HierbaNetV1: A Novel Feature Extraction Framework for Deep Learning-Based Weed Identification

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Presentation Overview

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01. Introduction

- AI-based weeding is a sustainable alternative to manual methods
- Weed infestation leads to reduced crop yields and increased labor costs

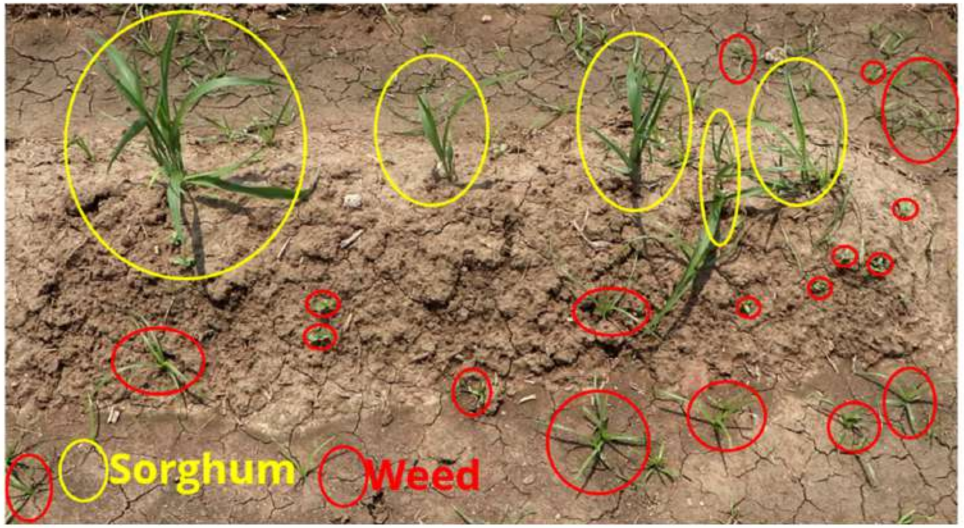

Fig 1.1. Presence of crops and weeds in Sorghum field - Research experimental area

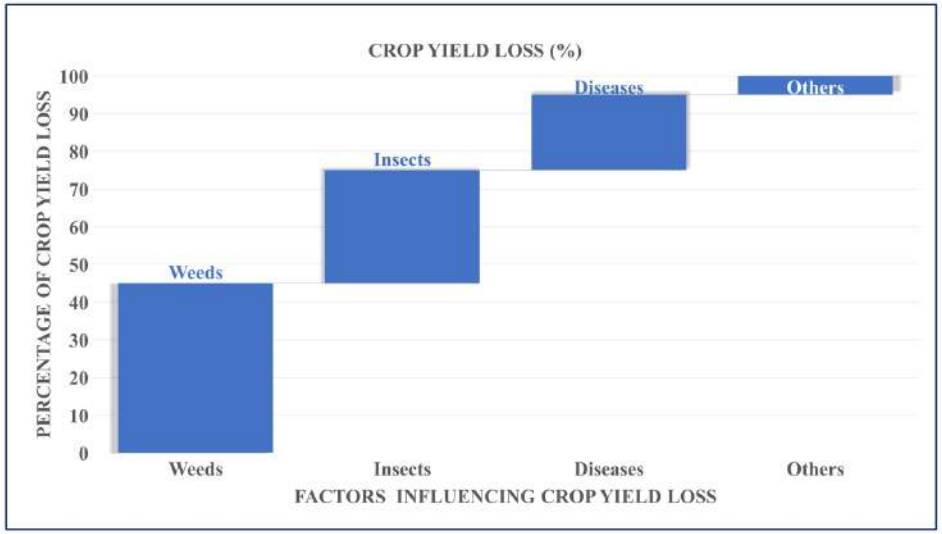

Fig 1.2. Crop yield loss [1]

02. Objectives

Motivation: *AI for weed identification in Indian farms*

- **Objective 1:** To create crop-weed image datasets from the Indian agricultural field for weed identification.
- **Objective 2:** To design a novel feature extraction technique for varying-sized Region-of-Interests in sorghum-weed image datasets.
- **Objective 3:** To design a feature pyramid network that generates rich semantic features for fine-grained object localization.

03. Proposed framework

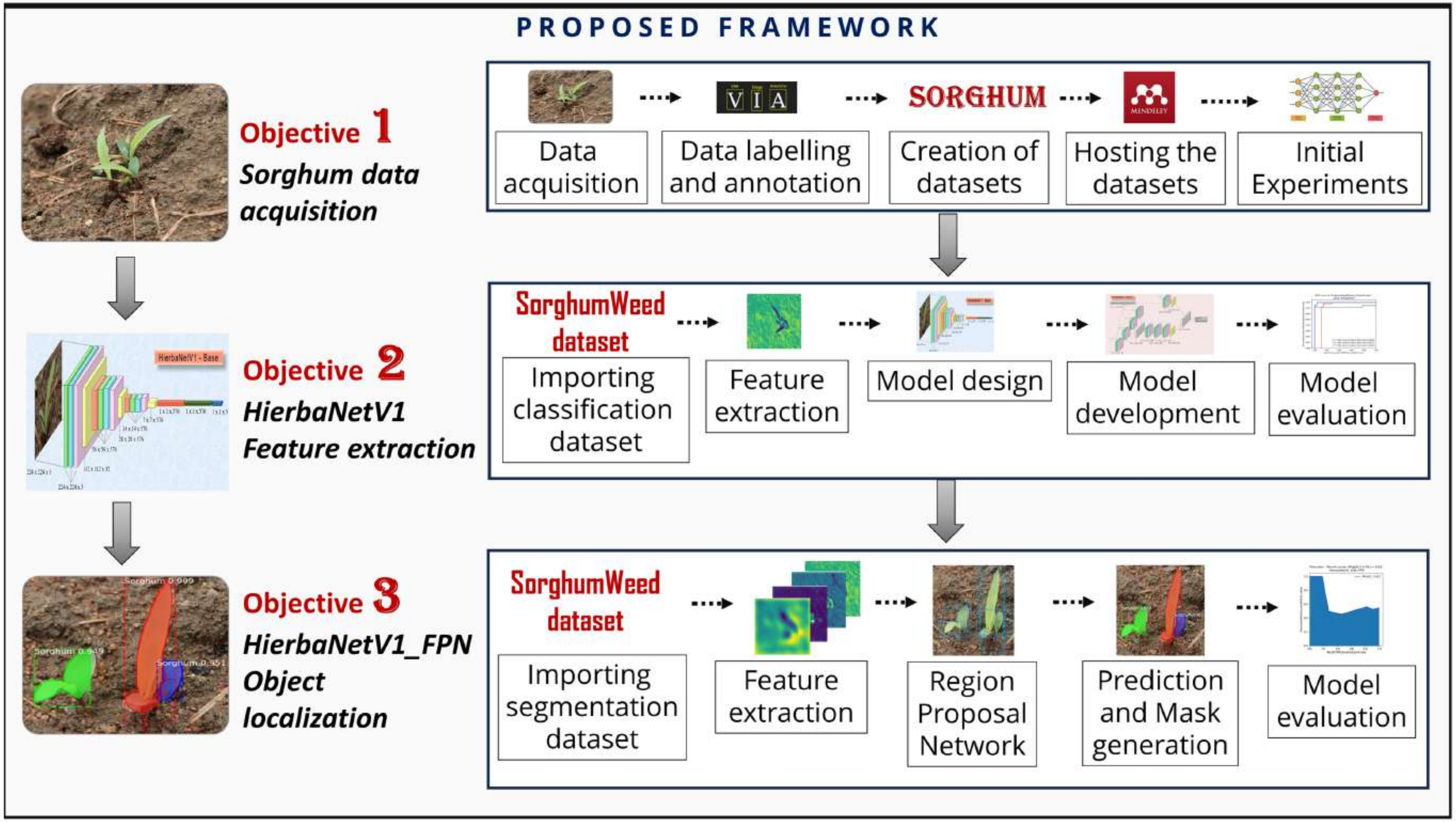

Fig 3.1. Proposed framework

Objective 1

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04. Objective 1 : Sorghum-Weed dataset creation

Literature review

#	Dataset	Geograp. Location	Duration	Images	Species	Purpose
1	Weed25 [2]	China	2021 to 2022	4,023	25 weeds	Detection
2	4 Weed Dataset [3]	USA	2021	618	4 weeds	Classification
3	Lincolnbeet dataset [4]	United Kingdom	2021	4405	Beet and malicious weeds	Detection
4	Ronin open DB [5]	Europe	2020	118	6 crops and 8 weeds	Detection
5	Maize-Commonbean-weeds dataset [6]	Central France	2019	2489	2 crops and 4 weeds	Segmentation
6	GrassClover [7]	Denmark	2017 to 2018	31,600	2 Clovers, 3 weeds and grass	Segmentation
7	DeepWeeds [8]	Australia	2017 to 2018	17509	8 weed species	Classification
8	Sugar Beets 2016 [9]	Germany	2016	5 TB	Sugar beets and 9 weeds	Segmentation

04. Objective 1 : Sorghum-Weed dataset creation

- **Problem statement - 01**

  There is no publicly available crop-weed research dataset from Indian agricultural fields

- **Objective - 01**

  To create crop-weed image datasets from the Indian agricultural field for weed identification.

1. *Published an article entitled "SorghumWeedDataset_Classification And SorghumWeedDataset_Segmentation Datasets For Classification, Detection, and Segmentation In Deep Learning" in a SCI indexed Elsevier journal "Data in Brief" on 09.12.2023 with ImpactFactor 1.2 and CiteScore 2.6. https://doi.org/10.1016/j.dib.2023.109935*
2. *Michael, Justina; M, Thenmozhi (2023), "SorghumWeedDataset_Classification", Mendeley Data, V1, doi: 10.17632/4gkcyxjyss.1*
3. *Michael, Justina; M, Thenmozhi (2023), "SorghumWeedDataset_Segmentation", Mendeley Data, V1, doi: 10.17632/y9bmtf4xmr.1*

04. Objective 1 : Sorghum-Weed dataset creation

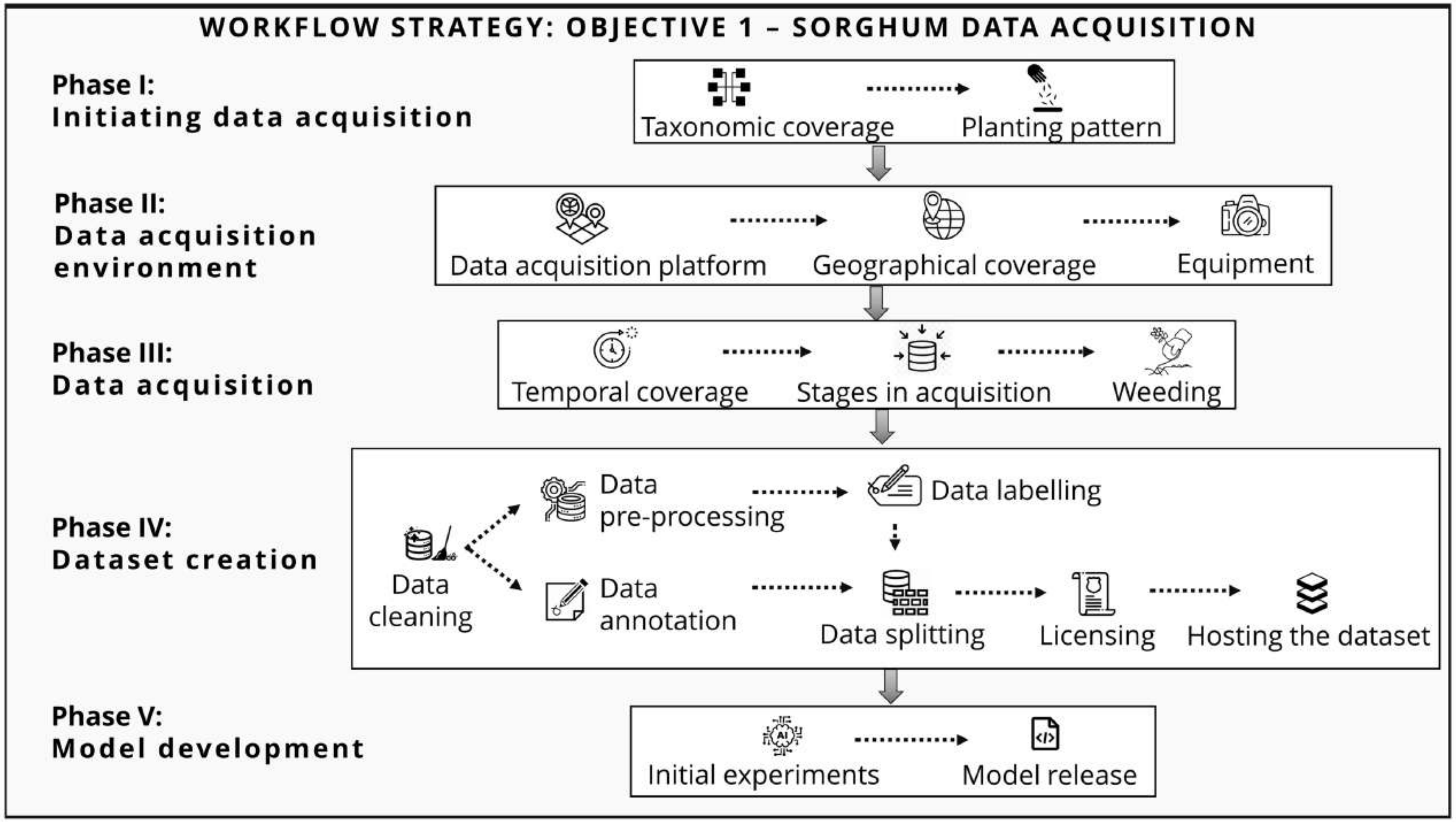

Fig 4.1. Workflow strategy of sorghum data acquisition

04. Objective 1 : Sorghum-Weed dataset creation

Phase I: Taxonomic coverage

- **Specie selection**
  - Scientific name: Sorghum Bicolor L. Moench *(Primary research object)*
  - Common name: **Sorghum** (aka Great Milliet)
  - Tamil name: சோளம்
  - Family: Poaceae
- **Weed categories**
  - Broadleaf weeds (dicotyledonous)
  - Grass weeds (monocotyledonous)

04. Objective 1 : Sorghum-Weed dataset creation

Phase I: Planting pattern I

- **Purpose**

  To capture instance(s) of a single object category (crop/weed) in an image for solving the classification problem.

Fig 4.2. Planting pattern I - Actual S4 plot on Day 15 after sowing

TABLE 4.1. Planting pattern for dibbling system

Planting attributes	Values
Planting type	Dibbling
Crop spacing	Uniform
Planting system	Rectangular
Plots	S1, S2, S3, and S4
Per plot size	4 feet × 3 feet
Rows/plot and Seeds/Row	3 no's and 25 no's
Raised row height	15 cm
Dibbled depth	5 cm
Inter-row spacing	45 cm
Inter-crop spacing	10 cm
Total sorghum population	300 no's

04. Objective 1 : Sorghum-Weed dataset creation

Phase I: Planting pattern II

- **Purpose**

  To capture instance(s) of a multiple object category (crop/weed) in an image for solving the segmentation problem.

TABLE 4.2. Planting pattern for broadcasting system

Planting attributes	Values
Planting type	Broadcasting
Crop spacing	Random
Plots	S5 and S6
Per plot size	4 feet × 3 feet
Total sorghum population	80 to 100 no's

Fig 4.3. Planting pattern II – Actual S6 plot on Day 15 after sowing

04. Objective 1 : Sorghum-Weed dataset creation

Phase II: Data acquisition environment

Data acquisition platform

(871.2 sq feet)

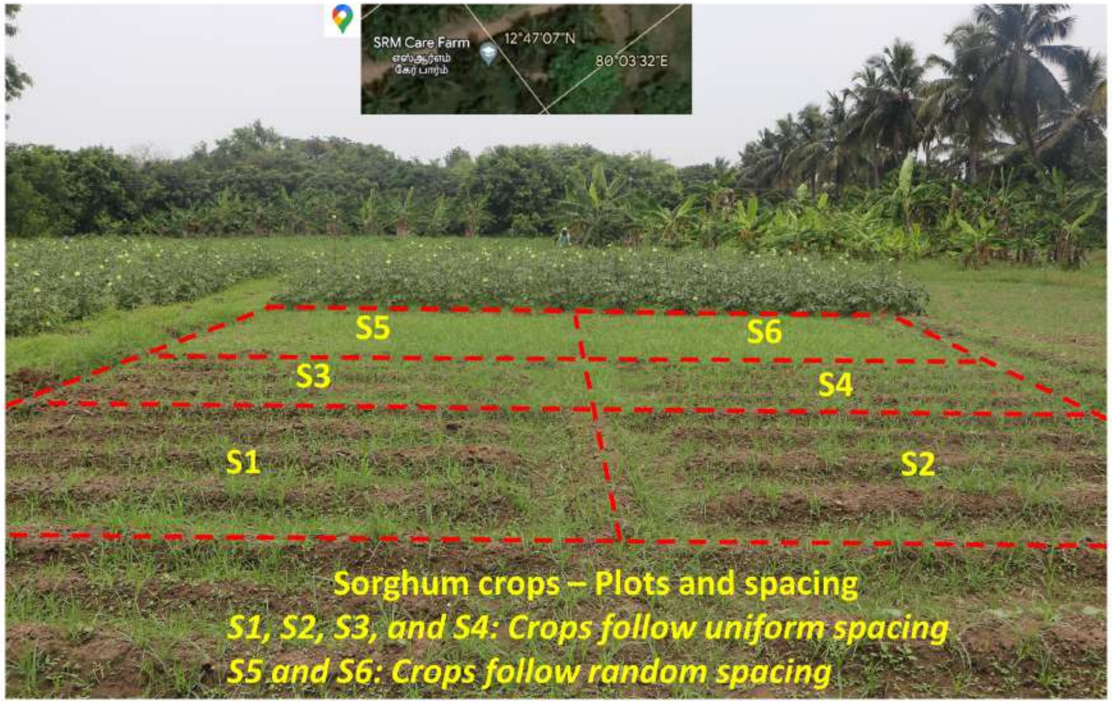

Fig 4.4. Actual sorghum field layout

Geographical coverage

TABLE 4.3. Geographical coverage of sorghum data acquisition

Geographical Attributes	Values
Location	SRM Care farm, Chengalpattu district
Latitude	12.787003386255583
Longitude	80.05900471261096
Google maps link	https://goo.gl/maps/Zq4yF8CddEyoZuWL6

04. Objective 1 : Sorghum-Weed dataset creation

Phase II: Equipment

TABLE 4.4. Instrument specification of sorghum data acquisition

Instrument Attributes	Values
Instrument	Canon EOS 80D – DSLR camera
Type of data	Image
Data format	.jpg with RGB colors
Sensor type	22.3 mm x 14.9 mm CMOS
Pixels	24.20 megapixels
Height and width	6000 x 4000 pixels
Shutter speed	30-1/8000 seconds

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04. Objective 1 : Sorghum-Weed dataset creation

Phase III: Temporal coverage

TABLE 4.5. Temporal coverage of sorghum data acquisition

Temporal Attributes	Values
Duration	April and May 2023
Weather conditions	1. Sunshine 2. High wind 3. Gentle rain
Light	1. Morning light 2. Afternoon light
Height	20 cm to 40 cm from the plant

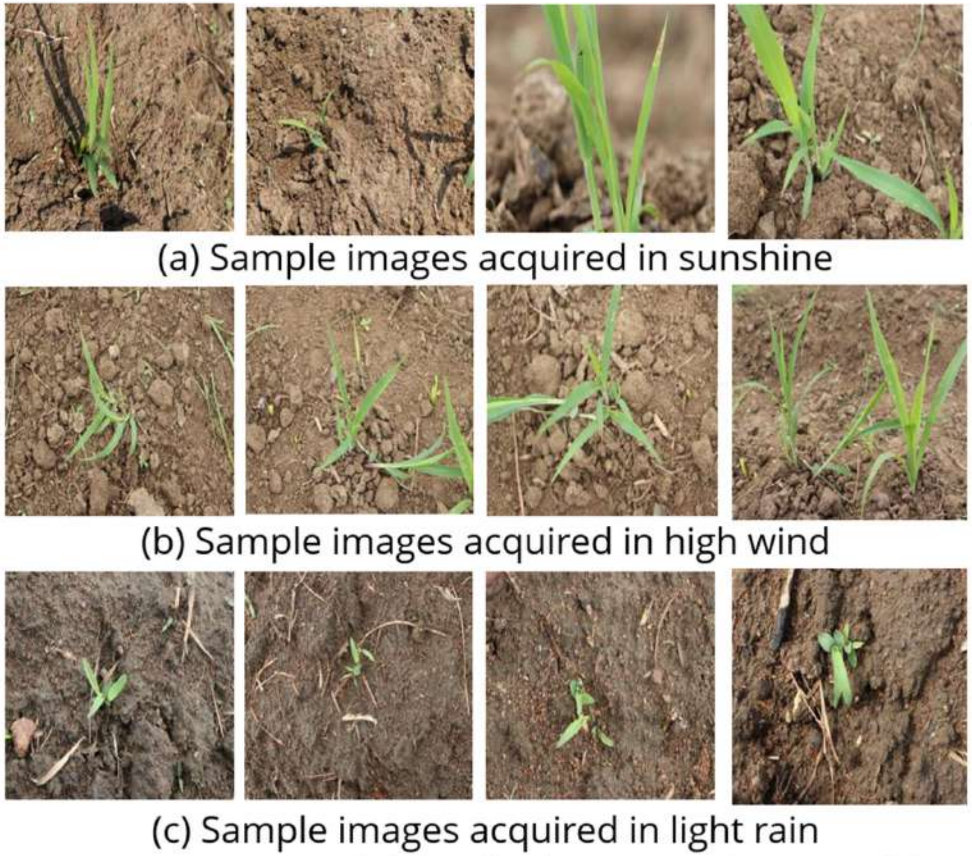


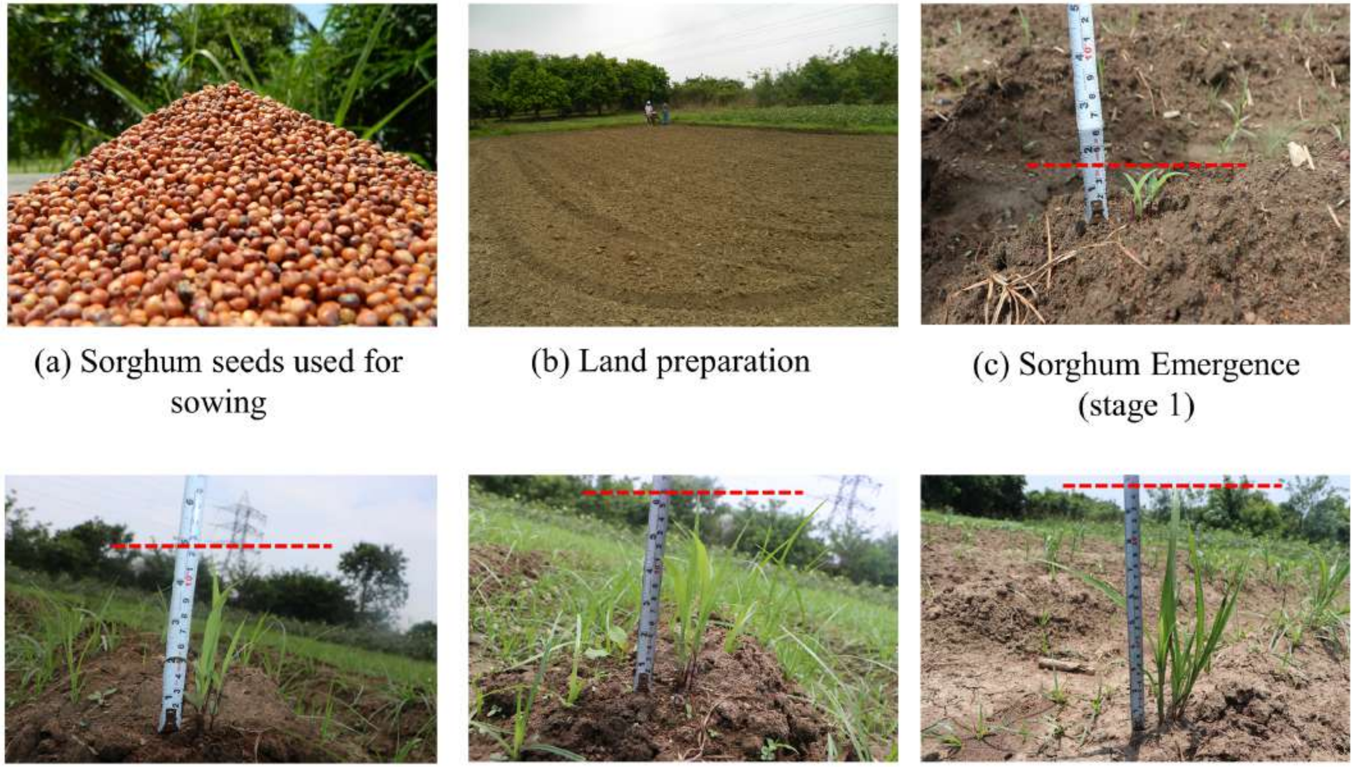
Fig 4.5 Data acquisition in three weather conditions

04. Objective 1 : Sorghum-Weed dataset creation

Phase III: Data acquisition

TABLE 4.6. Focused growth stages of sorghum for data acquisition

#	Stage	Day
1	Emergence	Day 6
2	Three leaf	Day 9
3	Five leaf	Day 15
4	Growing point differentiation	Day 23
5 to 10	Flag leaf visible to Physiological maturity	Not considered



(a) Sorghum seeds used for sowing

(b) Land preparation

(c) Sorghum Emergence (stage 1)

(d) Three-Leaf (stage 2)

(e) Five-Leaf (stage 3)

(f) Growing point differentiation (stage 4)

Fig 4.6. Growth stages of sorghum focused for data acquisition

04. Objective 1 : Sorghum-Weed dataset creation

Phase IV: Data cleaning

TABLE 4.7. Sorghum data monitoring and control specifications

Process	Classification	Segmentation
Name of the dataset	SorghumWeedDataset_Classification	SorghumWeedDataset_Segmentation
Data cleaning	4312 of 5652 images were chosen	252 of 386 images were chosen
Data pre-processing	Resizing to 224 × 224 pixels	NA and 6000 × 4000 retained
Data labelling	Class 0 – Sorghum, Class 1 – Grass and Class 2 – Broadleaf weed	NA
Data annotation	NA	VIA [10] Class 0 – Sorghum, Class 1 – Grass and Class 2 – Broadleaf weed
Data splitting	TVT ratio - 7:2:1	TVT ratio - 8:1:1
Licensing	CC BY 4.0 license	CC BY 4.0 license

04. Objective 1 : Sorghum-Weed dataset creation

Phase IV: Data labelling (Classification dataset)

Fig 4.8. Sample images from each class in 'SorghumWeedDataset_Classification' dataset

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04. Objective 1 : Sorghum-Weed dataset creation

Phase IV: Data annotation (Segmentation dataset)

Manual Annotation

- Tool: **V**GG **I**mage **A**nnotator [10]
- Duration – 100 hours (≈)

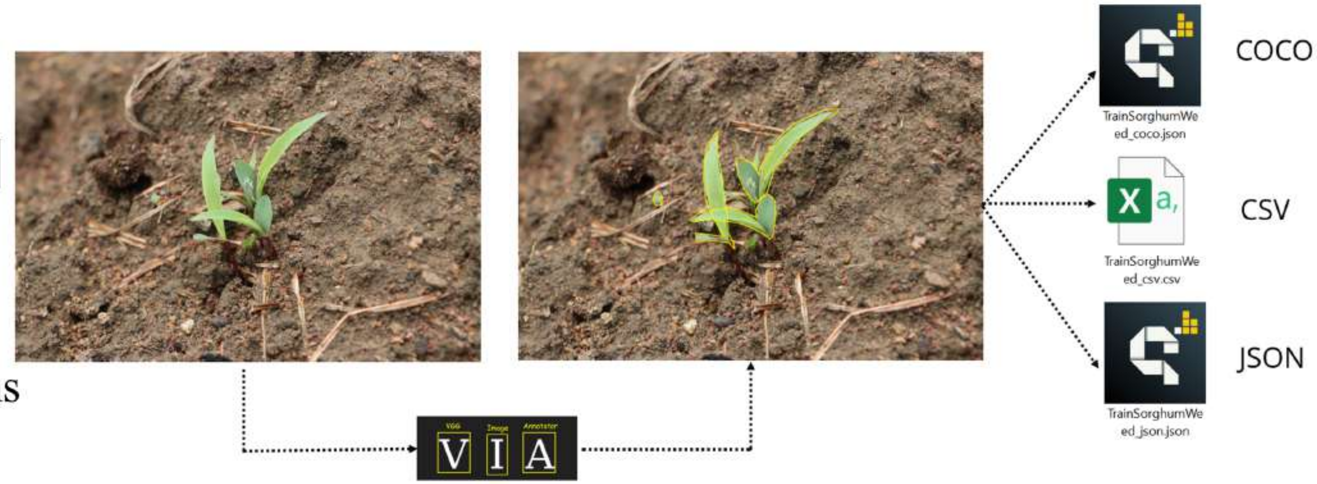

Fig 4.9. Raw data and pixel-wise annotations for three instances of sorghum crop

Fig 4.10. Raw data and pixel-wise annotations for several instances of sorghum crop, grass weeds and broadleaf weeds

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04. Objective 1 : Sorghum-Weed dataset creation

Phase IV: Expected outcome of the datasets

SorghumWeedDataset_Classification

(a)

Fig 4.7. Sample images from datasets

SorghumWeedDataset_Segmentation

(b)

Outcome: Categorize the input as

1. Sorghum - Class 0
2. Grass weeds – Class 1
3. Broadleaf weeds – Class 2

Outcome: For each ROI

1. Draw a bounding box
2. Perform pixel-wise segmentation
3. Generate an instance mask
4. Class name of the ROI

04. Objective 1 : Sorghum-Weed dataset creation

Phase IV: Data splitting

TABLE 4.8. 'SorghumWeedDataset_Classification' TVT split

Class ID	Class Name	No. of samples			
		Train (70%)	Val (20%)	Test (10%)	Total
Class 0	Sorghum	983	281	140	1404
Class 1	Grass	1027	293	147	1467
Class 2	BroadLeaf Weed	1009	288	144	1441
Total		3019	862	431	**4312**

TABLE 4.9. 'SorghumWeedDataset_Segmentation' TVT split

Train (80%)	Val (10%)	Test (10%)	Total
202	25	25	**252**

TABLE 4.10. 'SorghumWeedDataset_Segmentation' research objects TVT split

Research objects / TVT	Sorghum	Grass	BL weed	Total
Train	1848	570	2544	4962
Validate	141	16	81	238
Test	172	23	160	355
Total	2161	609	2785	**5555**

04. Objective 1 : Sorghum-Weed dataset creation

Phase V: Hosting the dataset

TABLE 4.11. Hosting the datasets

Parameters	SorghumWeedDataset_Classification	SorghumWeedDataset_Segmentation
Repository	Mendeley Data	Mendeley Data
Publisher	Elsevier	Elsevier
Accessibility	Open-access	Open-access
Published on	26 Sep 2023	26 Sep 2023
Version	1	1
Dataset size	63.8 MB *(Images)*	2.84 GB *(Images and annotation files)*
Usage	918 and 139 *(views and downloads as on 10.07.2025)*	837 and 95 *(views and downloads as on 10.07.2025)*
DOI	10.17632/4gkcyxjyss.1	10.17632/y9bmtf4xmr.1
URL	https://data.mendeley.com/datasets/4gkcyxjyss/1	https://data.mendeley.com/datasets/y9bmtf4xmr/1
GitHub Repo	https://github.com/JustinaMichael/SorghumWeedDataset_Classification	https://github.com/JustinaMichael/SorghumWeedDataset_Segmentation

04. Objective 1 : Sorghum-Weed dataset creation

Phase V: Building an AI model

Initial Experimentation - Results

TABLE 4.12. Performance of Pre-trained models on 'SorghumWeedDataset_Classification'

Model / Metrics	Training Loss	Training Accuracy	Validation Loss	Validation Accuracy	Testing loss	Testing accuracy
DenseNet201 [11]	0.2228	0.9685	0.7697	0.9582	0.4413	**0.9605**
VGG19 [12]	0.2675	0.8983	0.2019	0.9361	**0.2215**	0.9419
MobileNetV2 [13]	0.6925	0.9562	0.7818	0.9593	1.8539	0.9187
ResNet152V2 [14]	0.4831	0.9519	0.7140	0.9477	1.2332	0.9443

Published a code capsule entitled "CNN_Sorghum_Weed_Classifier: An Artificial Intelligence-based Software for Pre-processing and Experimenting 'SorghumWeedDataset_Classification' dataset in Python"in Code Ocean on 15.12.2023 with DOI https://doi.org/10.24433/CO.7479881.v1

04. Objective 1 : Sorghum-Weed dataset creation

Research outcome of objective-1

- Acquisition, creation and publication of the first Indian open-access crop-weed research datasets in Mendeley Data repository.
  i. 'SorghumWeedDataset_Classification'
  ii. 'SorghumWeedDataset_Segmentation'
- Initial experiments are conducted on the datasets and the code is released in CodeOcean.

Objective - 2

05. Objective 2: HierbaNetV1-Feature extractor

Literature review

#	Reference	Yr	Architecture	Inference	Limitations
9	Xu, Ke, et al. [15], Precision Agriculture	2024	WeedsNet	Dual-path feature extraction network is constructed to extract features of weeds from RGB and depth images simultaneously.	The model do not provide precise localization or segmentation at the pixel level for robotic systems to act upon.
10	Jin et al. [16], IEEE Access	2021	CenterNet	Vegetable detection followed by weed extraction from background using a color index-based Segmentation.	In situations with high variability (lighting, soil type, plant health) in lighting or soil conditions, the color-index based segmentation will not distinguish weeds from the background.
11	Hu, Kun, et al. [17], Computers and Electronics in Agriculture	2020	Graph weeds net	Three-scale weed graph with global and local patterns. Apply CNN for each patch to obtain a feature set of weed patches.	The model's ability to detect weeds in different growth stages is not addressed.
12	Sa, Inkyu, et al. [18] IEEE Robotics and Automation Letters	2017	weedNet	SegNet with a balanced frequency of appearance (FoA) of a class through penalization.	In SegNet, the segmentation of smaller objects are not as precise compared to larger objects, leading to errors in small weed detection.

05. Objective 2: HierbaNetV1-Feature extractor

➢ **Problem statement - 02**

Feature extraction methods focus on a specific degree of complexity thus preventing to identify ROIs of all sizes.

➢ **Objective - 02**

To create HierbaNetV1 - a novel feature extraction technique that extracts significant representations from varying-sized Region-of-Interests.

(a)

(b)

Fig 5.1 Samples with varying sized ROIs

1. *Michael J,Manivasagam T. 2024. HierbaNetV1: a novel feature extraction framework for deep learning-based weed identification. PeerJ Comput. Sci. 10:e2518 DOI 10.7717/peerj-cs.2518* ***[Q1, PeerJ Computer Science, SCI, IF-3.8, CS-4.2]***
2. *Published an article entitled "HierbaNetV1: A novel convolutional neural network architecture" in the journal "Science Talks", Elsevier on Jan 2024. https://doi.org/10.1016/j.sctalk.2024.100316*
3. *Filed the provisional specification of the patent entitled "HierbaNetV1: A CNN-based customized architecture with intensive feature extraction for classification" in Indian Patent Office with Patent application no. 202441050194 on 01.07.2024.*

05. Objective 2: HierbaNetV1-Feature extractor

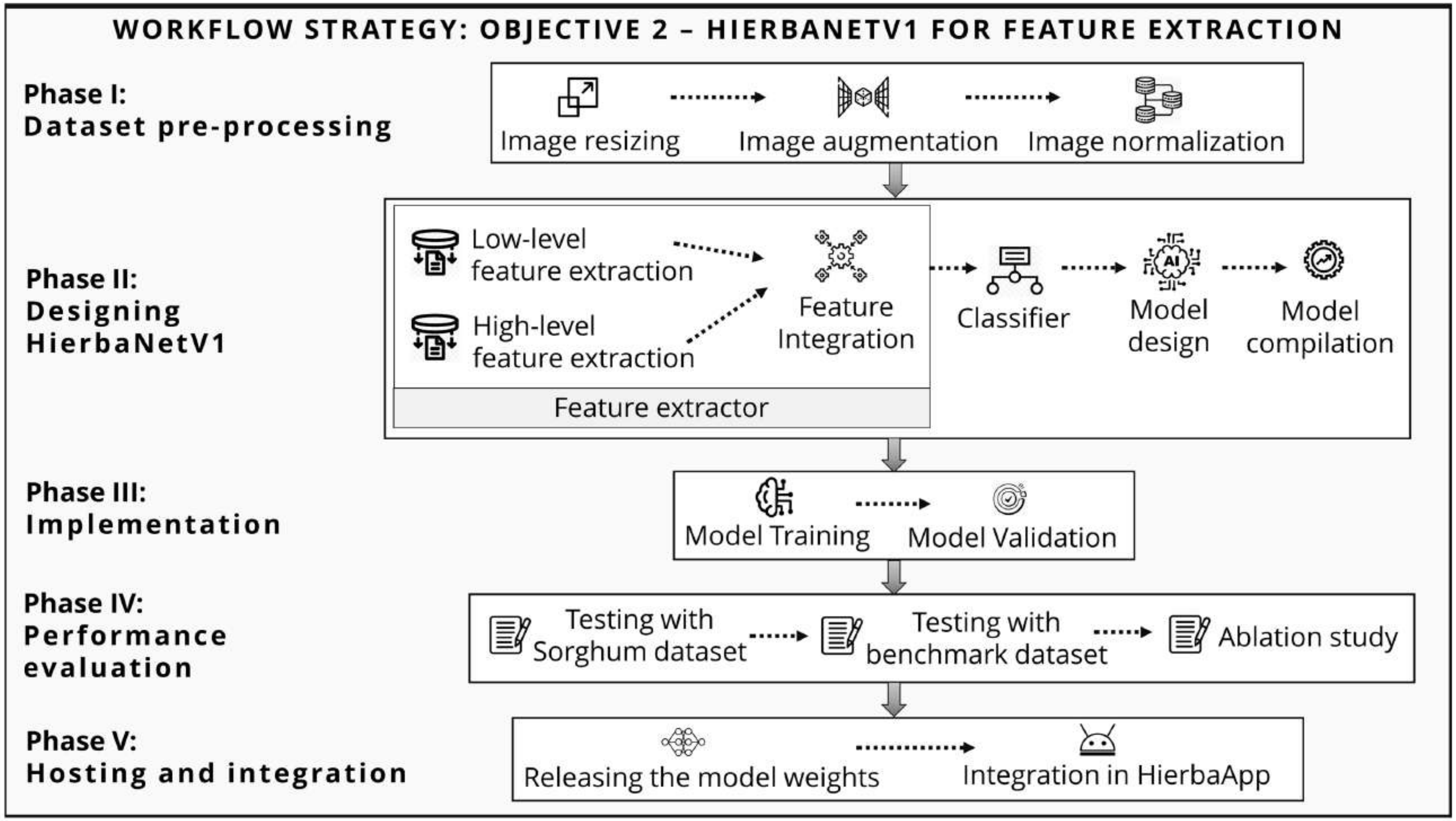

Fig 5.2. Workflow strategy of HierbaNetV1 for feature extraction

05. Objective 2: HierbaNetV1-Feature extractor

Phase I: Dataset Pre-processing

TABLE 5.1. Pre-processing 'SorghumWeedDataset_Classification' dataset for feature extraction with HierbaNetV1

Methods	Values	
Image resizing	224 × 224	
Image augmentation	Rotation	45^{o}
	Zoom	25%
	Slant	25%
	Flip	Horizontal and Vertical
	Shift	30% Width and Height
	Brightness	0.2 to 0.9
Image normalization	Range: 0 to 1	

05. Objective 2: HierbaNetV1-Feature extractor

Phase II: Design HierbaNetV1

Ideation: To perform intensive feature extraction focusing on multiple levels of complexity, irrespective of the ROI size, and emphasize low-level features consistently.

Convolution – ***Eq 1***

$$y_{conv}(h,w) = \sum_{i=0}^{m-1}\sum_{j=0}^{n-1} x(h+i,\ w+j)\ w(i,j) + b$$

Batch Normalization - ***Eq 2***

$$y_{bn}(h,w) = \gamma \cdot \frac{y_{conv}(h,w) - \mu}{\sqrt{\sigma^2 + \epsilon}} + \beta$$

Activation function - ***Eq 3***

$$y_{act}(h,w) = \begin{cases} y_{bn}(h,w), & if\, y_{bn}(h,w) > 0 \\ \propto \cdot\, y_{bn}(h,w), & otherwise \end{cases}$$

Dimensionality reduction - ***Eq 4***

$$y_{pool}(h,w) = \max_{(i,j)\in pool\_region} y_{act}(h+i, w+j)$$

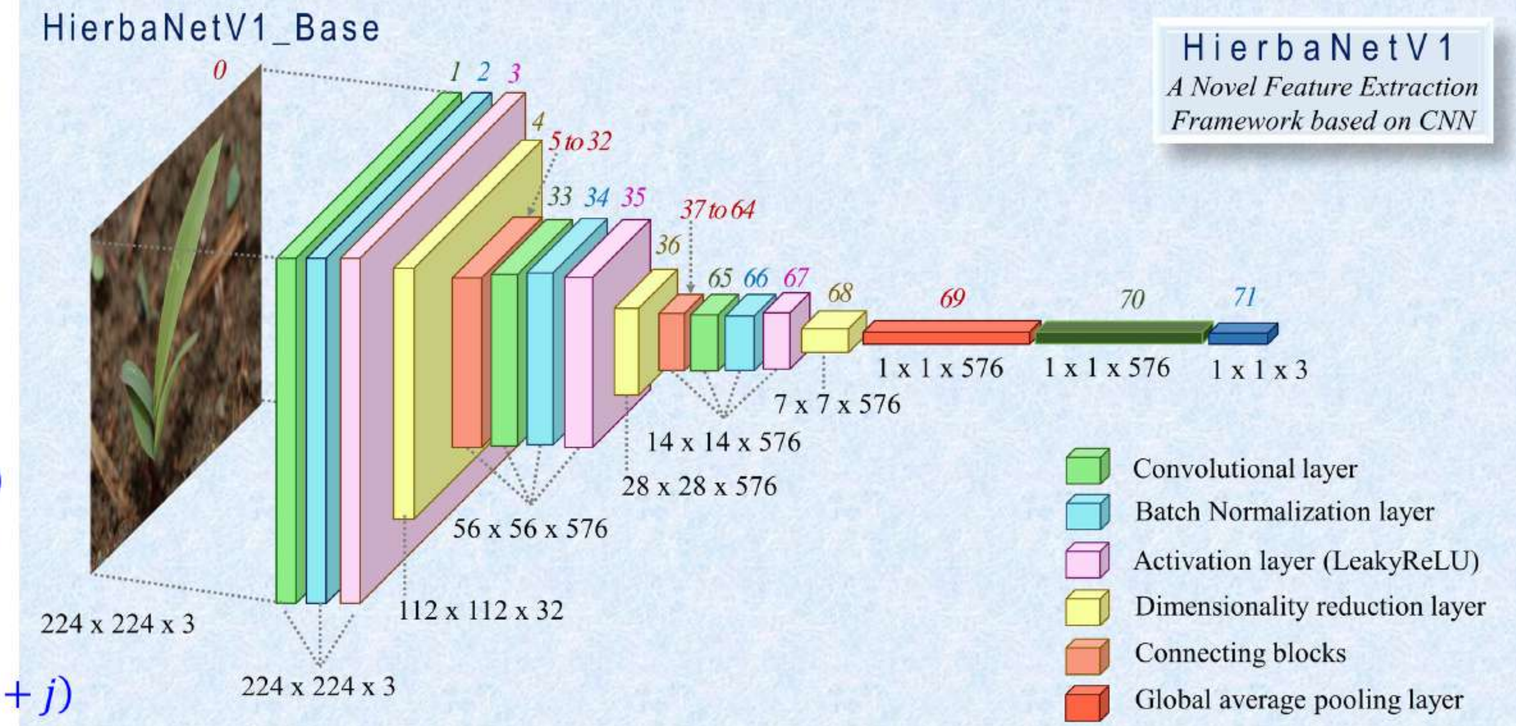

Fig 5.3. Architecture of HierbaNetV1

05. Objective 2: HierbaNetV1-Feature extractor

Phase II: Design HierbaNetV1 Block I

***begin** FeatureExtraction_HierbaNetV1*

$F_{h1}=\sigma(B_{norm}(X*W_{1x1}+b_1))$ *//Module1*

$F_{h3}=\sigma(B_{norm}(X*W_{3x3}+b_2))$

$F_{h5}=\sigma(B_{norm}(X*W_{5x5}+b_3))$

$F_{h7}=\sigma(B_{norm}(X*W_{7x7}+b_4))$

$F_H=F_{h1}+F_{h3}+F_{h5}+F_{h7}$

$F_H=\sigma(B_{norm}(F_H*W_{3x3}+b_5))$

$F_H=\sigma(B_{norm}(F_H*W_{3x3}+b_6))$

$F_H=\sigma(B_{norm}(F_H*W_{3x3}+b_7))$

$F_L=\sigma(B_{norm}(X*W_{3x3}+b_8))$ *//Module2*

$F=F_H+F_L$ *//Module1+2*

end

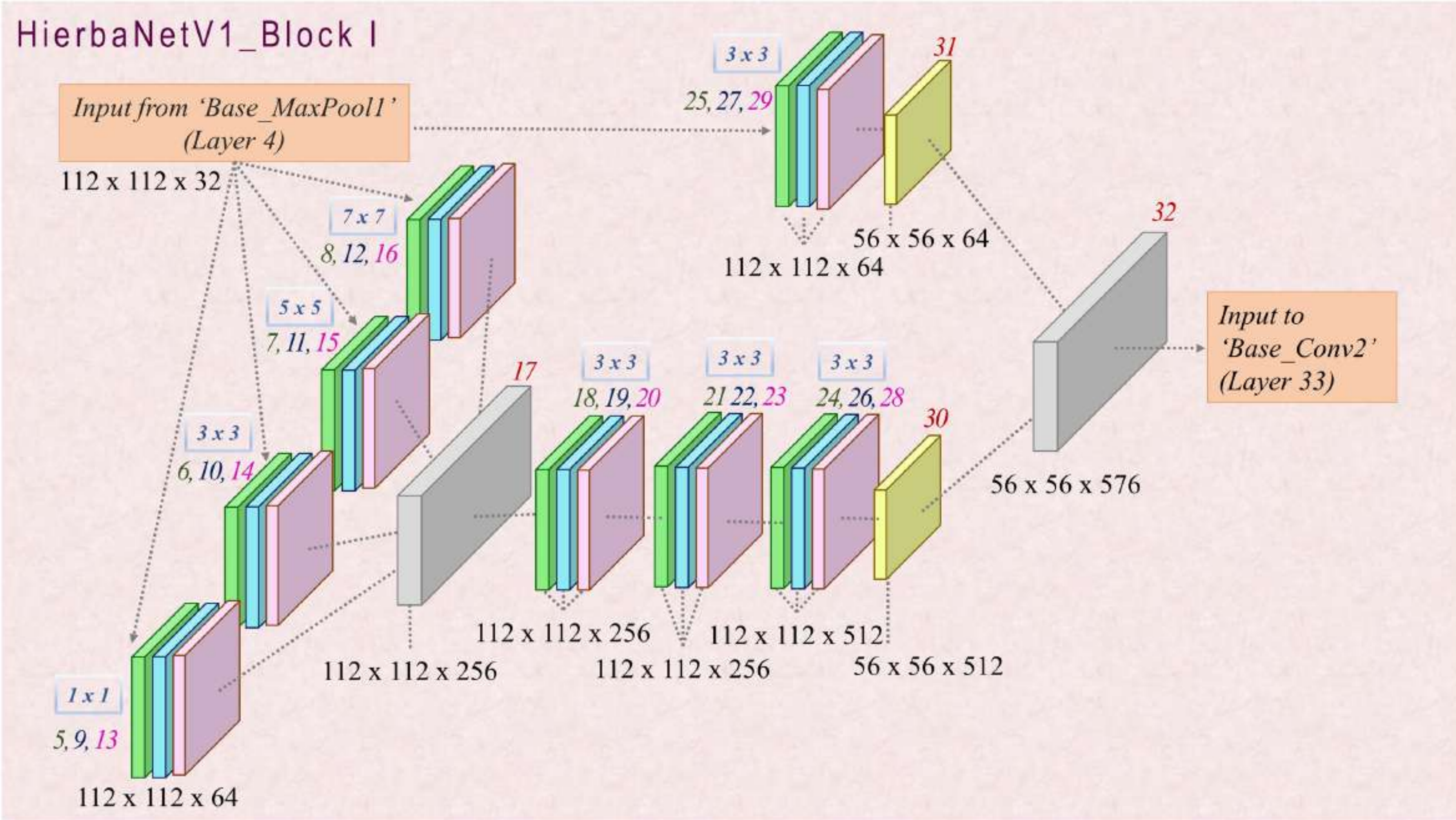

Fig 5.4. Architecture of HierbaNetV1_Block-I

05. Objective 2: HierbaNetV1-Feature extractor

Phase II: Design HierbaNetV1 Block II

begin *FeatureExtraction_HierbaNetV1*

$F_{h1}=\sigma(B_{norm}(X*W_{1x1}+b_1))$ *//Module1*

$F_{h3}=\sigma(B_{norm}(X*W_{3x3}+b_2))$

$F_{h5}=\sigma(B_{norm}(X*W_{5x5}+b_3))$

$F_{h7}=\sigma(B_{norm}(X*W_{7x7}+b_4))$

$F_H=F_{h1}+F_{h3}+F_{h5}+F_{h7}$

$F_H=\sigma(B_{norm}(F_H*W_{3x3}+b_5))$

$F_H=\sigma(B_{norm}(F_H*W_{3x3}+b_6))$

$F_H=\sigma(B_{norm}(F_H*W_{3x3}+b_7))$

$F_L=\sigma(B_{norm}(X*W_{3x3}+b_8))$ *//Module2*

$F=F_H+F_L$ *//Module1+2*

end

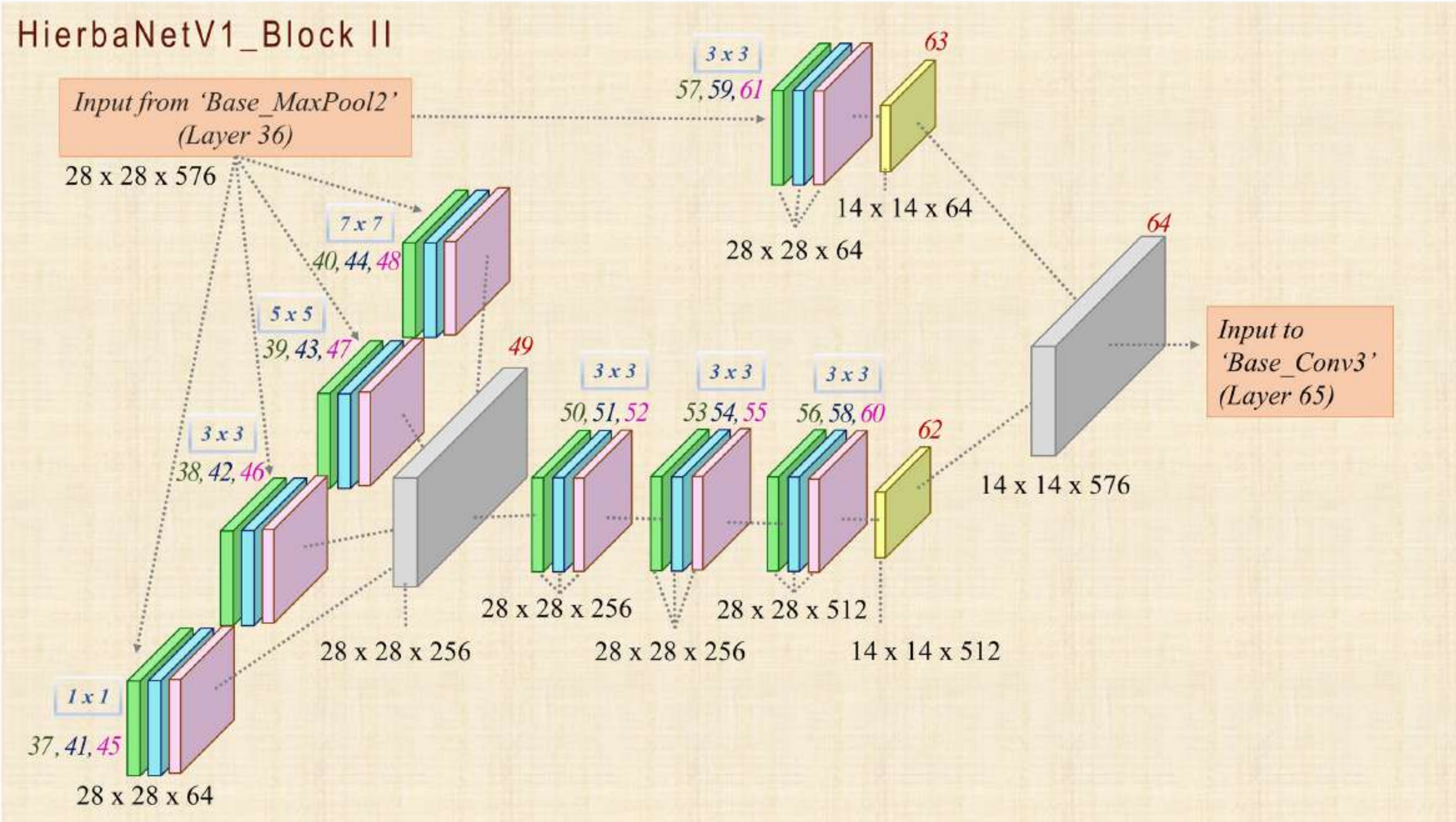

Fig 5.5. Architecture of HierbaNetV1_Block-II

05. Objective 2: HierbaNetV1-Feature extractor

Phase II: Design HierbaNetV1 Block II

Diving deeper into Module 1 and Module 2

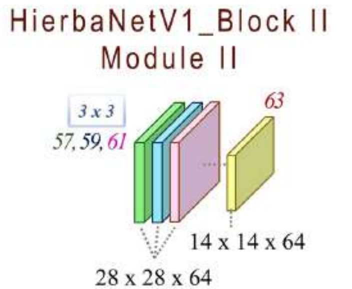

Fig 5.6. (b) Module II of HierbaNetV1_Block-II

- **Module I – High Level Feature Extraction**

  Learns diversified features with multiple levels of complexity irrespective of the ROI size.

- **Module II – Low Level Feature Extraction**

  Passes low-level features to deeper layers to minimize information loss and for the availability of basic features for final decision-making.

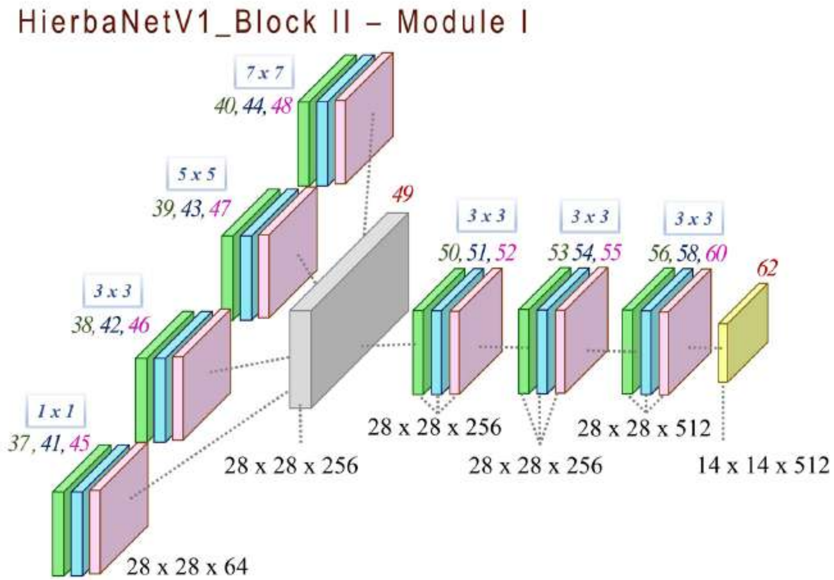

Fig 5.6. (a) Module I of HierbaNetV1_Block-II

05. Objective 2: HierbaNetV1-Feature extractor

HierbaNetV1 - Base

A Convolutional Neural Network (CNN) Based Architecture For Classification

05. Objective 2: HierbaNetV1-Feature extractor

Phase II: Design HierbaNetV1

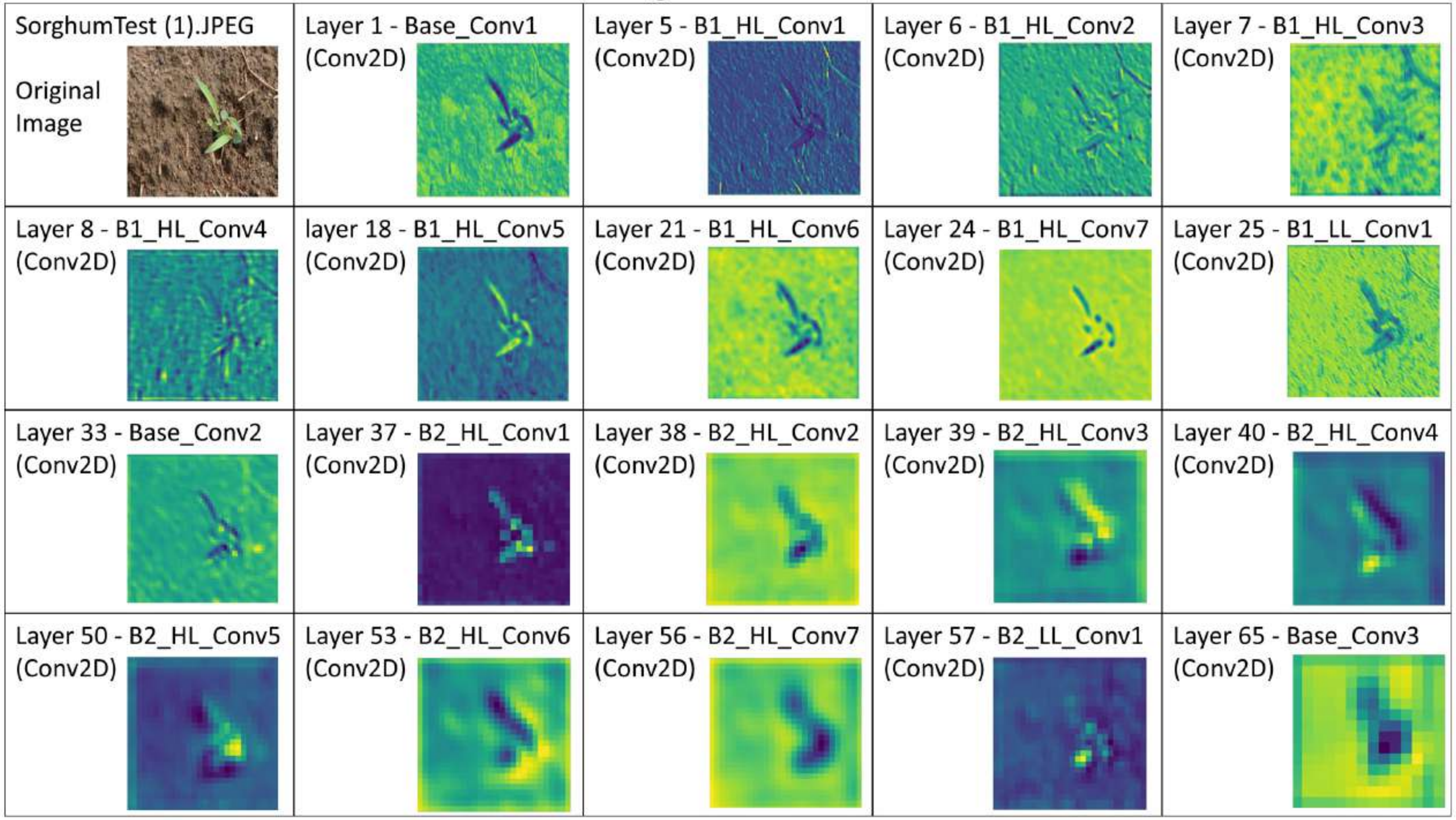

Fig 5.7. Illustration of feature maps from the 19 consecutive convolutional layers in HierbaNetV1

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05. Objective 2: HierbaNetV1-Feature extractor

Phase II: Design HierbaNetV1

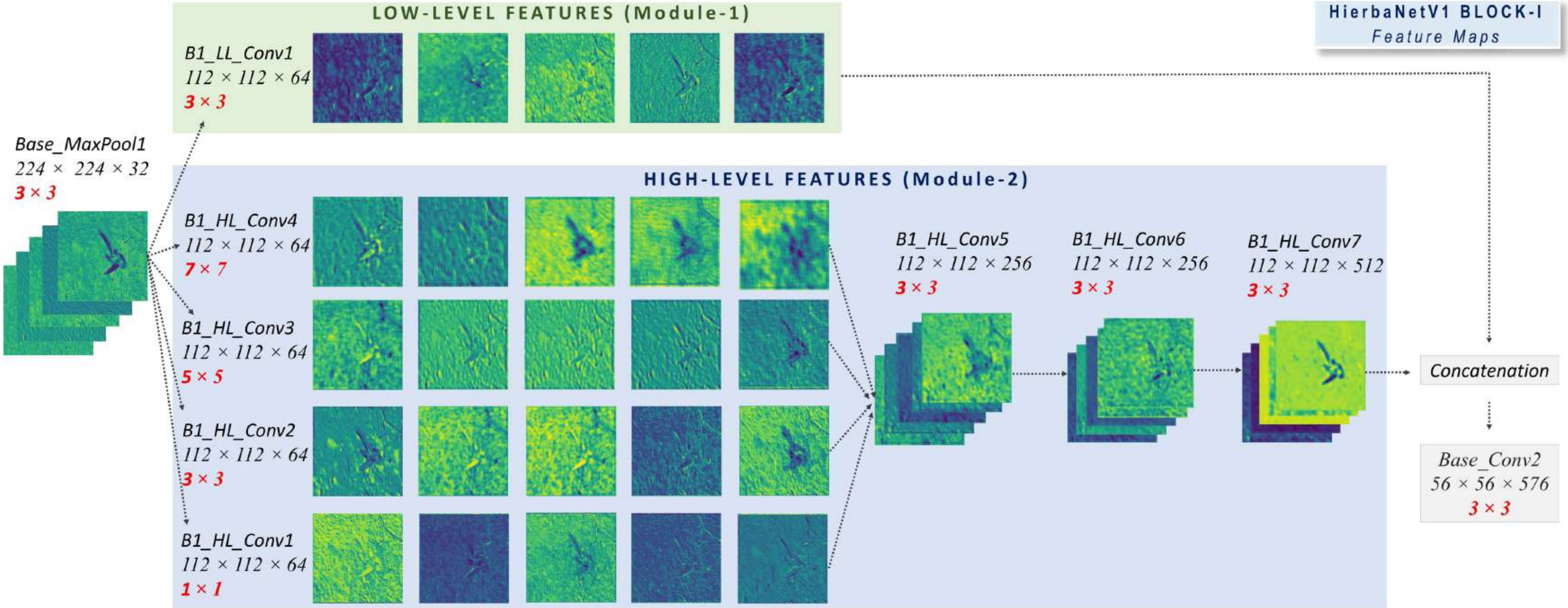


Fig 5.8. Illustration of feature maps from the Block-I convolutional layers in HierbaNetV1

05. Objective 2: HierbaNetV1-Feature extractor

Phase II: Design HierbaNetV1

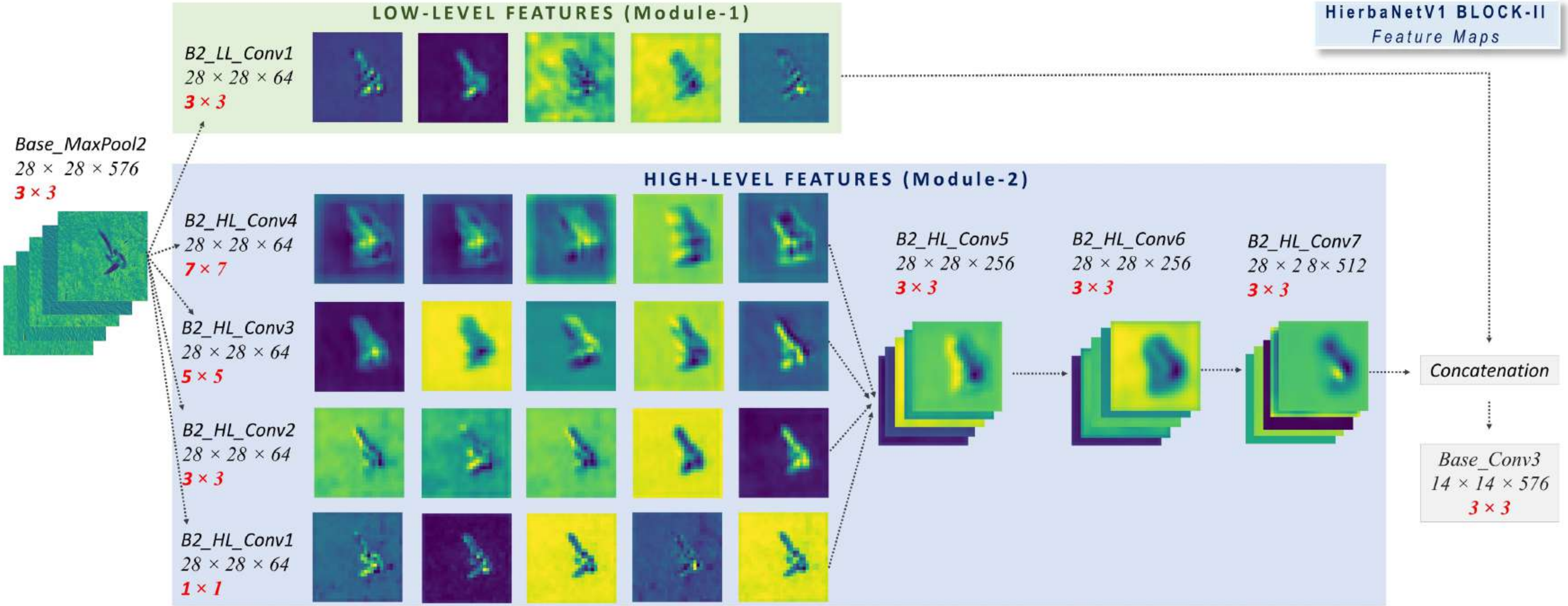


Fig 5.9. Illustration of feature maps from the Block-II convolutional layers in HierbaNetV1

05. Objective 2: HierbaNetV1-Feature extractor

Phase III: Implementation

TABLE 5.2. HierbaNetV1 training platform

Hardware configuration	
Hardware	**Version**
NVIDIA-SMI Driver	525.85.12
CUDA Toolkit	12.0
89.6 gigabytes of high RAM	NVIDIA A100
Training time	2.00 hours

(a)

Software configuration	
Module	**Version**
Python	3.10.12
keras	2.12.0
tensorflow	2.12.0
scikit-learn	1.2.2
pillow	9.4.0
numpy	1.22.4
matplotlib	3.7.1
seaborn	0.12.2
pandas	1.5.3

(b)

05. Objective 2: HierbaNetV1-Feature extractor

Phase III: Implementation

TABLE 5.3. HierbaNetV1 training parameters

Parameters	
Name	**Value**
Trainable	14,323,587
Non-trainable	7,744
Total	14,331,331

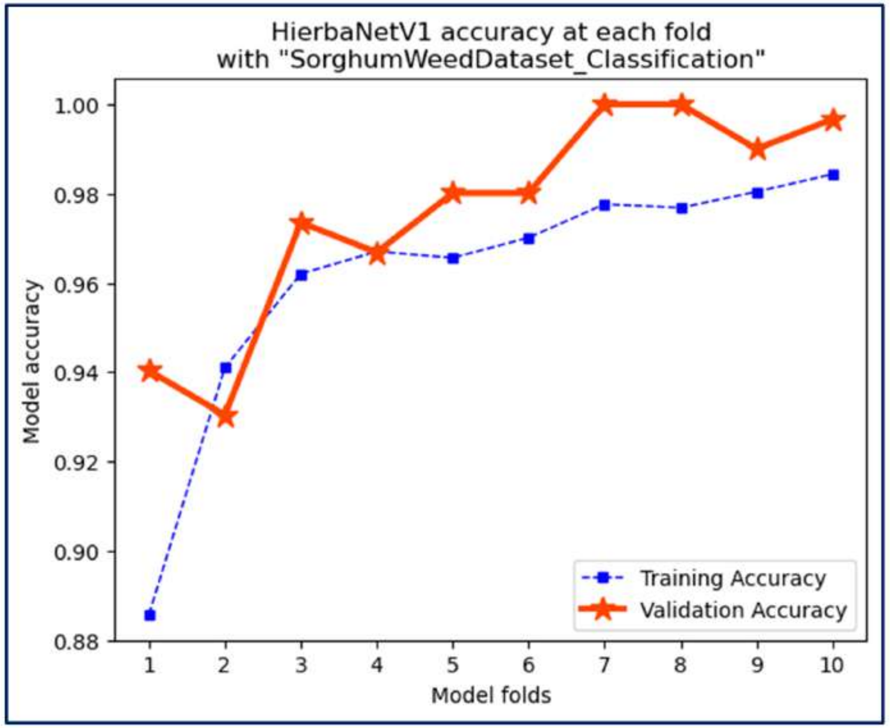
(a)

Hyper-parameters	
Name	**Value**
Epochs	50
Batch size	32
Iteration	218
Validation type	Stratified 10-fold CV
Size of the input image	224 × 224
Optimizer, Learning rate, Epsilon	Adam, 0.001, 1e-07
Activation function in the hidden layer	LeakyReLU (0.001)
Activation function in the top layer	Softmax
Weight initialization	Glorot Uniform

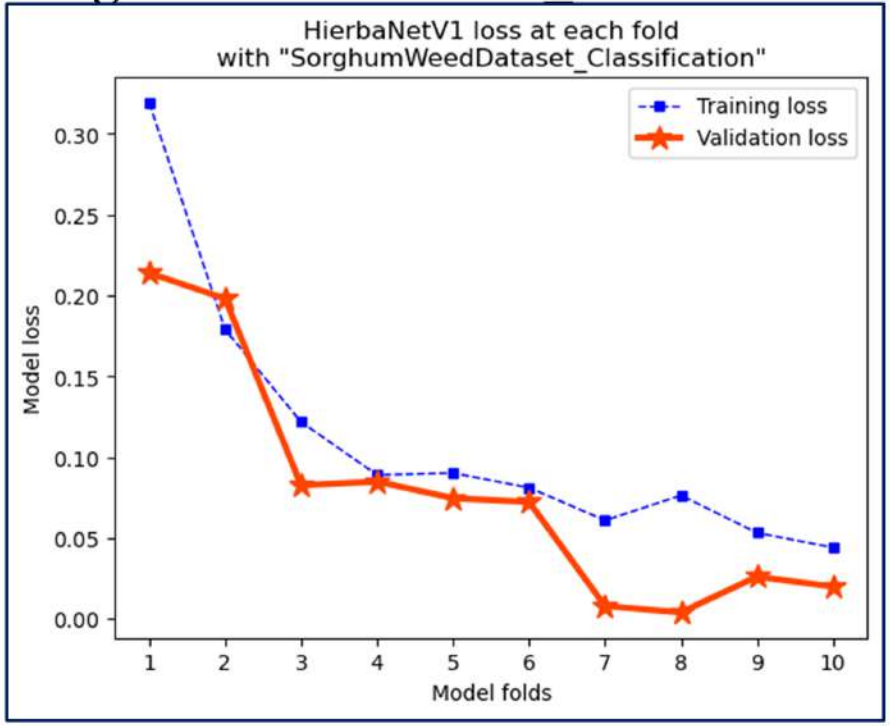
(b)

05. Objective 2: HierbaNetV1-Feature extractor

Phase IV: Performance evaluation – HierbaNetV1 on 'SorghumWeedDataset_Classification'



(a)



(b)

Fig 5.10. Accuracy and loss graphs of Stratified 10-fold cross validation of HierbaNetV1

The trained model weights of HierbaNetV1 are available at the GITHUB REPOSITORY https://github.com/JustinaMichael/HierbaNetV1-A-Novel-CNN-Architecture.git

05. Objective 2: HierbaNetV1-Feature extractor

Phase IV: Performance evaluation - Metrics for model evaluation

$$True\ Positive\ (TP) = Number\ of\ correctly\ predicted\ postive\ samples$$

$$True\ Negative\ (TN\ ) = Number\ of\ correctly\ predicted\ negative\ samples$$

$$False\ Positive\ (FP) = Number\ of\ incorrectly\ predicted\ postive\ samples$$

$$False\ Negative\ (FN) = Number\ of\ incorrectly\ predicted\ negative\ samples$$

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

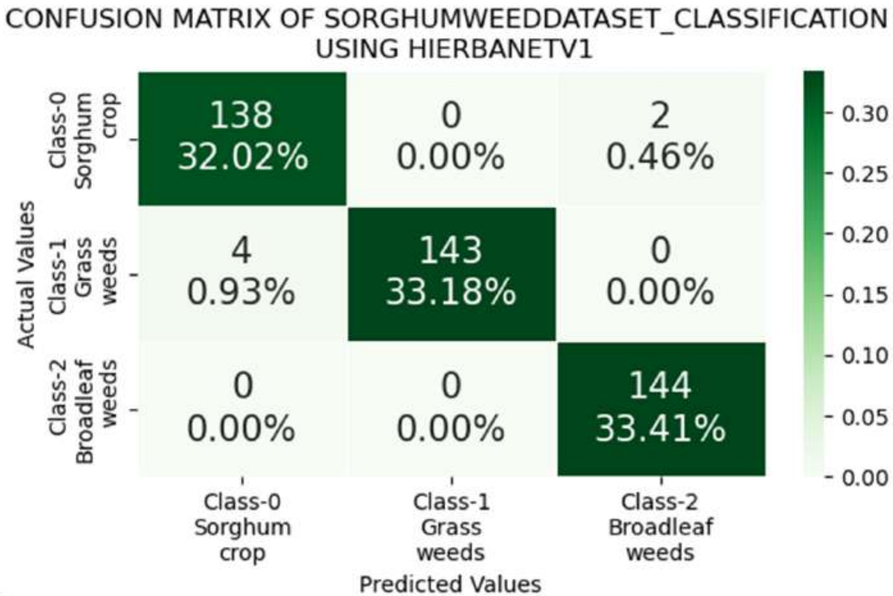
$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

$$F1 - score = 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall}$$

$$Loss = -\sum_{i=1}^{c} y_i \cdot \log(\hat{y}_i)$$

Fig 5.11. Confusion matrix of 'SorghumWeedDataset_ Classification using HierbaNetV1



05. Objective 2: HierbaNetV1-Feature extractor

Phase IV: Testing HierbaNetV1 against pre-trained and SOTA models on own dataset

TABLE 5.4. Performance evaluation of HierbaNetV1 against pre-trained models and SOTA models

Model	Accuracy	Precision	Recall	F1-score	Loss
HierbaNetV1	**0.9861**	**0.9860**	**0.9860**	**0.9860**	**0.0700**
Pre-trained models					
InceptionV3 [19]	0.9791	0.9795	0.9795	0.9792	1.5472
VGG19 [12]	0.9698	0.9704	0.9702	0.9698	0.1444
ResNet152V2 [14]	0.9675	0.9685	0.9681	0.9676	1.4649
DenseNet201 [11]	0.9582	0.9601	0.9590	0.9583	1.0096
MobileNetV2 [13]	0.9327	0.9336	0.9321	0.9323	2.2053
SOTA models					
CNN-Transformer [24]	0.9606	0.9604	0.9605	0.9605	1.1503
DarkNet53 [25]	0.9397	0.9395	0.9397	0.9395	2.5037
RCNN-Weed [26]	0.9142	0.9140	0.9142	0.9140	3.0356

Reproducible HierbaNetV1 code is present in the code capsule at https://codeocean.com/capsule/5579071/tree/v1.

05. Objective 2: HierbaNetV1-Feature extractor

Phase IV: Testing HierbaNetV1 against pre-trained models on benchmark datasets

TABLE 5.5. Performance evaluation of HierbaNetV1 against pre-trained model on benchmark datasets

Models	Acc	Loss
HierbaNetV1	**0.9399**	**0.6295**
DenseNet201	0.8184	1.8521
ResNet50	0.7889	2.7827
VGG16	0.7854	1.3263
MobileNetV2	0.7465	2.7304

(a) DeepWeeds dataset

Models	Acc	Loss
HierbaNetV1	**0.9874**	**0.0923**
ResNet152V2	0.9664	1.3769
InceptionV3	0.9643	1.4371
VGG19	0.9538	0.2673
MobileNetV2	0.9454	2.1052

(b) Soybean weed dataset

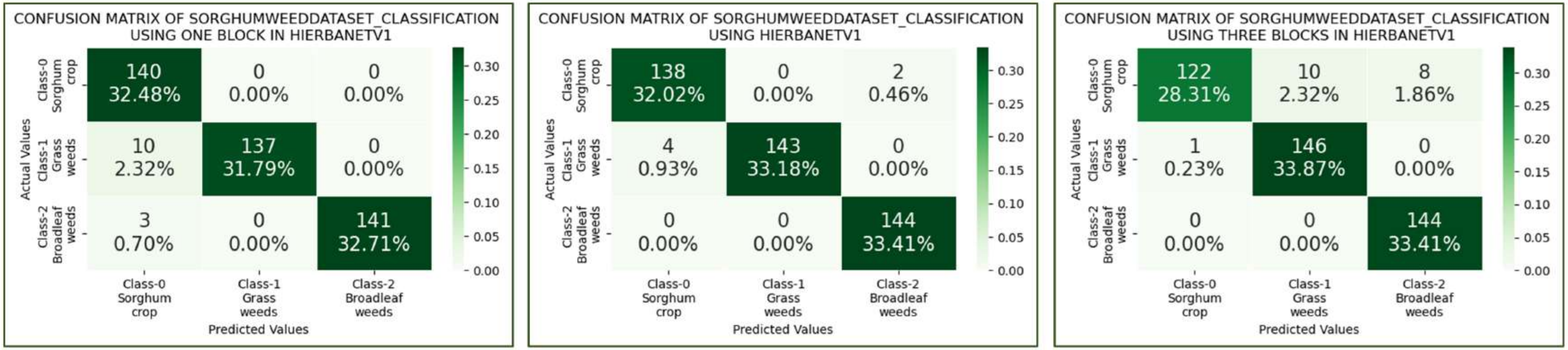
Models	Acc	Loss
HierbaNetV1	**0.8222**	**1.5297**
InceptionV3	0.7778	2.8493
ResNet50	0.7444	2.4700
MobileNetV2	0.7222	2.9701
VGG19	0.6889	1.5235

(c) CottonWeedID15 dataset

05. Objective 2: HierbaNetV1-Feature extractor

Phase IV: Ablation Study

- Architecture variations for ablation study:
    a) HierbaNetV1 with Block-I
    b) HierbaNetV1 with Block-I and Block-II (Proposed method)
    c) HierbaNetV1 with Block-I, Block-II, and Block-III



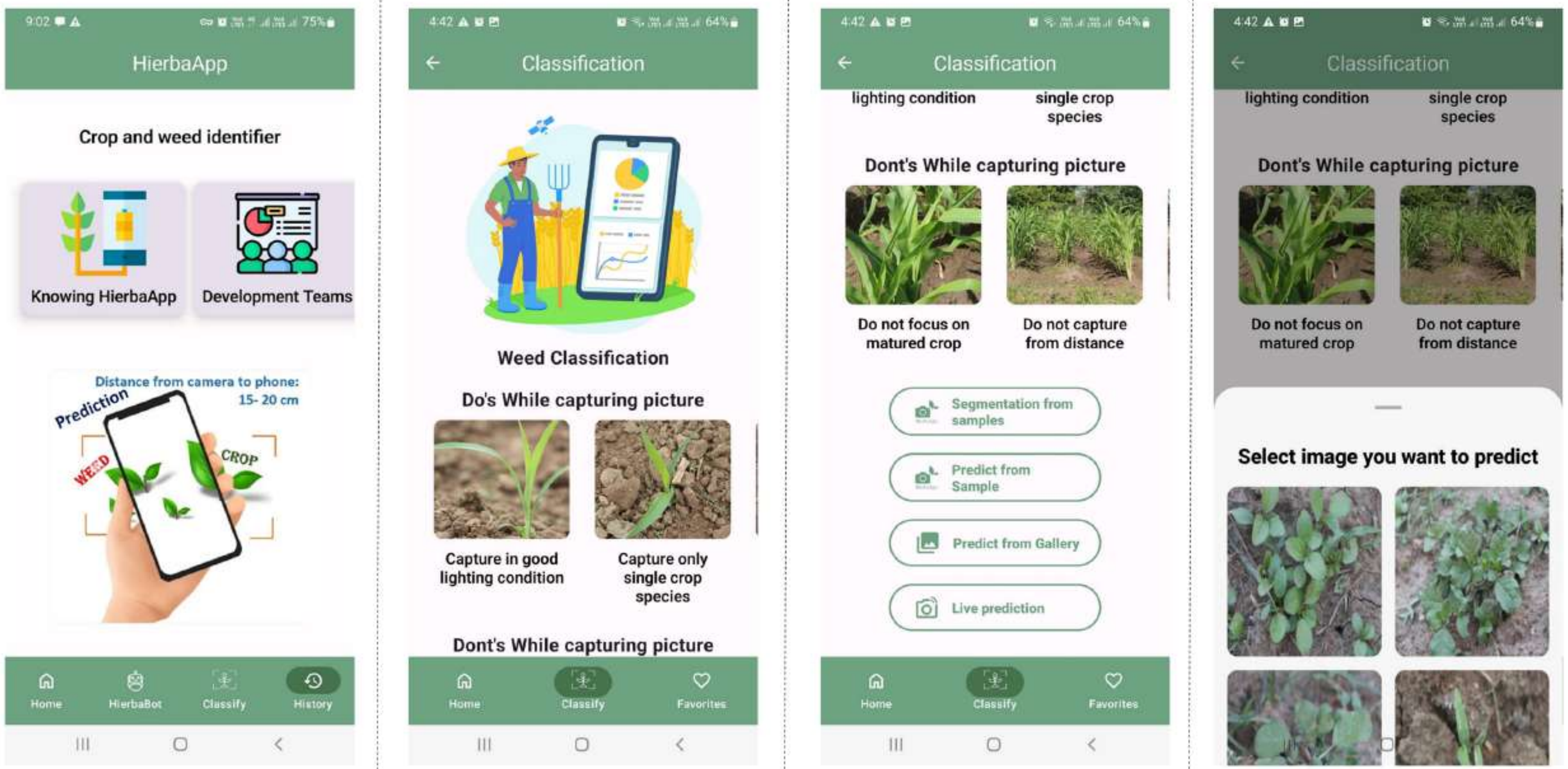
(a) (b) (c)

Fig 5.12. Ablation study - HierbaNetV1 with its variants

05. Objective 2: HierbaNetV1-Feature extractor

Phase V: Integration of HierbaNetV1 with HierbaApp

Fig 5.13.
(a) Home screen of HierbaApp,
(b) List of DO's while capturing images,
(c) List of DON'T'S while capturing images,
(d) Selecting images for prediction



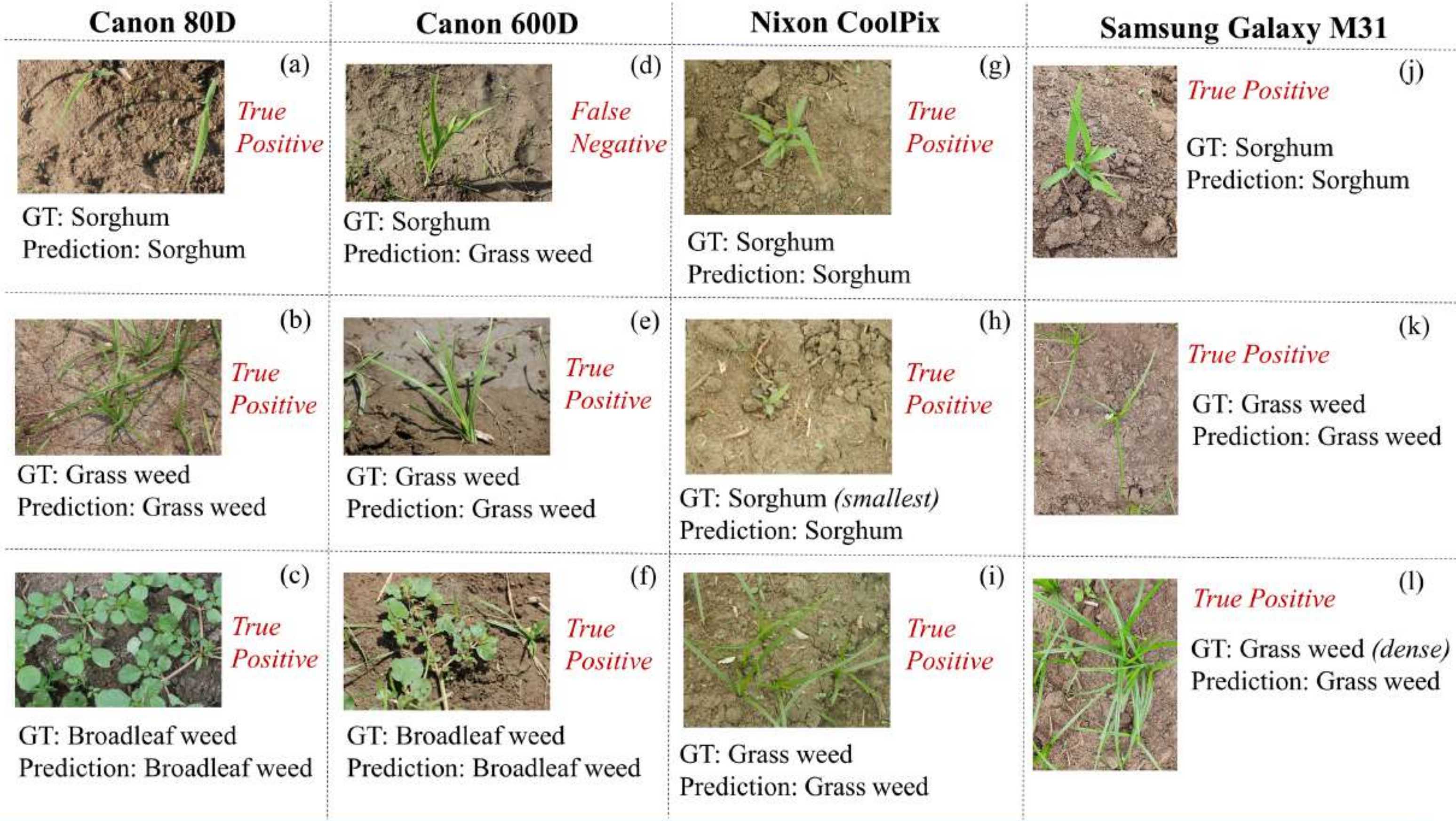
(a) (b) (c) (d)

HierbaApp is accessible in the Google Play Store at https://play.google.com/store/apps/details?id=com.hierba.app 3

05. Objective 2: HierbaNetV1-Feature extractor

Phase V: Real-time weed detection using various equipment

Fig 5.14. Real-time in-field images for detection:
(a), (b), (c) from Canon 80D;
(d), (e), (f) from Canon 600D;
(g), (h), (i) from Nixon CoolPix;
and (j), (k), (l) from Samsung Galaxy M31
each accompanied by their corresponding ground truth

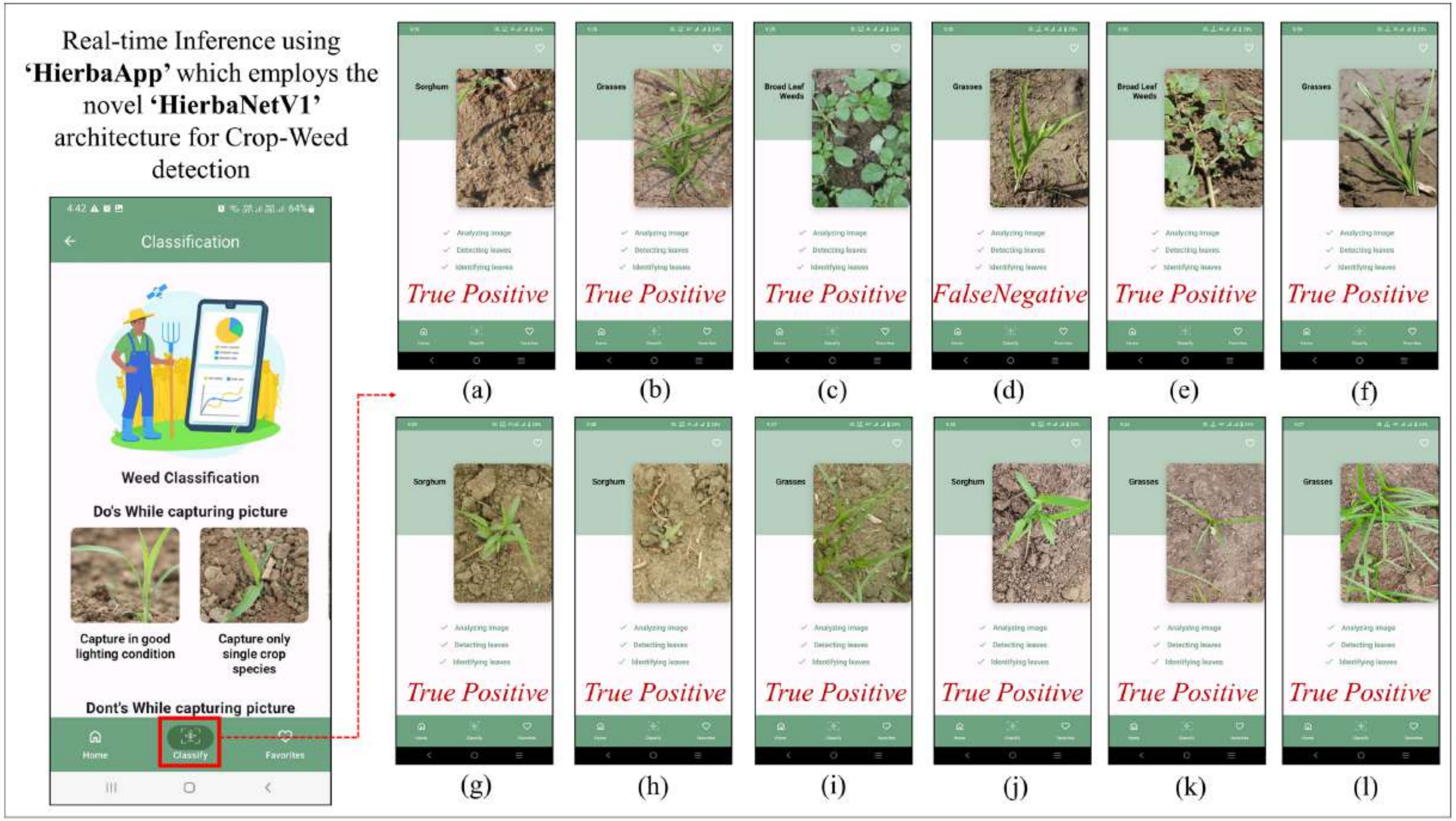


HierbaApp is accessible in the Google Play Store at https://play.google.com/store/apps/details?id=com.hierba.app

05. Objective 2: HierbaNetV1-Feature extractor

Phase V: Validation of results from real-time weed detection

Fig 5.15. Real-time inference using 'HierbaApp' which employs 'HierbaNetV1' for crop-weed detection. (a) to (l) shows the detection results of the respective images in Figure 5.10



Number of images tested: 12

True positives: 11/12

Accuracy: 92%

HierbaApp is accessible in the Google Play Store at https://play.google.com/store/apps/details?id=com.hierba.app

05. Objective 2: HierbaNetV1-Feature extractor

Phase V: Validation of results from real-time weed detection

Prototype of 'Agrobot'

Date of validation: 22.04.2025
Number of images tested: 10
True positives: 8/10
Accuracy: 80%
Primary specifications
- Raspberry Pi
- HierbaNetV1 for detection
- Pi camera
- Red\Green LEDs for crop\weed identification

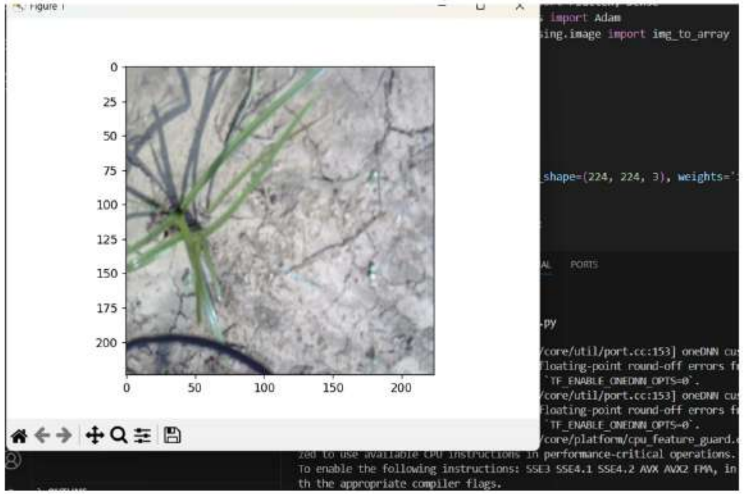


Fig 5.16. Real-time inference using a prototype of 'Agrobot' which employs 'HierbaNetV1' for crop-weed detection on 22.04.2025

Filed a patent entitled "Artificial intelligent based Agro-Bot device for weed identification and removal in random spacing plants" with Application No.202241069244 A, Date of filing of Application :30/11/2022, Publication Date: 09/12/2022 and Journal No/Issue No: 49/2022.

05. Objective 2: HierbaNetV1-Feature extractor

Research outcome of objective-2

- Design and implementation of a novel feature extraction framework – 'HierbaNetV1'
- Releasing the trained model weights and reproducible code of 'HierbaNetV1'
- HierbaNetV1 is validated in real-time with HierbaApp and Agrobot

Objective - 3

06. Objective 3: HierbaNetV1_MRCNN for Object Localization

Literature review

#	Reference	Yr	Architecture	Inference	Limitations
14	Rai, Nitin, and Xin Sun. [15], Computers and Electronics in Agriculture	2024	WeedVision	Integration of C3x module convolves the filters vertically and then horizontally thereby improving prediction.	The model was not trained using a multi-scale training technique
16	Genze, Nikita, et al. [16], Plant Methods	2023	DeBlurWeed Seg	Deblurring and segmentation model for crop-weed segmentation in motion blurred images is done through NAFNet and WeedSeg.	The model is unable to identify the class of the pixel-wise annotation, resulting in uncertainty about whether the patch represents a crop or a weed.
17	Xu, Beibei, et al. [17], Computers and Electronics in Agriculture	2023	Instance segmentation Weed	Colour index contrast between plants and soil. Integrated architecture extracts multi-scale semantic information weed patch boundaries.	The model does not extract features across multiple scales, including both low-level and high-level feature maps.
18	Shuangyu Xie, et al. [18], IEEE Robotics And Automation Letters.	2021	Nutsedge skeleton-based probabilistic map	NSMP differentiates central leaf midrib part of the nutsedge, while reducing the boundary segmentation.	Focusing solely on the weed's skeleton limits the effectiveness of this approach for weeds with varying morphological characteristics.

06. Objective 3: HierbaNetV1_MRCNN for Object Localization

- **Research Gap:**

  Finer object localization for small objects are harder as the feature pyramid network performs down sampling and up sampling frequently.

- **Objective 3:**

  To build HierbaNetV1_FPN - a feature pyramid network that generates rich semantic features for fine-grained object localization.

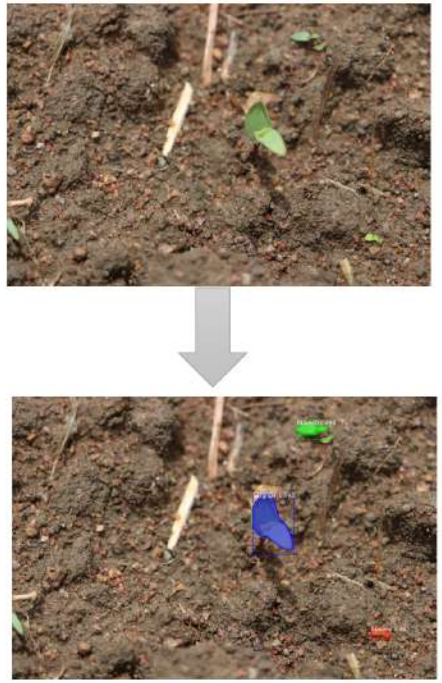


Fig 6.1. Precise Localization and Segmentation

HierbaNetV1_MRCNN: A customized instance segmentation architecture for crop-weed segmentation" is submitted to the journal

06. Objective 3: HierbaNetV1_MRCNN for Object Localization

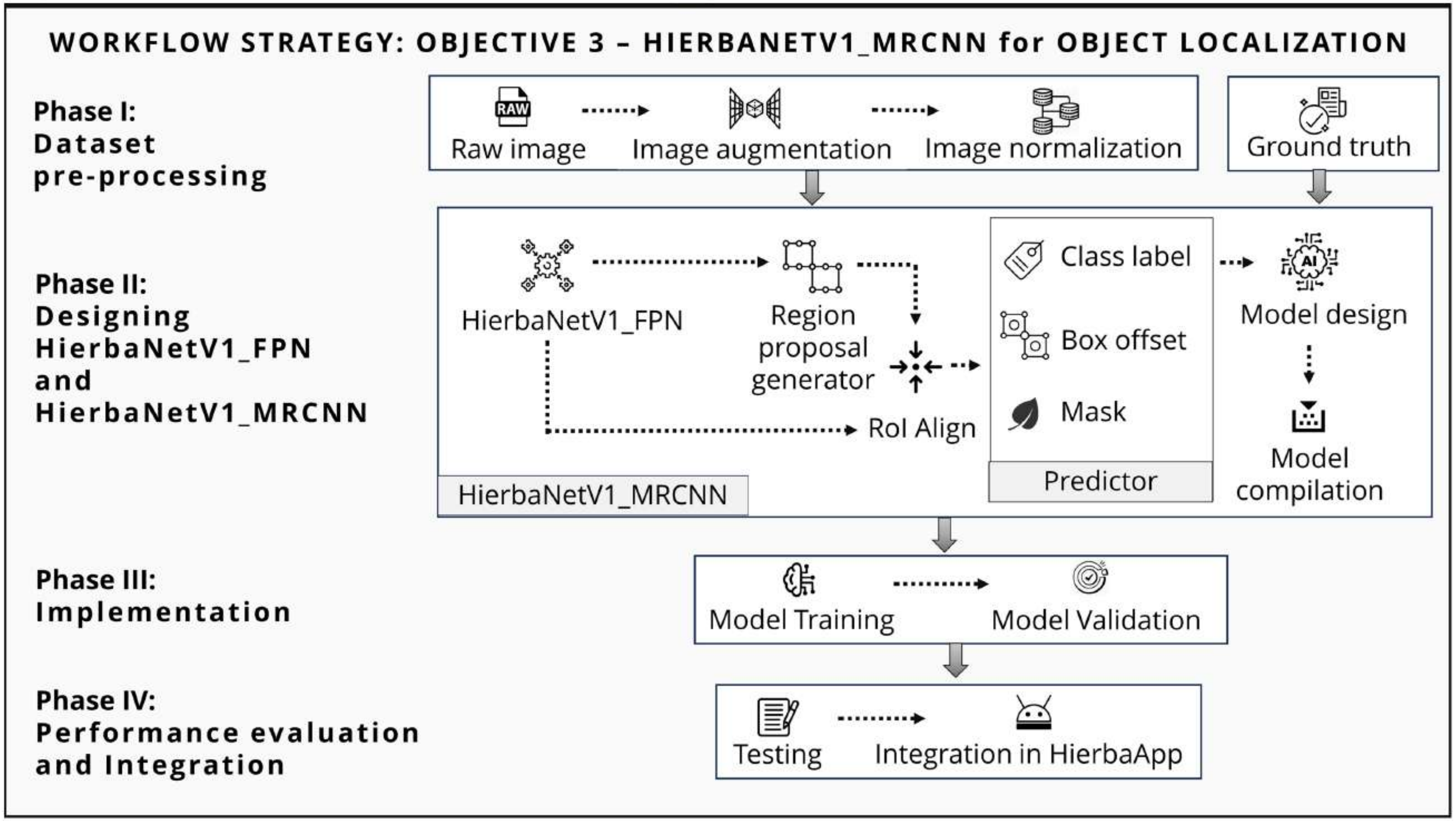


Fig 6.2. Workflow strategy of HierbaNetV1_MRCNN withHierbaNetV1_FPN for object localization

06. Objective 3: HierbaNetV1_MRCNN for Object Localization

Phase I: Dataset Pre-processing

TABLE 6.1. Pre-processing methods of 'SorghumWeedDataset_Segmentation' for HierbaNetV1_MRCNN training

Methods	Values	
Image augmentation	Rotation	45^{o}
	Zoom	25%
	Slant	25%
	Flip	Horizontal and Vertical
	Shift	30% Width and Height
	Brightness	0.2 to 0.9
Image normalization	Range: 0 to 1	

06. Objective 3: HierbaNetV1_MRCNN for Object Localization

Phase I: Dataset Pre-processing – Ground truth of the annotated images

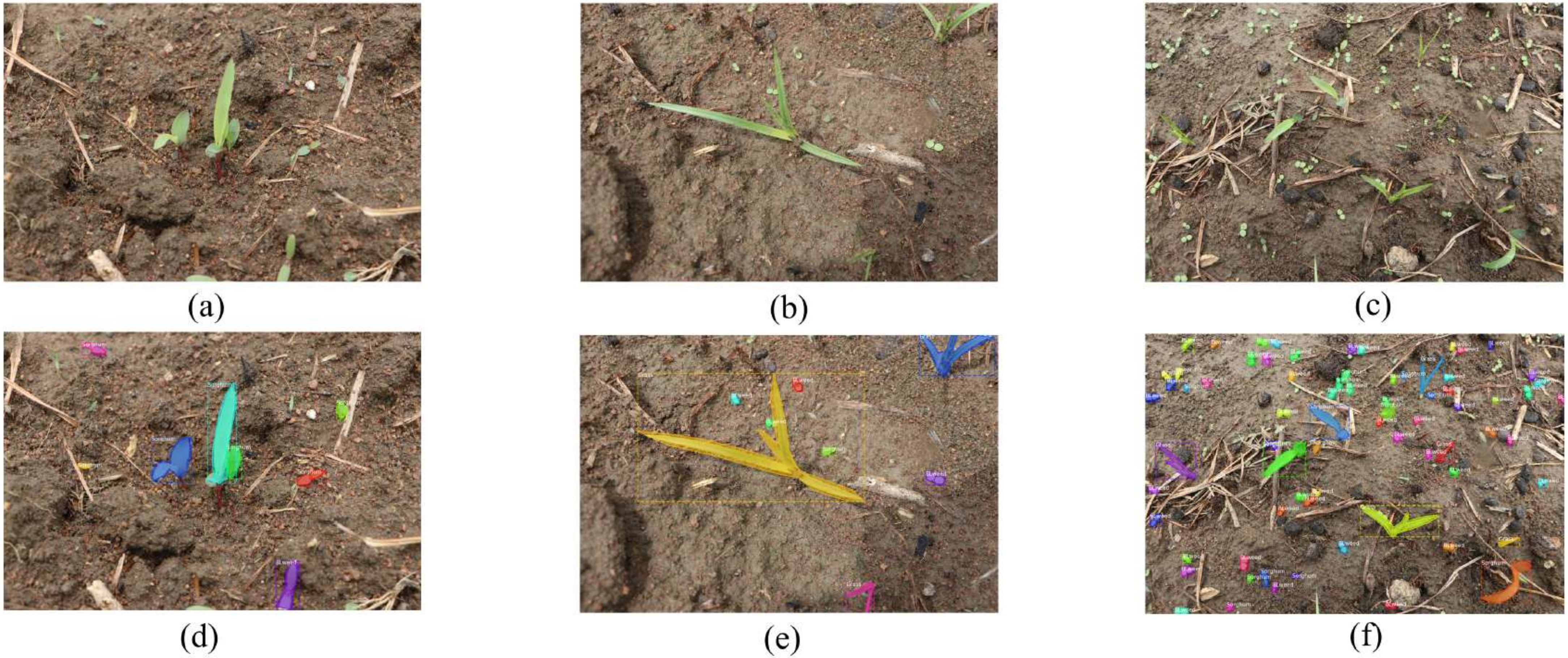


Fig 6.3. Raw data and Ground truth of 'SorghumWeedDataset_Segmentation'

06. Objective 3: HierbaNetV1_MRCNN for Object Localization

Phase II: Designing HierbaNetV1_MRCNN

RPN – ***Eq.1***

$P = sigmoid(W_k * F + bk)$

ROI Align – ***Eq.2***

$F_{roi}(i,j) = \sum_{(x,y)\in bin(i,j)} w_{xy} \cdot F(x,y)$

Object detection head-Classifier – ***Eq.3***

$P_c = softmax(Wc * Froi + bc)$

Object detection head-Regressor – ***Eq.4***

$t_{bbox} = Wr * Froi + br$

Mask generation head – ***Eq.5***

$M = sigmoid(W_m * Froi + bm)$

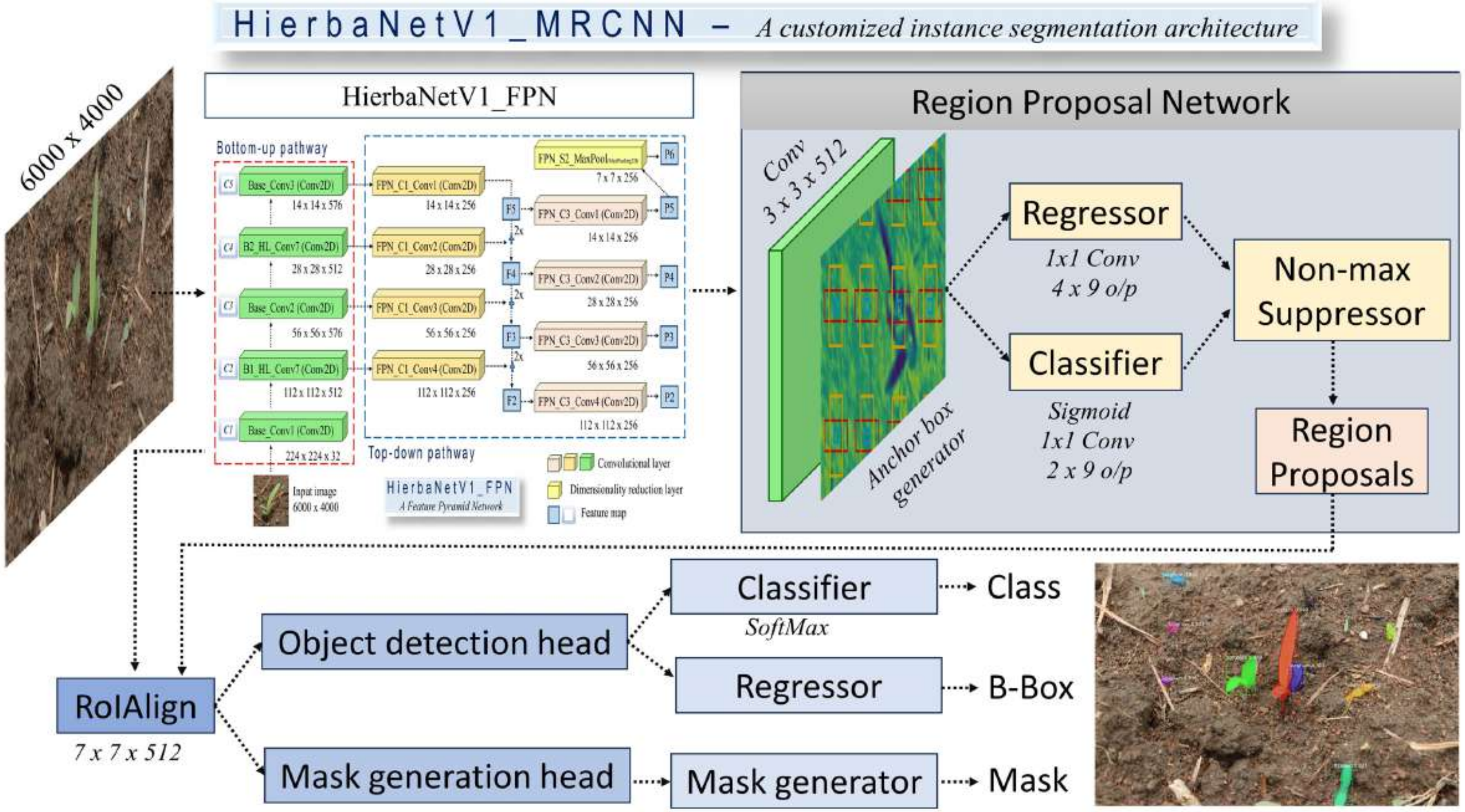


Fig 6.4. Architecture of HierbaNetV1_MRCNN

06. Objective 3: HierbaNetV1_MRCNN for Object Localization

Phase II: Designing HierbaNetV1_FPN

- HierbaNetV1_FPN is designed and developed as an extension of HierbaNetV1.
- **Ideation:** To solve the problem of scale variation by creating an effective Feature Pyramid Network that provides high-resolution features and rich semantics features at various scales.
- It comprises of two modules;
    i. Module I – HierbaNetV1_FPN bottom-up pathway
    ii. Module II – HierbaNetV1_FPN top-down pathway

06. Objective 3: HierbaNetV1_MRCNN for Object Localization

Phase II: Designing HierbaNetV1_ FPN

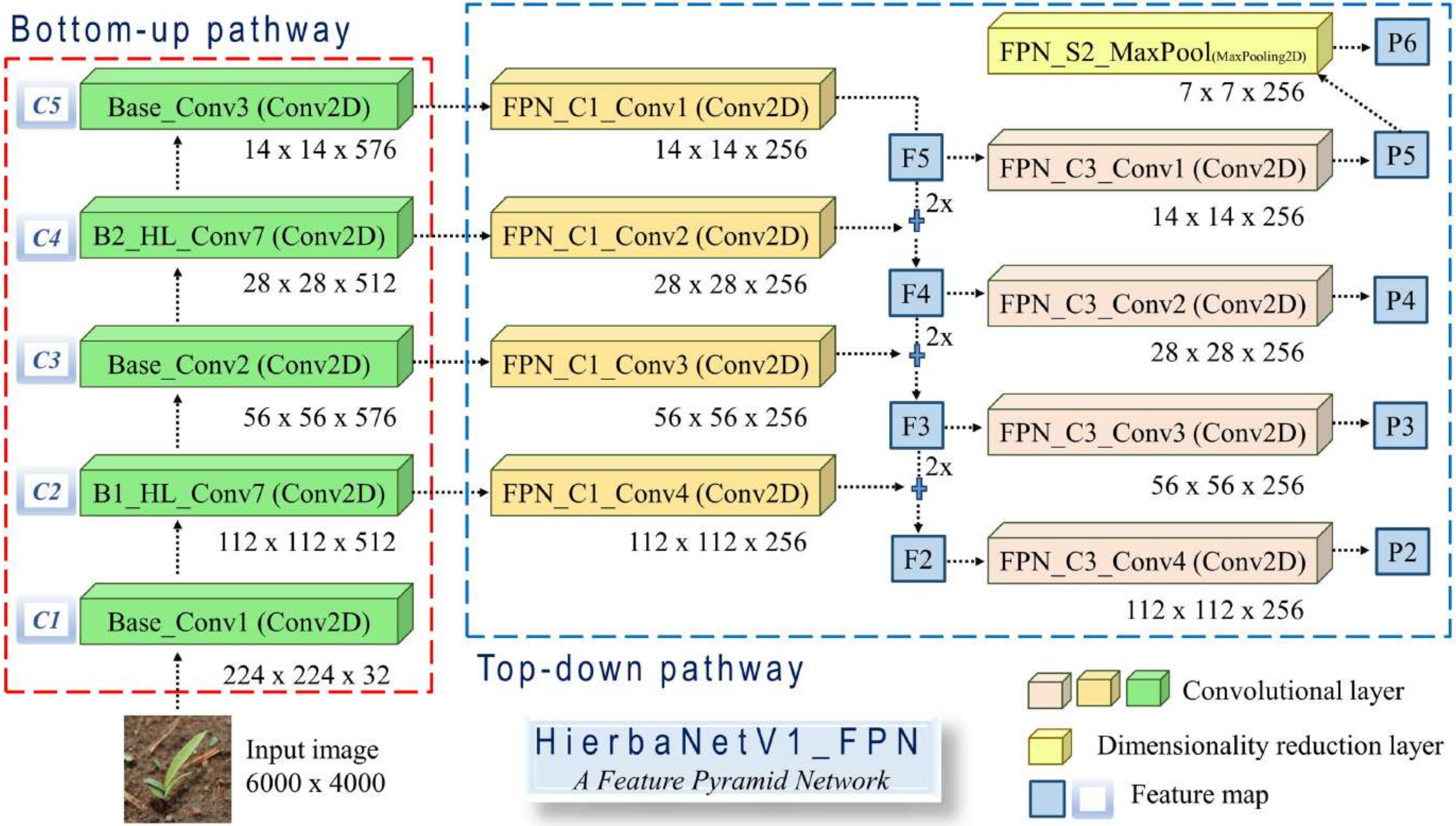


Fig 6.5. Architecture of HierbaNetV1_FPN with HierbaNetV1 as the base

06. Objective 3: HierbaNetV1_MRCNN for Object Localization

Phase II: Designing HierbaNetV1_FPN

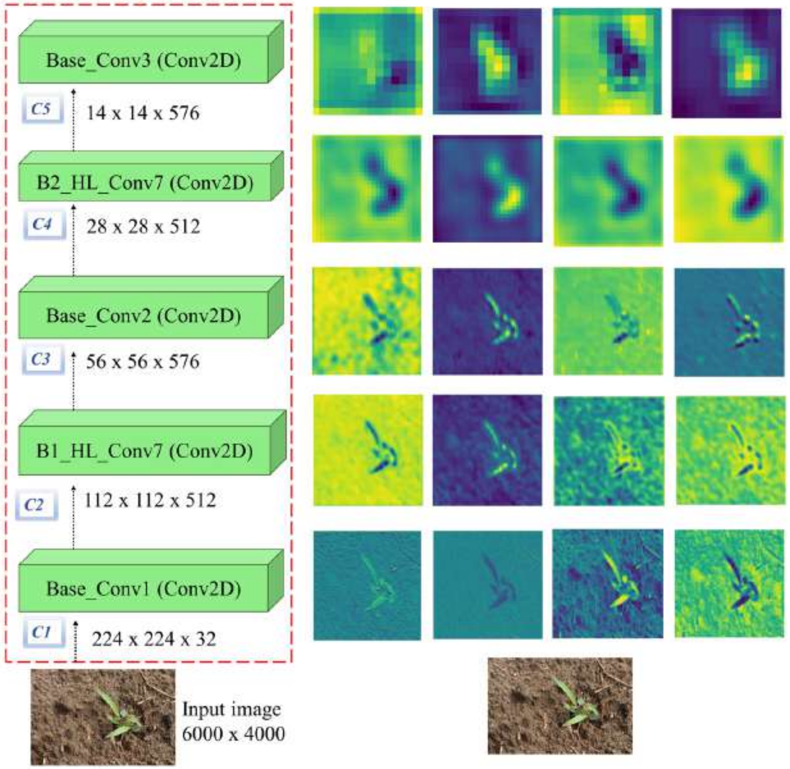


Fig 6.6. Generation of feature maps at C1, C2, C3, C4, and C5

TABLE 6.2. Mapping HierbaNetV1_FPN with HierbaNetV1 for bottom-up pathway

Name of the layer	Layer in HierbaNetV1	Mapped layer in HierbaNetV1_FPN	Depth of feature maps	Size of feature map
Base_Conv1 (Conv2D)	Layer 1	C1	32	224 × 224
B1_HL_Conv7 (Conv2D)	Layer 24	C2	512	112 × 112
Base_Conv2 (Conv2D)	Layer 33	C3	576	56 × 56
B2_HL_Conv7 (Conv2D)	Layer 56	C4	512	28 × 28
Base_Conv3 (Conv2D)	Layer 65	C5	576	14 × 14

06. Objective 3: HierbaNetV1_MRCNN for Object Localization

Phase III: Implementation

TABLE 6.3. HierbaNetV1_MRCNN and HierbaNetV1_FPN training configurations

Name	Value
Backbone	HierbaNetV1_FPN
Number of classes	3 + 1
Epochs	684
Rpn_anchor_scales	(32, 64, 128)
Rpn_anchor_ratios	[0.5, 1, 2]
Rpn_anchor_stride	1
Rpn_nms_threshold	0.7
Detection_min_confidence	0.9
Optimizer and Learning rate	Adam, 0.001
Top_down_pyramid_size	256

06. Objective 3: HierbaNetV1_MRCNN for Object Localization

Phase III: Implementation

TABLE 6.4. HierbaNetV1_MRCNN training platform

Hardware configuration	
Hardware	**Version**
Processor	i5-1035G4
CPU	1.10GHz
RAM	8 GB
Training time	112.00 hours

(a)

Software configuration	
Module	**Version**
Python	3.10.12
keras	2.12.0
tensorflow	2.12.0
numpy	1.22.4
matplotlib	3.7.1
seaborn	0.12.2
pandas	1.5.3
mrcnn	0.1
imgaug	0.4
skimage	0.19.3

(b)

06. Objective 3: HierbaNetV1_MRCNN for Object Localization

Phase IV: Performance Evaluation

TABLE 6.5 – PR-AUC

Mean Average Precision	Value
mAP@50	**0.78**
mAP@75	**0.63**
mAP@[0.5:0.95]	**0.62**

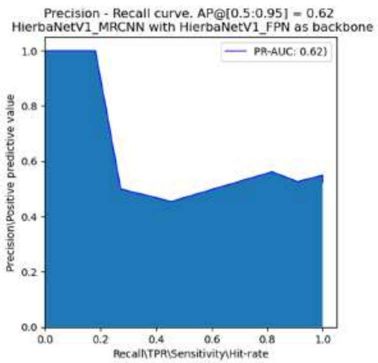
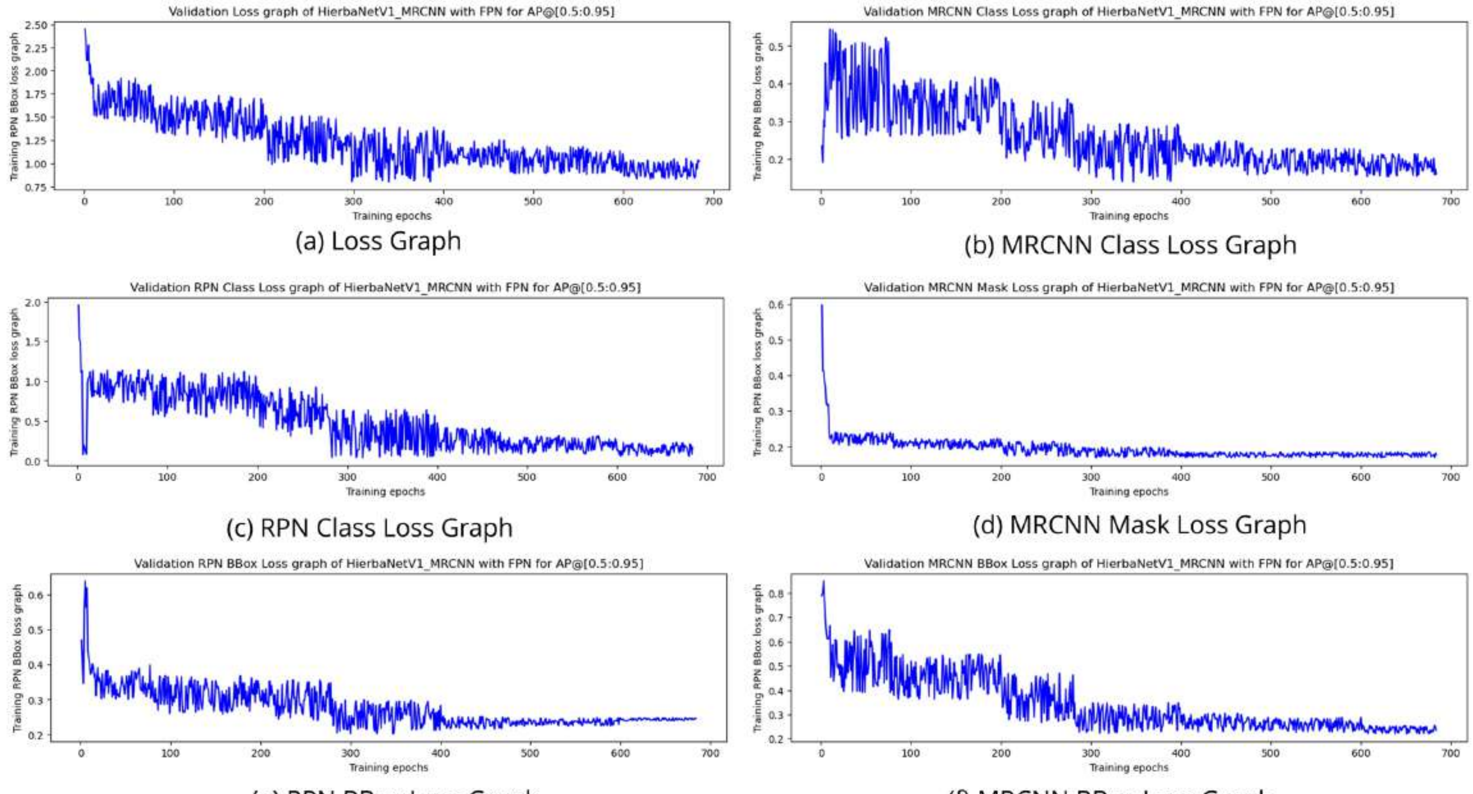


Fig 6.7. PR curve for mAP@[0.5:0.95]



(a) Loss Graph

(b) MRCNN Class Loss Graph

(c) RPN Class Loss Graph

(d) MRCNN Mask Loss Graph

(e) RPN BBox Loss Graph

(f) MRCNN BBox Loss Graph

Fig 6.8. Loss Graph for mAP@[0.5:0.95]

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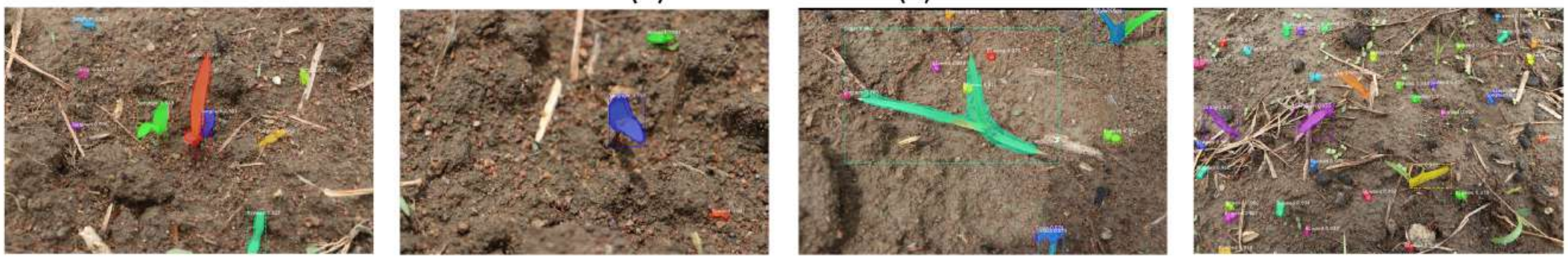
06. Objective 3: HierbaNetV1_MRCNN for Object Localization

Phase IV: Performance Evaluation

Fig 6.9. Results of 'HierbaNetV1_MRCNN' with 'HierbaNetV1_FPN' as backbone on mAP@[0.5:0.95] over 'SorghumWeedDataset_ Segmentation'

(a) Samples from SorghumWeedDataset_Segmentation, showing sorghum, grass and broadleaf weed

(b) Ground truth of (a)



(c) Pixel-wise segmented output generated by MRCNN with HierbaNetV1 as backbone

06. Objective 3: HierbaNetV1_MRCNN for Object Localization

Phase IV: Performance Evaluation

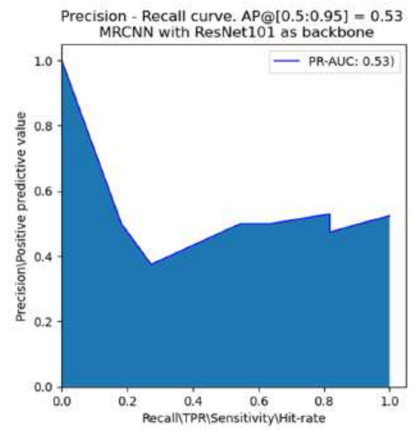
Comparison of proposed method with pre-trained model

- HierbaNetV1_MRCNN is compared with MRCNN with ResNet5101 FPN as backbone.

TABLE 6.6 – Comparison of proposed method with pre-trained model over 'SorghumWeedDataset_Segmentation'

Mean Average Precision	HierbaNetV1_MRCNN with FPN	MRCNN with ResNet101 FPN
mAP@50	**0.78**	0.73
mAP@75	**0.63**	0.58
mAP@[0.5:0.95]	**0.62**	0.53

Fig 6.10. PR curve of MRCNN with ResNet101 FPN as backbone with mAP@[0.5:0.95]



06. Objective 3: HierbaNetV1_MRCNN for Object Localization

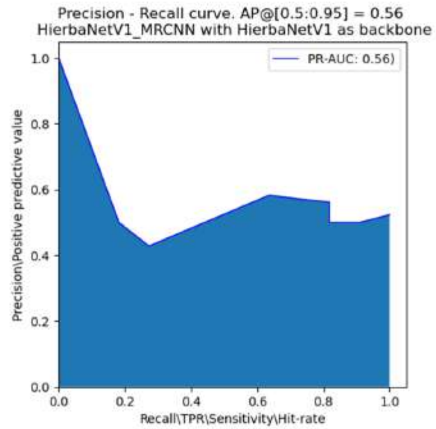
Phase IV: Ablation study

- An ablation study is conducted using an architecture variation in HierbaNetV1_MRCNN with HierbaNetV1 as backbone.

TABLE 6.7 – Ablation study: 'HierbaNetV1_MRCNN' with 'HierbaNetV1' as backbone over 'SorghumWeedDataset_Segmentation'

Mean Average Precision	HierbaNetV1_MRCNN with FPN	HierbaNetV1_MRCNN without FPN
mAP@50	**0.78**	0.75
mAP@75	**0.63**	0.61
mAP@[0.5:0.95]	**0.62**	0.56

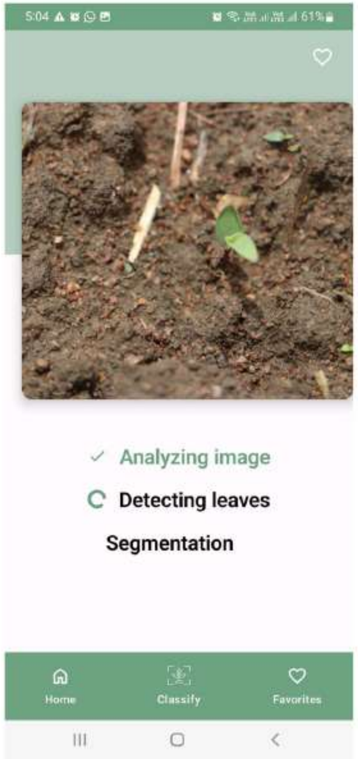
Fig 6.11. PR curve of HierbaNetV1_MRCNN with HierbaNetV1 as backbone with mAP@[0.5:0.95]



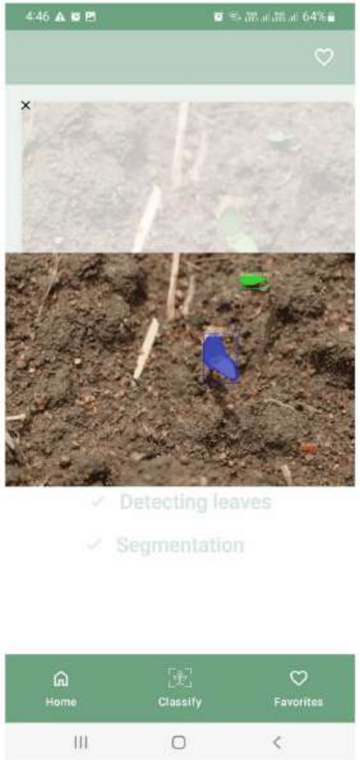
06. Objective 3: HierbaNetV1_MRCNN for Object Localization

Phase IV: Integration of HierbaNetV1_MRCNN with HierbaApp

Fig 6.12. "HierbaApp" solving the segmentation problem of "SorghumWeedDataset_ Segmentation" using "HierbaNetV1_MRCNN"



(a) Detecting a sample image with HierbaNetV1_MRCNN at backend



(b) Segmenting ROIs from (a) with HierbaNetV1_MRCNN at backend

(c) Segmenting ROIs in a dense image with HierbaNetV1_MRCNN at backend

06. Objective 3: HierbaNetV1_MRCNN for Object Localization

Research outcome of objective-3

- Design and implementation of a unique feature pyramid network, 'HierbaNetV1_FPN'
- Design and implementation of a customized instance segmentation architecture, 'HierbaNetV1_MRCNN'
- Integration of 'HierbaNetV1_MRCNN' in HierbaApp for real-time pixel-wise segmentation of sorghum crop and weeds.

07. Conclusion

- Two open-access crop-weed research datasets namely 'SorghumWeedDataset_Classification' and 'SorghumWeedDataset_Segmentation' are acquired and created from Indian agricultural fields with initial experimentation accuracy of 96.05%.
- HierbaNetV1, a novel feature extraction technique is proposed that improves object identification accuracy by 0.7 and reduces loss by 1.48.
- HierbaNetV1_FPN and HierbaNetV1_MRCNN are designed for improved object localization with 5.0% increase in mAP.

08. Future Enhancements

- Dataset creation will be expanded for other crops and weeds.
- HierbaNetV1 will be further improved to reduce the space and time.
- Agrobot, a weeding robot for Indian fields will be built.

09. Publications

JOURNAL ARTICLES

1. Michael J,Manivasagam T. 2024. HierbaNetV1: a novel feature extraction framework for deep learning-based weed identification. PeerJ Comput. Sci. 10:e2518 DOI 10.7717/peerj-cs.2518 **[Q1, PeerJ Computer Science, SCI, IF-3.8, CS-4.2]**
2. Justina, Michael J., and M. Thenmozhi. "SorghumWeedDataset_Classification and SorghumWeedDataset_Segmentation datasets for classification, detection, and segmentation in deep learning." Data in Brief 52 (2024): 109935. https://doi.org/10.1016/j.dib.2023.109935 **[Q3, Elsevier, SCI, IF-1.2, CS-2.6]**
3. Michael, J. Justina, and M. Thenmozhi. "HierbaNetV1: A novel convolutional neural network architecture." Science Talks (2024). https://doi.org/10.1016/j.sctalk.2024.100316 **[Elsevier]**

CONFERENCE PROCEEDINGS

1. Michael, J. Justina, and M. Thenmozhi, "Survey on Weeding Tools, Equipment, AI-IoT Robots with Recent Advancements," 2023 International Conference on Integration of Computational Intelligent System (ICICIS), IEEE, 2023. https://doi.org/10.1109/ICIRCA54612.2022.9985603 **[Scopus: IEEE Xplore]**
2. Michael, J. Justina, and M. Thenmozhi. "Outlier detection in maize field using Isolation Forest: A one-class classifier." 2023 International Conference on Networking and Communications (ICNWC). IEEE, 2023. https://doi.org/10.1109/ICNWC57852.2023.10127404 **[Scopus: IEEE Xplore]**
3. Michael, J. Justina, and M. Thenmozhi. "Weed Identification and Removal: Deep Learning Techniques and Research Advancements." 2022 4th International Conference on Inventive Research in Computing Applications (ICIRCA). IEEE, 2022. https://doi.org/10.1109/ICIRCA54612.2022.9985603 **[Scopus: IEEE Xplore]**
4. Michael, J. Justina, and M. Thenmozhi. “Artificial intelligence based WeedBot for weed identification and removal in dense fields” 2022 3rd International Weed Conference, Anand Agriculture University, Gujarat.

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09. Publications

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BOOK CHAPTERS

1. Justina Michael, J., Thenmozhi, M. (2023). Evaluation of Deep Learning CNN Models with 24 Metrics Using Soybean Crop and Broad-Leaf Weed Classification. In: Ranganathan, G., Papakostas, G.A., Rocha, Á. (eds) Inventive Communication and Computational Technologies. ICICCT 2023. Lecture Notes in Networks and Systems, vol 757. Springer, Singapore. https://doi.org/10.1007/978-981-99-5166-6_6 **[Scopus:Springer:LNNS]**
2. Justina, M., Thenmozhi, M. (2024). Analyzing the Effectiveness of Image Augmentation for Soybean Crop and Broadleaf Weed Classification. In: Das, S., Saha, S., Coello Coello, C.A., Bansal, J.C. (eds) Advances in Data-Driven Computing and Intelligent Systems. ADCIS 2023. Lecture Notes in Networks and Systems, vol 892. Springer, Singapore. https://doi.org/10.1007/978-981-99-9521-9_27 **[Scopus:Springer:LNNS]**

PATENT

1. Filed a patent entitled "Artificial intelligent based Agro-Bot device for weed identification and removal in random spacing plants" in Indian Patent Office with application No.202241069244 A, Date of filing of Application:30/11/2022, Publication Date: 09/12/2022 and Journal No/Issue No: 49/2022.
2. Filed the provisional specification of the patent entitled "HierbaNetV1: A CNN-based customized architecture with intensive feature extraction for classification" in Indian Patent Office with application no. 202441050194 on 01.07.2024.

DATASET PUBLICATIONS

1. Michael, Justina; M, Thenmozhi (2023), "SorghumWeedDataset_Classification", Mendeley Data, V1, doi: 10.17632/4gkcyxjyss.1
2. Michael, Justina; M, Thenmozhi (2023), "SorghumWeedDataset_Segmentation", Mendeley Data, V1, doi: 10.17632/y9bmtf4xmr.1

School of Computing

09. Publications

SRM INSTITUTE OF SCIENCE & TECHNOLOGY

CODE CAPSULE PUBLICATIONS

1. Justina Michael J, Thenmozhi M (2023) CNN_Sorghum_Weed_Classifier: An Artificial Intelligence-based Software for Pre-processing and Experimenting 'SorghumWeedDataset_Classification' dataset in Python [Source Code]. https://doi.org/10.24433/CO.7479881.v1
2. Justina Michael J, Thenmozhi M (2024) Implementation Of HierbaNetV1 - A Novel Convolutional Neural Network Architecture [Source Code]. https://doi.org/10.24433/CO.1923872.v1

CONTRIBUTION TO THE RESEARCH COMMUNITY

1. Released the HierbaNetV1 trained weights in the Github repository on Feb 2024. https://github.com/JustinaMichael/HierbaNetV1-A-Novel-CNN-Architecture.git

CONTRIBUTION TO THE SOCIETY (AGRICULTURALISTS)

1. Published 'HierbaApp' – An Android mobile application for weed identification in Google Play Store on 12.06.2024. https://play.google.com/store/apps/details?id=com.hierba.app

OTHER ACHIEVEMENTS

1. Received ISWS Student Travel Grant Award – 2022, from the Indian Society of Weed Science (ISWS)
2. Won Gold medal in Research day 2024 from SRMIST, KTR
3. Won the best poster presentation award in DPRC-2025 from SRMIST, KTR
4. Won the best poster presentation award in DPRC-2022 from SRMIST, KTR
5. Contributed as an oral speaker in the "3rd International Weed Conference" held at Gujarat in December 2022.

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Thank You