

Configuration Manual

MSc Research Project
Practicum Part 2

Nachiket Mehendale

Student ID: X23272473

School of Computing
National College of Ireland

Supervisor: Prof. Ade Fajemisin

**National College of Ireland
Project Submission Sheet
School of Computing**



Student Name:	Nachiket Mehendale
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Configuration Manual

Nachiket Mehendale
X23272473

1 Introduction

This configuration manual provides step-by-step instructions for setting up and executing the Enhanced Crop Weed Detection project using an optimized Swin Transformer architecture. The manual covers environment setup, dataset configuration, code execution procedures, and result interpretation to enable complete reproduction of the research findings. The document ensures that researchers can replicate the experimental setup and validate the proposed optimization techniques. All necessary components including datasets, code structure, and execution guidelines are detailed for seamless project reproduction.

2 System Requirements

Platform: Kaggle Notebooks

Hardware: NVIDIA Tesla P100 GPU, 13GB RAM

Software: Python 3.11, PyTorch 2.0, CUDA 11.8

Required Libraries:

```
import torch
import torch.nn as nn
import torch.optim as optim
import torchvision
import numpy as np
from sklearn.metrics import precision_score, recall_score, f1_score
import os
import time
import gc
```

Most libraries are pre-installed in Kaggle. Install, only if required:

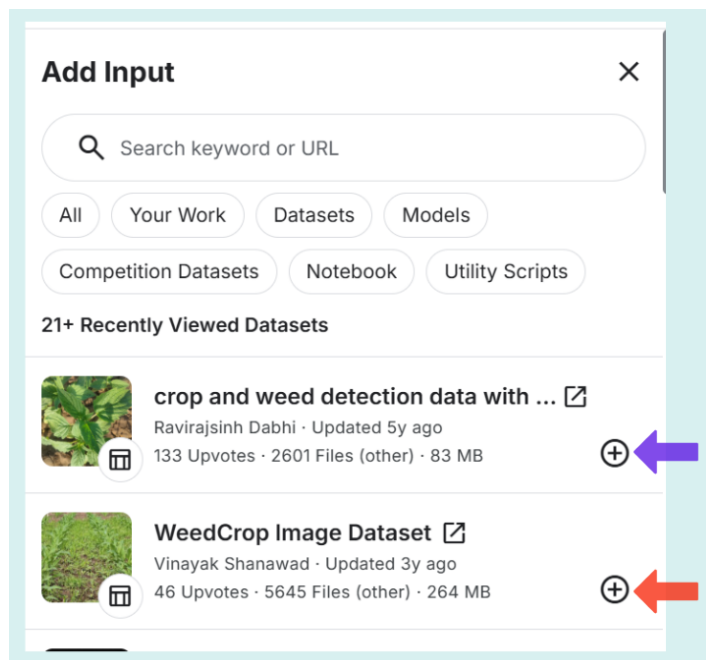
```
!pip install torch torchvision scikit-learn
```

3 Dataset Setup

3.1 Add Datasets to Kaggle Notebook

Make sure the following datasets are present in the executable Kaggle notebook and if not: Search for these datasets in the Add Input section of Kaggle Notebook and click on + symbols. This section is located on the top right corner in the Kaggle notebook.

- 1) **WeedCrop Image Dataset** -----Primary dataset
- 2) **crop and weed detection data with bounding boxes** -----Secondary dataset



Primary and secondary datasets can be found in Kaggle at following locations:

- 1) <https://www.kaggle.com/datasets/vinayakshanawad/weedcrop-image-dataset>
- 2) <https://www.kaggle.com/datasets/ravirajsinh45/crop-and-weed-detection-data-with-bounding-boxes/data>

Note: Once you have added them or if they are already present in the notebook, + symbol becomes –

3.2 Verify Dataset Paths

In the executable Kaggle notebook file, make sure the dataset paths are set as follows:

```
# Primary dataset - used in Dataset Setup and Conversion module
source_dir = '/kaggle/input/weedcrop-image-dataset/WeedCrop.v1i.yolov5pytorch'
# Secondary dataset - used in transfer learning module
transfer_path = '/kaggle/input/crop-and-weed-detection-data-with-bounding-boxes/agri_data/data'
```

4 Code Execution

4.1 Notebook Structure

The code implementation is organized and consists of key sections covering:

- Library imports and dependencies
- Dataset conversion and preprocessing
- Model architecture definitions
- Optimization techniques implementation
- Training and evaluation functions
- Transfer learning setup
- Main execution pipeline

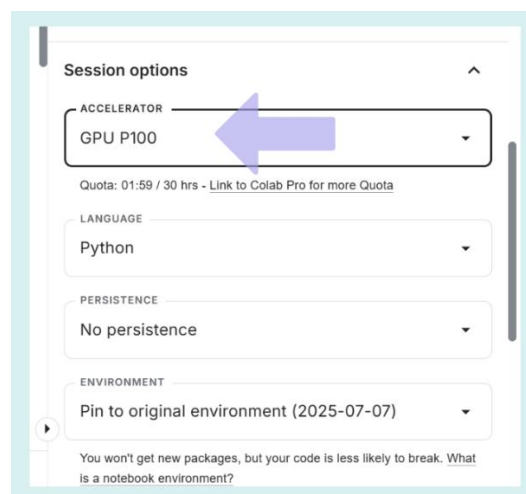
4.2 Execution Steps

- **Import Implementation:** The python implementation file is located at: https://github.com/Nachiket-AM/X23272473_MSCAI1_Research_Practicum_Part_2 Open/import it in Kaggle platform. Or you can directly access Kaggle notebook at: <https://www.kaggle.com/code/cdnmehen/swin-transformer-optimization-x23272473-mscai1/edit> or access it from OneDrive link as follows : [x23272473_Swin_Transformer_Optimization.ipynb](https://www.kaggle.com/code/cdnmehen/swin-transformer-optimization-x23272473-mscai1/edit) (Ctrl + Click to follow the link)

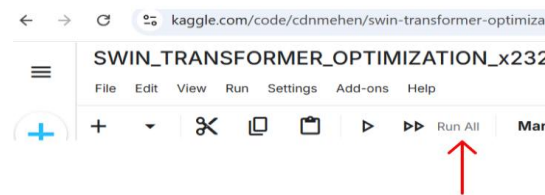
- **Dataset Configuration:** Make sure datasets are added, and path is defined in the executable Kaggle notebook file as mentioned in point no 3.1 and 3.2

- **Enable GPU:** In Kaggle notebook settings, select Accelerator → GPU P100

(This setting is present under the “Session options” section located on the right bottom side of the notebook)



- Select “Run All” cells option from the executable Kaggle notebook



5 Model Architectures

In this project we have implemented 4 deep learning models:

Model	Description
Default Swin Transformer	Standard hierarchical Swin architecture
Optimized Swin Transformer	Enhanced version with novel optimization techniques
CNN Model	Traditional convolutional neural network baseline
Vision Transformer	Standard ViT implementation

Optimization Techniques in Optimized Swin:

- DTC: Dynamic Token Clustering - reduces computational complexity
- APS: Adaptive Patch Splitting - optimizes patch size selection
- SCSA: Selective Cross-Scale Attention - efficient multi-scale processing

6 Training Configuration

Hyperparameters (identical for all models):

- Epochs: 5
- Batch Size: 6
- Learning Rate: 0.001
- Optimizer: AdamW
- Loss: CrossEntropyLoss

7 Results

7.1 All Models Performance Comparison

All models achieved comparable accuracy on the test dataset:

Model	Test Accuracy (%)	Precision	Recall	F1 Score
Default Swin	82.29	0.823	0.823	0.823
Optimized Swin	83.33	0.833	0.833	0.833
CNN	81.25	0.813	0.812	0.812
Vision Transformer	83.33	0.836	0.833	0.833

7.2 Computational Efficiency Analysis (Default Vs Optimized SWIN)

Metric	Default Swin	Optimized Swin	Improvement
Parameters (M)	60.46	0.27	99.60%
Model Size (MB)	231.5	1	99.60%
Inference Time (ms)	10.4	22.1	-113.00%
FLOPs (G)	409.91	0.69	99.80%
Attention Efficiency	1	0	100.00%
Accuracy/Param (M)	1.36	311.32	22772.30%

The optimized Swin model achieved a 99.6% decrease in parameters or weights (from 60.46M to 0.27M) and model size (from 231.5MB to 1MB), while maintaining similar accuracy but with increased inference time from 10.4ms to 22.1ms. The efficiency gains resulted in a remarkable 22,772% improvement in accuracy per parameter, though at the cost of eliminated attention mechanisms and slower inference speed.

7.3 Transfer Learning Analysis

Secondary dataset performance:

Metric	Value
Final Transfer Training Accuracy	78.85%
Final Transfer Validation Accuracy	79.17%
Transfer Learning Epochs	5
Feature Extraction	Partially Frozen (head + last 2 stages trained)
Transfer Training Accuracy	78.85%
Transfer Validation Accuracy	79.17%

8 Conclusion

This configuration supports recreation of the optimized Swin Transformer research. The entire execution shows notable computational performance without losing crop-weed classification performance. The documented setup procedures and sequential execution approach enables reliable reproduction of the study results.