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

warnings.filterwarnings("ignore")

```

Configuration & Reproducibility

```
SEED = 42
BASE_PATH = "/kaggle/input/csiro-biomass"
IMG_SIZE = 224
BATCH_SIZE = 16
NUM_EPOCHS = 20
LEARNING_RATE = 1e-3

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

```
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

```
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

```
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]
        img = Image.open(os.path.join(self.image_dir, row.image_path)).convert("RGB")
        if self.transform:
            img = self.transform(img)
        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 img, 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])
])

```

Weighted Loss & 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, 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()

```

CNN Architecture With Dropout

```
class CNNWithDropout(nn.Module):
    def __init__(self, num_filters=256, num_blocks=3, dropout=0.0, num_outputs=5):
        super().__init__()
        layers = []
        in_channels = 3

        for _ in range(num_blocks):
            layers += [
                nn.Conv2d(in_channels, num_filters, 3, padding=1),
                nn.BatchNorm2d(num_filters),
                nn.ReLU(inplace=True),
```

```
                nn.MaxPool2d(2),
                nn.Dropout(dropout)
            ]
            in_channels = num_filters

        layers.append(nn.AdaptiveAvgPool2d(1))
        self.features = nn.Sequential(*layers)
        self.regressor = nn.Linear(num_filters, num_outputs)

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

```

One-Epoch Train / Eval 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
    with torch.set_grad_enabled(training):
        for imgs, targets in loader:
            imgs, targets = imgs.to(DEVICE), targets.to(DEVICE)
            preds = model(imgs)
            loss = criterion(preds, targets)
            if training:
                optimizer.zero_grad()
                loss.backward()
                optimizer.step()
            b = imgs.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

```

Experiment Setup – Dropout & Weight Decay Grid

```
dropout_options = [0.0, 0.2, 0.4, 0.6]
weight_decay_options = [0.0, 1e-4, 1e-3]

results = {}

```

Training Loop Across Grid

```
for dropout in dropout_options:
    for wd in weight_decay_options:
        key = f"dropout_{dropout}_wd_{wd}"
        print(f"\n============================")
        print(f" Training: {key}")
        print(f"============================")

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

        model = CNNWithDropout(dropout=dropout).to(DEVICE)
        optimizer = optim.Adam(model.parameters(), lr=LEARNING_RATE, weight_decay=wd)

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

```
        best_val_r2 = -1e9

        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)

            best_val_r2 = max(best_val_r2, va_r2)

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

        results[key] = {
            "avg_train_r2": np.mean(train_r2s),
            "avg_val_r2": np.mean(val_r2s),
            "best_val_r2": best_val_r2,
            "avg_val_loss": np.mean(val_losses),
            "val_r2s": val_r2s
        }

```

```
==============================
 Training: dropout_0.0_wd_0.0
==============================
Epoch 1 | Train R²: -0.1828 | Val R²: -2.8919
Epoch 2 | Train R²: 0.0664 | Val R²: -0.0347
Epoch 3 | Train R²: 0.1575 | Val R²: 0.0125
Epoch 4 | Train R²: 0.1793 | Val R²: -0.1400
Epoch 5 | Train R²: 0.1811 | Val R²: 0.0934
Epoch 6 | Train R²: 0.0074 | Val R²: 0.0233
Epoch 7 | Train R²: 0.2040 | Val R²: 0.2315
Epoch 8 | Train R²: 0.1569 | Val R²: 0.1580
Epoch 9 | Train R²: 0.2087 | Val R²: 0.0561
Epoch 10 | Train R²: 0.1859 | Val R²: 0.0485
Epoch 11 | Train R²: 0.2280 | Val R²: -0.1283
Epoch 12 | Train R²: 0.1222 | Val R²: 0.0917
Epoch 13 | Train R²: 0.3197 | Val R²: 0.2016
Epoch 14 | Train R²: 0.2769 | Val R²: -0.7384
Epoch 15 | Train R²: 0.1959 | Val R²: -0.1416
Epoch 16 | Train R²: 0.2922 | Val R²: 0.1280
Epoch 17 | Train R²: 0.2755 | Val R²: 0.1336
Epoch 18 | Train R²: 0.2298 | Val R²: 0.2124
Epoch 19 | Train R²: 0.2706 | Val R²: 0.0161
Epoch 20 | Train R²: 0.2796 | Val R²: 0.2443

==============================
 Training: dropout_0.0_wd_0.0001
==============================
Epoch 1 | Train R²: -0.4445 | Val R²: -1.5451
Epoch 2 | Train R²: 0.0694 | Val R²: -0.3542
Epoch 3 | Train R²: 0.0678 | Val R²: 0.1681
Epoch 4 | Train R²: 0.1028 | Val R²: 0.0184
Epoch 5 | Train R²: 0.1653 | Val R²: 0.1500
Epoch 6 | Train R²: 0.1500 | Val R²: 0.1379
Epoch 7 | Train R²: 0.2069 | Val R²: 0.1629
Epoch 8 | Train R²: 0.1840 | Val R²: 0.0771
Epoch 9 | Train R²: 0.1435 | Val R²: 0.0471
Epoch 10 | Train R²: 0.1802 | Val R²: 0.0877
Epoch 11 | Train R²: 0.2338 | Val R²: 0.1225
Epoch 12 | Train R²: 0.1835 | Val R²: 0.2038
Epoch 13 | Train R²: 0.2293 | Val R²: 0.2397
Epoch 14 | Train R²: 0.2674 | Val R²: 0.1602
Epoch 15 | Train R²: 0.1730 | Val R²: 0.2021
Epoch 16 | Train R²: 0.2386 | Val R²: 0.1055
Epoch 17 | Train R²: 0.1016 | Val R²: 0.2603
Epoch 18 | Train R²: 0.0866 | Val R²: 0.2133
Epoch 19 | Train R²: 0.2817 | Val R²: -0.1765
Epoch 20 | Train R²: 0.1682 | Val R²: 0.1217

==============================
 Training: dropout_0.0_wd_0.001
==============================
Epoch 1 | Train R²: -0.2934 | Val R²: -0.9866
Epoch 2 | Train R²: 0.1050 | Val R²: -0.2240
Epoch 3 | Train R²: 0.1921 | Val R²: 0.1693
Epoch 4 | Train R²: 0.1502 | Val R²: 0.1464
Epoch 5 | Train R²: 0.1962 | Val R²: 0.1770
```

```
Epoch 6 | Train R²: 0.1200 | Val R²: 0.1763
```

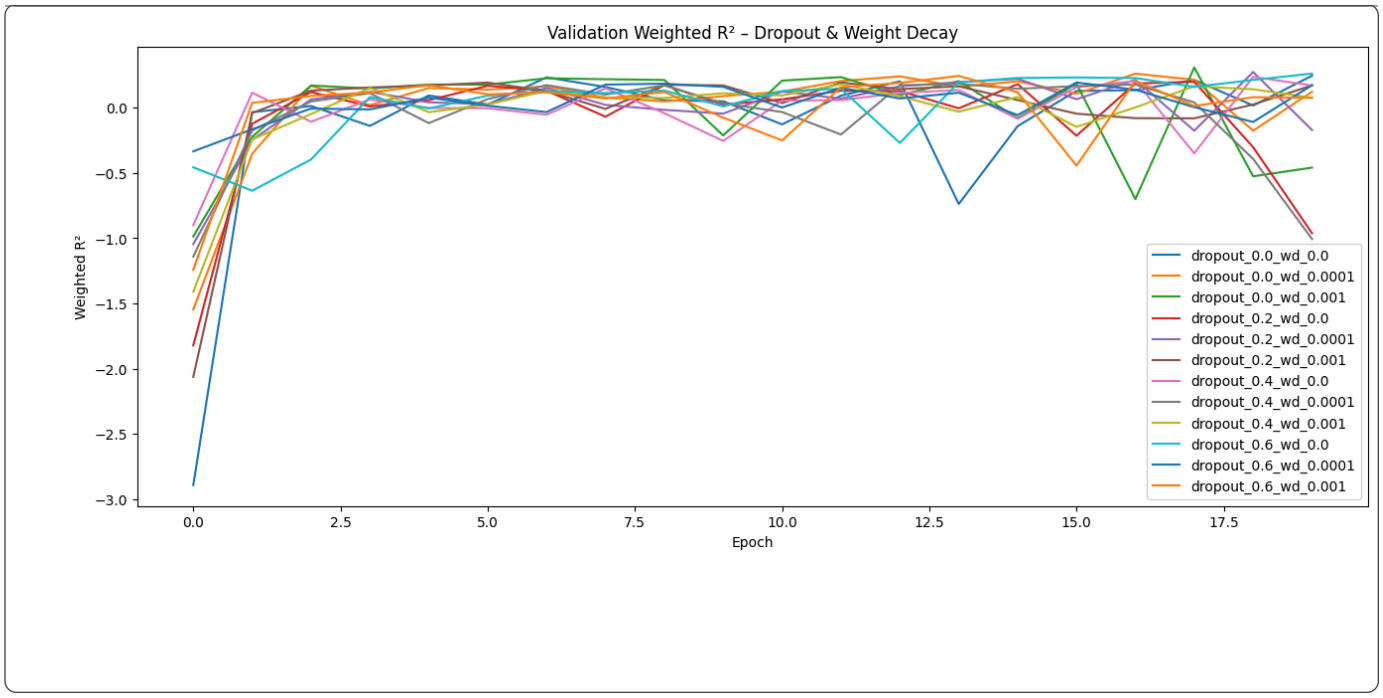
Summary Table

```
summary_df = pd.DataFrame([
    {
        "Config": k,
        "Avg Val R²": results[k]["avg_val_r2"],
        "Best Val R²": results[k]["best_val_r2"],
        "Avg Val Loss": results[k]["avg_val_loss"]
    }
    for k in results
]).sort_values("Avg Val R²", ascending=False)

display(summary_df)

```

	Config	Avg Val R²	Best Val R²	Avg Val Loss
10	dropout_0.6_wd_0.0001	0.036435	0.192588	0.125264
9	dropout_0.6_wd_0.0	0.028142	0.260552	0.127469
1	dropout_0.0_wd_0.0001	0.020124	0.260305	0.127786
4	dropout_0.2_wd_0.0001	0.002020	0.272927	0.128306
11	dropout_0.6_wd_0.001	-0.005603	0.242948	0.131975
6	dropout_0.4_wd_0.0	-0.017695	0.235882	0.132386
5	dropout_0.2_wd_0.001	-0.021093	0.192886	0.133282
8	dropout_0.4_wd_0.001	-0.026578	0.178534	0.133049
2	dropout_0.0_wd_0.001	-0.031743	0.307861	0.136458
7	dropout_0.4_wd_0.0001	-0.074824	0.182548	0.139986
3	dropout_0.2_wd_0.0	-0.096932	0.198283	0.137878
0	dropout_0.0_wd_0.0	-0.121201	0.244329	0.140897

Validation R^2 Curves

```
plt.figure(figsize=(16,6))
for k in results:
    plt.plot(results[k]["val_r2s"], label=k)
plt.title("Validation Weighted R² – Dropout & Weight Decay")
plt.xlabel("Epoch")
plt.ylabel("Weighted R²")
plt.legend()
plt.show()

```


Validation Weighted R² – Dropout & Weight Decay
Weighted R²
Epoch
0.0
−0.5
−1.0
−1.5
−2.0
−2.5
−3.0
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
dropout_0.0_wd_0.0
dropout_0.0_wd_0.0001
dropout_0.0_wd_0.001
dropout_0.2_wd_0.0
dropout_0.2_wd_0.0001
dropout_0.2_wd_0.001
dropout_0.4_wd_0.0
dropout_0.4_wd_0.0001
dropout_0.4_wd_0.001
dropout_0.6_wd_0.0
dropout_0.6_wd_0.0001
dropout_0.6_wd_0.001