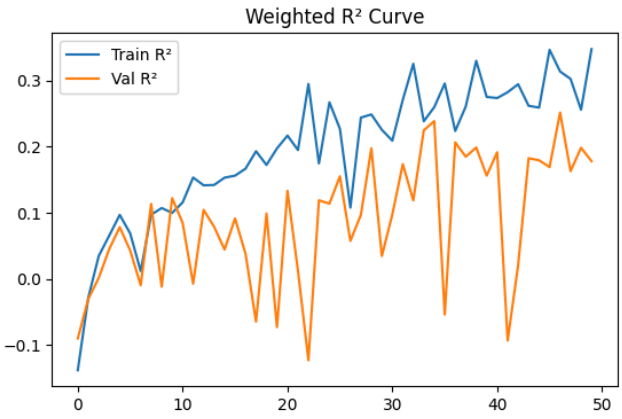
```
Epoch 1/50 | Train Loss: 0.2013, R²: -0.1382 | Val Loss: 0.1561, R²: -0.0901
Epoch 2/50 | Train Loss: 0.1956, R²: -0.0285 | Val Loss: 0.1466, R²: -0.0304
Epoch 3/50 | Train Loss: 0.1838, R²: 0.0347 | Val Loss: 0.1373, R²: 0.0016
Epoch 4/50 | Train Loss: 0.1781, R²: 0.0654 | Val Loss: 0.1318, R²: 0.0451
Epoch 5/50 | Train Loss: 0.1736, R²: 0.0968 | Val Loss: 0.1295, R²: 0.0782
```

```
Epoch 6/50 | Train Loss: 0.1712, R²: 0.0686 | Val Loss: 0.1311, R²: 0.0428
Epoch 7/50 | Train Loss: 0.1704, R²: 0.0118 | Val Loss: 0.1343, R²: -0.0096
Epoch 8/50 | Train Loss: 0.1630, R²: 0.0971 | Val Loss: 0.1242, R²: 0.1134
Epoch 9/50 | Train Loss: 0.1673, R²: 0.1071 | Val Loss: 0.1351, R²: -0.0118
Epoch 10/50 | Train Loss: 0.1645, R²: 0.0998 | Val Loss: 0.1211, R²: 0.1220
Epoch 11/50 | Train Loss: 0.1660, R²: 0.1156 | Val Loss: 0.1238, R²: 0.0847
Epoch 12/50 | Train Loss: 0.1615, R²: 0.1533 | Val Loss: 0.1319, R²: -0.0073
Epoch 13/50 | Train Loss: 0.1573, R²: 0.1415 | Val Loss: 0.1195, R²: 0.1043
Epoch 14/50 | Train Loss: 0.1590, R²: 0.1420 | Val Loss: 0.1208, R²: 0.0789
Epoch 15/50 | Train Loss: 0.1531, R²: 0.1531 | Val Loss: 0.1255, R²: 0.0444
Epoch 16/50 | Train Loss: 0.1538, R²: 0.1561 | Val Loss: 0.1187, R²: 0.0914
Epoch 17/50 | Train Loss: 0.1527, R²: 0.1667 | Val Loss: 0.1243, R²: 0.0379
Epoch 18/50 | Train Loss: 0.1491, R²: 0.1930 | Val Loss: 0.1324, R²: -0.0647
Epoch 19/50 | Train Loss: 0.1545, R²: 0.1723 | Val Loss: 0.1192, R²: 0.0988
Epoch 20/50 | Train Loss: 0.1532, R²: 0.1973 | Val Loss: 0.1365, R²: -0.0730
Epoch 21/50 | Train Loss: 0.1478, R²: 0.2167 | Val Loss: 0.1123, R²: 0.1331
Epoch 22/50 | Train Loss: 0.1418, R²: 0.1948 | Val Loss: 0.1270, R²: 0.0123
Epoch 23/50 | Train Loss: 0.1396, R²: 0.2947 | Val Loss: 0.1408, R²: -0.1231
Epoch 24/50 | Train Loss: 0.1464, R²: 0.1746 | Val Loss: 0.1137, R²: 0.1189
Epoch 25/50 | Train Loss: 0.1408, R²: 0.2670 | Val Loss: 0.1121, R²: 0.1137
Epoch 26/50 | Train Loss: 0.1371, R²: 0.2269 | Val Loss: 0.1188, R²: 0.1551
Epoch 27/50 | Train Loss: 0.1527, R²: 0.1078 | Val Loss: 0.1234, R²: 0.0574
Epoch 28/50 | Train Loss: 0.1401, R²: 0.2439 | Val Loss: 0.1199, R²: 0.0968
Epoch 29/50 | Train Loss: 0.1412, R²: 0.2487 | Val Loss: 0.1055, R²: 0.1974
Epoch 30/50 | Train Loss: 0.1438, R²: 0.2254 | Val Loss: 0.1224, R²: 0.0345
Epoch 31/50 | Train Loss: 0.1378, R²: 0.2090 | Val Loss: 0.1129, R²: 0.0974
Epoch 32/50 | Train Loss: 0.1322, R²: 0.2709 | Val Loss: 0.1058, R²: 0.1735
Epoch 33/50 | Train Loss: 0.1314, R²: 0.3252 | Val Loss: 0.1098, R²: 0.1186
Epoch 34/50 | Train Loss: 0.1328, R²: 0.2383 | Val Loss: 0.1049, R²: 0.2246
Epoch 35/50 | Train Loss: 0.1350, R²: 0.2597 | Val Loss: 0.1007, R²: 0.2385
Epoch 36/50 | Train Loss: 0.1334, R²: 0.2955 | Val Loss: 0.1357, R²: -0.0540
Epoch 37/50 | Train Loss: 0.1401, R²: 0.2237 | Val Loss: 0.1073, R²: 0.2063
Epoch 38/50 | Train Loss: 0.1286, R²: 0.2605 | Val Loss: 0.1073, R²: 0.1848
Epoch 39/50 | Train Loss: 0.1278, R²: 0.3298 | Val Loss: 0.1051, R²: 0.1987
Epoch 40/50 | Train Loss: 0.1279, R²: 0.2751 | Val Loss: 0.1154, R²: 0.1561
Epoch 41/50 | Train Loss: 0.1378, R²: 0.2734 | Val Loss: 0.1059, R²: 0.1915
Epoch 42/50 | Train Loss: 0.1261, R²: 0.2823 | Val Loss: 0.1337, R²: -0.0932
Epoch 43/50 | Train Loss: 0.1300, R²: 0.2943 | Val Loss: 0.1224, R²: 0.0208
Epoch 44/50 | Train Loss: 0.1291, R²: 0.2617 | Val Loss: 0.1050, R²: 0.1824
Epoch 45/50 | Train Loss: 0.1293, R²: 0.2590 | Val Loss: 0.1027, R²: 0.1793
Epoch 46/50 | Train Loss: 0.1245, R²: 0.3464 | Val Loss: 0.1056, R²: 0.1691
Epoch 47/50 | Train Loss: 0.1272, R²: 0.3136 | Val Loss: 0.1008, R²: 0.2515
Epoch 48/50 | Train Loss: 0.1280, R²: 0.3024 | Val Loss: 0.1150, R²: 0.1629
Epoch 49/50 | Train Loss: 0.1291, R²: 0.2558 | Val Loss: 0.1069, R²: 0.1982
Epoch 50/50 | Train Loss: 0.1264, R²: 0.3475 | Val Loss: 0.1043, R²: 0.1780
```

Training Curves (Loss & R^2)

```
plt.figure(figsize=(14,4))

plt.subplot(1,2,1)
plt.plot(train_losses, label="Train Loss")
plt.plot(val_losses, label="Val Loss")
plt.legend()
plt.title("Loss Curve")

plt.subplot(1,2,2)
plt.plot(train_r2s, label="Train R²")
plt.plot(val_r2s, label="Val R²")
plt.legend()
plt.title("Weighted R² Curve")

plt.show()

```





Load Best Model

```
best_model = BiomassCNN().to(DEVICE)
best_model.load_state_dict(torch.load("best_model.pth", map_location=DEVICE))
best_model.eval()

```

```
BiomassCNN(
  (features): Sequential(
    (0): Conv2d(3, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (1): ReLU()
    (2): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
    (3): Conv2d(32, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (4): ReLU()
    (5): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
    (6): Conv2d(64, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (7): ReLU()
    (8): AdaptiveAvgPool2d(output_size=1)
  )
  (regressor): Linear(in_features=128, out_features=5, bias=True)
)
```

Test Inference & Submission

```
test_dir = f"{BASE_PATH}/test"
submission_rows = []

with torch.no_grad():
    for file in tqdm(sorted(os.listdir(test_dir))):
        image = Image.open(os.path.join(test_dir, file)).convert("RGB")
        tensor = image_transforms(image).unsqueeze(0).to(DEVICE)

        preds_scaled = best_model(tensor).cpu().numpy()
        preds = target_scaler.inverse_transform(preds_scaled)[0]

        image_id = file.replace(".jpg", "")
        for name, value in zip(TARGET_COLUMNS, preds):
            submission_rows.append({
                "sample_id": f"{image_id}__{name}",
                "target": max(0, value)
            })

```

```
100%|██████████| 1/1 [00:00<00:00,  6.92it/s]
```

```
submission_df = pd.DataFrame(submission_rows)
submission_df.head()

```

	sample_id	target
0	ID1001187975__Dry_Green_g	17.660715
1	ID1001187975__Dry_Dead_g	18.764156
2	ID1001187975__Dry_Clover_g	2.354568
3	ID1001187975__GDM_g	20.842461
4	ID1001187975__Dry_Total_g	38.504654

```
submission_df.to_csv("submission.csv", index=False)
```