Imports

```python
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")

```

Config & Reproducibility

```python
SEED = 42
BASE_PATH = "/kaggle/input/csiro-biomass"
IMG_SIZE = 224
BATCH_SIZE = 16
NUM_EPOCHS = 20
LEARNING_RATE = 1e-3
WEIGHT_DECAY = 1e-4  # ✅ Added this
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 & Pivot Dataset

```python
df = pd.read_csv(os.path.join(BASE_PATH, "train.csv"))
df = df.pivot_table(index="image_path", columns="target_name", values="target").reset_index()
df.fillna(0, inplace=True)

TARGET_COLUMNS = ['Dry_Green_g','Dry_Dead_g','Dry_Clover_g','GDM_g','Dry_Total_g']
print("Dataset shape:", df.shape)

```

```
Dataset shape: (357, 6)
```

Train/Validation Split & Scaling

```python
train_df, val_df = train_test_split(df, test_size=0.2, random_state=SEED, shuffle=True)
scaler = StandardScaler()
scaler.fit(train_df[TARGET_COLUMNS].values)

```

```
▾ StandardScaler
StandardScaler()
```

Dataset Class & DataLoaders

```python
class BiomassDataset(Dataset):
    def __init__(self, df, image_dir, transform=None, scaler=None):
        self.df = df.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")
        if self.transform:
            image = self.transform(image)
        target = np.array([getattr(row, t) for t in TARGET_COLUMNS], dtype=np.float32)
        if self.scaler:
            target = self.scaler.transform(target.reshape(1,-1))[0]
        return image, torch.tensor(target)

transform = transforms.Compose([
    transforms.Resize((IMG_SIZE, IMG_SIZE)),
    transforms.ToTensor(),
    transforms.Normalize([0.485,0.456,0.406],[0.229,0.224,0.225])
])

train_dataset = BiomassDataset(train_df, os.path.join(BASE_PATH,"train"), transform, scaler)
val_dataset = BiomassDataset(val_df, os.path.join(BASE_PATH,"train"), transform, scaler)

train_loader = DataLoader(train_dataset, batch_size=BATCH_SIZE, shuffle=True, num_workers=2)
val_loader = DataLoader(val_dataset, batch_size=BATCH_SIZE, shuffle=False, num_workers=2)

```

Weighted Loss & Metric

```python
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, preds, targets):
        return ((preds-targets)**2 * self.weights).mean()

criterion = WeightedMSELoss(TARGET_WEIGHTS)

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)
    return (1 - (weights*ss_res).sum() / ((weights*ss_tot).sum()+1e-8)).item()

```

Flexible CNN Model for Experimenting with Blocks

```python
class FlexibleCNN(nn.Module):
    def __init__(self, num_blocks=3, base_channels=32, num_outputs=5):
        super().__init__()
        layers = []
        in_channels = 3
        out_channels = base_channels
        for i in range(num_blocks):
            layers.append(nn.Conv2d(in_channels, out_channels, 3, padding=1))
            layers.append(nn.BatchNorm2d(out_channels))
            layers.append(nn.ReLU(inplace=True))
            layers.append(nn.MaxPool2d(2))
            in_channels = out_channels
            out_channels *= 2
        layers.append(nn.AdaptiveAvgPool2d(1))
        self.features = nn.Sequential(*layers)
        self.regressor = nn.Linear(in_channels, num_outputs)
    def forward(self, x):
        x = self.features(x)
        return self.regressor(x.flatten(1))

```

Epoch Function

```
def run_epoch(model, loader, optimizer=None):
    training = optimizer is not None
    model.train() if training else model.eval()
    total_loss, total_r2, n = 0.0, 0.0, 0
    with torch.set_grad_enabled(training):
        for images, targets in loader:
            images, targets = images.to(DEVICE), targets.to(DEVICE)
            preds = model(images)
            loss = criterion(preds, targets)
            if training:
                optimizer.zero_grad()
                loss.backward()
                optimizer.step()
            b = images.size(0)
            total_loss += loss.item()*b
            total_r2 += weighted_r2_score(targets, preds, TARGET_WEIGHTS)*b
            n += b
    return total_loss/n, total_r2/n

```

Training & Plotting for Multiple Block Configurations

```
block_options = [2, 3, 4, 5]
results = {}

for num_blocks in block_options:
    print(f"\nTraining CNN with {num_blocks} blocks...")

    model = FlexibleCNN(
        num_blocks=num_blocks,
        base_channels=32,
        num_outputs=len(TARGET_COLUMNS)
    ).to(DEVICE)

    optimizer = optim.Adam(
        model.parameters(),
        lr=LEARNING_RATE,
        weight_decay=WEIGHT_DECAY
    )

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

    for epoch in range(NUM_EPOCHS):
        tr_l, tr_r2 = run_epoch(model, train_loader, optimizer)
        va_l, va_r2 = run_epoch(model, val_loader)

        train_losses.append(tr_l)
        val_losses.append(va_l)
        train_r2s.append(tr_r2)
        val_r2s.append(va_r2)

        print(
            f"Epoch {epoch+1} | "
            f"Train Loss: {tr_l:.4f}, Train R²: {tr_r2:.4f} | "
            f"Val Loss: {va_l:.4f}, Val R²: {va_r2:.4f}"
        )

    results[num_blocks] = {
        "avg_train_loss": np.mean(train_losses),
        "avg_val_loss": np.mean(val_losses),
        "avg_train_r2": np.mean(train_r2s),
        "avg_val_r2": np.mean(val_r2s),
        "train_losses": train_losses,
        "val_losses": val_losses,
        "train_r2s": train_r2s,
        "val_r2s": val_r2s
    }
```

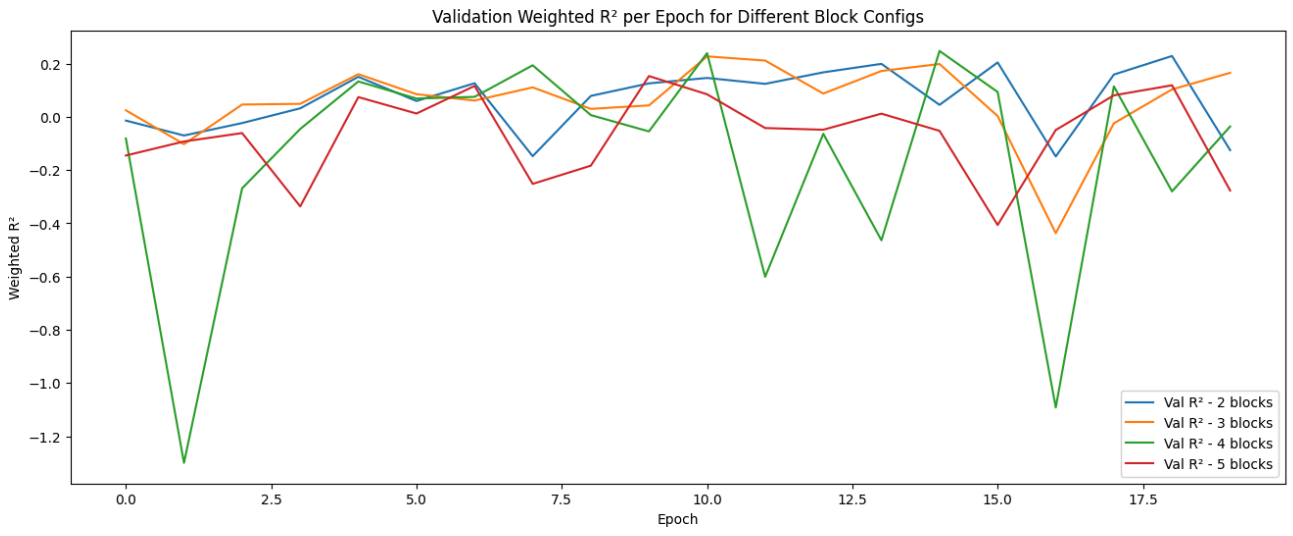
```
Training CNN with 2 blocks...
Epoch 1 | Train Loss: 0.1805, Train R²: 0.0260 | Val Loss: 0.1372, Val R²: -0.0138
Epoch 2 | Train Loss: 0.1622, Train R²: 0.1278 | Val Loss: 0.1375, Val R²: -0.0699
Epoch 3 | Train Loss: 0.1563, Train R²: 0.1682 | Val Loss: 0.1335, Val R²: -0.0231
Epoch 4 | Train Loss: 0.1572, Train R²: 0.1252 | Val Loss: 0.1287, Val R²: 0.0322
Epoch 5 | Train Loss: 0.1547, Train R²: 0.1783 | Val Loss: 0.1150, Val R²: 0.1507
Epoch 6 | Train Loss: 0.1531, Train R²: 0.1753 | Val Loss: 0.1222, Val R²: 0.0597
Epoch 7 | Train Loss: 0.1527, Train R²: 0.1818 | Val Loss: 0.1164, Val R²: 0.1266
Epoch 8 | Train Loss: 0.1501, Train R²: 0.1815 | Val Loss: 0.1453, Val R²: -0.1476
Epoch 9 | Train Loss: 0.1564, Train R²: 0.1456 | Val Loss: 0.1204, Val R²: 0.0788
Epoch 10 | Train Loss: 0.1509, Train R²: 0.1843 | Val Loss: 0.1162, Val R²: 0.1260
Epoch 11 | Train Loss: 0.1504, Train R²: 0.1838 | Val Loss: 0.1137, Val R²: 0.1464
Epoch 12 | Train Loss: 0.1447, Train R²: 0.1619 | Val Loss: 0.1155, Val R²: 0.1242
Epoch 13 | Train Loss: 0.1476, Train R²: 0.1585 | Val Loss: 0.1109, Val R²: 0.1675
Epoch 14 | Train Loss: 0.1437, Train R²: 0.2168 | Val Loss: 0.1086, Val R²: 0.1993
Epoch 15 | Train Loss: 0.1490, Train R²: 0.1277 | Val Loss: 0.1239, Val R²: 0.0452
Epoch 16 | Train Loss: 0.1458, Train R²: 0.1995 | Val Loss: 0.1056, Val R²: 0.2047
Epoch 17 | Train Loss: 0.1429, Train R²: 0.2322 | Val Loss: 0.1454, Val R²: -0.1486
Epoch 18 | Train Loss: 0.1468, Train R²: 0.1292 | Val Loss: 0.1137, Val R²: 0.1592
Epoch 19 | Train Loss: 0.1437, Train R²: 0.2671 | Val Loss: 0.1034, Val R²: 0.2289
Epoch 20 | Train Loss: 0.1431, Train R²: 0.2689 | Val Loss: 0.1410, Val R²: -0.1249

Training CNN with 3 blocks...
Epoch 1 | Train Loss: 0.1924, Train R²: -0.0895 | Val Loss: 0.1296, Val R²: 0.0249
Epoch 2 | Train Loss: 0.1670, Train R²: 0.0867 | Val Loss: 0.1395, Val R²: -0.1025
Epoch 3 | Train Loss: 0.1583, Train R²: 0.1680 | Val Loss: 0.1237, Val R²: 0.0465
Epoch 4 | Train Loss: 0.1534, Train R²: 0.1692 | Val Loss: 0.1215, Val R²: 0.0490
Epoch 5 | Train Loss: 0.1518, Train R²: 0.1901 | Val Loss: 0.1148, Val R²: 0.1606
Epoch 6 | Train Loss: 0.1547, Train R²: 0.0961 | Val Loss: 0.1199, Val R²: 0.0853
Epoch 7 | Train Loss: 0.1480, Train R²: 0.2074 | Val Loss: 0.1208, Val R²: 0.0613
Epoch 8 | Train Loss: 0.1472, Train R²: 0.1821 | Val Loss: 0.1163, Val R²: 0.1110
Epoch 9 | Train Loss: 0.1487, Train R²: 0.1626 | Val Loss: 0.1243, Val R²: 0.0302
Epoch 10 | Train Loss: 0.1424, Train R²: 0.2109 | Val Loss: 0.1229, Val R²: 0.0432
Epoch 11 | Train Loss: 0.1427, Train R²: 0.2572 | Val Loss: 0.1049, Val R²: 0.2274
Epoch 12 | Train Loss: 0.1367, Train R²: 0.2930 | Val Loss: 0.1024, Val R²: 0.2117
Epoch 13 | Train Loss: 0.1368, Train R²: 0.2382 | Val Loss: 0.1147, Val R²: 0.0877
Epoch 14 | Train Loss: 0.1431, Train R²: 0.2087 | Val Loss: 0.1083, Val R²: 0.1726
Epoch 15 | Train Loss: 0.1335, Train R²: 0.3172 | Val Loss: 0.1008, Val R²: 0.1989
Epoch 16 | Train Loss: 0.1404, Train R²: 0.0771 | Val Loss: 0.1341, Val R²: 0.0031
Epoch 17 | Train Loss: 0.1457, Train R²: 0.2047 | Val Loss: 0.1723, Val R²: -0.4369
Epoch 18 | Train Loss: 0.1319, Train R²: 0.3001 | Val Loss: 0.1244, Val R²: -0.0241
Epoch 19 | Train Loss: 0.1337, Train R²: 0.2853 | Val Loss: 0.1097, Val R²: 0.1034
Epoch 20 | Train Loss: 0.1295, Train R²: 0.2766 | Val Loss: 0.1016, Val R²: 0.1657

Training CNN with 4 blocks...
Epoch 1 | Train Loss: 0.2287, Train R²: -0.4154 | Val Loss: 0.1458, Val R²: -0.0812
Epoch 2 | Train Loss: 0.1663, Train R²: 0.0855 | Val Loss: 0.2762, Val R²: -1.3003
Epoch 3 | Train Loss: 0.1602, Train R²: 0.1319 | Val Loss: 0.1591, Val R²: -0.2684
Epoch 4 | Train Loss: 0.1500, Train R²: 0.2015 | Val Loss: 0.1345, Val R²: -0.0453
Epoch 5 | Train Loss: 0.1477, Train R²: 0.2491 | Val Loss: 0.1156, Val R²: 0.1333
Epoch 6 | Train Loss: 0.1474, Train R²: 0.1949 | Val Loss: 0.1253, Val R²: 0.0690
Epoch 7 | Train Loss: 0.1532, Train R²: 0.1102 | Val Loss: 0.1300, Val R²: 0.0753
Epoch 8 | Train Loss: 0.1433, Train R²: 0.2530 | Val Loss: 0.1077, Val R²: 0.1940
Epoch 9 | Train Loss: 0.1406, Train R²: 0.2460 | Val Loss: 0.1317, Val R²: 0.0068
Epoch 10 | Train Loss: 0.1334, Train R²: 0.3139 | Val Loss: 0.1346, Val R²: -0.0545
Epoch 11 | Train Loss: 0.1248, Train R²: 0.3586 | Val Loss: 0.1011, Val R²: 0.2397
Epoch 12 | Train Loss: 0.1323, Train R²: 0.2518 | Val Loss: 0.1944, Val R²: -0.6009
```

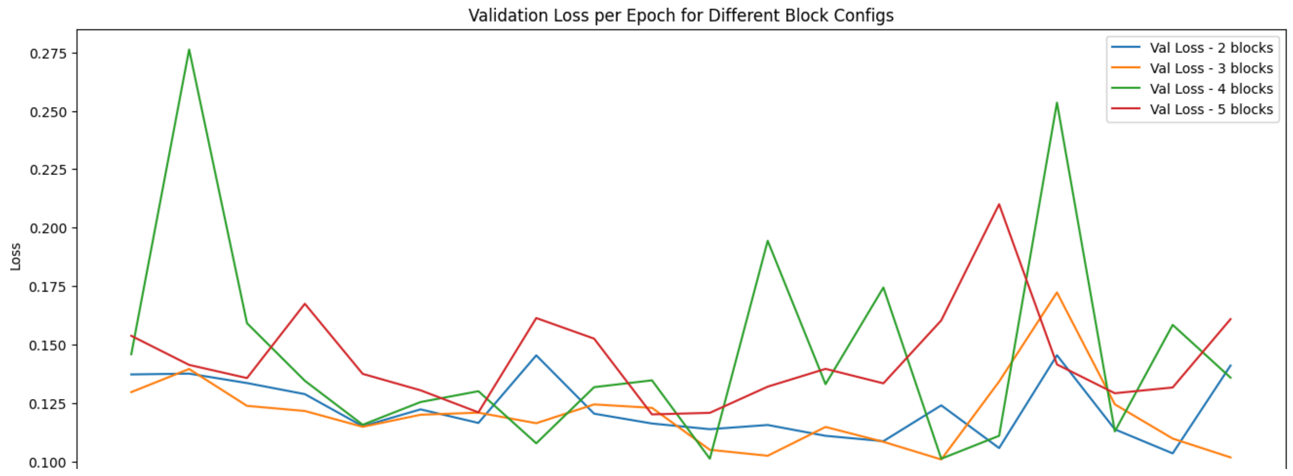
```
summary_blocks = pd.DataFrame.from_dict(results, orient="index")
summary_blocks.index.name = "Num_Blocks"
summary_blocks.reset_index(inplace=True)
```

```python
summary_blocks

```

	Num_Blocks	avg_train_loss	avg_val_loss	avg_train_r2	avg_val_r2	train_losses	val_losses	tr
0	2	0.151590	0.122704	0.171976	0.066071	[0.18048036344218674, 0.16215475808110152, 0.1...	[0.13716513332393435, 0.13750191695160335, 0.1...	[0.026010393259 0.12778112595
1	3	0.146894	0.120324	0.192086	0.060947	[0.19244544411960401, 0.1670037924197682, 0.15...	[0.12960321373409694, 0.13949323693911234, 0.1...	[-0.08948538387 0.08673575802
2	4	0.139775	0.146794	0.229320	-0.155584	[0.22871638494625426, 0.16630231210014276, 0.1...	[0.14583172731929356, 0.27624425292015076, 0.1...	[-0.41539807863 0.08554171930
3	5	0.147634	0.143968	0.125531	-0.064501	[0.38782147584777127, 0.16790938325095595, 0.1...	[0.1536963176396158, 0.1412452773915397, 0.135...	[-1.8450714594 0.10485507396

```python
# ----------------------------
# Plot curves for all block options
# ----------------------------
plt.figure(figsize=(16,6))
for num_blocks in block_options:
    plt.plot(results[num_blocks]["val_r2s"], label=f"Val R² - {num_blocks} blocks")
plt.title("Validation Weighted R² per Epoch for Different Block Configs")
plt.xlabel("Epoch")
plt.ylabel("Weighted R²")
plt.legend()
plt.show()

plt.figure(figsize=(16,6))
for num_blocks in block_options:
    plt.plot(results[num_blocks]["val_losses"], label=f"Val Loss - {num_blocks} blocks")
plt.title("Validation Loss per Epoch for Different Block Configs")
plt.xlabel("Epoch")
plt.ylabel("Loss")
plt.legend()
plt.show()

```


Validation Weighted R² per Epoch for Different Block Configs
Weighted R²
Epoch
Val R² - 2 blocks
Val R² - 3 blocks
Val R² - 4 blocks
Val R² - 5 blocks


Validation Loss per Epoch for Different Block Configs
Loss
Val Loss - 2 blocks
Val Loss - 3 blocks
Val Loss - 4 blocks
Val Loss - 5 blocks