

Configuration Manual

MSc Research Project
Master's in data Analytics

Vishnu Vardhan Reddy Rikkula
Student ID: X23409452

School of Computing
National College of Ireland

Supervisor: Mr. Jaswinder Singh

National College of Ireland
MSc Project Submission Sheet
School of Computing



Student Name: Vishnu Vardhan Reddy Rikkula

Student ID: 23409452

Programme: Master's in data Analytics

Year: 2025-2026

Module: Research Practicum

Lecturer: Mr. Jaswinder Singh

Submission

Due Date: 28-01-2026

Project Title: Self-Supervised Learning for Class-Imbalanced Guava Disease Detection: A Contrastive Reconstruction Enhancement Approach

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I hereby certify that the information contained in this (my submission) is information pertaining to research I conducted for this project. All information other than my own contribution will be fully referenced and listed in the relevant bibliography section at the rear of the project.

ALL internet material must be referenced in the bibliography section. Students are required to use the Referencing Standard specified in the report template. To use other author's written or electronic work is illegal (plagiarism) and may result in disciplinary action.

Signature: Vishnu Vardhan Reddy Rikkula

Date: 28-01-2026

PLEASE READ THE FOLLOWING INSTRUCTIONS AND CHECKLIST

Attach a completed copy of this sheet to each project (including multiple copies)	☐
Attach a Moodle submission receipt of the online project submission, to each project (including multiple copies).	☐
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Assignments that are submitted to the Programme Coordinator Office must be placed into the assignment box located outside the office.

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Signature:	
Date:	
Penalty Applied (if applicable):	

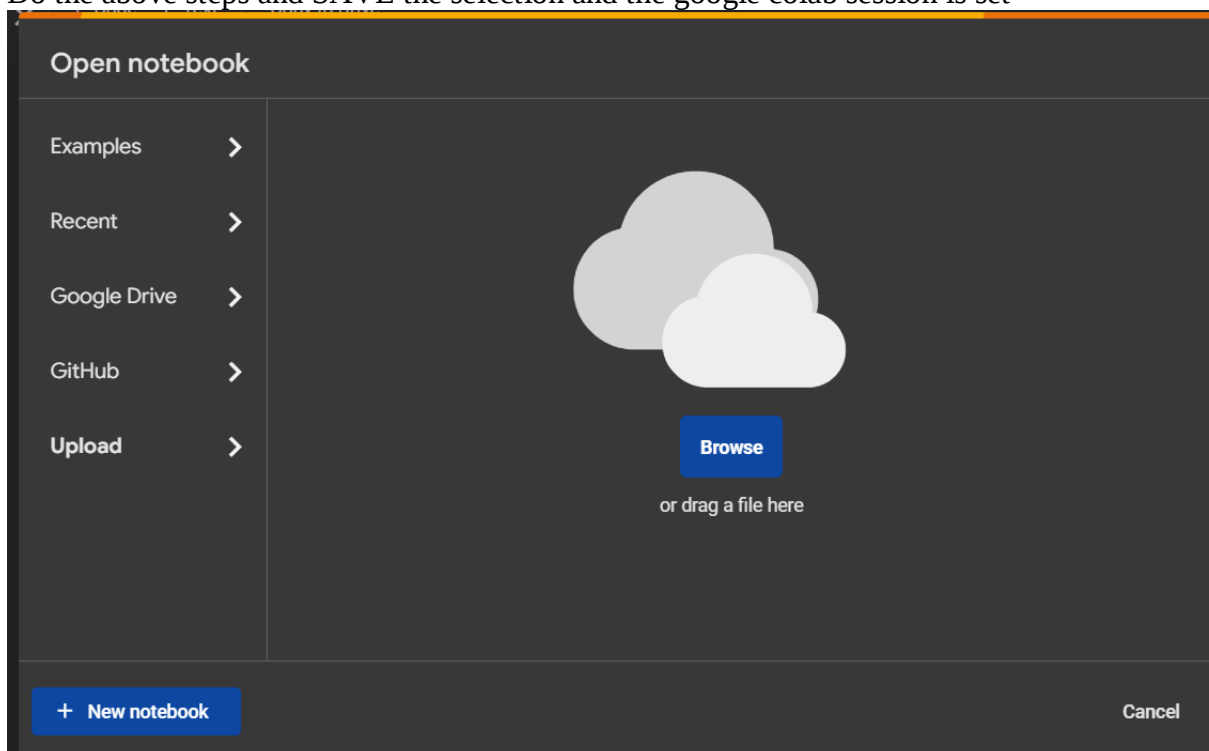
Configuration Manual

Vishnu Vardhan Reddy Rikkula
X23409452

1. Connecting a Colab session to Google Drive for file access

- Step 1 : Launching the colab environment (navigating to google colab website)
- Step 2: Sign in into the google account
- Step 3:uploading the ipynb file /notebook
- Step 4: Enabling the GPU Acceleration (in this change the runtime)
- Step 5 : change the hardware accelerator to T4 GPU

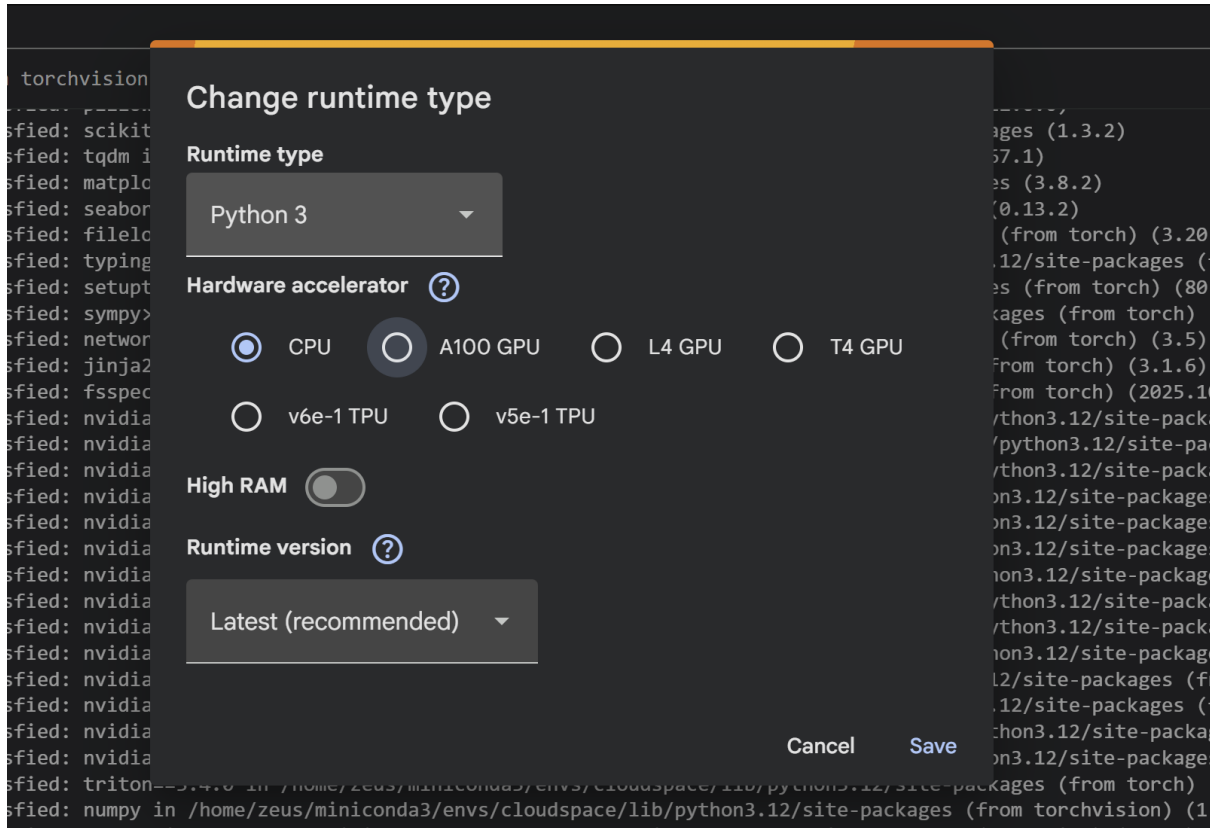
Do the above steps and SAVE the selection and the google colab session is set



2. Preparing the session environment

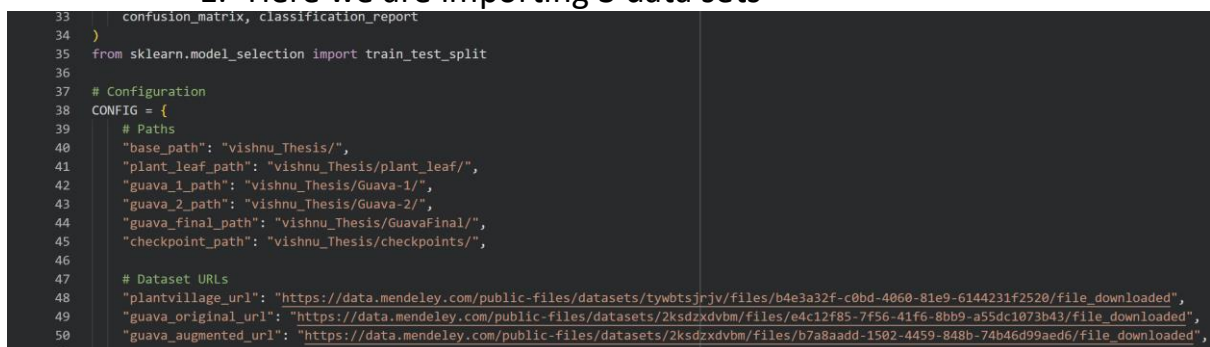
- Step 1: open the google colab session
- Step 2: Sign in to your Gmail

- Step 3: start a new notebook
- Step 4 : Activate the GPU acceleration
- Step 5: Create a folder on the website
1. Upload the notebook



3.Data import

- Step 1: Setting up the configuration and data import
1. Here we are importing 3 data sets



- Step 2: Downloading the data import to the notebook

```

13     class_dirs = [d for d in directory.iterdir() if d.is_dir()]
14     total = 0
15     for cls_dir in class_dirs:
16         for p in cls_dir.rglob("*"):
17             if p.is_file() and is_image(p):
18                 total += 1
19     return len(class_dirs), total
20
21 def download_plantvillage():
22     base_path = Path(CONFIG["base_path"])
23     base_path.mkdir(parents=True, exist_ok=True)
24
25     zip_path = base_path / "plant_leaf.zip"
26     extract_root = Path(CONFIG["plant_leaf_path"])
27
28     # Check if already extracted
29     if extract_root.exists():
30         num_classes, num_images = count_images_in_dir(extract_root)
31         if num_images > 60000:
32             print("PlantVillage already downloaded and extracted")
33             print("Path:", extract_root)
34             print("Classes:", num_classes)
35             print("Images:", num_images)
36             return extract_root
37
38     extract_root.mkdir(parents=True, exist_ok=True)
39
40     # Download
41     print("Downloading PlantVillage dataset...")
42     url = CONFIG["plantvillage_url"]
43     exit_code = subprocess.call(["curl", "-L", url, "-o", str(zip_path)])
44     ..

```

1

2 # =====

3 # CELL 3: Download and Merge Guava Dataset (Fine-tuning)

4 # =====

5

```

6 def get_file_hash(filepath):
7     hash_md5 = hashlib.md5()
8     with open(filepath, "rb") as f:
9         for chunk in iter(lambda: f.read(4096), b""):
10             hash_md5.update(chunk)
11     return hash_md5.hexdigest()
12
13
14 def normalize_class_name(name):
15     name = name.strip().rstrip("/")
16     name = name.replace("Healthy", "Healthy")
17     name = name.replace("Insects eatten class", "Insects eaten")
18     return name
19
20
21 def download_guava_datasets():
22     base_path = Path(CONFIG["base_path"])
23     base_path.mkdir(parents=True, exist_ok=True)
24
25     # Download Guava Original
26     zip1_path = base_path / "guava_original.zip"
27     extract1_root = Path(CONFIG["guava_1_path"])
28
29     if not extract1_root.exists() or count_images_in_dir(extract1_root)[1] < 500:
30         extract1_root.mkdir(parents=True, exist_ok=True)
31         print("Downloading Guava Original dataset...")
32         url = CONFIG["guava_original_url"]
33         exit_code = subprocess.call(["curl", "-L", url, "-o", str(zip1_path)])

```

4.Results

```
1
2 # =====
3 # CELL 9: Pre-Training Loop (PlantVillage)
4 # =====
5
6 def pretrain_cre(model, train_loader, config, device):
7     """
8     Pre-train CRE model on PlantVillage dataset.
9     """
10    model = model.to(device)
11    model.train()
12
13    # Optimizer
14    optimizer = optim.AdamW(
15        model.parameters(),
16        lr=config["pretrain_lr"],
17        weight_decay=config["pretrain_weight_decay"]
18    )
19
20    # Scheduler with warmup
21    total_steps = config["pretrain_epochs"] * len(train_loader)
22    warmup_steps = config["warmup_epochs"] * len(train_loader)
23
24    def lr_lambda(step):
25        if step < warmup_steps:
26            return step / warmup_steps
27        else:
28            progress = (step - warmup_steps) / (total_steps - warmup_steps)
29            return 0.5 * (1 + np.cos(np.pi * progress))
30
31    scheduler = optim.lr_scheduler.LambdaLR(optimizer, lr_lambda)
32
33    # Mixed precision
34    scaler = torch.amp.GradScaler("cuda")
35
```

```
***
Decoder depth: 2
Patch size: 16
Projection Head initialized
Input dim: 768
Hidden dim: 2048
Output dim: 256

CRE Model initialized
Num patches: 196
Mask ratio: 0.5
Lambda contrastive: 0.5

Starting CRE Pre-training
-----
Epochs: 50
Batch size: 256
Learning rate: 0.00015
Total batches per epoch: 240
-----
Epoch 1/50: 100%|██████████| 240/240 [07:38<00:00, 1.91s/it, recon=0.8754, contrast=4.2374, total=2.9941]
Epoch 1/50 | Recon Loss: 1.0437 | Contrastive Loss: 5.2291 | Total Loss: 3.6583 | LR: 0.000015 | Time: 458.3s
Epoch 2/50: 100%|██████████| 240/240 [07:33<00:00, 1.89s/it, recon=0.7493, contrast=2.8540, total=2.1763]
Epoch 2/50 | Recon Loss: 0.7858 | Contrastive Loss: 3.3971 | Total Loss: 2.4843 | LR: 0.000030 | Time: 453.2s
Epoch 3/50: 100%|██████████| 240/240 [07:36<00:00, 1.90s/it, recon=0.6871, contrast=2.0158, total=1.6951]
Epoch 3/50 | Recon Loss: 0.7083 | Contrastive Loss: 2.3186 | Total Loss: 1.8676 | LR: 0.000045 | Time: 456.3s
Epoch 4/50: 100%|██████████| 240/240 [07:35<00:00, 1.90s/it, recon=0.6725, contrast=1.8392, total=1.5921]
Epoch 4/50 | Recon Loss: 0.6732 | Contrastive Loss: 1.7922 | Total Loss: 1.5693 | LR: 0.000060 | Time: 455.5s
Epoch 5/50: 100%|██████████| 240/240 [07:32<00:00, 1.89s/it, recon=0.6497, contrast=1.2109, total=1.2552]
Epoch 5/50 | Recon Loss: 0.6673 | Contrastive Loss: 1.4776 | Total Loss: 1.4061 | LR: 0.000075 | Time: 452.7s
Epoch 6/50: 100%|██████████| 240/240 [07:28<00:00, 1.87s/it, recon=0.6568, contrast=1.1781, total=1.2458]
Epoch 6/50 | Recon Loss: 0.6637 | Contrastive Loss: 1.2771 | Total Loss: 1.3023 | LR: 0.000090 | Time: 448.5s
Epoch 7/50: 100%|██████████| 240/240 [07:36<00:00, 1.90s/it, recon=0.6607, contrast=1.0349, total=1.1781]
Epoch 7/50 | Recon Loss: 0.6599 | Contrastive Loss: 1.1333 | Total Loss: 1.2265 | LR: 0.000105 | Time: 456.1s
Epoch 8/50: 100%|██████████| 240/240 [07:34<00:00, 1.89s/it, recon=0.6583, contrast=0.9167, total=1.1167]
Epoch 8/50 | Recon Loss: 0.6586 | Contrastive Loss: 1.0134 | Total Loss: 1.1653 | LR: 0.000120 | Time: 454.6s
```

```

1
2 # =====
3 # CELL 11: Fine-Tuning Loop (Guava) - With Focal Loss for Hard Samples
4 # =====
5
6 class FocalLoss(nn.Module):
7     """Focal loss to focus on hard-to-classify samples."""
8     def __init__(self, alpha=None, gamma=2.0, reduction='mean'):
9         super().__init__()
10        self.alpha = alpha # Class weights
11        self.gamma = gamma # Focusing parameter
12        self.reduction = reduction
13
14    def forward(self, inputs, targets):
15        ce_loss = F.cross_entropy(inputs, targets, weight=self.alpha, reduction='none')
16        pt = torch.exp(-ce_loss)
17        focal_loss = ((1 - pt) ** self.gamma) * ce_loss
18
19        if self.reduction == 'mean':
20            return focal_loss.mean()
21        elif self.reduction == 'sum':
22            return focal_loss.sum()
23        return focal_loss
24
25
26 def finetune_classifier(model, train_loader, val_loader, config, device):
27     """Fine-tune classifier on Guava dataset with Focal Loss."""
28     model = model.to(device)
29
30     # Optimizer
31     optimizer = optim.AdamW(
32         filter(lambda p: p.requires_grad, model.parameters()),
33         lr=config["finetune_lr"],
34         weight_decay=0.02
35     )
36
37     # Class weights - balanced for both minority classes
38     class_weights = torch.tensor([
39         1.0 # Apple leaves that (1385)

```

```

1
2 # =====
3 # CELL 12: Evaluation Functions
4 # =====
5
6 def compute_metrics(y_true, y_pred, class_names):
7     """Compute comprehensive metrics."""
8     metrics = {}
9
10    # Overall metrics
11    metrics["accuracy"] = accuracy_score(y_true, y_pred) * 100
12    metrics["macro_f1"] = f1_score(y_true, y_pred, average="macro")
13    metrics["micro_f1"] = f1_score(y_true, y_pred, average="micro")
14    metrics["macro_precision"] = precision_score(y_true, y_pred, average="macro")
15    metrics["macro_recall"] = recall_score(y_true, y_pred, average="macro")
16
17    # Per-class metrics
18    per_class_precision = precision_score(y_true, y_pred, average=None, zero_division=0)
19    per_class_recall = recall_score(y_true, y_pred, average=None, zero_division=0)
20    per_class_f1 = f1_score(y_true, y_pred, average=None, zero_division=0)
21
22    metrics["per_class"] = {}
23    for i, class_name in enumerate(class_names):
24        metrics["per_class"][class_name] = {
25            "precision": per_class_precision[i],
26            "recall": per_class_recall[i],
27            "f1": per_class_f1[i],
28            "support": int(np.sum(np.array(y_true) == i))
29        }
30
31    return metrics
32
33
34 def generate_confusion_matrix(y_true, y_pred, class_names):
35     """Generate confusion matrix."""
36     cm = confusion_matrix(y_true, y_pred)
37     return cm
38

```

... Running evaluation on test set...

Evaluating: 100%|██████████| 11/11 [00:18<00:00, 1.67s/it]
EVALUATION RESULTS

Test Accuracy: 97.71%
Macro F1: 0.9406
Micro F1: 0.9771
Macro Precision: 0.9528
Macro Recall: 0.9297

Per-Class Metrics:

Class	Precision	Recall	F1-Score	Support
Algal leaves spot	0.9673	0.9952	0.9810	208
Dry leaves	0.9909	1.0000	0.9954	109
Healthy fruit	1.0000	0.9808	0.9903	104
Healthy leaves	0.9000	0.8182	0.8571	22 *
Insects eaten	0.8696	0.8000	0.8333	25 *
Red rust	0.9892	0.9840	0.9866	187

* = Minority class

Minority Class Focus:

Healthy leaves - Recall: 0.8182 (Target: 0.80) [PASS]
Insects eaten - Recall: 0.8000 (Target: 0.80) [PASS]

Confusion Matrix:

```
[[207  0  0  0  1  0]
 [  0 109  0  0  0  0]
 [  0  0 102  0  1  1]
 [  3  0  0 18  1  0]
```

Running evaluation on test set...

Evaluating: 100%|██████████| 11/11 [00:18<00:00, 1.67s/it]
EVALUATION RESULTS

Test Accuracy: 97.71%
Macro F1: 0.9406
Micro F1: 0.9771
Macro Precision: 0.9528
Macro Recall: 0.9297

5. References

Google Colab (Reference): <https://colab.research.google.com/>

Bangladesh Guava Disease Dataset. (2024). Guava leaf disease images from Bangladesh. Mendeley Data, v1. DOI: 10.17632/2ksdzxdvbm.1.

PlantVillage Dataset. (2019). Plant leaf diseases dataset with augmentation. Mendeley Data, v1. DOI: 10.17632/tywbtsjrjv.1.