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DECTECTING WEED PLANTS IN FIELDS USING AI TECHNIQUES

Dr. RAAFIYA GULMEHER[1], ZAINAB FATIMA[2]

DEPT. OF COMPUTER SCIENCE AND ENGINEERING, KHAJA BANDA NAWAZ UNIVERSITY

Abstract - Weed infestation is a major challenge in agriculture, significantly affecting crop yield, quality, and overall farm productivity. Conventional weed detection methods, such as manual inspection and uniform herbicide application, are labor-intensive, time-consuming, and environmentally harmful. With recent advancements in Artificial Intelligence (AI) and computer vision, automated and precise weed detection has become feasible. This paper presents an AI-based approach for detecting weed plants in agricultural fields using deep learning techniques. Field images captured through cameras or unmanned aerial vehicles are processed using convolutional neural networks to accurately differentiate weeds from crops. The proposed system focuses on efficient feature extraction, robust classification, and reliable weed localization under varying field conditions. The AI-based approach supports precision agriculture by enabling targeted weed control, reducing chemical usage, minimizing labor costs, and promoting sustainable farming practices. The results demonstrate the potential of AI techniques to improve weed management efficiency and enhance agricultural productivity.

1. INTRODUCTION

Agriculture plays a critical role in ensuring food security and economic stability worldwide. However, crop production is significantly affected by weed infestation, which remains one of the most persistent challenges in modern farming. Weeds compete with crops for essential resources such as nutrients, water, sunlight, and space, leading to reduced crop growth and yield. Studies have shown that uncontrolled weed growth can cause yield losses of up to 30–40% in major crops, making effective weed management a crucial requirement in agriculture. Conventional weed control techniques primarily involve manual weeding and chemical herbicide application. Manual weeding, although effective, is highly labor-intensive, time-consuming, and economically unfeasible for large-scale farming. The availability of skilled agricultural labor is also decreasing in many regions. Chemical herbicides, while widely used, are often applied uniformly across entire fields, resulting in excessive chemical usage. This practice not only increases production costs but also leads to soil degradation, water contamination, and adverse effects on human health and biodiversity. Furthermore, the indiscriminate use of herbicides contributes to the development of herbicide-resistant weed species, posing a long-term threat to sustainable agriculture. To overcome these limitations, precision agriculture has emerged as an innovative approach that focuses on optimized resource utilization and targeted field management. Precision agriculture aims to apply the right treatment at the right place and at the right time. In this context, accurate and automated weed detection is a key enabling technology. Identifying weeds at an early growth stage allows selective weed control, thereby minimizing crop damage and reducing chemical usage. Recent advances in Artificial Intelligence (AI), particularly in computer vision and deep learning, have revolutionized image-based analysis tasks. Deep learning models such as Convolutional Neural Networks (CNNs) are capable of automatically learning complex visual features from images, making them highly effective for plant classification problems. Unlike traditional image processing techniques that rely on handcrafted features, deep learning models adapt to variations in lighting, background, plant shape, and scale, which are commonly encountered in real agricultural environments.AI-based weed detection systems analyze images captured using ground-based cameras, mobile devices, or unmanned aerial vehicles (drones).

These systems can accurately differentiate weeds from crops and localize weed regions within the field. Object detection models further enhance this capability by identifying the exact position of weeds, enabling site-specific weed management techniques such as targeted spraying or robotic weed removal. Such intelligent systems reduce labor dependency, minimize herbicide usage, and improve overall farming efficiency.

1.1 Background

Weed management is a fundamental aspect of agricultural practice, as weeds directly affect crop productivity and farming efficiency. Weeds compete with crops for essential resources such as nutrients, water, sunlight, and space, leading to reduced crop growth and significant yield losses. Effective weed control is therefore essential to ensure food security and sustainable agricultural production, especially in regions where farming is the primary source of livelihood.

Recent advancements in Artificial Intelligence (AI) and computer vision have opened new possibilities for precision agriculture. AI-based systems can analyze visual data and automatically identify patterns that distinguish weeds from crops. Deep learning models, particularly convolutional neural networks (CNNs), have shown remarkable performance in image classification and object detection tasks. By leveraging these techniques, weed detection can be automated with high accuracy under varying field conditions.

This paper focuses on the application of AI techniques for detecting weed plants in agricultural fields. The proposed approach uses image-based analysis to differentiate weeds from crops, enabling targeted weed management. Such an intelligent system can significantly reduce labor requirements, minimize chemical usage, and promote sustainable agricultural practices. The study serves as a foundational step toward developing real-time, automated weed detection and control systems for modern farming.

Traditionally, weed control has been performed through manual weeding or chemical herbicide application. Manual weed removal is labor-intensive, time-consuming, and economically impractical for large-scale farms. In addition, the availability of agricultural labor has been steadily declining due to urbanization and mechanization. Chemical herbicides, although effective in controlling weeds, are often applied uniformly across entire fields without distinguishing between crops and weeds. This results in excessive chemical usage, increased production costs, environmental pollution, soil degradation, and potential health risks to humans and animals. Overuse of herbicides has also led to the emergence of herbicide-resistant weed species, making weed control increasingly difficult.

With the advancement of agricultural technologies, precision agriculture has emerged as a promising solution to these challenges. Precision agriculture focuses on optimizing agricultural inputs by applying treatments only where and when they are needed. Accurate identification of weeds is a key requirement for implementing precision weed management. However, distinguishing weeds from crops in real field conditions is challenging due to variations in plant appearance, growth stages, lighting conditions, and background complexity.

Recent developments in Artificial Intelligence (AI) and computer vision have enabled automated analysis of agricultural images. Deep learning techniques, particularly convolutional neural networks (CNNs), have demonstrated exceptional performance in image classification and object detection tasks. These models can automatically learn discriminative features from large datasets, allowing them to accurately differentiate between crops and weeds under diverse field conditions. AI- based weed detection systems utilize images captured from cameras, mobile devices, or unmanned aerial vehicles (drones) to analyze crop fields efficiently and non-invasively.

The integration of AI techniques into weed detection systems provides a foundation for smart and sustainable farming practices. By enabling precise weed identification and localization, AI-driven solutions support targeted herbicide application and autonomous weed removal, thereby reducing environmental impact and operational costs. This background highlights the necessity and relevance of AI-based weed detection as a key component of modern precision agriculture systems.

1.2 Problem Statement

Weed infestation is a major challenge in agricultural fields, causing significant reduction in crop yield and quality. Traditional weed management methods such as manual weeding and blanket application of chemical herbicides are inefficient, labor-intensive, and environmentally harmful. Manual weed removal requires substantial human effort and time, making it impractical for large-scale farming, while excessive herbicide usage leads to soil degradation, water pollution, health risks, and the development of herbicide-resistant weed species.

Moreover, conventional weed control techniques lack precision, as they do not distinguish between crops and weeds during treatment. This results in unnecessary chemical exposure to crops and surrounding ecosystems. Variations in weed species, crop growth stages, lighting conditions, and field environments further complicate accurate weed identification using traditional approaches.

Therefore, there is a need for an automated, accurate, and efficient weed detection system that can operate under real-field conditions. An AI-based solution capable of identifying and differentiating weeds from crops using visual data can enable precision weed management. Such a system can support targeted herbicide application, reduce labor dependency, minimize environmental impact, and improve overall agricultural productivity.

1.3 Objectives

The main objective of this research is to develop an artificial intelligence–based approach for accurately detecting weed plants in agricultural fields using image analysis techniques. The specific objectives of the study are as follows:

1. To study and analyze existing weed detection and management techniques used in agriculture.
2. To design an AI-based framework for automatic detection of weed plants from field images.
3. To apply deep learning techniques, particularly convolutional neural networks, for distinguishing weeds from crops.
4. To evaluate the feasibility of image-based weed detection under varying field conditions such as lighting, background, and plant growth stages.
5. To reduce dependency on manual labor by automating the weed identification process.
6. To support precision agriculture by enabling targeted weed control and minimizing excessive herbicide usage.
7. To improve agricultural productivity by enhancing weed detection accuracy and efficiency.
8. To establish a foundation for future development of real-time and autonomous weed management systems.

1.4 Scope of the Project

The scope of this project is focused on the design and development of an artificial intelligence–based system for detecting weed plants in agricultural fields using image processing and deep learning techniques. The project primarily emphasizes the application of computer vision and AI algorithms to distinguish weeds from crops in static field images under varying environmental conditions.

This study includes the collection and analysis of agricultural image datasets containing both crop and weed species. Image pre-processing techniques such as resizing, normalization, and data augmentation are applied to improve model robustness. Deep learning models, particularly convolutional neural networks, are explored and trained to perform weed identification and classification with acceptable accuracy.

The scope of the project is limited to weed detection and classification and does not include physical weed removal or automated spraying in the current phase. The system is evaluated using standard performance metrics to assess its feasibility for real-world agricultural applications. This Phase-1 project establishes a foundational framework that can be extended in future phases to support real-time weed detection, drone-based monitoring, targeted herbicide spraying, and integration with autonomous agricultural robots.

2. LITERATURE REVIEW

Weed detection is an important step in precision agriculture because weeds compete with crops for nutrients, water, sunlight, and space, leading to reduced yield and quality. Traditional weed monitoring methods such as manual scouting and uniform herbicide spraying are time-consuming, expensive, and harmful to the environment. To solve these limitations, Artificial Intelligence (AI) techniques are increasingly used to detect weeds automatically using computer vision, allowing site-specific weed management and selective spraying. In recent years, deep learning has become the most dominant AI approach due to its ability to learn features automatically from complex field environments where weed and crop appearances overlap and vary due to lighting, growth stages, and soil background.

Deep learning-based weed detection has rapidly advanced through the use of images captured from field cameras, mobile phones, robots, and drones (UAVs). A major contribution in this area is the use of deep convolutional neural networks (CNNs) and object detection frameworks which provide fast and accurate identification of weed plants. For example, **Wang et al. (2022)** introduced an improved YOLOv5-based model (TIA-YOLOv5) designed for real-time weed and crop detection under complex field conditions, addressing challenges such as small weed objects and background confusion. This approach demonstrated the importance of data augmentation and model modifications for achieving high-speed detection suitable for real-time precision spraying systems. Similarly, **Tetila et al. (2024)** evaluated YOLOv5 models for real-time weed species detection in soybean fields and reported that YOLO-based models are highly effective for real-time field usage due to their balance between accuracy and computation speed, supporting practical deployment on agricultural machines and edge devices. Moreover, **Deng et al. (2024)** developed HAD-YOLO for weed detection, emphasizing lightweight design with high detection speed, which is important for real-time implementation in robotic weed control and smart sprayers.

Apart from object detection, semantic segmentation plays a key role in weed identification because it detects weeds at the pixel level rather than simply drawing bounding boxes. This is very useful when weeds overlap crops or when accurate weed area mapping is required for site-specific herbicide application. **Sahin et al. (2023)** proposed a crop–weed segmentation framework using multispectral imagery and a U-Net model with a ResNet-50 backbone, where the authors also improved segmentation accuracy by applying Conditional Random Fields (CRF) to reduce wrongly classified pixels. Their results confirmed that segmentation models trained on multispectral inputs can outperform RGB-only methods because multispectral data improves separation between vegetation and soil background. Similarly, **Khan et al. (2023)** introduced a drone-based weed–crop segmentation approach using an encoder–decoder architecture to classify each pixel into weed, crop, and background categories, highlighting that UAV imagery is highly useful for large-scale field monitoring but requires advanced deep learning to handle scale variations and mixed vegetation.

Researchers have also focused on handling limited annotated datasets and improving generalization across different crop types and field conditions. Semi-supervised learning has been proposed as a solution where only a small portion of data is labeled. For instance, **Nong et al. (2022)** developed a semi-supervised segmentation model (SemiWeedNet) to improve weed and crop segmentation performance under complex environments where weed size and density vary. Such approaches reduce dependency on expensive pixel-level annotations and support the scalability of AI weed detection. Furthermore, the availability of benchmark datasets has supported rapid model development and comparison. **Wang et al. (2022)** introduced the **Weed25 dataset** containing weed images across growth stages and species diversity, making it valuable for training deep learning classifiers and weed identification systems. Although earlier datasets like DeepWeeds exist, modern studies increasingly demand datasets captured in real farm environments, including occlusions, shadows, and mixed weed species distributions.

Recent studies have expanded weed detection to UAV-based platforms for large field coverage and rapid monitoring. UAV weed detection allows high-resolution imaging and fast surveying of crop fields, but it remains challenging due to weed–crop similarity and variations in image resolution depending on flight altitude. A systematic literature review by **Sandoval-Pillajo et al. (2025)** analyzed deep learning approaches for weed detection in UAV imagery and reported that object detection, segmentation, and classification models are widely used, with growing interest in lightweight and edge-deployable architectures. This work emphasized that UAV-based weed mapping has become an emerging and impactful research direction due to the ability of drones to monitor large farms efficiently. Additionally, transformer-based architectures are also emerging in weed detection research due to their global feature learning capability. For example, **Garibaldi-Márquez et al. (2025)** reported that transformer models can be effective for site-specific weed detection in real-world cornfields, strengthening the view that transformer-based deep learning methods can improve robustness under real field variability and reduce false detections.

Another important trend in weed detection research is the integration of advanced enhancement techniques and newer model families. For instance, **Tao et al. (2025)** combined UAV-based super-resolution reconstruction (SRR) with semantic segmentation and evaluated transformer-based methods alongside CNNs, showing that image enhancement improves feature extraction from low-quality UAV images and boosts weed segmentation quality in challenging field scenarios. Similarly, **Pai et al. (2025)** introduced PSPEdgeWeedNet, an edge-aware segmentation network aimed at improving boundary detection for crop–weed separation, demonstrating that incorporating edge features helps achieve more precise segmentation in complex agricultural field images. Studies have also explored YOLOv8-based models in recent work, where **Sonawane et al. (2024)** presented a method using YOLOv8 for crop and weed segmentation in difficult agricultural scenes, highlighting that modern YOLO versions can provide improved performance in speed and accuracy compared to older architectures.

Overall, the literature shows that AI-driven weed detection has progressed from classical machine learning to deep learning models such as YOLO for real-time detection, U-Net and encoder–decoder networks for pixel-level segmentation, and transformers for improved feature learning and robustness. However, common research challenges still remain, including limited labeled datasets, heavy computational requirements for large-scale deployment, overlapping vegetation, variation in weed growth stages, and generalization across different field conditions. Future research increasingly focuses on lightweight edge AI models for deployment on smart sprayers and robots, domain adaptation techniques to handle different crop systems, and hybrid approaches combining multispectral imaging, drones, and deep learning to improve real-world weed management outcomes.

Recent developments in deep learning have significantly transformed weed detection research. Convolutional Neural Networks (CNNs) have been widely adopted due to their ability to automatically learn discriminative features directly from raw images. Studies have demonstrated that CNN-based models outperform traditional machine learning approaches in terms of accuracy and robustness. Researchers have successfully applied CNN architectures for crop–weed classification, achieving high performance even under varying illumination and background conditions.

Object detection and semantic segmentation models have further enhanced weed detection capabilities. Deep learning–based object detection frameworks such as YOLO and Faster R-CNN enable precise localization of weeds within images, making them suitable for precision agriculture applications such as targeted spraying. Similarly, semantic segmentation techniques classify each pixel in an image as crop, weed, or background, allowing fine-grained weed identification. However, these methods often require large annotated datasets and high computational resources. Despite the progress achieved through deep learning, several challenges remain. The visual similarity between crops and weeds, occlusion due to dense vegetation, and variability in field environments continue to affect detection accuracy. Additionally, most existing studies are conducted under controlled conditions, and their scalability to real-world agricultural fields remains a concern. Based on the reviewed literature, AI-based weed detection using deep learning shows strong potential for improving agricultural practices. However, there is still a need for efficient, scalable, and cost-effective solutions that can operate reliably under real-field conditions. This project builds upon existing research by exploring AI techniques for weed detection and establishing a foundation for precision agriculture applications.

2.1 Traditional Methods

Traditional weed detection and management methods have been widely used in agriculture for several decades. These methods mainly rely on manual observation, mechanical techniques, and chemical control to identify and remove weeds from crop fields. Although effective to some extent, traditional approaches suffer from several limitations that reduce their efficiency and sustainability.

Manual weed detection involves visual inspection of crop fields by farmers or agricultural workers, followed by hand weeding or mechanical removal. This method is simple and accurate when performed carefully; however, it is extremely labor-intensive, time-consuming, and costly, particularly for large-scale farms. The availability of skilled labor has also decreased in recent years, making manual weed control increasingly impractical.

Mechanical weed control techniques use tools such as hoes, cultivators, and tractor-mounted equipment to remove weeds. While these methods reduce labor requirements compared to manual weeding, they often disturb the soil structure and may damage crop plants if not operated precisely. Mechanical methods are also less effective in densely planted fields and during early crop growth stages.

Chemical weed control using herbicides is the most commonly adopted traditional method due to its effectiveness and ease of application. Herbicides are usually sprayed uniformly across the entire field without distinguishing between crops and weeds. Although this approach reduces weed growth, it leads to excessive chemical usage, increased production costs, environmental pollution, and potential health hazards. Prolonged herbicide application has also resulted in the emergence of herbicide-resistant weed species, posing a serious challenge to long-term weed management.

Overall, traditional weed detection and control methods lack precision, adaptability, and sustainability. These limitations highlight the need for intelligent and automated solutions, such as AI-based weed detection systems, which can accurately identify weeds and support targeted weed management practices.

2.2 Image Processing Techniques

Fig. 2.2. Sample agricultural field images containing crops and weed plants.

Image processing techniques form the foundational approach for early automated weed detection systems. These techniques analyze visual characteristics of crop field images to separate weeds from crops using pixel-level information. Images are initially captured from agricultural fields using cameras mounted on ground vehicles, drones, or handheld devices. The quality of these images directly affects the accuracy of further processing.

1 Image Pre-processing

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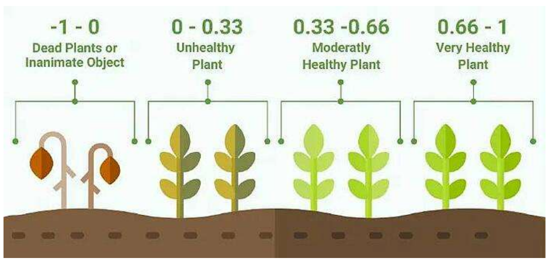
Fig. 1. Image pre-processing operations such as noise removal and normalization.



Pre-processing is applied to enhance image quality and reduce noise caused by lighting variations, shadows, and camera limitations. Common pre-processing operations include image resizing, smoothing, contrast enhancement, and normalization. These steps improve the visibility of plant regions and prepare the image for segmentation and feature extraction.

2 Color-Based Segmentation

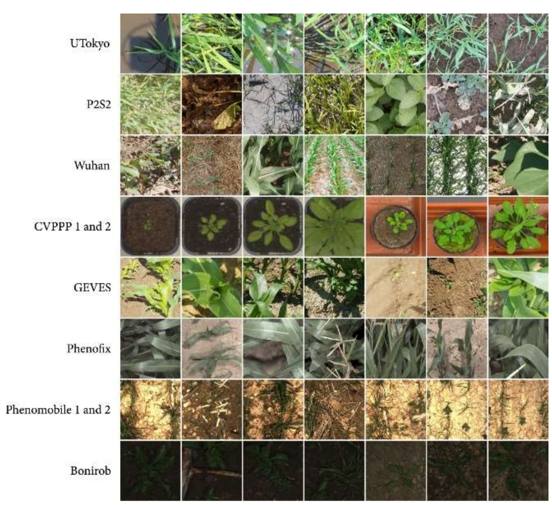
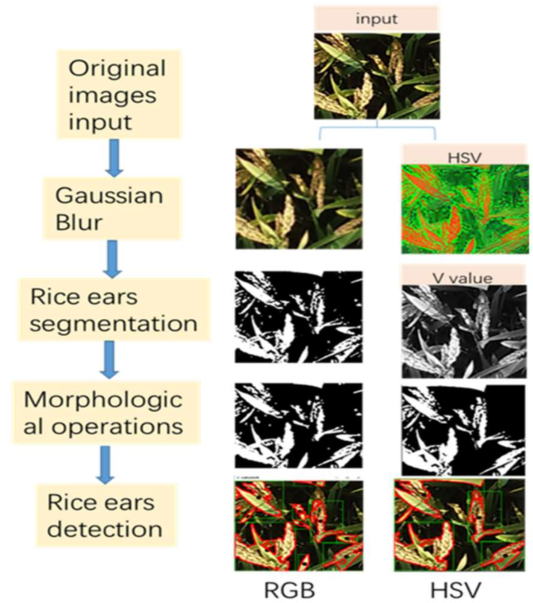
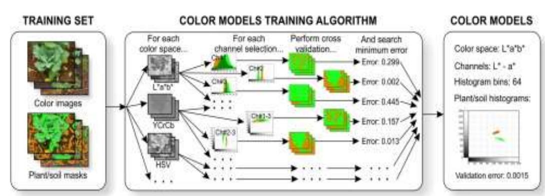


Fig. 2. Color-based segmentation separating vegetation from soil background.





Color-based segmentation is widely used to separate vegetation from the soil background. Images are often converted from RGB color space to HSV or Lab color space, where green vegetation can be more effectively isolated. Thresholding techniques are then applied to extract plant regions based on color intensity values.

3 Thresholding and Morphological Operations

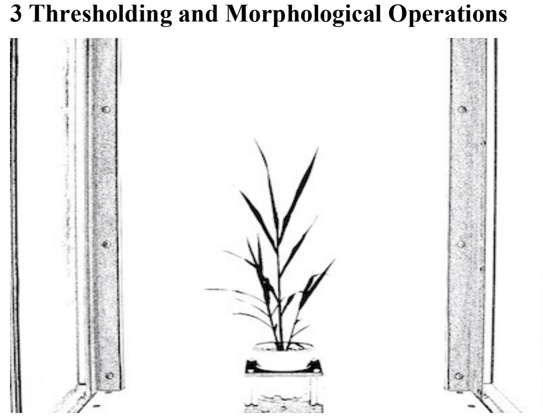
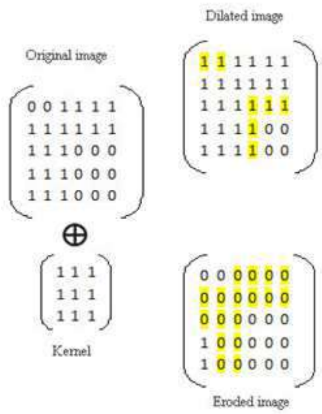


Fig. 3. Binary thresholding and morphological operations applied to plant images.



Thresholding converts grayscale or color images into binary images, distinguishing plant pixels from the background. Morphological operations such as erosion, dilation, opening, and closing are applied to remove noise, fill gaps, and refine the shape of detected plant regions. These steps improve segmentation accuracy and object boundaries.

4 Feature Extraction and Analysis

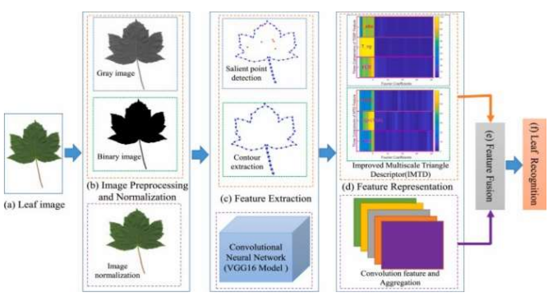
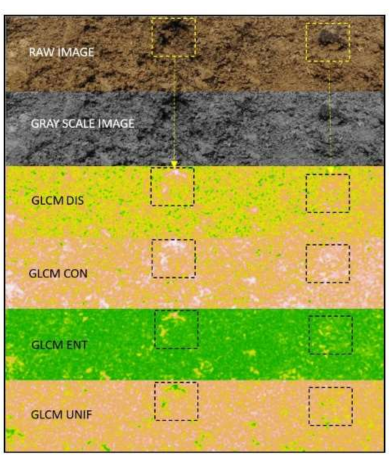
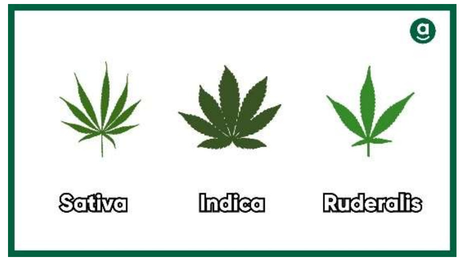


Fig. 4. Feature extraction based on leaf shape and texture characteristics.



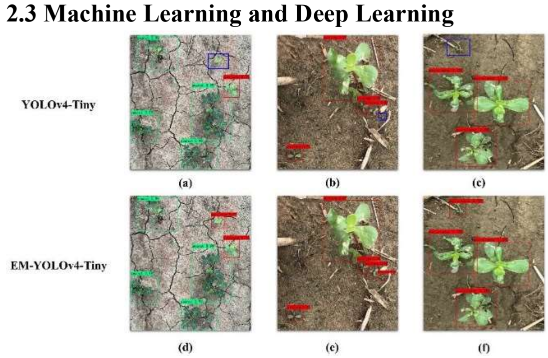


After segmentation, handcrafted features such as leaf shape, size, texture, perimeter, and aspect ratio are extracted from plant regions. These features are used to differentiate weeds from crops. However, feature-based methods are sensitive to plant growth stages, occlusion, and similarity between crop and weed structures.

Limitations of Image Processing Techniques

Although image processing techniques are computationally efficient and easy to implement, their performance decreases in complex real-field conditions. Variations in lighting, shadows, overlapping plants, and similar visual characteristics between crops and weeds reduce accuracy. Due to these limitations, modern weed detection systems increasingly rely on AI and deep learning models, which automatically learn robust features from data.

2.3 Machine Learning and Deep Learning



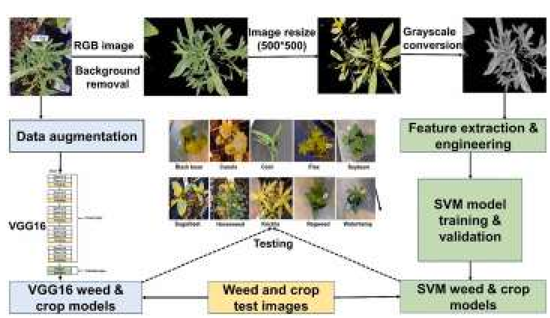


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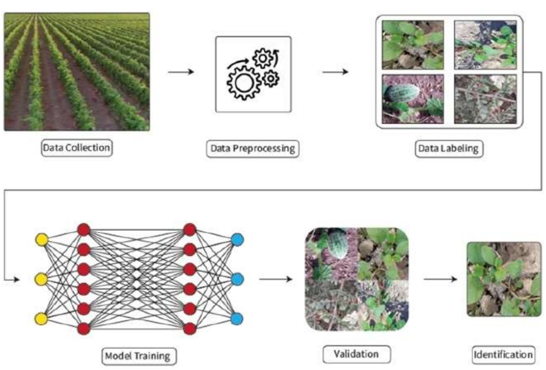
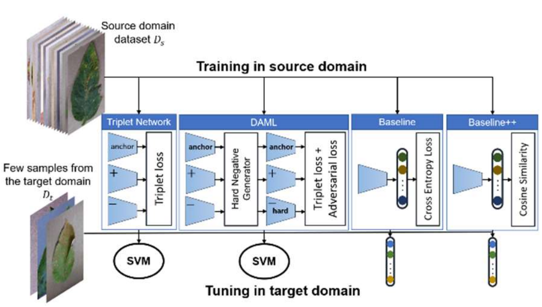
Fig. 2.3 . Machine learning–based classification of crops and weeds using extracted features.

Machine Learning (ML) techniques have been widely explored for weed detection to overcome the limitations of traditional image processing methods. In ML-based approaches, features such as color, texture, shape, and edge information are first extracted from segmented plant regions. These handcrafted features are then used to train classifiers such as Support Vector Machines (SVM), k-Nearest Neighbors (k-NN), Decision Trees, and Random Forests to differentiate weeds from crops, as illustrated in **Fig. 2.3**. Although machine learning methods provide better accuracy than rule-based image processing, their performance heavily depends on the quality of feature extraction and struggles with complex field environments.

1 Deep Learning Techniques





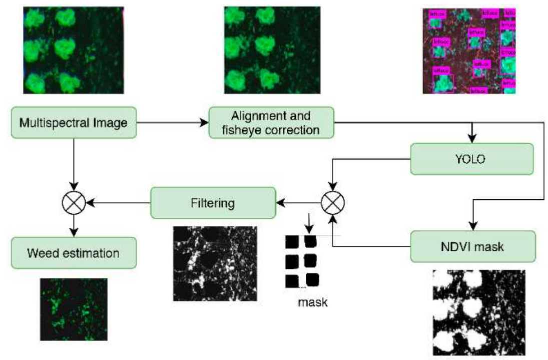
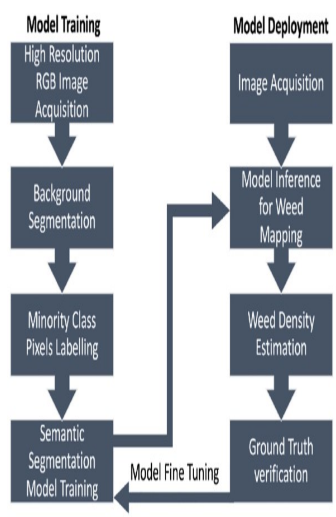


Fig. 1. Deep learning–based weed detection using convolutional neural networks.

Deep Learning (DL), a subset of machine learning, has significantly improved weed detection accuracy by eliminating the need for manual feature extraction. Convolutional Neural Networks (CNNs) automatically learn hierarchical features directly from raw images, making them robust to variations in lighting, background, plant size, and growth stages. As shown in **Fig. 1**, CNN-based models perform both feature extraction and classification in an end-to-end manner, resulting in superior performance compared to traditional ML techniques.

3 PROPOSED METHODOLOGIES



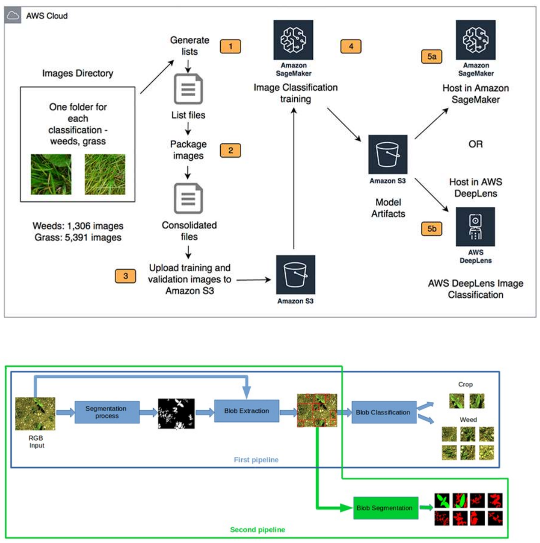
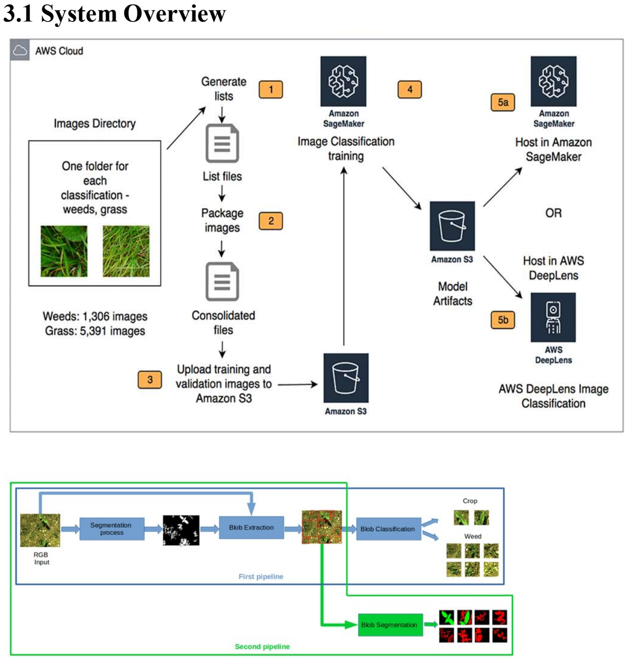


Fig. 3 . Overall methodology of the proposed AI-based weed detection system.

The proposed methodology aims to automatically detect weed plants in agricultural fields using Artificial Intelligence and deep learning techniques. The system follows a structured pipeline consisting of image acquisition, pre-processing, feature learning, weed detection, and result visualization, as illustrated in **Fig. 3**. Each stage of the methodology is designed to ensure accurate and efficient weed identification under real-field conditions.

3.1 System Overview



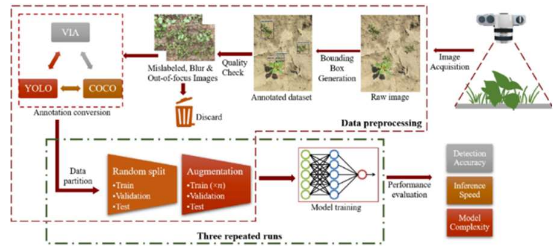


Fig. 3.1. Overall system overview of the AI-based weed detection framework.

The proposed system is an Artificial Intelligence–based framework designed to automatically detect weed plants in agricultural fields using image analysis and deep learning techniques. As illustrated in **Fig. 3.1**, the system follows a modular architecture that enables efficient processing of field images, accurate weed identification, and clear visualization of results. The primary objective of the system is to support precision agriculture by enabling selective weed management while minimizing manual intervention and chemical usage.

1 System Components

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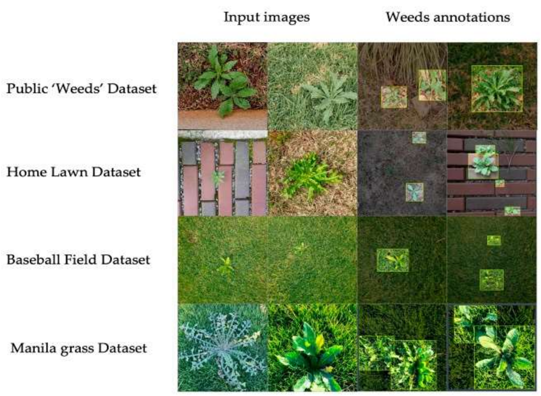

Fig. 1. Major components of the weed detection system.

The system consists of the following key components, as shown in **Fig. 1**:

1. **Image Acquisition Module**

This module captures images of crop fields using ground-based cameras or unmanned aerial vehicles (drones). Images are collected under different lighting conditions and growth stages to ensure system robustness.

2 **Pre-processing Module**

Captured images undergo pre- processing operations such as resizing, normalization, noise reduction, and data augmentation. This step enhances image quality and prepares the data for efficient model training and inference.

3 **AI-Based Detection Module**

The core intelligence of the system is implemented using deep learning models, particularly convolutional neural networks. This module automatically extracts features from images and classifies plants as either crops or weeds. In detection-based approaches, weed locations are also identified.

4 **Result Analysis and Visualization Module**

The detection results are displayed by overlaying bounding boxes or markers on the original images. This module also computes performance metrics and provides visual outputs for interpretation.

2 Working Principle

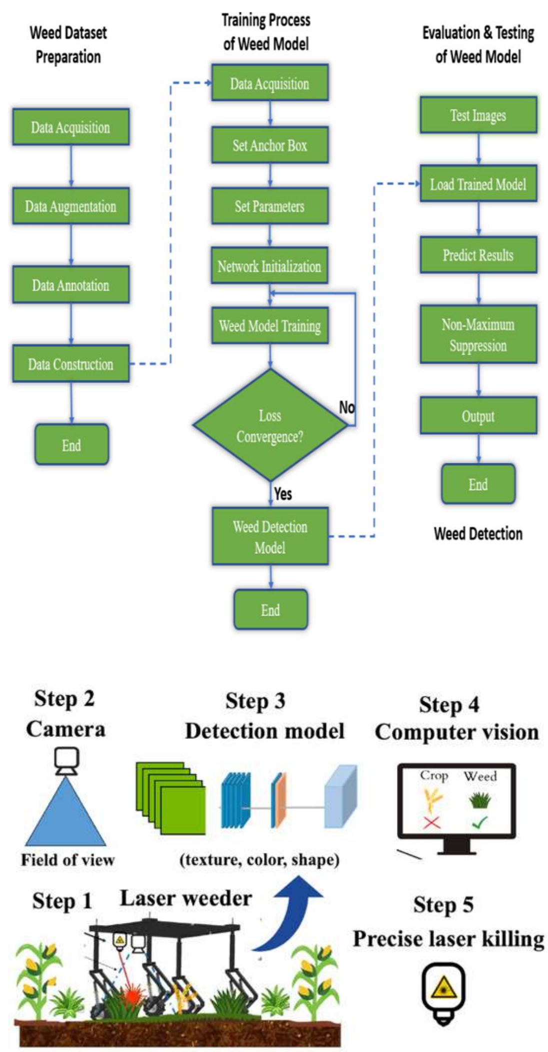

Fig. 2. Workflow of the proposed AI-based weed detection system.

The system operates by first capturing field images, which are then pre-processed and passed to the trained AI model for analysis. The model identifies weed plants and differentiates them from crops. Finally, the detection results are visualized and stored for further agricultural decision-making, as depicted in **Fig. 2**.

3.2 Data Collection

Data collection is a crucial step in the development of an AI-based weed detection system, as the performance of deep learning models largely depends on the quality and diversity of the dataset. The dataset used in this study consists of images

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captured from agricultural fields containing both crop plants and common weed species

1 Image Sources

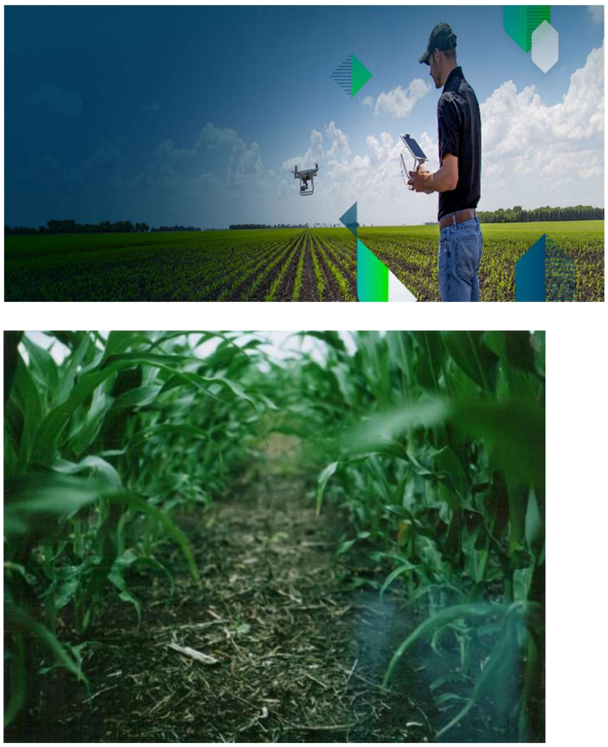

Fig. 1. Image acquisition using ground-based cameras and drone platforms.

Images are collected using ground-based cameras and unmanned aerial vehicles (drones), as shown in **Fig. 1**. These platforms enable image capture from different viewpoints and heights, providing diverse visual representations of crops and weeds. The use of multiple acquisition sources improves the robustness of the dataset.

2 Data Diversity

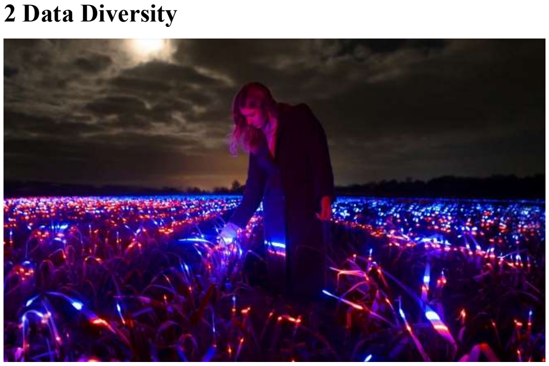

Fig. 2. Field images captured under varying lighting conditions and plant growth stages.

To ensure generalization of the AI model, images are collected under varying environmental conditions, including different lighting scenarios, backgrounds, soil textures, and plant growth stages, as shown in **Fig. 2**. This diversity helps the model learn robust features that perform well in real-field environments.

3 Data Annotation

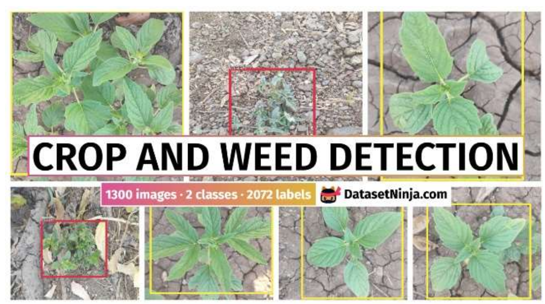

Fig. 3. Annotation of weed and crop regions in agricultural images.

The collected images are manually annotated to label crop and weed regions. Annotation involves drawing bounding boxes or assigning class labels to each plant region, as illustrated in **Fig. 3**. Labeled data is essential for supervised learning and accurate model training.

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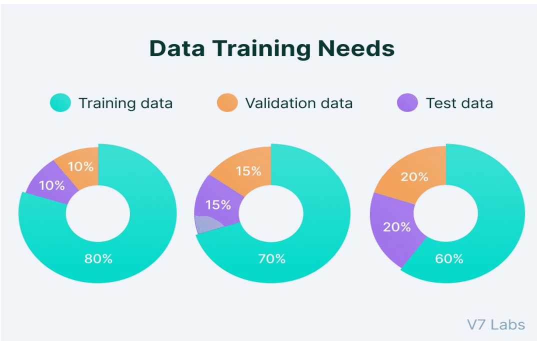
4 Dataset Preparation



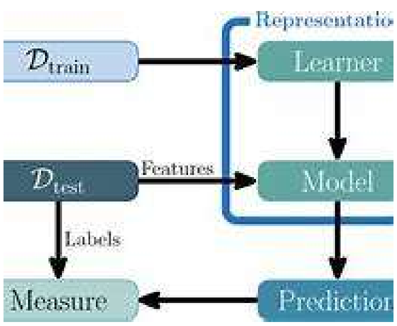
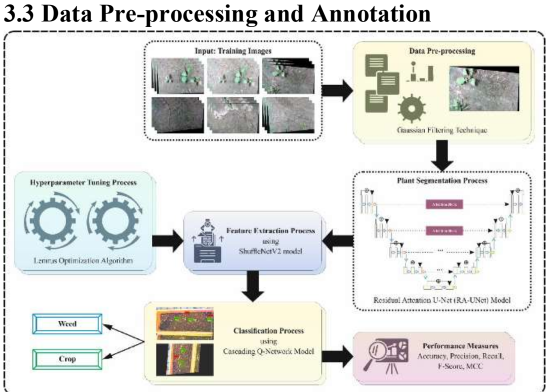


Fig. 4. Dataset division into training, validation, and testing sets.

After annotation, the dataset is divided into training, validation, and testing subsets, as shown in **Fig. 4**. This division ensures unbiased performance evaluation and prevents overfitting during model training.

3.3 Data Pre-processing and Annotation



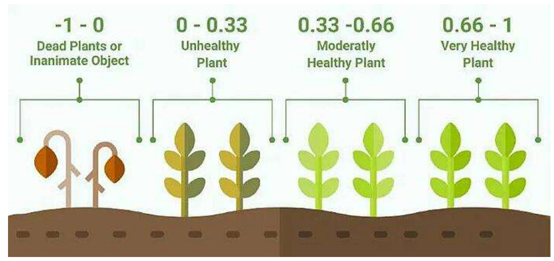
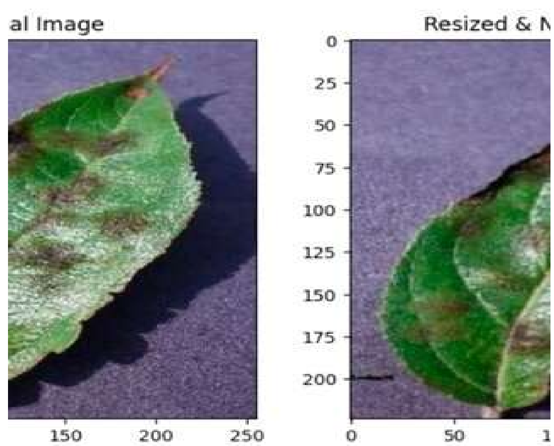


Fig. 3.3. Pre-processing steps applied to agricultural field images.

Data pre-processing and annotation are essential steps to improve the quality of the dataset and ensure accurate performance of AI models. Raw images collected from agricultural fields often contain noise, illumination variations, shadows, and background clutter. Therefore, pre-processing techniques are applied to enhance image quality and prepare the data for effective model training, as illustrated in **Fig. 3.3**.

1 Image Pre-processing



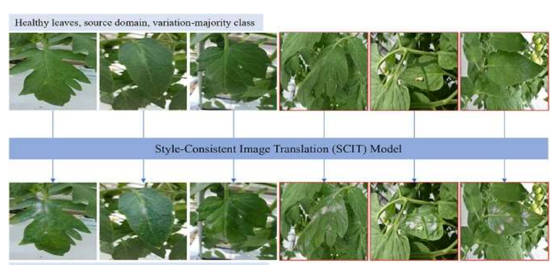


Fig. 1. Image resizing, normalization, and data augmentation techniques.

The pre-processing stage includes resizing all images to a fixed resolution compatible with the input requirements of the deep learning model. Pixel values are normalized to standardize

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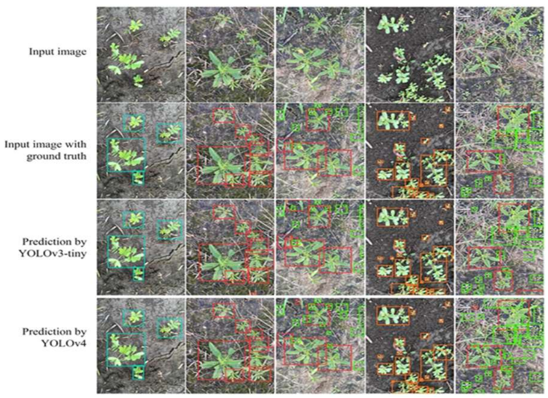
intensity levels and accelerate model convergence. Noise reduction and contrast enhancement techniques are applied to minimize the effect of lighting variations. To increase dataset diversity and prevent overfitting, data augmentation techniques such as rotation, flipping, scaling, and cropping are employed, as shown in **Fig. 1**.

2 Annotation Process



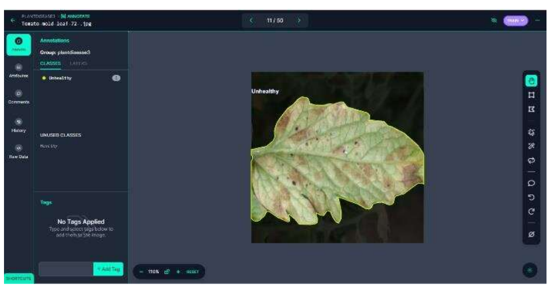


Fig. 2. Manual annotation of weed and crop regions using bounding boxes.

Annotation involves labeling the collected images to identify crop and weed regions. In this study, manual annotation is performed using image labeling tools, where bounding boxes are drawn around weed plants and crops, and corresponding class labels are assigned. Accurate annotation, as illustrated in **Fig. 2**, is crucial for supervised learning and directly influences detection accuracy.

3.4 AI Model Selection (Initial Plan)

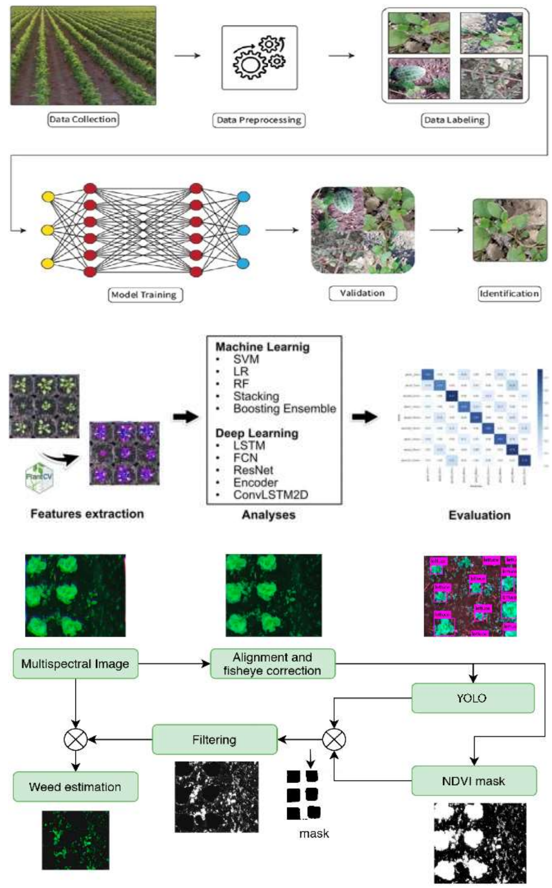
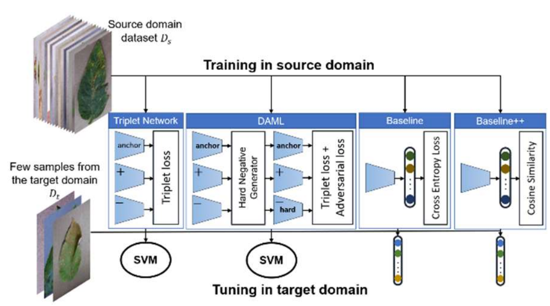


Fig. 3.4. Overview of AI model selection strategy for weed detection.

Selecting an appropriate Artificial Intelligence (AI) model is a critical step in developing an accurate and efficient weed detection system. The initial plan focuses on choosing models that can effectively differentiate weed plants from crops under varying agricultural field conditions while maintaining computational efficiency. As shown in **Fig. 3.4**, the selection process considers model accuracy, robustness, scalability, and feasibility for future real-time deployment.

1 Choice of Deep Learning Approach



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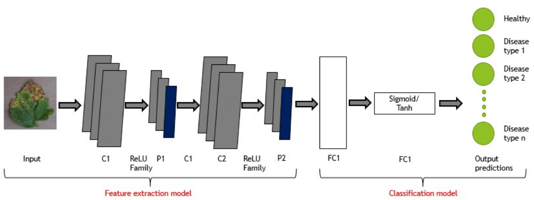

Fig. 1. Convolutional Neural Network (CNN) architecture for plant image classification.

In the initial phase, Convolutional Neural Networks (CNNs) are selected as the primary AI models due to their proven effectiveness in image-based classification tasks. CNNs automatically learn hierarchical features such as edges, textures, shapes, and complex plant structures directly from raw images. This capability makes them well suited for distinguishing weeds from crops, even when visual differences are subtle (**Fig. 1**).

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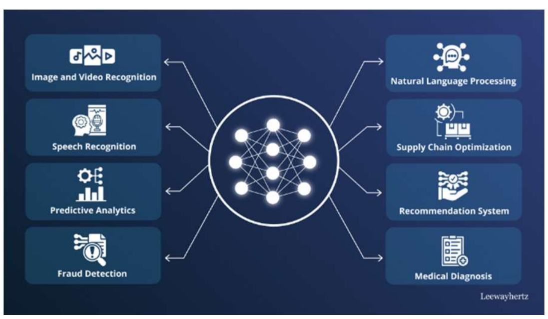
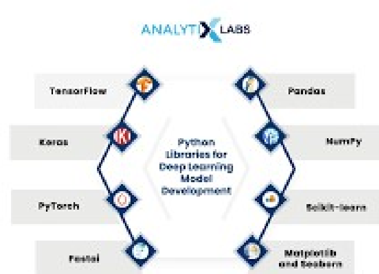
3.5 Development Environment





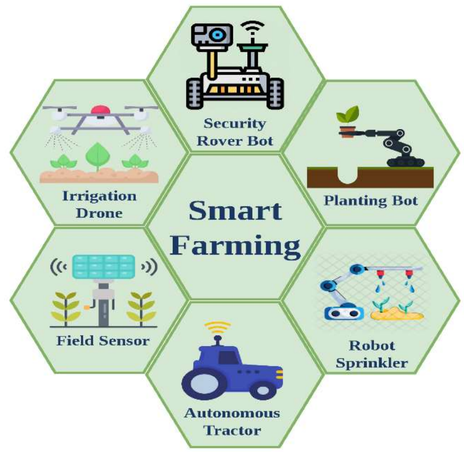


Fig. 3.5. Development environment used for implementing the AI-based weed detection system.

The development environment plays a crucial role in the successful implementation and evaluation of the proposed AI-based weed detection system. The system is developed using a combination of software frameworks, programming tools, and hardware resources that support deep learning, image processing, and experimental evaluation, as illustrated in **Fig. 3.5**.

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