HIERBANETV1: A NOVEL FEATURE EXTRACTION FRAMEWORK FOR DEEP LEARNING-BASED WEED IDENTIFICATION

SYNOPSIS OF THE THESIS

Submitted by

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DECLARATION

I hereby declare that, the dissertation entitled, **"HIERBANETV1: A NOVEL FEATURE EXTRACTION FRAMEWORK FOR DEEP LEARNING-BASED WEED IDENTIFICATION"** to be submitted for the Degree of Doctor of Philosophy is my original work and the dissertation has not formed the basis for the award of any degree, diploma, associateship or fellowship of similar other titles. It has not been submitted to any other University or Institution for the award of any degree or diploma.

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Name of the Supervisor **: Dr. M. THENMOZHI**
(With Seal)

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CHAPTER 1

INTRODUCTION

"Artificial intelligence (AI) is not just about enhancing efficiency, it's about addressing some of society's biggest challenges", says the computer scientist Yoshua Bengio. Artificial intelligence solves common real-world problems in several sectors including agriculture which is the subject of this study. This research deals with the challenges faced in AI-based crop-weed identification as weeds are responsible for forty-five percent of the crop yield loss [1-2]. The importance of weed identification, the role of AI in weed identification, research motivation, current studies in AI-based weeding, problem statements, and the research objectives are presented in this chapter.

1.1 BACKGROUND

Weeds are undesirable plants grown in the incorrect location, and they need to be pulled out while still in the early stages of growth. The following section describes the importance of identifying and removing weeds from agricultural fields and AI-based weed removal methods.

Importance of weed identification and removal: Weeds negatively impact living beings and the environment. Weeds harm the environment and living beings, making their removal essential. They compete with crop growth essentials and reduce yields. Weeds also attract pests and spread diseases, threatening plant health. Invasive species can outcompete native plants, decreasing biodiversity, while dry weeds increase wildfire risks. Weed removal enhances aesthetics, protects ecosystems, and ensures plant productivity and safety. Keeping weeds out is crucial for maintaining plant health and productivity.

AI for weed identification: AI-based models for weed identification are more advantageous than manual methods or other weed identification approaches. AI-enabled systems can identify weeds precisely as they are trained with large amounts of crop and weed images. They recognize various weed species with extreme precision. These systems provide continuous 24/7 monitoring, allowing real-time detection and early intervention to prevent weed spread. AI solutions are scalable, covering small to vast agricultural areas, and are cost-effective in the long term by reducing reliance on manual labor and chemical herbicides. Moreover, they can adapt to changing weed populations and environmental conditions through regular updates, ensuring long-term reliability in weed management.

1.2 MOTIVATION

There is a significant disconnect between farming and technology in developing nations like India. Research and development in this field would make farming more productive and sustainable. The following describes the research motivation of this thesis:

i) **Manual weed identification vs AI-based weed identification:** Manual weed identification is labor-intensive, time-consuming, environmentally harmful, economically burdensome, and sometimes depends upon human judgment. However, AI-based weeding is precise, effective, environmentally friendly, herbicide-free, and boosts productivity. The key motive of this research is to advance AI-based weed identification.

ii) **AI for weed identification in Indian farms:** Weed identification practices in India vary significantly from those used globally. In developed countries, AI-based weed identification is currently in practice. In contrast, smart farming has only recently been promoted in developing countries like India. This remains the driving force to extend our research to transform traditional farming into smart farming.

By developing a strong crop-weed identification system that benefits farmers, consumers, and the environment, this thesis advances agricultural technology overall.

1.3 RELATED WORKS

A crop-weed identification system based on artificial intelligence has garnered significant attention lately. The following discusses some recent studies done in crop-weed datasets, Convolutional Neural Network (CNN)-weed architectures, and Mask Regional Convolutional Neural Network (MRCNN)-weed architectures.

1.3.1 Crop-weed benchmark datasets

Many crop-weed benchmark datasets are accessible to the general public. A few are listed in Table 1.1:

Table 1.1: Crop-weed benchmark datasets

Dataset	Geograp. Location	Duration	Images	Species	Purpose
Weed25 [3]	China	2021 to 2022	4,023	25 weeds	Detection
4 Weed Dataset [4]	USA	2021	618	4 weeds	Classification
Lincolnbeet dataset [5]	United Kingdom	2021	4405	Beet and malicious weeds	Detection
Ronin open DB [6]	Europe	2020	118	6 crops and 8 weeds	Detection
Maize-Commonbean-weeds dataset [7]	Central France	2019	2489	2 crops and 4 weeds	Segmentation
GrassClover [8]	Denmark	2017 to 2018	31,600	2 Clovers, 3 weeds and grass	Segmentation
DeepWeeds [9]	Australia	2017 to 2018	17509	8 weed species	Classification
Sugar Beets 2016 [10]	Germany	2016	5 TB	Sugar beets and 9 weeds	Segmentation

1.3.2 CNN-weed architectures

Recent studies show the development of CNN-Weed architectures which include a few of the below architectures: Sa, Inkyu, et al. developed weedNet in which SegNet with a balanced frequency of appearance (FoA) of a class through penalization is applied [11]. Hu, Kun, et al. introduced Graph Weeds Net where a three-scale weed graph with global and local patterns is used and CNN is applied for each patch to obtain a feature set of weed patches [12]. Jin et al. developed CenterNet for vegetable detection followed by weed extraction from a background using a color index-based segmentation [13]. Xu, Ke, et al. introduced a weed feature extraction method named WeedsNet using a two-path network one from RGB and the other from depth images parallelly [14].

1.3.3 MRCNN-weed architectures

Some of the current research on MRCNN-weed architectures are as follows: Rai, Nitin, and Xin Sun. improve prediction by introducing WeedVision through the integration of a C3x module in which the kernels vertically and horizontally convolve [15]. Genze, Nikita, et al. developed a model named DeBlurWeedSeg for deblurring and segmenting motion-blurred crop-weed images is done through NAFNet and WeedSeg [16]. Xu, Beibei, et al. introduced a weed instance segmentation method where color index contrast between plants and soil was used. This integrated architecture extracts multi-scale semantic information on weed patch boundaries [17]. Shuangyu Xie, et al. built a Nutsedge skeleton-based probabilistic map that decreases border segmentation and distinguishes the nutsedge's central leaf midrib portion [18].

1.4 PROBLEM STATEMENTS

Despite the advancements of artificial intelligence-based weed identification in agriculture, there remain several unresolved issues and limitations that need to be addressed.

i) There is no publicly available crop-weed research dataset from Indian agricultural fields.
ii) Feature extraction methods focus on a specific degree of complexity thus preventing to identification of Region Of Interest (ROI) of all sizes.
iii) Finer object localization for small objects is harder as the feature pyramid network performs down-sampling and up-sampling frequently.

By addressing the aforementioned issues and limitations, this research aims to contribute to the advancement of AI-based weed identification technologies.

1.5 OBJECTIVES

In light of these challenges, this research aims to build an advanced weed identification system through the following objectives:

i) To create sorghum-weed image datasets from the Indian agricultural field for weed identification.

ii) To design a novel feature extraction technique for varying-sized Region-of-Interests in sorghum-weed image datasets.

iii) To design a feature pyramid network that generates rich semantic features for fine-grained object localization.

By implementing the objectives, this research develops a robust AI-powered weed identification system that could detect, localize, and segment Indian crops and weeds.

1.6 THESIS STRUCTURE OVERVIEW

The proposed framework implemented in the thesis of this synopsis is depicted in Figure 1.1 with three objectives and is framed as follows:

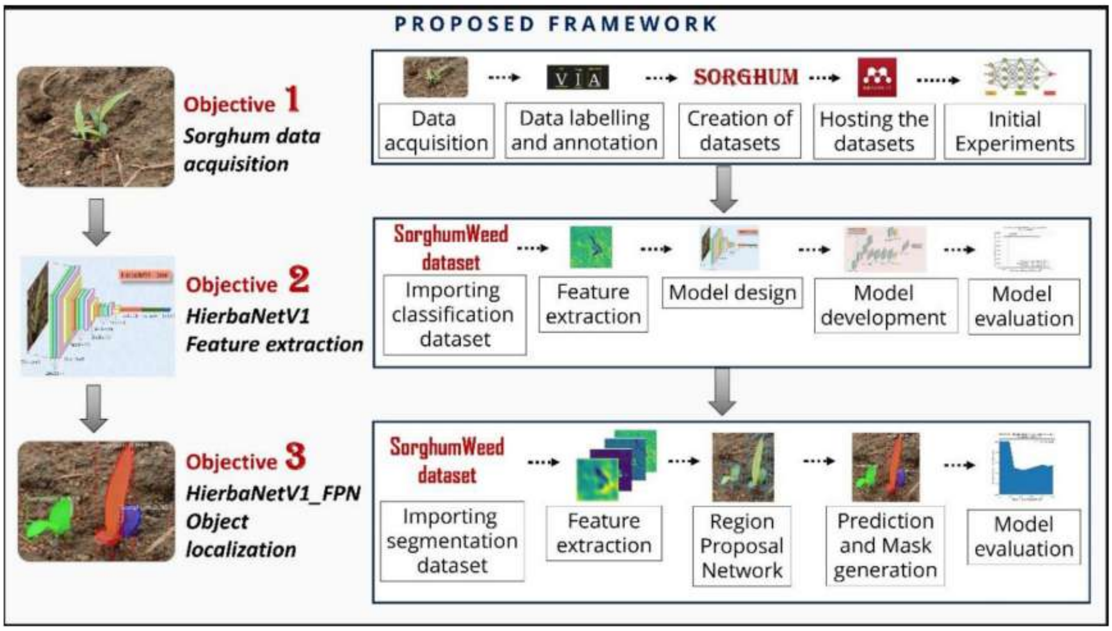


Figure 1.1: Proposed framework

Chapter 1 discusses weed and its importance in identification and removal, AI in weed identification and current weed management practices followed in India. Besides, the research motivation, objective, and contribution are stated.

A literature review of crop-weed benchmark datasets, cutting-edge CNN-weed architectures, and MRCNN-weed architectures is presented in **Chapter 2**. Also, the research gaps are identified after a detailed study.

Chapter 3 details the data acquisition process, creation, and hosting of the "SorghumWeedDataset_Classification" dataset and the "SorghumWeedDataset_Segmentation" followed by the research outcome.

Preprocessing of SorghumWeedDataset_Classification, design, and development of the novel "HierbaNetV1" architecture with each layer's specifics, pseudocode, implementation, comparison with the existing models, ablation study, time complexity analysis, and research outcome are explained in **Chapter 4.**

Chapter 5 discusses the preprocessing of SorghumWeedDataset_Segmentation, design, and development of the unique Feature Pyramid Network "HierbaNetV1_FPN", and a customized instance segmentation architecture "HierbaNetV1_MRCNN", pseudocode, implementation, comparison with the existing model, ablation study, and research outcome.

Integration of HierbaNetV1 and HierbaNetV1_MRCNN within HierbaApp, a mobile application for real-time weed detection aimed at agriculturalists is discussed in **Chapter 6**. The chapter also covers the design, development, integration, deployment, and real-time inference of HierbaApp.

Eventually, **Chapter 7** concludes with a discussion of future works. In addition, the computation of layer-wise parameters and neurons in HierbaNetV1 is discussed in **Appendix 1** and layer-wise feature maps generated in HierbaNetV1 are portrayed in **Appendix 2**.

CHAPTER 2

SORGHUM DATA ACQUISITION AND DATASET CREATION

"You would better know what you are going to do with data before you collect it", says Mark Twain, Father of American Literature. Data collection for crop-weed identification is crucial for advancing scientific research and driving innovation in autonomous weeding. This chapter provides an overview of the dataset creation and data acquisition techniques used in this research.

2.1 SORGHUM DATA ACQUISITION

The complete data acquisition and dataset creation process is executed in five phases as depicted in the workflow strategy Figure 2.1.

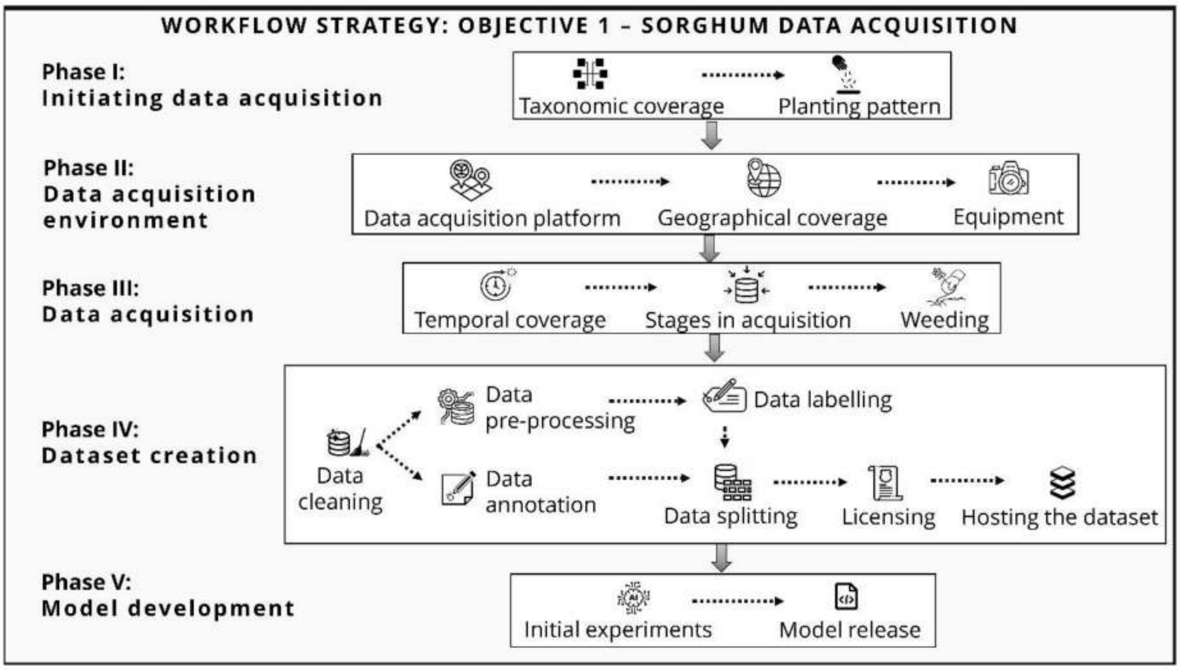


Figure 2.1: Workflow strategy of sorghum data acquisition and dataset creation

Taxonomic coverage: The primary research object focused on in this study is 'Sorghum Bicolor L. Moench' and its respective weeds. Weeds are broadly categorized into two; namely broadleaf weeds and grasses.

Planting pattern: Dibbling and broadcasting are the two planting patterns followed while sowing the sorghum seeds. The crops in dibbled fields follow uniform crop spacing and the crops in broadcasting fields follow random crop spacing. Instance(s) of a single object category (crop/weed) in an image is captured from dibbled fields. Multiple instance(s) of a multiple object category (crop/weed) in an image are captured from broadcasted fields.

Data acquisition platform: The research experimental area is shown in Figure 2.2 from where the data is acquired. The land has a total area of 871.2 square feet.

Geographical coverage: The geospatial coverage of the acquired data samples is from SRM Care Farm, Chengalpattu district, Tamil Nadu, India (603209). The latitude and longitude for collected data samples are 12.787003386255583 and 80.05900471261096. (Google Maps link: https://goo.gl/maps/Zq4yF8CddEyoZuWL6)

Equipment: The instrument used for data acquisition is a Canon EOS 80D – Digital Single-Lens Reflex (DSLR) camera with Joint Photographic Experts Group (.jpg) Red-Green-Blue (RGB) colors data format.

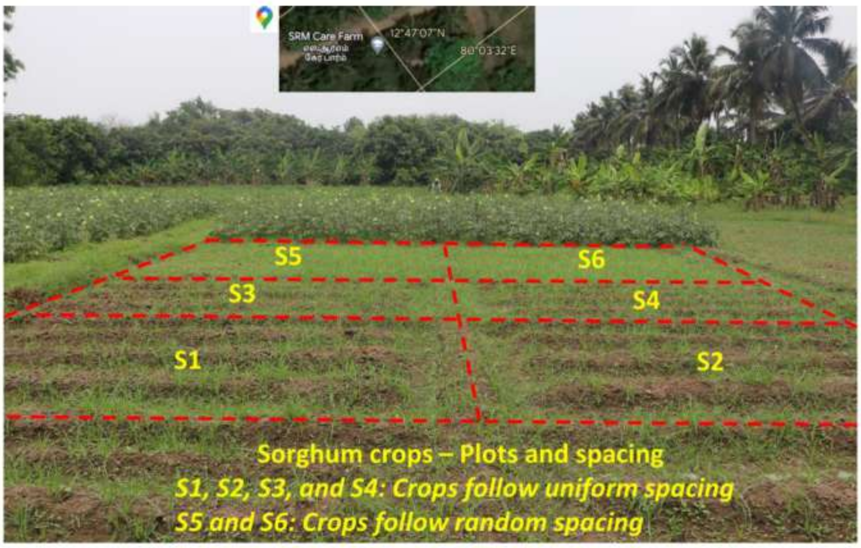


Figure 2.2: Research experimental area of the sorghum field

Temporal coverage: The data is acquired during April and May 2023.

Stages in acquisition: The first four growth stages of sorghum are focused on during the data acquisition process thus prioritizing early detection. The four stages are

i) Initial stage: Emergence
ii) Second growth stage: Three-leaf
iii) Third growth stage: Five-leaf
iv) Fourth growth stage: Growing point differentiation

Weeding: Data is acquired before and after first- and second-hand weeding

Data cleaning: 4312 of 5652 images were chosen for the classification dataset. 252 of 386 images were chosen for the segmentation dataset.

Data pre-processing: Images from the classification dataset are resized to 224×224 pixels whereas images from the segmentation dataset are retained with 6000×4000 pixels.

Data labeling: The images in the classification dataset are split into three classes.

i) Class 0 – Sorghum
ii) Class 1 – Grass
iii) Class 2 – Broadleaf weed

Data annotation: The images in the segmentation dataset are annotated using VGG (Visual Geometry Group) Image Annotator (VIA) [19] with the same three classes as classification.

Data splitting: The classification and segmentation datasets are split with a Train:Validate:Test (TVT) ratio of 7:2:1 and 8:1:1 respectively.

Documentation: The entire data acquisition process and dataset creation are well documented in [20].

Licensing: Both datasets are licensed under the 'CC BY 4.0 license'.

Hosting the dataset: The classification and segmentation datasets are hosted in Mendeley Data Repository at the location https://data.mendeley.com/datasets/4gkcyxjyss/1 [21] and https://data.mendeley.com/datasets/y9bmtf4xmr/1 respectively.

Initial experiments: Initial experiments are done with the classification dataset. The dataset is trained, validated, and tested on DenseNet201, VGG19, MobileNetV2, and ResNet152V2. The results show the high top-1 result is produced by DenseNet201 with 96.05% accuracy and a minimum loss by VGG19 with 0.2215.

Model release: The trained model is released in Code Ocean in an interactive code capsule that can be executed with a reproducible run [23].

2.2 SORGHUMWEEDDATASET_CLASSIFICATION

"SorghumWeedDataset_Classification" is the classification dataset with 4312 images in total. The TVT split-up ratio of the three classes is tabulated in Table 2.1.

Table 2.1: "SorghumWeedDataset_Classification" TVT split

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

2.3 SORGHUMWEEDDATASET_SEGMENTATION

"SorghumWeedDataset_Segmentation" is the segmentation dataset with 252 images and 5555 segments in total. The TVT split-up ratio of the three classes is tabulated in Table 2.2. The TVT split-up ratio of the segments is tabulated in Table 2.3.

Table 2.2: "SorghumWeedDataset_Segmentation" TVT split

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

Table 2.3: "SorghumWeedDataset_Segmentation" research objects TVT split

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

2.4 RESEARCH OUTCOMES

i) Acquisition, creation, and publication of the first Indian open-access crop-weed research datasets.

   a) "SorghumWeedDataset_Classification"

   b) "SorghumWeedDataset_Segmentation"

ii) Initial experiments are conducted on the datasets.

CHAPTER 3

FEATURE EXTRACTION WITH HIERBANETV1

Identifying and extracting relevant features from the input data is the core characteristic of feature extraction. CNN extract features using a series of convolutional layers. Here, we introduce "HierbaNetV1" - a novel CNN-based feature extraction architecture that extracts meaningful features from the input data. This chapter briefs the ideation, design, implementation, and performance evaluation of HierbaNetV1. Building HierbaNetV1 is executed in five phases as represented in the workflow strategy Figure 3.1.

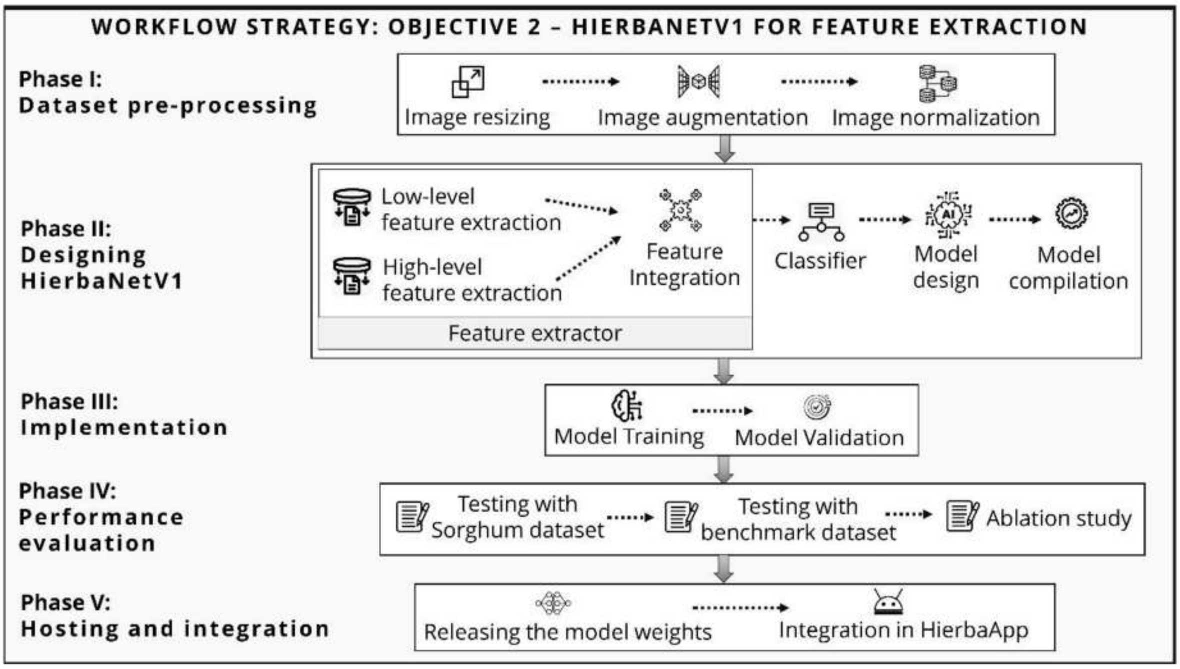


Figure 3.1: Workflow strategy of HierbaNetV1 for feature extraction

3.1 IDEATION

The idea behind HierbaNetV1 is to perform intensive feature extraction from each data sample focusing on multiple levels of complexity, irrespective of the ROI size, and emphasize low-level features consistently. The specifics of HierbaNetV1's operation are provided in [24, 25].

3.2 DESIGNING HIERBANETV1

HierbaNetV1 is designed with 19 convolutional layers; three in the base architecture (as illustrated in Figure 3.2), eight in Block I (as shown in Figure 3.3), and eight in Block II (as in Figure 3.4). The convolution is always followed by batch normalization which is succeeded by the activation by LeakyReLU. The base architecture uses dimensionality reduction three times, and each block uses it twice. Blocks I and II extract low and high level features using Modules I and II.

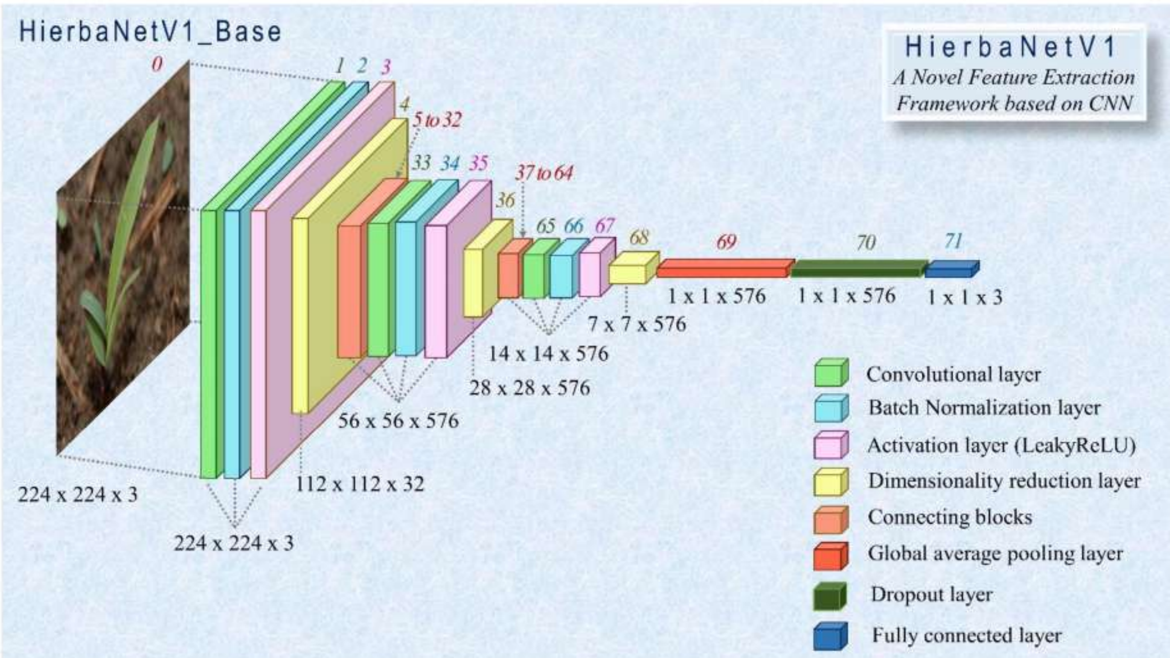


Figure 3.2: Core design of HierbaNetV1

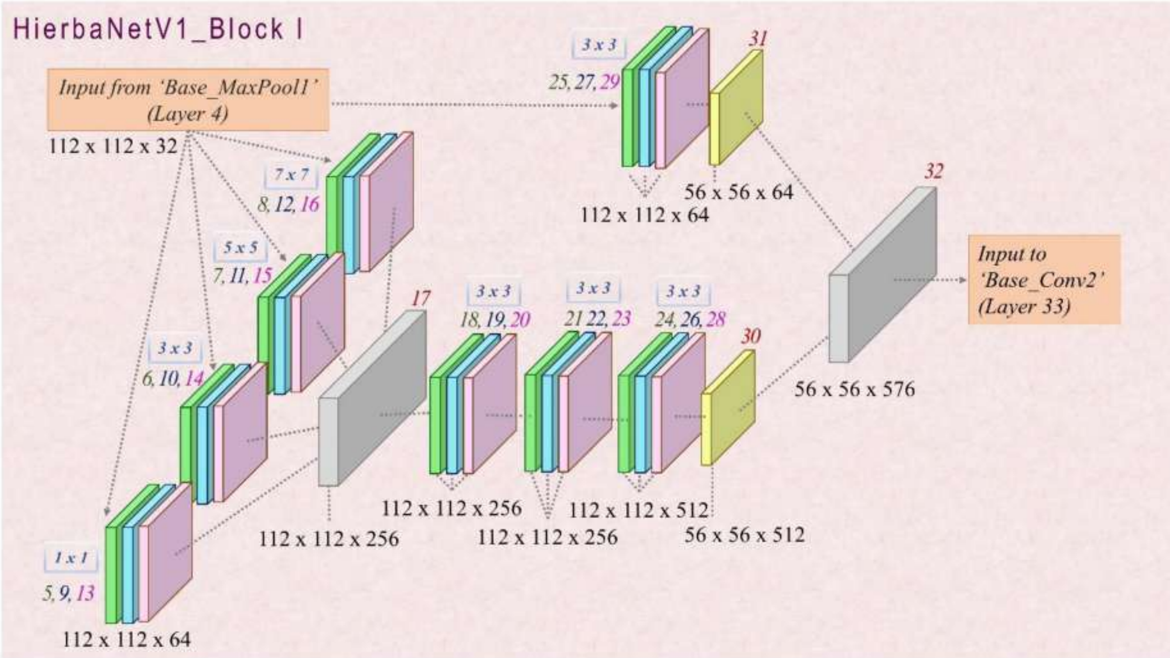


Figure 3.3: Framework of HierbaNetV1_Block-I

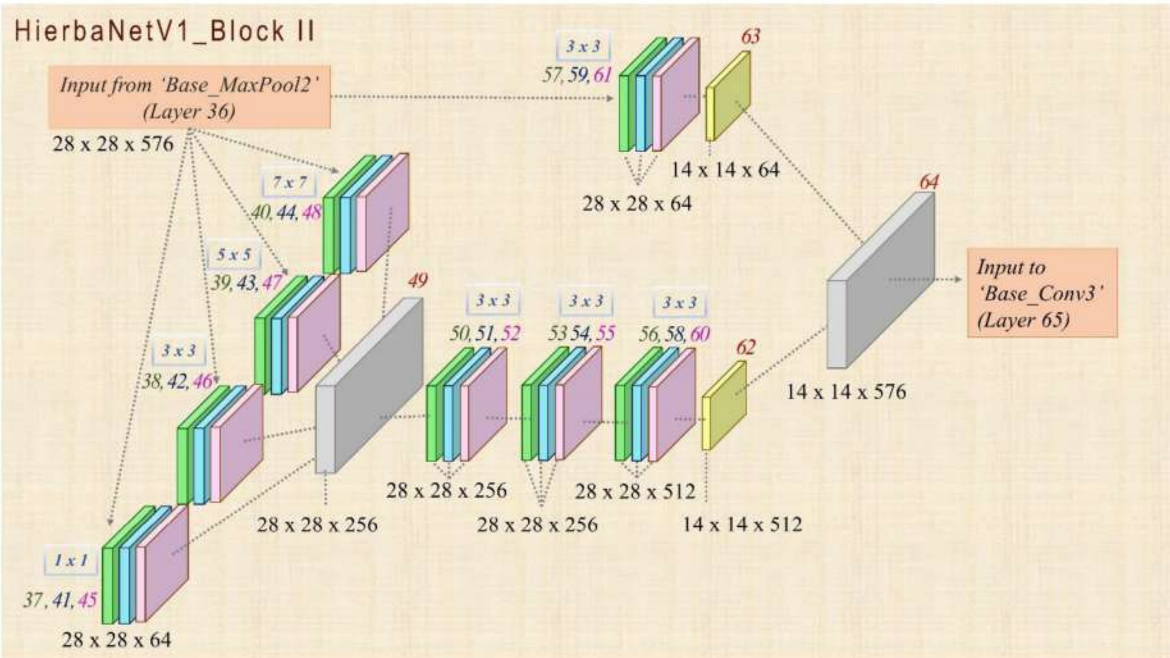


Figure 3.4: Framework of HierbaNetV1_Block-II

Module I - Low-level feature extraction: Module I convolves, batch normalizes, uses LeakyReLU to activate, and reduces dimensions before concatenation.

Module II - High-level feature extraction: Module II functions parallelly with four different kernel sizes such as 1×1, 3×3, 5×5, and 7×7. The input convolves, batch normalizes, and activates using LeakyReLU in parallel with four different kernels. The output feature maps from each kernel are concatenated to form a wide variety of feature maps. These feature maps again convolve, batch normalize, and activate using LeakyReLU thrice followed by a dimensionality reduction.

Feature integration: Feature maps generated from Module I and II are concatenated to form a set of features with multiple complexities. These are fed to the base architecture which produces 3872 feature maps for a single instance.

3.3 IMPLEMENTATION

The architecture of HierbaNetV1 is designed and implemented in Python 3.10.12. NVIDIA System Management Interface (NVIDIA-SMI) Driver with Compute Unified Device Architecture (CUDA) Toolkit and 89.6 gigabytes of high Random Access Memory (RAM) is used for training the model. The model is trained and validated on SorghumWeedDataset_Classification with the value of k as 10 in Stratified K-fold Cross-Validation (SKCV). The HierbaNetV1 design produced the model summary of 72 layers from which the summary of 19 convolutional layers is tabulated in Table 3.1. The convolutions in the base architecture, block I and block II are as follows:

i) Layers 1, 33, and 65 - Convolutions in the base
ii) Layers 5, 6, 7, 8, 18, 21, 24, and 25 – Convolutions in Block I
iii) Layers 37, 38, 39, 40, 50, 53, 56, and 57 - – Convolutions in Block II

The implementation of HierbaNetV1 is provided in the code capsule [26] and the trained model weights are available publicly at https://github.com/JustinaMichael/HierbaNetV1-A-Novel-CNN-Architecture.git thus encouraging weed research.

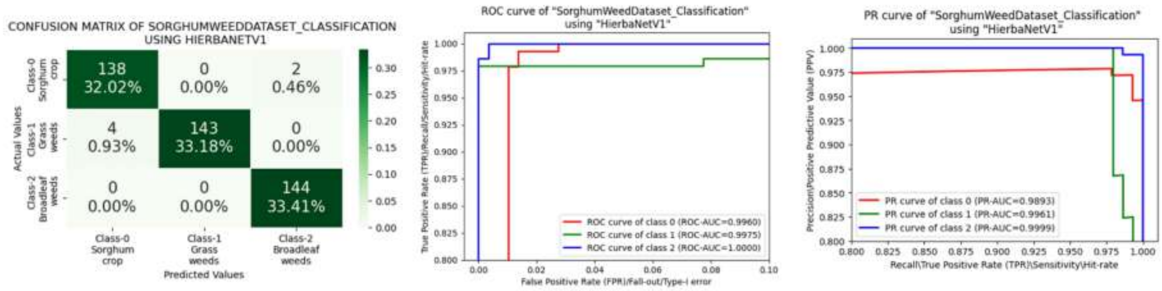
3.4 PERFORMANCE EVALUATION

The trained model is tested on the unseen data from SorghumWeedDataset_Classification which produces a top-1 accuracy and loss of 98.06% and 0.07 respectively. A total of 431 samples were tested among which 140 are from Class 0 – Sorghum, 147 samples belong to Class 1 – Grass, and 144 are from Class 2 – BroadLeafWeed.

Table 3.1: HierbaNetV1 model summary of convolutional layers (Conv1 to Conv19)

Layer #	Layer name	Output shape	Filter Size	Number of Feature maps ('n')
1	Base_Conv1 (Conv2D)	(None, 224, 224, 32)	3x3	32
5	B1_HL_Conv1 (Conv2D)	(None, 112, 112, 64)	1x1	64
6	B1_HL_Conv2 (Conv2D)	(None, 112, 112, 64)	3x3	64
7	B1_HL_Conv3 (Conv2D)	(None, 112, 112, 64)	5x5	64
8	B1_HL_Conv4 (Conv2D)	(None, 112, 112, 64)	7x7	64
18	B1_HL_Conv5 (Conv2D)	(None, 112, 112, 256)	3x3	256
21	B1_HL_Conv6 (Conv2D)	(None, 112, 112, 256)	3x3	256
24	B1_HL_Conv7 (Conv2D)	(None, 112, 112, 512)	3x3	512
25	B1_LL_Conv1 (Conv2D)	(None, 112, 112, 64)	3x3	64
33	Base_Conv2 (Conv2D)	(None, 56, 56, 576)	3x3	575
37	B2_HL_Conv1 (Conv2D)	(None, 28, 28, 64)	1x1	64
38	B2_HL_Conv2 (Conv2D)	(None, 28, 28, 64)	3x3	64
39	B2_HL_Conv3 (Conv2D)	(None, 28, 28, 64)	5x5	64
40	B2_HL_Conv4 (Conv2D)	(None, 28, 28, 64)	7x7	64
50	B2_HL_Conv5 (Conv2D)	(None, 28, 28, 256)	3x3	256
53	B2_HL_Conv6 (Conv2D)	(None, 28, 28, 256)	3x3	256
56	B2_HL_Conv7 (Conv2D)	(None, 28, 28, 512)	3x3	512
57	B2_LL_Conv1 (Conv2D)	(None, 28, 28, 64)	3x3	64
65	Base_Conv3 (Conv2D)	(None, 14, 14, 576)	3x3	576
Total feature maps generated for each instance				**3872**

The model correctly predicts 138 sorghum samples out of 140, 143 grass out of 147, and all 144 broadleaf weed samples. Therefore, the model has 6 incorrect predictions. Two sorghum crops are mistaken for broadleaf weeds, and four grass weeds are mistaken for sorghum crops by the model which is shown in the confusion matrix of Figure 3.5.(a). In Figure 3.5.(b), the ROC curve is portrayed at different thresholds. Five ROC curves indicate one for each class along with their micro and macro average curves. The highest Area Under Curve (AUC) value is 1.0 for broadleaf weeds, followed by 0.9975 for the grasses and 0.996 for sorghum crops. The micro and macro average ROC-AUC are observed as 0.9981 and 0.9983. Similarly, the PR curve is represented in Figure 3.5.(c) With a PR-AUC value of 0.9999, the broadleaf weed class has the highest value, followed by the grass class (0.9961) and the sorghum class (0.9893).



(a) Confusion matrix using HierbaNetV1 (b) ROC curve using HierbaNetV1 (c) PR curve using HierbaNetV1

Figure 3.5: Performance evaluation of HierbaNetV1

3.5 RESEARCH OUTCOMES

i) Design and implementation of a novel feature extraction framework – 'HierbaNetV1'

ii) Releasing the trained model weights of HierbaNetV1 on 'SorghumWeedDataset_Classification' in the GitHub repository.

iii) Integration of HierbaNetV1 in HierbaApp for real-time classification of sorghum crops and weeds.

CHAPTER 4

OBJECT LOCALIZATION WITH HIERBANETV1_FPN

Object localization refers to precisely locating the ROI. This research proposes a unique feature pyramid network termed HierbaNetV1_FPN that facilitates improved object localization. HierbaNetV1 provides high-resolution feature maps at multiple scales thus resolving the problem of scale variation. This chapter briefs the ideation, design, implementation, and performance evaluation of HierbaNetV1_FPN and HierbaNetV1_MRCNN. The process is executed in four phases as portrayed in Figure 4.1.

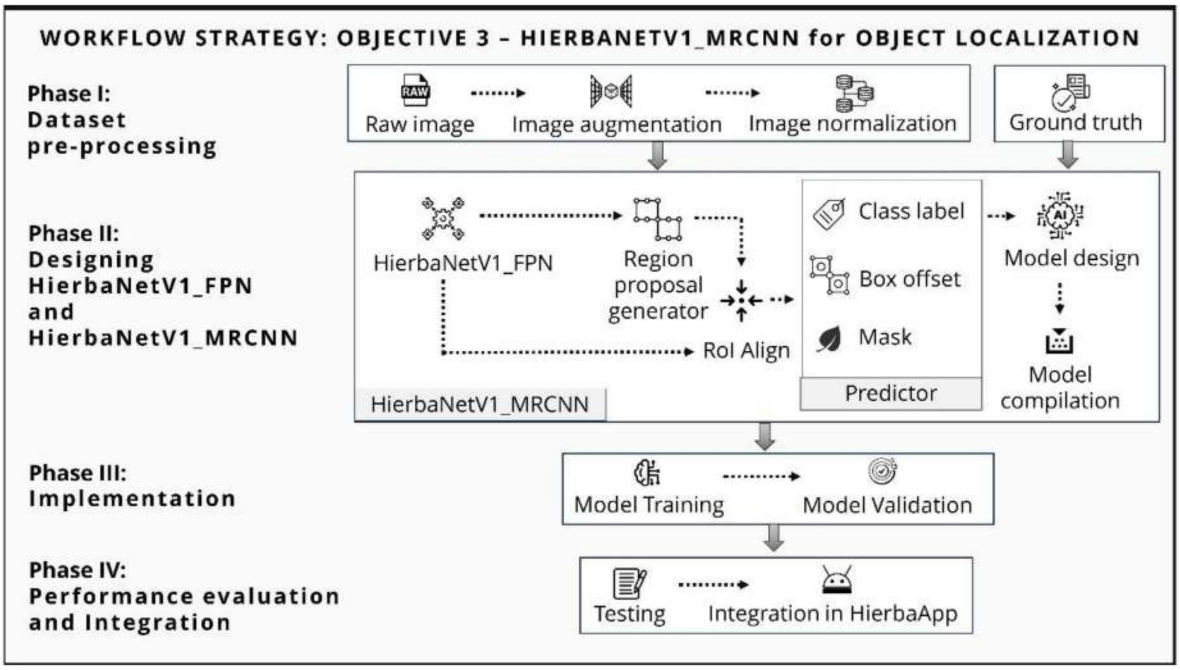


Figure 4.1: HierbaNetV1_MRCNN with HierbaNetV1_FPN for object localization - Workflow strategy

4.1 IDEATION

The ideation behind HierbaNetV1_FPN is to solve the problem of scale variation by creating an effective Feature Pyramid Network (FPN) that provides high-resolution features and rich semantics features at various scales. Furthermore, to employ HierbaNetV1_FPN as the backbone of the instance segmentation architecture named, "HierbaNetV1_MRCNN".

4.2 DESIGNING HIERBANETV1_FPN

HierbaNetV1_FPN comprises two modules; Module I – HierbaNetV1 bottom-up pathway and Module II – HierbaNetV1 top-down pathway, as illustrated in Figure 4.2.

Module I – HierbaNetV1 bottom-up pathway: Feature extraction is performed with HierbaNetV1 as the backbone in a bottom-up pathway. Features are down-sampled at four levels and are extracted as follows:

i) C2: B1_HL_Conv7 (Conv2D) with dimensions 112×112×512
ii) C3: Base_Conv2 (Conv2D) with dimensions 56×56×576
iii) C4: B2_HL_Conv7 (Conv2D) with dimensions 28×28×512
iv) C5: Base_Conv3 (Conv2D) with dimensions 14×14×576

Module II – HierbaNetV1 top-down pathway: Feature maps are up-sampled in the top-down pathway thus generating multi-scale feature maps with better semantic information. The depths of C2, C3, C4, and C5 are reduced to 256 by convolving them with 1×1 kernel, yielding the following layers:

i) FPN_C1_Conv1 (Conv2D) with dimensions 112×112×256
ii) FPN_C1_Conv2 (Conv2D) with dimensions 56×56×256
iii) FPN_C1_Conv3 (Conv2D) with dimensions 28×28×256
iv) FPN_C1_Conv4 (Conv2D) with dimensions 14×14×256

4.3 DESIGNING HIERBANETV1_MRCNN

HierbaNetV1_MRCNN is an instance segmentation architecture as portrayed in Figure 4.3 that works with HierbaNetV1_FPN as a backbone.

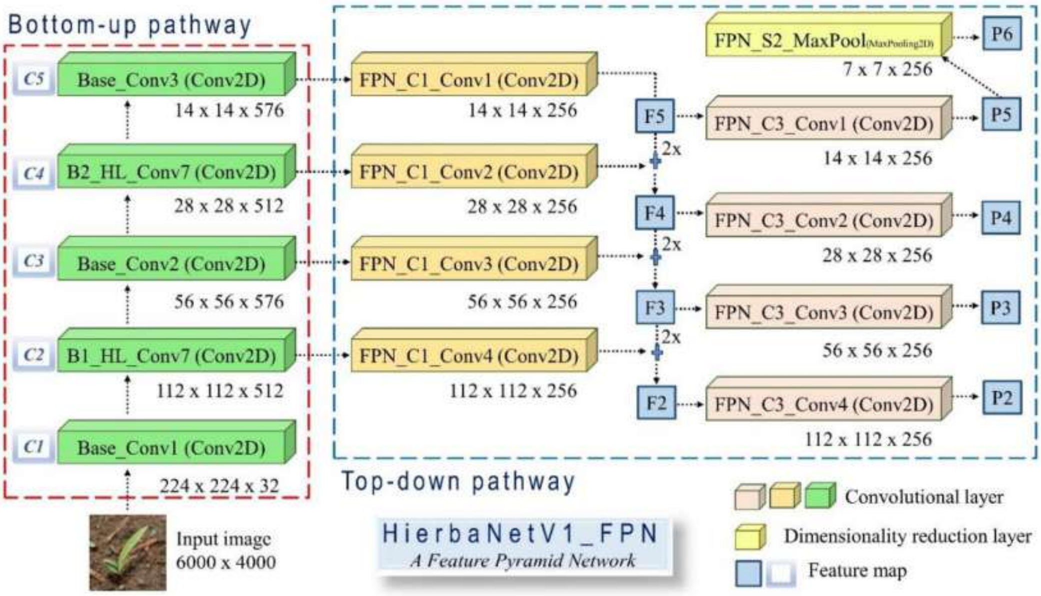


Figure 4.2: Framework of HierbaNetV1_FPN with HierbaNetV1 as the base

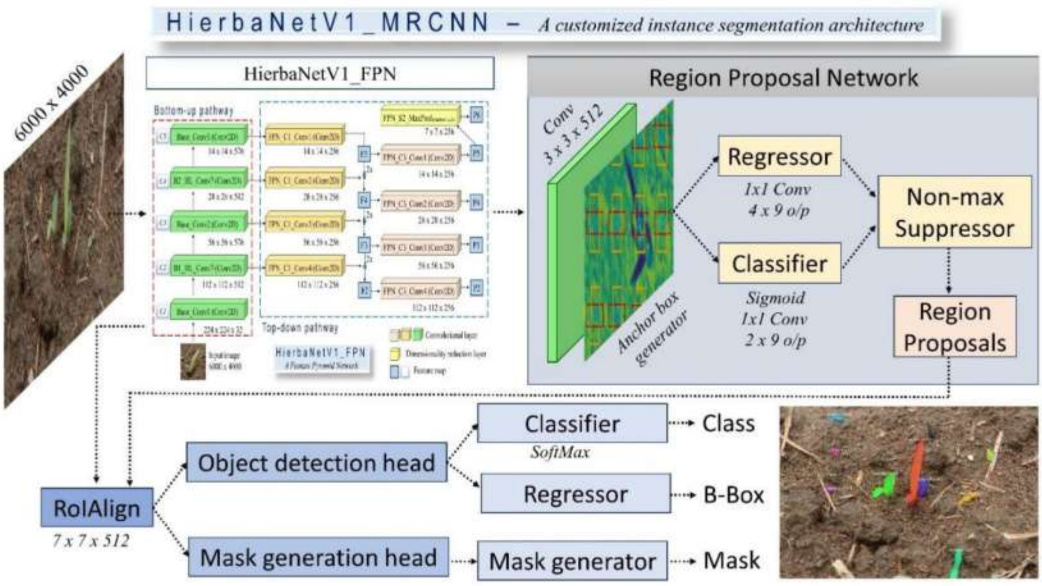


Figure 4.3: Framework of HierbaNetV1_MRCNN with backbone HierbaNetV1_FPN

Step 1: Feature extraction using 'HierbaNetV1_FPN'

Step 2: Generate proposals using the 'Region Proposal Network (RPN)'

Step 3: Align the proposals with 'RoIAlign'

Step 4: Predicting class label using 'Detection Head'

Step 5: Generate segmentation mask using 'Mask Head'

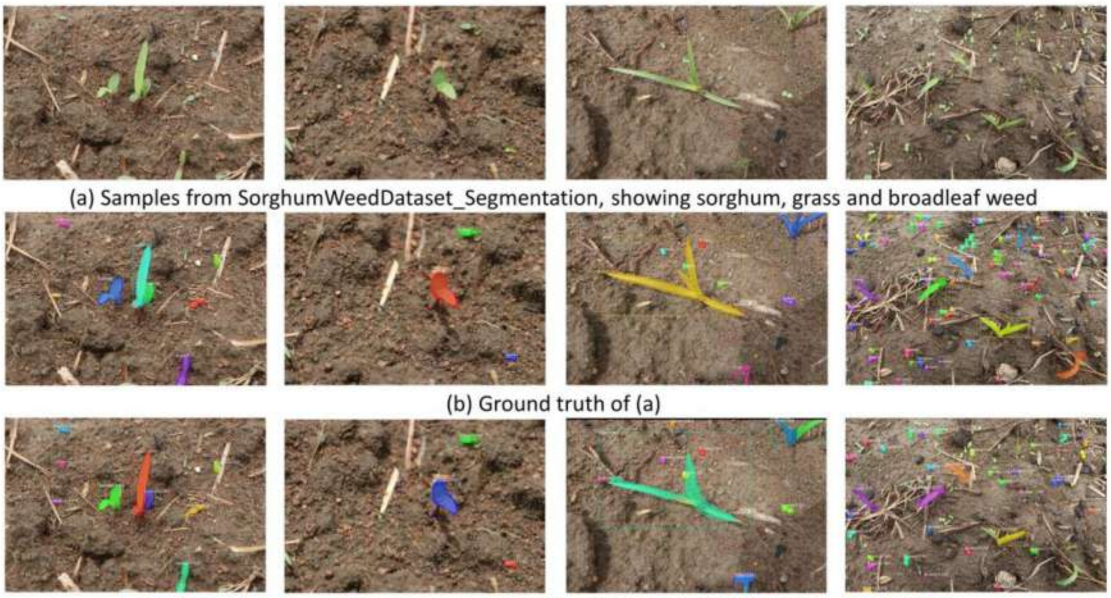
4.4 IMPLEMENTATION

HierbaNetV1_MRCNN is trained and validated on SorghumCropWeedDataset_Segmentation with 3 + 1 (background) classes. The model is trained and validated for 684 epochs. The RPN anchor scales are 32, 64, and 128. Anchor ratios for the RPN are, in order, 0.5, 1, and 2 with 1 as the RPN anchor stride. 0.7 is the threshold for RPN non-maximum suppression with a pool size of 7, and a top-down pyramid size of 256. Adam is chosen for optimization with a 0.001 learning rate.

4.5 PERFORMANCE EVALUATION

HierbaNetV1_MRCNN is tested with 25 images that yield the following results. Figure 4.4 (a), shows the raw test images with their respective ground truth illustrated in Figure 4.4 (b), and predicted masks in Figure 4.4 (c) generated by HierbaNetV1_MRCNN.

The model produces an overall PR-AUC value of 0.62 with Intersection Over Union (IOU) thresholds AP@[0.5-0.95]. The loss graph is shown in Figure 4.5 with the highest and lowest model losses of 2.4492 and 0.8 respectively.



(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

Figure 4.4: Prediction with HierbaNetV1_MRCNN

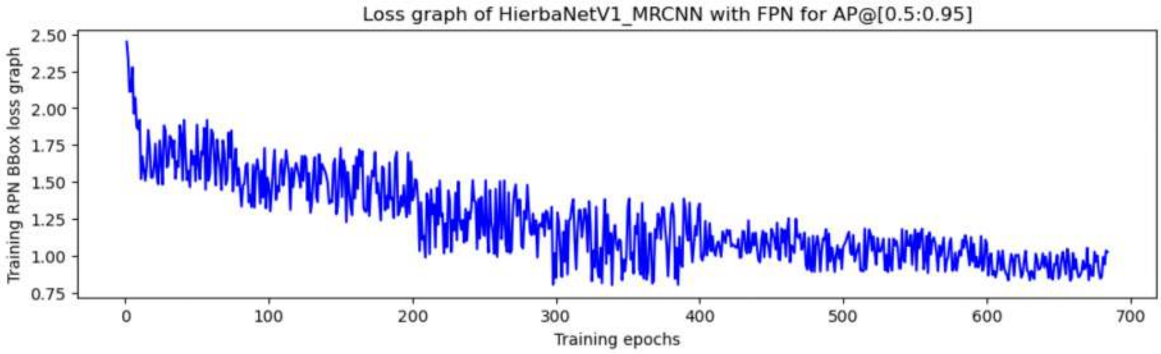


Figure 4.5: Loss graph of HierbaNetV1_MRCNN

4.6 RESEARCH OUTCOMES

i) Design and implementation of a unique feature pyramid network, 'HierbaNetV1_FPN'

ii) Design and implementation of a customized instance segmentation architecture, 'HierbaNetV1_MRCNN'

iii) Integration of 'HierbaNetV1_MRCNN' in HierbaApp for real-time pixel-wise segmentation of sorghum crop and weeds.

CHAPTER 5

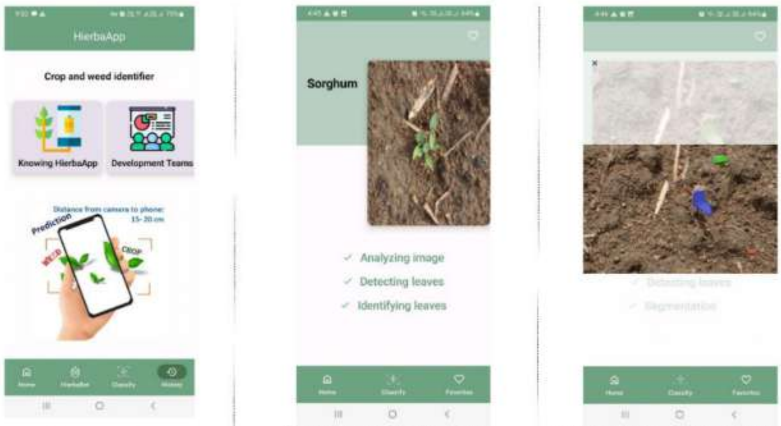
REAL-TIME INFERENCE WITH HIERBAAPP

The ultimate goal of this research is to assist farmers agriculturalists in managing their fields more effectively. To bring this concept into practice, this research develops 'HierbaApp' - an Android mobile application that incorporates the pre-trained HierbaNetV1 and HierbaNetV1_MRCNN models. HierbaApp distinguishes sorghum crops from their associated weeds. This chapter provides an overview of the design, development, integration, real-time weed detection, and result validation with HierbaApp.

5.1 DEVELOPMENT OF HIERBAAPP

HierbaApp is designed and developed as a part of this research for crop-weed identification thus leveraging CNNs for on-the-spot weed identification. The trained models "HierbaNetV1" and "HierbaNetV1_MRCNN" are integrated with this mobile application to differentiate the sorghum crop from its weeds. HierbaApp is thoughtfully designed to be user-friendly, allowing individuals with no prior experience in AI to navigate and use it comfortably. It can detect, classify, and segment sorghum, grass, and broadleaf weeds. The application is accessible in the Google Play Store at https://play.google.com/store/apps/details?id=com.hierba.app. Nowadays Android devices are most commonly used among farmers and hence we consider mobile-based crop-weed detection as a good choice for manual detection with a minimum computational requirement and low-cost deployment.

Figure 5.1 shows the overall working of HierbaApp with images from SorghumWeedDataset_Classification and SorghumWeedDataset_Segmentation datasets. Figure 5.1 (a) shows the home screen of HierbaApp. The classification task of a sorghum sample from the classification dataset using HierbaApp with HierbaNetV1 operating in the background is shown in Figure 5.1 (b). The projected pixel-wise segmentation and mask of a sorghum sample from the segmentation dataset using HierbaApp with HierbaNetV1_MRCNN at its backend are shown in Figure 5.1 (c).



(a) HierbaApp – Home screen

(b) HierbaApp – Sorghum image prediction using 'HierbaNetV1' at its backend

(c) HierbaApp – Localization and mask generation using 'HierbaNetV1_MRCNN' at its backend

Figure 5.1: HierbaApp predictions using HierbaNetV1 and HierbaNetV1_MRCNN

5.2 REAL-TIME WEED DETECTION

We utilized four different types of equipment with varying resolutions to capture and detect real-time crops and weeds. Live images of crops and weeds in the field were taken using a Canon 80D, Canon 600D, Nikon CoolPix, and Samsung Galaxy M31. In total, 16 image samples were collected, comprising four samples each of sorghum, grass weeds, and broadleaf weeds. These samples, along with their corresponding ground truth, are illustrated in Figure 5.2.

5.3 VALIDATION OF DETECTION RESULTS

HierbaApp employs HierbaNetV1 for classification and HierbaNetV1_MRCNN for segmentation at its backend. Test results are validated and the real-time inference using HierbaApp with the application's live prediction results is illustrated in Figure 5.3. Among the 16 real-time images, 15 are True Positives and one is False Negative. As HierbaNetV1 predicts research objects with high True Positives irrespective of the equipment used, we state that our novel architectures are generalized and are suitable for weed detection in real-world agricultural settings.

HierbaNetV1 is also evaluated using a Raspberry Pi 4.0 and a Pi camera. The Pi camera captured plant images from an initial test setup, which were then processed by HierbaNetV1 running on the Raspberry Pi. The model classified the input images into their respective classes. This serves as a Proof of Concept (POC) for the future development of a weeding robot named 'HierbaRobo'.

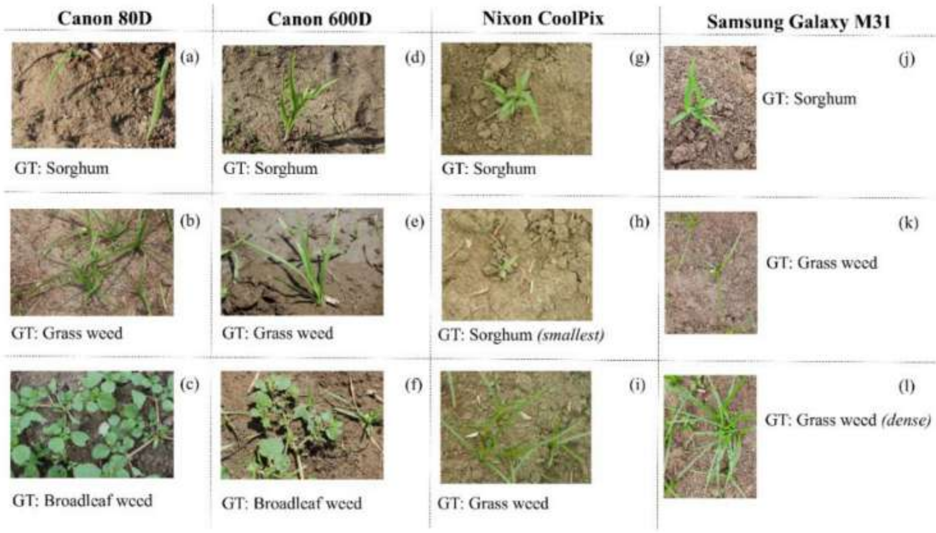


Figure 5.2. Real-time images for detection using four different equipment

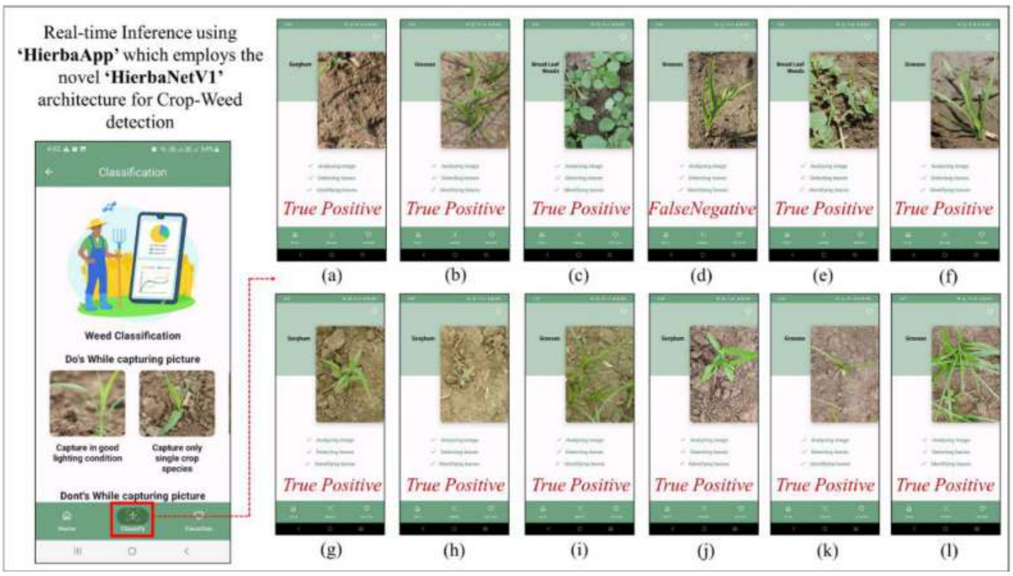


Figure 5.3. Real-time inference using 'HierbaApp'

CHAPTER 6

CONCLUSION

In summary, the research "HierbaNetV1: A Novel Feature Extraction Framework for Deep Learning-Based Weed Identification" has examined the effectiveness of deep learning algorithms for addressing weeding problems in agricultural settings. This chapter offers the research's conclusion as well as suggestions for future improvements.

6.1 CONCLUSION

The research highlights the need and importance of precision agriculture for sustainable weed management. The research findings are as follows; Two open-access crop-weed research datasets are acquired and created from Indian agricultural fields. They are

a) "SorghumWeedDataset_Classification" dataset
b) "SorghumWeedDataset_Segmentation" dataset

HierbaNetV1, a novel feature extraction technique is proposed for effective object identification. The proposed model proves to be a SOTA architecture by outperforming existing models by 0.7%. The trained weights of HierbaNetV1 are publicly available, thus allowing HierbaNetV1 to be used as a pre-trained model for any crop-related projects.

HierbaNetV1_FPN, a unique feature pyramid network is built to generate multi-scale feature maps. HierbaNetV1_MRCNN, a customized instance segmentation is designed with HierbaNetV1_FPN as its backbone thus facilitating improved object localization. By achieving the highest mAP of 0.62 for varying IOU thresholds of AP@[0.5:0.95], HierbaNetV1_MRCNN outperforms existing models.

HierbaApp, an Android mobile application is built by integrating HierbaNetV1 and HierbaNetV1_MRCNN for sorghum crop and its weed identification. HierbaApp can detect, classify, and segment sorghum, grass, and broadleaf weeds.

6.2 FUTURE ENHANCEMENTS

There are numerous ways to broaden the scope of this research; some of them are covered here. The "SorghumWeedDataset_Classification" dataset and the "SorghumWeedDataset_Segmentation" dataset comprise three classes namely sorghum, grass, and broadleaf weeds. By adding more Indian crops and weeds to the datasets, it will be possible to develop a general smart weeding system without being restricted to any one particular crop.

HierbaNetV1 is built with accuracy in mind. To enhance further, the model can be updated for performing fast detections. Incorporating the trained models into real-time decision-making applications will require more investigation [27]. Farmers would benefit from the deployment with the least number of resources for regular weed control procedures.

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1. Filed a patent entitled "Artificial intelligent based Agro-Bot device for weed identification and removal in random spacing plants" in the Indian Patent Office with Patent 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 the Indian Patent Office with Patent application no. 202441050194 on 01.07.2024.

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