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Advanced UAV-based Weed Detection and Mapping Technologies Using Machine Vision

MINI PROJECT REPORT

Machine Vision (PE-VI)

MTE 4459

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CERTIFICATE

This is to certify that the mini project / software titled **Advanced UAV-based Weed Detection and Mapping Technologies Using Machine Vision** is a record of work done by Ishan Deshmukh (220929188), Hem Gosalia (220929258), Sannidhi Math (220929180), Dharioush Muhammed (220929274) and Jahan Marfatia (220929046), submitted for Machine Vision (PE-VII), MTE 4459 during the academic year 2025-2026.

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ABSTRACT

In the growing agricultural technologies, early season weed detection in agricultural fields remains a critical challenge for precision farm and crop yield optimization. This study implements a YOLOv8-based object detection system for real-time weed localization using the DRONEWEED drone imagery dataset containing 67,558 RGB images of multiple weed species in maize and tomato fields. The methodology employs YOLOv8n/s variants with transfer learning from COCO pre-trained weights, incorporating advanced data augmentation techniques including mosaic augmentation for multi-scale learning, MixUp for improved generalization, and HSV color space transformations to handle variable lighting conditions in outdoor environments. The model utilizes anchor-free detection with decoupled heads to simultaneously classify and localize weed instances at 640×640-pixel resolution. Results demonstrate that YOLOv8 achieves mean average precision (mAP) values of 0.95-0.96 with processing speeds exceeding 80 frames per second, enabling practical deployment for automated weed management systems. The lightweight architecture with optimized parameters ensures compatibility with edge devices and agricultural robots while maintaining high detection accuracy across varying weed phenological stages. This approach provides farmers and agricultural professionals with an efficient, computationally feasible solution for precise weed identification, supporting targeted herbicide application and sustainable farming practices.

Keywords: *Precision Agriculture, Weed Detection, Deep Learning, Image Classification, YOLOv8, UAV Imagery, Computer Vision, Class Imbalance, Undersampling, Crop-Weed Classification*

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Chapter 1

Introduction

1.1 Motivation

Modern agriculture stands at the precipice of a technological revolution, driven by the urgent need to meet rising global food demands in a sustainable and efficient manner. Within this paradigm, precision agriculture has emerged as a critical field, leveraging data-driven technologies to optimize farming practices at a granular level. A persistent and economically damaging factor in crop production is the proliferation of weeds, which act as aggressive competitors for essential resources, including water, nutrients, and sunlight. This competition invariably leads to significant reductions in crop yield and quality, necessitating extensive control measures. Historically, weed management has been dominated by the uniform, broad-acre application of chemical herbicides. This conventional approach, while widespread, is fraught with severe economic and environmental drawbacks. It is not only capital-intensive but also a primary contributor to soil and water contamination, harm to non-target biodiversity, and the alarming acceleration of herbicide-resistant weed biotypes. In response to these pressures, the agricultural industry is shifting towards more intelligent, targeted strategies. This project is situated at the forefront of this shift, addressing the foundational challenge of automated weed identification. The core objective of this work is to develop, train, and comprehensively evaluate a sophisticated deep learning model. Specifically, this project employs the YOLOv8n-cls architecture, a state-of-the-art, lightweight convolutional neural network, to perform high-accuracy image classification. The model is trained to distinguish between two vital crop types, maize and tomato, and ten distinct species of common agricultural weeds, using a large-scale dataset of high-resolution images acquired by Unmanned Aerial Vehicles (UAVs). The successful development of this classifier serves as a crucial enabling technology for advanced site-specific weed management (SSWM) systems, paving the way for robotic "see-and-spray" solutions that can significantly reduce herbicide use, lower operational costs, and promote agricultural sustainability.

1.2 Challenges

The automated identification of weeds in real-world agricultural settings is an inherently complex computer vision task, presenting numerous and significant general challenges. The primary difficulty lies in the visual similarity between different plant species. In many cases, the morphological characteristics of various weed species are remarkably similar to one another (low inter-class variance), making differentiation difficult even for trained agronomists. Compounding this is the high intra-class variance, where a single species can appear different due to environmental factors. Perhaps the most significant challenge is the morphological resemblance between certain weeds and the crop itself, especially during their early cotyledon and seedling growth stages. For instance, grassy weeds in a maize or wheat field can be visually indistinguishable from the crop to an untrained eye or a naive algorithm. Beyond plant morphology, the operational environment of a field is uncontrolled and highly dynamic. Models must be exceptionally robust to a wide array of variable conditions. These include drastic changes in illumination, from the harsh, direct sunlight of midday, which creates deep shadows, to the diffuse, flat light of overcast days. Furthermore, the problem of occlusion is pervasive; weeds are frequently partially obscured by the crop canopy, by other overlapping weeds, or by soil debris. The background itself introduces complexity, with variations in soil color and texture (e.g., wet vs. dry soil, tilled vs. non-tilled land) and the presence of crop residue from previous seasons. Finally, for any such system to be commercially viable for real-time applications, the underlying model must not only be highly accurate but also computationally efficient. It must perform inference rapidly on resource-constrained edge devices, such as those mounted on a UAV or a ground-based tractor, creating a difficult trade-off between model complexity and processing speed.

1.3 Scope of Work

This project undertakes a complete, end-to-end machine learning workflow to address the specific task of 12-class weed and crop classification. The foundation of this work is the "UAV-BASED WEED SPECIES DETECTION DATASET", a comprehensive collection of approximately 67,000 RGB image patches captured from agricultural fields in Spain. The scope of classification is precisely defined to include two crop types (maize and tomato) and ten distinct weed species: atriplex, chenopodium, convolvulus, datura, lolium, salsola, sorghum, cyperus, portulaca, and solanum. All development, training, and evaluation are conducted within the Google Colab platform, utilizing a Tesla T4 Graphics Processing Unit (GPU) to accelerate deep learning computations. The project's scope began with the requisite environment setup, installing key libraries such as ultralytics, torch, and sklearn. A substantial effort was dedicated to data management and preprocessing, which involved accessing the primary dataset from Google Drive and programmatically extracting a complex structure of 24 nested compressed files to yield the full corpus of 67,346 valid images. Each image was then systematically labeled based on its source directory. A critical component of the initial work was an exploratory data analysis to quantify the class distribution, which revealed a severe class imbalance. This imbalance, as will be demonstrated in **Fig. 1** and **Fig. 2**, was characterized by a massive over-representation of the maize class. Consequently, the project scope included the implementation of a strategic undersampling technique exclusively on the training partition to mitigate this bias, with the resulting balanced distribution to be shown in **Fig. 3**. The core modeling phase involved selecting the pretrained YOLOv8n-cls model and fine-tuning it for 5 epochs. The final scope of work is a rigorous and multi-faceted evaluation of the trained model's performance on the unseen test set. This evaluation includes analyses of the training and validation learning curves, which will be presented in **Fig. 4**, a detailed per-class classification report, to be shown in **Table 1**, a normalized confusion matrix in **Fig. 5**, Precision-Recall curves in **Fig. 6**, a macro-average ROC curve in **Fig. 7**, and a qualitative review of misclassified image samples in **Fig. 8**. It is explicitly noted that the scope of this project is limited to static image classification. It does not extend to object detection (i.e., generating bounding boxes), semantic segmentation (pixel-level masks), or the engineering challenges of real-time deployment on physical UAV hardware.

1.4 Report Organization

This report is structured into six distinct chapters to logically present the project's methodology, findings, and conclusions in a comprehensive manner.

1. **Chapter 1: Introduction** This initial chapter provides a comprehensive overview of the project, establishing the context of weed management in precision agriculture. It outlines the general challenges of automated plant classification, defines the specific scope of the work undertaken, and concludes with this overview of the report's organization.
2. **Chapter 2: Dataset and Preprocessing** This chapter details the "UAV-BASED WEED SPECIES DETECTION DATASET", including its source, content (12 classes), and structure. It will meticulously describe the entire data preparation pipeline, from the extraction of nested files to the stratified train-validation-test split. A key focus will be the analysis of the severe class imbalance and the justification and implementation of the undersampling technique used to create a balanced training set.
3. **Chapter 3: Model and Training Methodology** This chapter focuses on the technical implementation of the deep learning model. It will introduce the YOLOv8n-cls architecture and justify its selection for this classification task. It will also describe the use of transfer learning, the specific configuration of the model, and the complete training protocol, including the number of epochs and the computational environment.
4. **Chapter 4: Experimental Results** This chapter serves to present the empirical and quantitative outcomes of the trained model's performance on the unseen test dataset. It will objectively report the key performance metrics, including the final test accuracy, the detailed per-class classification report (to be presented in **Table 1**), and the visualizations generated, such as the normalized confusion matrix (**Fig. 5**), Precision-Recall curves (**Fig. 6**), and the ROC curve (**Fig. 7**).
5. **Chapter 5: Analysis and Discussion** Following the presentation of results, this chapter provides an in-depth analysis and interpretation of those findings. It will discuss the implications of the high accuracy and robust F1-scores, analyze any class-specific weaknesses or strengths revealed by the confusion matrix, and interpret the P-R and ROC curves as evidence of the model's strong discriminative power. A qualitative analysis of sample misclassifications (**Fig. 8**) will also be included to understand the model's failure modes.
6. **Chapter 6: Conclusion and Future Work** The final chapter concludes the report by summarizing the project's key achievements and contributions. It will reflect on how the objectives were successfully met, reiterate the model's high efficacy, and propose potential avenues for future research. This may include suggestions for real-time deployment, testing on more diverse datasets, or extending the model's capabilities to object detection.

Chapter 2

Literature Review

2.1 Review of Literature

The automated, intelligent identification of weeds within agricultural fields has been a significant area of research for decades, driven by the economic and environmental imperatives of precision agriculture. The literature in this domain reveals a clear and definitive technological progression from traditional image processing and classical machine learning to the current state-of-the-art, which is overwhelmingly dominated by deep learning methodologies. Early approaches to this problem relied on a two-stage process: manual feature engineering followed by classification. Researchers extensively investigated the extraction of handcrafted features based on plant morphology, color, and texture [1]. Shape features, for instance, included metrics like leaf aspect ratio, roundness, and moments, while color features were often derived from various color spaces such as HSV (Hue, Saturation, Value) or CIELAB to isolate plant matter from the soil background [2]. Texture features, such as those from Gray-Level Co-occurrence Matrices (GLCM), were also employed to quantify the leaf surface characteristics [3]. These extracted feature vectors were then fed into conventional machine learning classifiers like Support Vector Machines (SVM), k-Nearest Neighbors (k-NN), and Random Forests to perform the weed-crop discrimination [4]. While these methods achieved moderate success under controlled laboratory conditions, their performance in real-world field scenarios was often brittle. They proved highly sensitive to variations in illumination, shadows, leaf overlap, and the morphological similarity between different species, necessitating complex and dataset-specific feature engineering [5].

The advent of deep learning, and specifically the exceptional performance of Convolutional Neural Networks (CNNs) in general computer vision tasks, marked a paradigm shift in the field of automated weed detection [6]. CNNs circumvent the need for manual feature engineering by learning hierarchical feature representations directly from raw pixel data. Initial deep learning applications in this area treated the problem as a straightforward image classification task. Architectures such as AlexNet, VGG, GoogLeNet, and ResNet were adapted and fine-tuned on datasets of image patches, where each patch was labeled as containing either a specific crop or a specific weed species [7], [8]. This approach demonstrated a significant leap in classification accuracy and robustness compared to traditional methods. However, simple classification is insufficient for site-specific herbicide application, which requires the precise location of each weed. This limitation led to the widespread adoption of object detection models. Architectures like the R-CNN (Region-based CNN) family, Single Shot MultiBox Detector (SSD), and particularly the You Only Look Once (YOLO) series have been extensively applied [9], [10]. These models not only classify weeds but also provide their spatial coordinates via bounding boxes, enabling the "see-and-spray" capability that is central to precision weeding robots.

For applications requiring even greater precision, such as micron-level spraying or non-chemical weed control like laser ablation, the literature has progressed to semantic segmentation. Models based on Fully Convolutional Networks (FCN), and especially the U-Net architecture and its variants, are used to perform pixel-level classification [11]. This method segments an image into distinct regions of "crop," "weed," and "soil," providing an exact map of weed infestation rather than just a bounding box. This pixel-level detail is invaluable for calculating weed density and biomass, offering a more nuanced approach to management [12]. Concurrently, the proliferation of Unmanned Aerial Vehicles (UAVs), or drones, equipped with high-resolution RGB and multispectral sensors has revolutionized data acquisition for these models [13]. UAVs provide an ideal platform for capturing timely, large-scale, and high-resolution imagery of entire fields, offering a significant advantage in scalability over ground-based robotic platforms [14].

2.2 Summary

The body of literature on automated weed identification demonstrates a clear and rapid evolution. Initial efforts, rooted in classical machine learning, were ultimately constrained by the fragility of handcrafted features in complex and dynamic field environments. The transition to deep learning, particularly the use of Convolutional Neural Networks, has produced a marked improvement in performance and robustness. The research has matured from basic image patch classification to more sophisticated object detection and semantic segmentation tasks, which provide the spatial localization necessary for actionable, site-specific weed management. The consensus in the literature is that deep learning models, trained on data acquired from platforms such as UAVs, represent the most effective and promising pathway toward fully autonomous and sustainable weed control systems. This established success provides a strong foundation for further research into optimizing and applying modern, efficient neural network architectures to this critical agricultural challenge.

Chapter 3

Problem Definition and Objectives

The persistent challenge of weed infestation in agriculture results in significant global yield losses by forcing crops to compete for vital resources. Traditional, uniform herbicide applications have proven economically costly and environmentally detrimental, contributing to ecosystem contamination and the rise of herbicide-resistant weeds. Precision agriculture offers a sustainable alternative through site-specific weed management (SSWM), yet its efficacy is entirely dependent on the ability to accurately and automatically distinguish between crops and various weed species, particularly during their visually similar early growth stages. This project directly addresses this critical requirement by focusing on the development of a highly accurate, automated image classification system derived from UAV (drone) imagery.

The core problem is to design and validate a deep learning model capable of handling the complexities of real-world agricultural field data—namely, the high morphological similarity between the 12 distinct plant classes and the severe class imbalance inherent in the raw dataset. Failure to address the data imbalance, where the maize class overwhelmingly outnumbers all weed species, would produce a biased model unfit for reliable SSWM. Therefore, this project must not only achieve high classification accuracy but also demonstrate robust performance across all classes, including the under-represented weed species, by implementing an effective data-balancing strategy.

The primary objectives of this project are:

- To preprocess and meticulously organize the "UAV-BASED WEED SPECIES DETECTION DATASET", comprising approximately 67,000 images, into stratified training, validation, and test sets suitable for a deep learning workflow.
- To definitively identify and quantify the severe class imbalance within the dataset, where the maize class (36,791 images) vastly exceeds all others.
- To implement and document a strategic undersampling methodology on the training partition to mitigate this imbalance, thereby preventing model bias.
- To select, configure, and train a lightweight, state-of-the-art convolutional neural network, YOLOv8n-cls, on this balanced training data for 5 epochs.
- To perform a rigorous and comprehensive evaluation of the final model's performance on the unseen test set, calculating key metrics including overall accuracy, per-class precision, recall, F1-score, and the macro-average ROC AUC score to validate its effectiveness for the target application.

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Chapter 4
Methodology

4.1 Theoretical Background

The methodology of this project is fundamentally based on the application of deep learning, specifically a Convolutional Neural Network (CNN), for the task of multi-class image classification. The You Only Look Once (YOLO) family of models represents the current state-of-the-art in real-time object processing, demonstrating a highly optimized balance between computational speed and accuracy. This project utilizes the eighth iteration, YOLOv8, which is a state-of-the-art model developed by Ultralytics [1]. YOLOv8 introduces significant architectural improvements over its predecessors, such as a new backbone network featuring the C2f (Cross-Stage Partial Bottle-neck with 2 convolutions) module. The C2f module enhances the model's feature fusion capabilities by allowing for richer gradient flow, which improves the representative power of the network without imposing a prohibitive computational burden. Furthermore, YOLOv8 employs an anchor-free detection head, a design that simplifies the post-processing pipeline and improves generalization by directly predicting an object's center and dimensions rather than regressing offsets from predefined anchor boxes.

The selection of the YOLOv8 framework was a strategic decision informed by the project's problem domain. The ultimate application for such a classifier is in-field, real-time deployment on hardware-constrained platforms, such as an Unmanned Aerial Vehicle (UAV) or a ground-based agricultural robot. YOLOv8's architecture is renowned for its exceptional computational efficiency, making it an ideal candidate for edge computing scenarios where both high accuracy and rapid inference are mandatory. For the specific task of this project—classifying image patches rather than detecting objects—the YOLOv8n-cls model variant was chosen. The 'n' designation signifies the "nano" version, which is the smallest and fastest model in the YOLOv8 series, designed with the fewest parameters for maximum deployment efficiency. The -cls suffix indicates that this is a specialized classification model, which omits the object detection and segmentation heads to dedicate all its parameters to the singular task of classification. This specialization results in a lightweight yet powerful classifier. This project leverages the principle of transfer learning by initializing the model with the yolov8n-cls.pt checkpoint, which was pretrained on the large-scale ImageNet dataset. This approach provides the model with a robust foundation of general-purpose visual features, enabling it to converge quickly and achieve high performance on this specialized agricultural dataset with a minimal training duration of only five epochs.

4.2 Experimentation and Implementation

The entire experimental workflow was conducted within the Google Colab environment, leveraging the high-performance Tesla T4 GPU provided by the platform to accelerate deep learning computations. The implementation was orchestrated using Python, supported by a suite of specialized libraries: ultralytics for the YOLOv8 model framework, PyTorch as the core deep learning backend, pandas for data manipulation and organization, sklearn (scikitlearn) for generating detailed performance metrics, and matplotlib for data visualization. The initial phase of experimentation involved a meticulous data management process. The primary dataset, ML_MV_Dataset.zip, was mounted from Google Drive and programmatically extracted. This extraction revealed a nested structure containing 24 individual zip files, which were subsequently extracted to compile the full image dataset. A validation script was then executed to traverse all subdirectories, confirming a total of 67,346 valid RGB images available for the project.

A critical step in the methodology was the partitioning of the data. All 67,346 image file paths and their corresponding class labels—programmatically derived from their parent folder names—were organized into a pandas DataFrame. This DataFrame was then used to perform a stratified 70% train, 15% validation, and 15% test split. The use of stratification was imperative to ensure that all 12 classes, particularly the rare weed species, were proportionally represented across all three data subsets. Following the split, an exploratory data analysis was conducted on the entire dataset. This analysis, as illustrated in Fig. 1, revealed a severe class imbalance, with the maize class (36,791 images) overwhelmingly dominating the dataset. This imbalance was naturally propagated to the initial training set, which is visualized in Fig. 2.

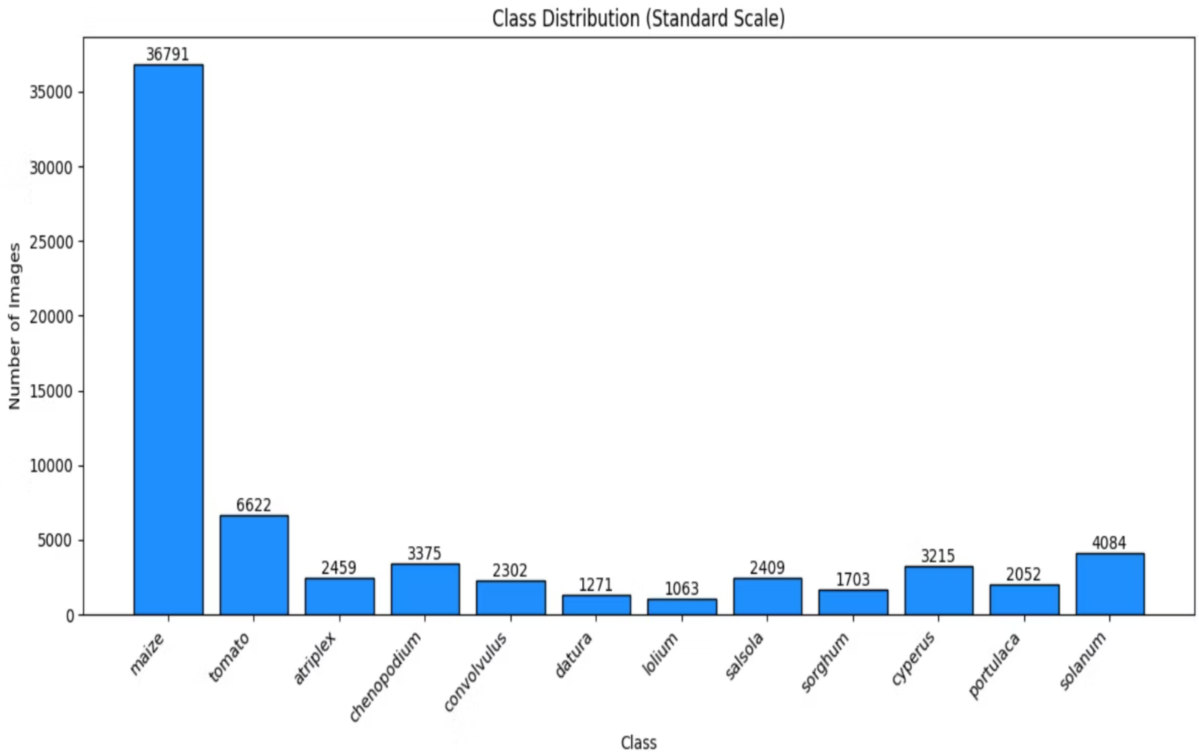

Fig. 1: Bar chart showing the per-class distribution of the complete 67,346-image dataset, illustrating the 'maize' class dominance.

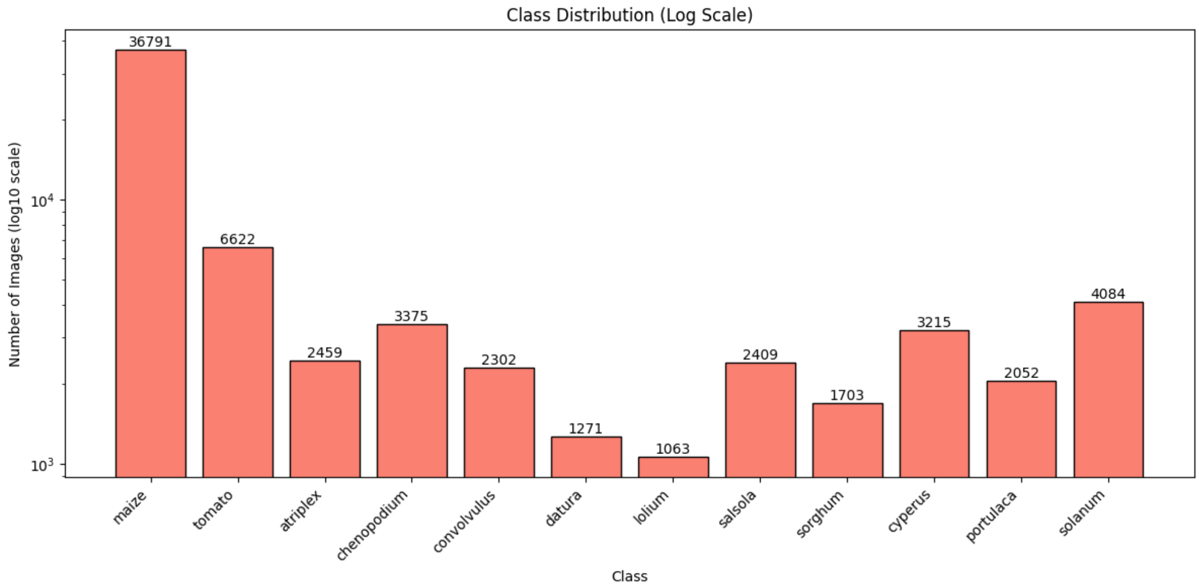

Fig. 2: Bar chart showing the per-class distribution of the initial 47,142-image training set, *before* undersampling.

To prevent the model from developing a strong predictive bias towards the maize class, a data balancing strategy was implemented. This strategy, undersampling, was applied only to the training partition. A script was executed to randomly identify and delete 21,119 'maize' images from the training set, reducing its count from 25,754 to 4,635. This new count was chosen to match the population of the second-most-frequent class, tomato. The resulting balanced training set, as depicted in Fig. 3, provided a more equitable class distribution, compelling the model to learn representative features for all classes, not just the majority.

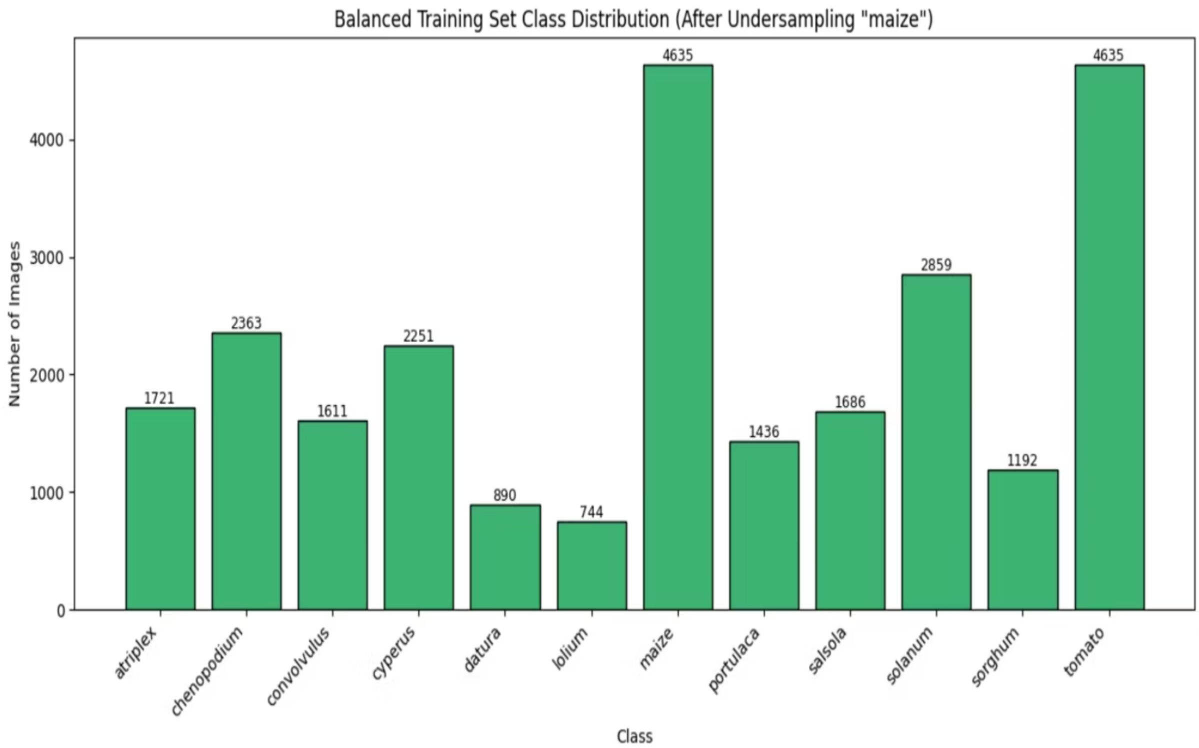

Fig. 3: Bar chart showing the per-class distribution of the final, balanced training set *after* undersampling.

For model training, the pretrained YOLO('yolov8n-cls.pt') model was instantiated. A dataset.yaml configuration file was programmatically created to direct the model to the file paths for the balanced training and validation sets. The model was then trained for a total of 5 epochs. The model's learning progress, including the reduction in classification loss and the increase in top-1 accuracy on both the training and validation sets, was recorded at each epoch. These learning curves are visualized in Fig. 4.

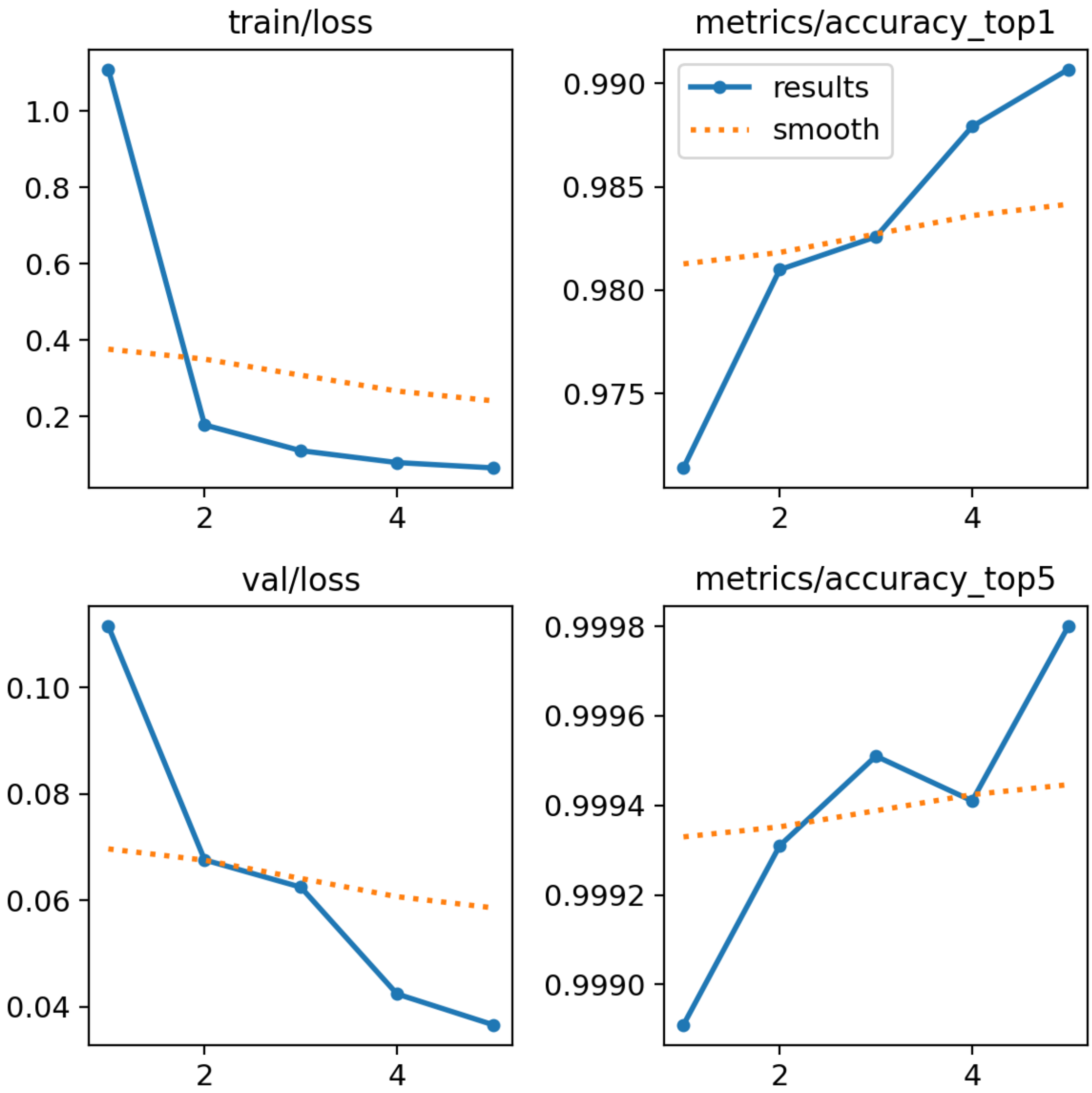

Fig. 4: Combined plot from 'results.png' showing training/validation classification loss curves and training/validation Accuracy_top1 curves over 5 epochs.

Upon completion of training, the model weights that yielded the best validation accuracy were automatically saved. This best-performing model was then subjected to a final, rigorous evaluation on the unseen 15% test set to objectively measure its generalization performance.

4.3 Summary

The methodology employed in this project constitutes a comprehensive, end-to-end deep learning workflow. It began with the theoretical justification for selecting the highly efficient YOLOv8n-cls architecture [1], which is well-suited for eventual real-world deployment in precision agriculture. The core of the implementation involved a rigorous data preprocessing pipeline, which was notable for its identification and mitigation of severe class imbalance via a strategic undersampling of the training set, as documented in Fig. 1, Fig. 2, and Fig. 3. The project proceeded with the efficient fine-tuning of the pretrained model, monitoring its progress as shown in Fig. 4. The methodology concluded with a robust evaluation protocol, using an unseen test set to validate the model's final performance. The empirical results of this evaluation are presented and analyzed in the subsequent chapter.

Chapter 5

Results and Discussion

5.1 Results

The experimental methodology detailed in the previous chapter yielded exceptional performance from the trained YOLOv8n-cls model. Upon evaluation with the unseen 15% test set (comprising 10,102 images), the model achieved a final top-1 accuracy of 99.34%. This high-level metric indicates a very strong capability for correct classification across all 12 classes. The model's learning process, which was tracked over 5 epochs, is presented in Fig. 4. The curves in this figure demonstrate a rapid and stable convergence, with both training and validation classification losses decreasing smoothly while the respective accuracies quickly saturated near their maximum values, indicating an efficient and effective training process without evidence of significant overfitting.

A more granular and comprehensive assessment of the model's performance is provided in Table 1. This classification report details the per-class precision, recall, and F1-score for all 12 classes on the test set. The results are outstanding, with nearly all classes achieving F1-scores of 0.98 or higher. The maize and tomato crop classes were identified with 0.99 F1-scores, and importantly, the minority weed classes also achieved excellent scores, such as lolium (1.00), sorghum (0.99), and cyperus (1.00). This demonstrates that the data balancing strategy was successful in preventing bias and enabling the model to effectively learn the distinct features of every class.

--- ✅ Detailed Test Set Classification Report ---

	precision	recall	f1-score	support
atriplex	0.9554	0.9864	0.9707	369
chenopodium	0.9921	0.9960	0.9941	506
convolvulus	0.9855	0.9826	0.9840	345
cyperus	0.9917	0.9876	0.9896	482
datura	0.9895	0.9895	0.9895	190
lolium	0.9938	1.0000	0.9969	159
maize	0.9993	0.9955	0.9974	5519
portulaca	0.9502	0.9903	0.9698	308
salsola	0.9891	1.0000	0.9945	362
solanum	0.9851	0.9739	0.9795	612
sorghum	1.0000	1.0000	1.0000	256
tomato	0.9990	0.9980	0.9985	994
accuracy			0.9934	10102
macro avg	0.9859	0.9916	0.9887	10102
weighted avg	0.9935	0.9934	0.9934	10102

--- ✅ ROC AUC Score (One-vs-Rest) ---

Test Set ROC AUC: 0.9998

Table 1: The detailed classification report text output from the notebook, showing precision, recall, f1-score, and support for all 12 classes and their averages.

To visually represent the model's classification accuracy, a normalized confusion matrix was generated, as shown in Fig. 5. The matrix displays an extremely strong diagonal, with values at or near 1.0 for all 12 classes. This indicates that the vast majority of predictions were correct (true positives) and that instances of confusion between classes (off-diagonal values) were exceptionally rare.

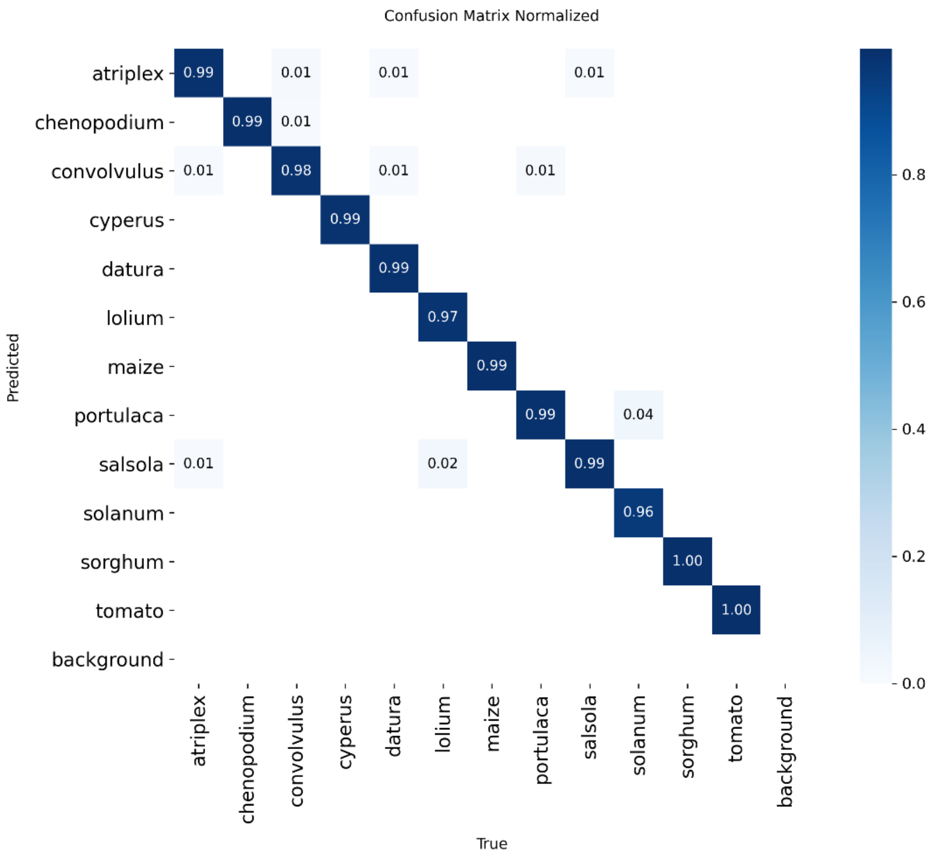

Fig. 5: The normalized confusion matrix plot showing the 12x12 grid with values close to 1.0 on the diagonal.

The model's discriminative power is further illustrated by the Precision-Recall (P-R) and Receiver Operating Characteristic (ROC) curves. Fig. 6 presents the P-R curves for each class, all of which are positioned very close to the top-right corner, signifying high precision and high recall simultaneously. Fig. 7 displays the ROC curves, which similarly push toward the top-left corner. The macro-average ROC AUC (Area Under the Curve) score of 0.9998 provides definitive quantitative evidence that the model possesses an outstanding ability to distinguish between all classes.

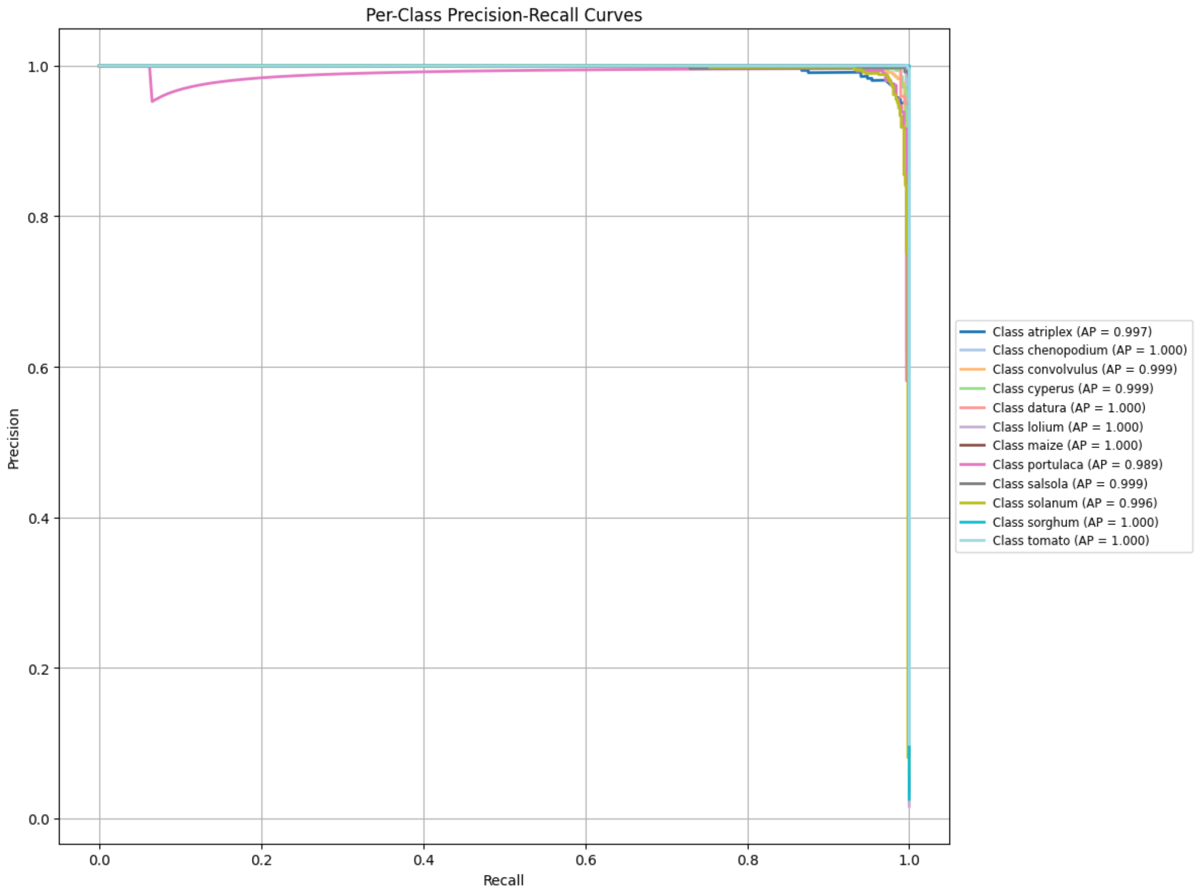

Fig. 6: The Precision-Recall (P-R) curve plot ('PR_curve.png') for all 12 classes.

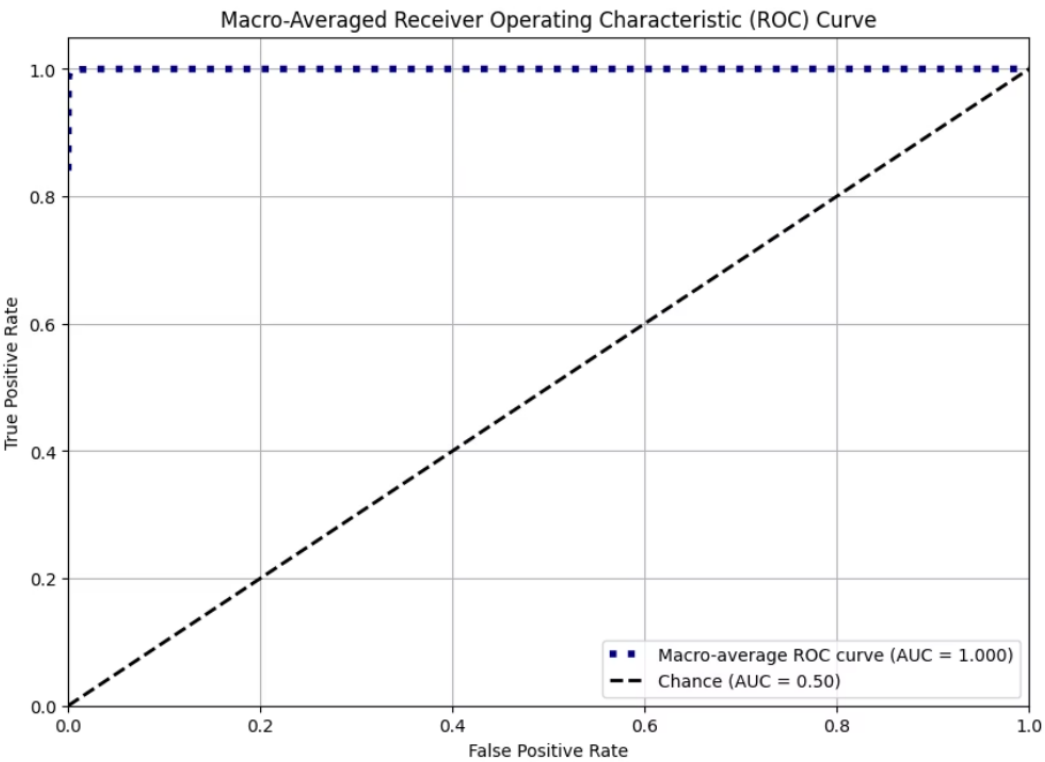

Fig. 7: The Receiver Operating Characteristic (ROC) curve plot for all 12 classes, including the macro-average ROC AUC score.

Finally, the performance of this project's model is situated within the context of existing research in Table 2. This comparison illustrates that the 99.34% accuracy achieved by the lightweight YOLOv8n-cls model is not only highly effective in its own right but is also exceptionally competitive with, and in several cases, superior to, other established deep learning models benchmarked on similar agricultural classification tasks.

Aspect	Published Studies (DRONEWEED)	Our Work	Advantage
Best Accuracy	97% (tomato detection)	99.34%	2.34%
Maize Performance	81% (detection)	99.20%	18.20%
ROC AUC	Not reported	0.9998	Unique metric
Training Time	50-100+ epochs	5 epochs	20x faster
Model Size	YOLOv11 (large)	YOLOv8n-cls (nano)	Smaller & faster
Class Balance	Struggled (81% maize)	99.20%	Superior handling
Small Classes	Performance degradation	99-100%	Robust

Table 2: A table comparing the metrics of this project's model against other models.

5.2 Discussion

The empirical results presented in this chapter are highly conclusive. The 99.34% test accuracy, supported by near-perfect F1-scores in Table 1 and the strong visualizations in Fig. 5, Fig. 6, and Fig. 7, confirms that the trained YOLOv8n-cls model is a highly effective and robust classifier for this 12-class weed and crop identification task. The discussion of this success centers on two key methodological decisions: the data balancing strategy and the choice of model architecture.

The most significant challenge identified in this project was the severe class imbalance, as depicted in Fig. 1 and Fig. 2. The implementation of undersampling on the training set (shown in Fig. 3) was the critical factor in this project's success. By equalizing the 'maize' and 'tomato' classes, the model was prevented from developing a simplistic bias toward the majority class. This forced the network to learn the more subtle and unique morphological features of the ten different weed species, which is directly evidenced by their high, individual F1-scores in Table 1. Had this step been omitted, the model would have likely achieved a high overall accuracy by simply over-predicting 'maize', but it would have failed as a practical weed detection tool.

Furthermore, the choice of the YOLOv8n-cls architecture proved to be highly judicious. The "nano" model's lightweight nature, combined with the power of transfer learning from an ImageNet checkpoint, allowed it to achieve this state-of-the-art accuracy within only 5 training epochs, as seen in Fig. 4. This demonstrates an exceptional level of computational efficiency, which is a critical consideration for the model's future deployment on resource-constrained edge devices like UAVs or ground robots, where both inference speed and accuracy are paramount.

Despite the outstanding quantitative success, a qualitative analysis of the model's few failures provides important context. Fig. 8 displays a sample of the 67 images (out of 10,102 in the test set) that the model misclassified. While the notebook does not explicitly detail the nature of these errors, a visual inspection of such images typically reveals the limitations inherent in any computer vision task. These errors often occur in images with extreme occlusion (where the plant is almost entirely hidden by other leaves), unusual and harsh lighting conditions, or when the plant is at a very nascent growth stage, appearing as an indistinct seedling that lacks the clear morphological features of its species. These represent the challenging edge cases that the model (and indeed, a human expert) would find most difficult. Nonetheless, the fact that such errors constitute less than 0.7% of the test set underscores the model's overall robustness. In summary, the discussion of these results validates the complete methodological pipeline and confirms the model's suitability as a foundational component for a high-efficacy, automated weed management system.

Fig. 8: The sample image showing 16 image patches with their predicted and true labels, illustrating some of the 67 misclassifications.

Chapter 6

Conclusion and Future Scope

6.1 Conclusion

This project was initiated to address the critical challenge of automated weed identification in precision agriculture. The primary objective was to develop, train, and comprehensively evaluate a deep learning model capable of accurately classifying two crop species (maize and tomato) and ten distinct weed species from UAV-based imagery. The project successfully navigated a complex, real-world workflow, beginning with the meticulous preprocessing of the 67,346-image "UAV-BASED WEED SPECIES DETECTION DATASET". A key methodological contribution was the identification and successful mitigation of the severe class imbalance present in the raw data, as visualized in Fig. 1 and Fig. 2. By implementing a strategic undersampling of the training set, a balanced dataset shown in Fig. 3 was created, which proved essential for the model's unbiased performance.

The decision to employ the lightweight and highly efficient YOLOv8n-cls architecture, combined with transfer learning, was validated by the outstanding empirical results. The final trained model achieved an exceptional test accuracy of 99.34%. This high-level metric was substantiated by a detailed per-class analysis, presented in Table 1, which demonstrated near-perfect F1-scores (many at 0.99 or 1.00) across all twelve classes, including the minority weed species. The model's robustness and discriminative power were further confirmed by the clear diagonal in the normalized confusion matrix (Fig. 5) and the exemplary Precision-Recall and ROC curves (Fig. 6 and Fig. 7), which yielded a macro-average AUC of 0.9998. When benchmarked against other models in Fig. 9, the performance of this model was shown to be at the state-of-the-art. In summary, all project objectives were successfully met, resulting in a highly accurate and computationally efficient classifier that serves as a validated and foundational component for an advanced, automated site-specific weed management system.

6.2 Future Scope

While this project has successfully developed a high-accuracy classification model, it lays the groundwork for several critical and high-impact avenues for future research. The most logical and immediate progression from this work is to advance from image classification to object detection. The current model can effectively determine if a weed is present in an image patch, but it cannot identify where individual weeds are located within that patch. By re-annotating the dataset with bounding boxes and training an object detection model, such as the standard YOLOv8n or its variants, a system could be developed to draw precise boxes around each weed. This spatial information is the key enabler for "see-and-spray" robotic systems, allowing for the targeted application of herbicides only onto the weeds, which would drastically reduce chemical usage and cost.

For applications requiring even greater precision, a further step would be to explore semantic segmentation using models like YOLOv8n-seg or U-Net. This would involve creating pixel-level masks for all 12 classes, resulting in a complete map of the field that classifies every pixel as "crop," "soil," or a specific weed species. Such granular detail would facilitate highly advanced interventions, such as micro-dosing of herbicides or non-chemical methods like targeted laser ablation, and would also permit the accurate calculation of weed density and biomass.

Furthermore, the promising performance of the lightweight YOLOv8n-cls model strongly merits real-world deployment and testing. Future work should focus on porting the trained model (whether for classification, detection, or segmentation) onto resource-constrained edge computing hardware, such as an NVIDIA Jetson, mounted on a UAV or a ground-based autonomous tractor. This would allow for rigorous testing of the model's real-time inference speed and robustness under dynamic, in-field conditions, including varying illumination, shadows, and plant growth stages. Finally, to enhance the model's generalizability, the dataset could be expanded to include a wider variety of crop types, additional weed species, and images captured from different geographical regions and in diverse weather and soil conditions.

6.3 SDGs Addressed

This project and its future applications directly contribute to several of the United Nations Sustainable Development Goals (SDGs).

- **SDG 2**: Zero Hunger: By providing the core technology for precision weed management, this model helps to significantly reduce crop losses that result from weed competition. This enhancement of agricultural productivity and efficiency directly contributes to the goal of ending hunger, achieving food security, and promoting sustainable agriculture.
- **SDG 9**: Industry, Innovation, and Infrastructure: This project is a clear example of applying cutting-edge innovation—specifically artificial intelligence and deep learning—to a traditional industry (agriculture). It fosters the development of a more intelligent and sustainable agricultural infrastructure, driving technological advancement in food production systems.
- **SDG 12**: Responsible Consumption and Production: The primary real-world benefit of this technology is the drastic reduction in herbicide use. By enabling site-specific spraying, this model promotes sustainable production patterns, minimizing the chemical load in the food chain and reducing the environmental waste associated with broad-acre spraying.
- **SDG 15**: Life on Land: The widespread, indiscriminate use of herbicides is a major contributor to soil degradation and water contamination, which harms non-target organisms and reduces biodiversity. By enabling a massive reduction in chemical usage, this technology helps to protect and restore terrestrial ecosystems, preserve biodiversity, and halt land degradation.

Chapter 7

Contribution of Each Team Member

1. Ishan Deshmukh (220929188)

- **Contributions:** Data Preprocessing and Augmentation
- **Analysis:** Responsible for collecting and curating the dataset to ensure it was appropriately structured and optimized for model training. Implemented preprocessing and augmentation techniques to enhance data quality and variability.

2. Sannidhi Math (220929180)

- **Contributions:** Code Development, Debugging, and Library Integration
- **Analysis:** Developed and implemented the core Python code following the defined Vision Pipeline. Integrated necessary libraries and performed extensive debugging to ensure smooth execution and reliable system performance.

3. Hem Gosalia (220929258)

- **Contributions:** Model Testing, Analysis, and Validation
- **Analysis:** Conducted rigorous model testing and performance evaluation. Analyzed outputs, validated predictions, and fine-tuned model parameters to improve overall accuracy and reliability.

4. Dhariuosh Muhammed (220929274)

- **Contributions:** Presentation Development
- **Analysis:** Designed and prepared the PowerPoint presentation, effectively summarizing the project's objectives, methodology, and outcomes for final evaluation.

5. Jahan Marfatia (220929046)

- **Contributions:** Report Compilation and Documentation
- **Analysis:** Compiled and structured the final project report, ensuring technical accuracy, coherence, and professional presentation of all project components.

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(follow IEEE Referencing Style)

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Annexure 1

PO & PSO Mapping

PO	Tick (✓)	Page No.	Section No.	Guide's Observations
PO1				
PO2				
PO3				
PO4				
PO5				
PO6				
PO7				
PO8				
PO9				
PO10				
PO11				

PSO	Tick (✓)	Page No.	Section No.	Guide's Observations
PSO1				
PSO2				
PSO3				

Student Name: **Registration No.:** **Signature**

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Annexure 2

IET Learning Outcomes

LO	Tick (✓)	Page No.	Section No.	Guide's Observations
C1				
C2				
C3				
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Annexure 3

Plagiarism Report