ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XIV, Issue IV, April 2025

Agrovision: Smart Solutions for Modern Farming.

Chinmay Asodekar[1], Kunal More[2], Shreyash Mandlik[3], Vishvesh Ghongade[4], Prof. Shreeya Palkar[5]

Department of Artficial Intelligence and Data Saience, Progerssive Education Society's Modern College Of Engineering, Shivaji Nagar, Pune, Maharashtra, India

DOI: https://doi.org/10.51583/IJLTEMAS.2025.140400115

Received: 01 May 2025; Accepted: 08 May 2025; Published: 22 May 2025

Abstract: AgroVision is a mobile-centric artificial intelligence- driven platform, particularly designed to enhance the efficiency and sustainability of contemporary agriculture operations, specif- ically focusing on small-scale farmers in resource-constrained areas. AgroVision offers personalized crop prescriptions using soil pH, moisture, and nutrient levels, as well as for weed and crop detection through the YOLOv8 algorithm. In contrast to hardware-locked proprietary agricultural innovations, AgroVi- sion can execute seamlessly on mobile devices via a Flutter app, allowing farmers to take pictures of their fields and input soil data directly. From this analysis, the insights provided by AgroVision are tailored to the user so that decisions can be made regarding maximized crop yield, deepening ecological impact, and ecological footprint minimization. While the development team faced challenges with low computational power and a lack of varied training data, they were still able to robustly optimize the models and apply data augmentation techniques to guarantee consistent system performance across different operational scenarios. Focused on bridging the accessibility gap for precision farming technologies and fostering data-driven practices in agriculture, AgroVision addresses gaps related to sustained and inclusive agricultural advancement.

Index Terms—Smart agriculture technology, Crop and weed detection using YOLOv8, Mobile app for agriculture, YOLOv8 in agriculture, AI-powered agriculture, Real-time farm image analysis

INTRODUCTION

Problem Discription

Today, agriculture is being faced with numerous critical issues retarding productivity, sustainability, and technological progress, especially at the farm level. Lack of affordable, farmer-friendly AI solutions is among the major concerns, and it deprives many of the population engaged in agriculture of the benefit of intelligent decision-support [1]. Perhaps, farmers might lack the capacity to determine the most suitable crops to plant on farms due to lacking knowledge of measures of soil fertility parameters, including pH, water content, and nutrient levels [2]. This limited awareness leads to ineffectual plant selection, decreased yields, and wasteful utilization of inputs [3]. Additionally, weed management adds to the issues; most of the farmers lack the capacity to identify accurately weeds, and hence chemical herbicides are used regardless of the potential consequences [4]. The use of indiscriminate chemical herbicides not only increases the price of production but also accelerates the development of herbicide-resistance in the weed species, and it further pollutes soils and water resources

[5]. Furthermore, conventional weed-detection processes like manual labor are time-consuming, variable, labor-intensive, and thus not practical for modern-day scalable agriculture [6]. Inadequacy of integrated, real-time data and technologically enabled information is a serious barrier to precision agricul- ture, and farmers lack a practical means for responding to emerging environmental and agro-requirements [7].

Objective

The problem this research tries to solve is to create a mobile-based intelligent agriculture system targeted at farmers enabling them to automate key agricultural processes such as crop and weed management with the help of image processing and artificial intelligence [1]. Many farmers, especially those located in rural and semi urban areas, do not possess sophisti- cated agricultural implements and tools that can enhance their management of resources as well as their yield output [2]. With the help of this project, we hope to propose a solution to these challenges using a mobile application that is user- friendly, lightweight, and robust enough to be used in field settings with very minimal use of training [3].

With the aid of this application, farmers will be able to take real-time video images of their fields with the help of cell phones. These images will be subjected to a deep learning based object detection algorithm called YOLO (You Only Look Once) to classify the images and most importantly crops and weeds [4]. The system will employ some form of visual presentation such as bounding boxes and other ways farm level crop system (FCS) depiction to flag crop species in question thereby improving farmers' ability to take intelligent action on many vegetation types in their fields [5].

Alongside detection using images, the application will also enable users to provide important soil data, including moisture content, pH level, and nutrient value. This data will be analyzed to evaluate soil health and provide suitable crop recommendations that are in synergy with soil conditions [6]. Incorporating soil diagnostics into the platform enhances the intelligence of the strategy, making crop planning a more dynamic endeavor that utilizes real-time environmental data as opposed to relying purely on visual assessment or intuitive methods [7].

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XIV, Issue IV, April 2025

The AgroVision system combines on-the-go crop and weed identification with soil-based crop advisory services to en-

hance farming efficiency, improve agricultural resource use, and encourage environmental sustainability [8]. The wider objective is the reduction of reliance on traditional methods which are often inefficient and involving chemicals, and at the same time, equipping farmers, particularly from marginalized communities, with solutionable and cost-effective tools [9]. All in all, this project advances digital agriculture and strengthens long-term food security by fostering innovation and equal opportunity to precision farming technologies [10].

Motivation

Agriculture continues to be a critical activity for sustain- ing global food needs, generating income, and providing employment in rural settings. On the other hand, modern agriculture is being impacted by a myriad of interrelated problems such as reduction in soil productivity, new weed species, climatic variability, and inefficient use of inputs like fertilizers and herbicides [1]. Traditional farming practices that depend on strain and manual work face challenges satisfying high demand of yields alongside sustainability and resources management requirements [2].

The reason behind developing AgroVision is the challenge of applying strategic technological innovations to agriculture, especially among smallholder and resource-poor farmers [3]. Most tools of precision agriculture provide value, but are overly complex, expensive, and depend on advanced hardware and infrastructures which many farmers do not have access to [4]. As a result, farmers are not able to take advantage of AI, machine learning, modern innovations, and real time analytics due to infrastructure limitations [5].

AgroVision was envisioned as an implementation of a comprehensive precision farming solution, where intelligent automation is brought to the field through mobile devices and accessible technology powered by machinery and robotics [6]. Its development was motivated by the desire of using existing farmer tools—mobile phones—and images and soil sample readings for decision making [7]. The motivation also stems from the need to create a system that is powerful yet workable, practical within the constraints of weak connectivity, minimal processing power, and other types of variability, such as environmental [8].

Finally, AgroVision is funded with an overall vision of embracing technology in agriculture to enhance agriculture, as opposed to replacing traditional practices [9]. It aims to further sustainable agriculture by mitigating environmental impact, increasing productivity, and most importantly, empowering farmers—the true guardians of the land—with the ability to control their future in an agriculture industry that is rapidly changing [10].

Literature Survey

The current literature shows considerable progress in the application of artificial intelligence and machine learning methods to agriculture, particularly for single-task activities like crop recommendation and weed detection. Nevertheless, most of these solutions are hardware-intensive, cloud-based, or

are for a single task. Additionally, few systems are optimized for mobile platforms with limited hardware needs, which are key to deployment in low-resource rural areas. AgroVision aims to fill in these gaps by providing a single, mobile-oriented platform with a combination of image-based detection and analysis of soil parameters in an easy-to-use interface. The system is designed for actual field application, offering smart agricultural assistance without requiring costly infrastructure.

S. G. L., N. V., and S. U. conducted an in-depth review of machine learning techniques used for predicting crop yields. They took a close look at various algorithms, including linear regression, SVM, decision trees, and random forest, evaluating their accuracy, performance, and how well they fit different types of agricultural datasets. The study underscored the importance of historical data—like rainfall, temperature, soil nutrients, and crop variety—and how machine learning can effectively process this information to provide valuable yield insights. The authors noted that while traditional models are easier to interpret, advanced ensemble models tend to deliver better accuracy. They concluded that leveraging predictive analytics in agriculture can revolutionize farming, making it more scientific and data-driven, which helps farmers make informed decisions and rely less on experience alone [1], [16].

R. S. Mohammed and colleagues introduced a highly ac- curate crop yield estimation model that combines IoT and remote sensing technologies. They crafted a framework that gathers real-time environmental data—like soil temperature and humidity—through sensors, while also deriving vegetation indices from satellite images. By processing these diverse data points with machine learning algorithms such as XGBoost and Gradient Boosting, they were able to enhance the accuracy and timeliness of yield predictions. The authors highlighted that these smart systems empower farmers by providing both a broad and detailed view of crop health and productivity, paving the way for agricultural practices that are not only scalable but also sustainable [2], [16].

Bhatt and S. Varma introduced a machine learning-based recommendation system that takes into account key soil pa- rameters such as pH, nitrogen, phosphorus, potassium, and rainfall to recommend the best crops to grow. They utilized algorithms like Naive Bayes, SVM, and Decision Trees to classify and suggest crops based on the given conditions. Notably, Naive Bayes achieved the highest accuracy among the methods tested. The authors pointed out that machine learning models can effectively uncover the connections be- tween environmental factors and crop performance, allowing for tailored, location-specific recommendations. They argued that this kind of smart advisory system could greatly enhance crop selection decisions, minimize trial-and-error in farming, and lead to better resource management [3], [16].

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XIV, Issue IV, April 2025

Meanwhile, J. D. Pujari, R. Yakkundimath, and A. S. Byadgi concentrated on identifying and classifying fungal diseases that affect crops through image processing techniques. They worked with image datasets of infected leaves, applying preprocessing methods followed by feature extraction based on texture, color, and shape. To identify the type of disease, they

employed classification algorithms like k-NN and SVM. Their study demonstrated a high level of accuracy in distinguishing between infected and healthy leaves. The authors expressed their belief that such automated detection systems could fa- cilitate early disease identification, thus reducing yield losses and optimizing fungicide use through targeted treatments [4], [16].

A. Thakur, Sonu, and R. Kumar came up with a cutting- edge object detection method that leverages the YOLO (You Only Look Once) architecture to effectively tell crops apart from weeds in real-time. They trained their model on care- fully annotated datasets and put it to the test in various field conditions. The results were impressive, showing that YOLO can accurately detect and classify objects with minimal delay, making it a great fit for real-time applications in agriculture. The authors emphasized that incorporating such object detection systems into automated setups can enhance weed management, cut down on herbicide use, and ultimately promote more eco-friendly farming practices [5], [16].

S. Jin and colleagues introduced an upgraded version of the Mask R-CNN model aimed at achieving more precise weed segmentation in agricultural settings. Their improvements fea- tured the integration of attention modules and depth-wise convolutions, which significantly boosted feature extraction and enhanced the model's ability to separate weeds from crops. This model achieved a remarkable mean average precision (mAP) score, showcasing its effectiveness in distinguishing between different plant structures. The authors pointed out that accurate segmentation is crucial for tasks like robotic weed removal and targeted spraying, and they believe that advanced deep learning techniques like their enhanced Mask R-CNN hold great promise for automating precision farming [6], [16].

G. Sethia, H. K. S. Guragol, S. Sandhya, J. Shruthi, and N. Rashmi came together to create an innovative weed removal bot that leverages computer vision techniques. This clever sys- tem captures real-time images from the field using a mounted RGB camera, identifies the type of plants with a convolutional neural network (CNN), and operates a robotic arm to pull out the weeds. They achieved an impressive detection accuracy of over 99% and showcased its real-time capabilities. The authors highlighted that merging robotics with AI can significantly enhance agricultural practices, making them more autonomous and reducing the need for manual labor, particularly on large- scale farms where timely weed management is essential [7], [16].

Celikkan, M. Saberioon, M. Herold, and N. Klein presented a cutting-edge probabilistic deep learning method for semantic segmentation of crops and weeds, which in- cludes uncertainty quantification in their model. By utilizing Bayesian networks and probabilistic modeling, they evaluated confidence levels in their predictions, which proves especially beneficial in tricky or overlapping areas. Their experiments revealed that factoring in uncertainty led to more reliable decision-making. The authors proposed that models aware of uncertainty can provide valuable insights for crucial agricul- tural decisions and enhance user trust in AI-driven solutions,particularly when applied in real-world, uncontrolled settings [8], [16].

Steininger and colleagues introduced the CropAndWeed dataset and delved into a multi-modal learning strategy for segmenting crops and weeds. They experimented with models like YOLOvS and DroneCVS, aiming to create lightweight yet effective models that are perfect for drone use. Their research highlighted how crucial dataset quality and hardware compatibility are for real-world applications. The authors concluded that drone-based weed detection systems, especially when trained on specific datasets, could significantly enhance the scalability and automation of weed control in expansive farmlands, aligning seamlessly with AgroVision's goals [9], [16].

Suma, T., Kumar, S. V., and Sandhya, B. R. developed a machine learning system designed to classify soil types and recommend appropriate fertilizers. By utilizing decision tree algorithms alongside soil datasets, they crafted a recom- mendation engine that helps farmers apply the right nutrients based on the soil's characteristics and the crops they wish to grow. Their study demonstrated that these personalized recommendations can help avoid over-fertilization and pro- mote healthier soil over time. The authors encouraged the widespread adoption of such smart systems to foster more sustainable and efficient farming practices, particularly in areas where resources are limited [10], [16].

Tulaskar, V. and colleagues developed a crop suggestion system that takes into account not just soil characteristics but also external elements like local weather conditions and market prices. Their machine learning model, which was trained on regional datasets, aimed to enhance both yield and profitability. The authors emphasized that future agricultural recommendation systems should extend beyond just agronomy and incorporate economic insights to help farmers maximize their returns. This approach adds a socio-economic layer to the technical foundation of AgroVision [11], [16].

Gaikwad, S. and team utilized decision tree classifiers to identify different soil types and suggest suitable crops. Their analysis was based on local soil datasets and underscored the importance of region-specific models for achieving accuracy. They found that integrating localized data into machine learn- ing models significantly improved prediction performance and built user trust. The authors pointed out the scalability of their method for developing agricultural advisory systems that are aware of specific locations [12], [16].

Barvin, P., and Sampradeepraj, T. conducted a thorough literature review on crop recommendation systems that uti- lize Graph Convolutional Neural Networks (GCNs). Their research showcased how GCNs can effectively model the spatial relationships

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XIV, Issue IV, April 2025

between various environmental factors, leading to better predictions of crop suitability. They pointed out that GCNs provide an innovative approach to integrat- ing diverse data sources—like weather, soil, and crop cycle information—into a unified model. The authors believe that these models have the potential to surpass traditional machine learning algorithms in dynamic, real-world situations [13],[16].

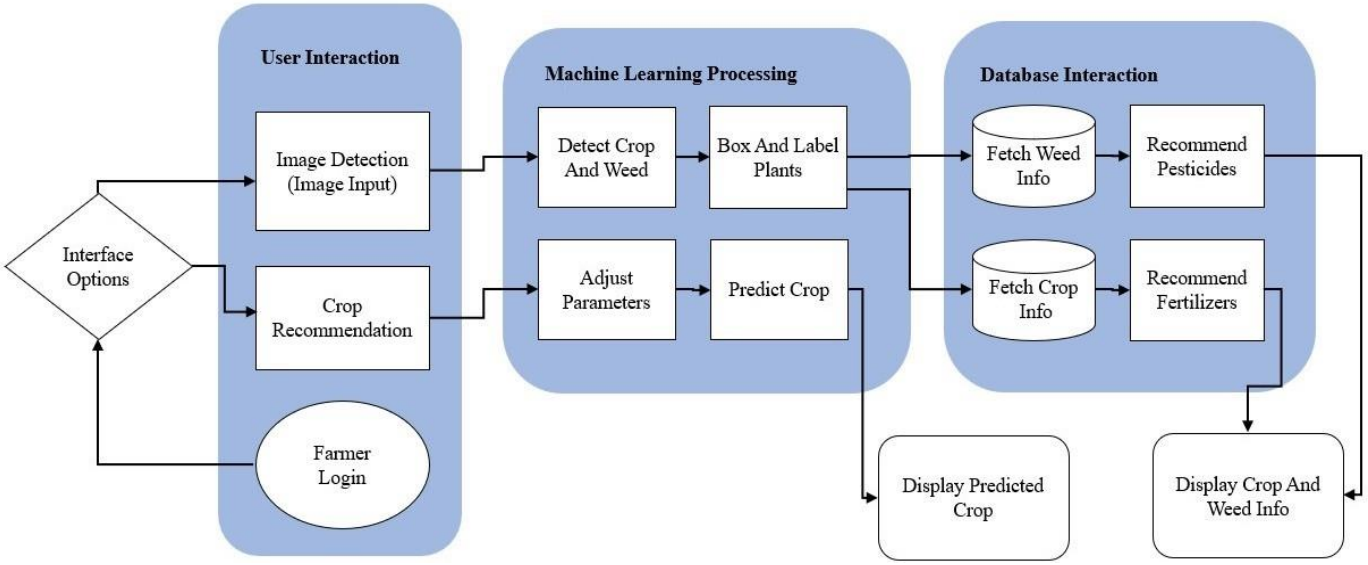
Hao-Ran Qu and Wen-Hao Su carried out an extensive review of deep learning models applied in crop and weed recognition systems. They examined performance metrics, deployment frameworks, and emerging trends such as explain- able AI and lightweight architectures. Their analysis showed that models like YOLOv5 and MobileNet strike a good balance between accuracy and speed. They stressed the importance of explainable AI to enhance technology acceptance among farmers, arguing that transparency in decision-making is vital for widespread adoption in agriculture [14], [16].

Hu et al. investigated various deep learning methods for weed recognition in large-scale grain farming systems. They reviewed convolutional neural networks, transfer learning tech- niques, and data augmentation strategies. The authors high- lighted challenges like dataset bias, noise, and scalability, and suggested adaptive learning frameworks that can continuously improve with incoming data. Their review reinforces the notion that smart agricultural systems need to be flexible, resilient, and capable of adapting to environmental changes, making a compelling case for AgroVision's continuous learn- ing framework [15], [16].

METHODOLOGY

System architecture

Fig. 1. System Architecture [16]



User Interaction Interface

This module is made to facilitate that farmers are able to access the system easily, even without much technical knowledge. The mobile application has an easy-to-use and icon-based interface. Users are able to log in, upload field images, and enter basic soil parameters such as pH, moisture, and nutrient levels. The app presents results in annotated images, with identified crops and weeds marked with color-coded bounding boxes. An overview dashboard presents the number of identified plant species and their names for simpler interpretation. Navigation among modules is made easy through simple icons and progress indicators. Future development plans involve offline use, voice-based guidance, and speech-to- text input support for low-literacy users. These design considerations are intended to enable the app to be used in actual field environments, particularly in rural and remote areas.

Machine Learning Processing

At the heart of the system lies this crucial component. The uploaded images are analyzed using the YOLO model, which effectively detects crops and weeds [5]. The identified objects are then labeled and highlighted with bounding boxes [9]. Additionally, soil parameters are scrutinized through machine learning models to suggest the most appropriate crops.

Database Interaction

This database is a treasure trove of information, storing images, soil data, details about detected plants, and recommendations. It offers valuable insights, including types of weeds, fertilizers, and pesticides, ensuring that farmers receive accurate, data-driven results.

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XIV, Issue IV, April 2025

Crop Prediction Display

This section presents the top crop recommendations based on the current soil and weather conditions. It also provides explanations for why a specific crop is suggested, empowering farmers to make well-informed decisions. [1], [3].

Crop and Weed Detection Results Display

Here, farmers can see the crops and weeds that have been identified, complete with labels and quantities. This information helps them understand the conditions of their fields and take necessary actions, such as applying the right pesticides.

Data Specification

The AgroVision system uses the **CropAndWeed Dataset** developed by Steininger et al. and its supplementary material [9], which provides a robust foundation for crop and weed detection and classification tasks in precision agriculture.

Dataset Collection and Composition: The dataset contains more than **8,034 high-resolution images** and approximately **112,000 annotated plant instances**. The images were cap- tured over a span of **four years** (March–July) from both:

Commercial cultivation sites (real-world agricultural fields)

Controlled experimental plots (outdoor environments with specifically cultivated crops and weeds)

Images were captured using a **semi-professional DSLR camera** with a **full-frame sensor** and a fixed **50mm lens** from a height of approximately 1.1 meters in a top-down view. Environmental conditions such as soil type, moisture, lighting, and weather were carefully varied to ensure dataset diversity [9].

Annotation Details: Each image is enriched with multi- modal annotations:

Bounding Boxes: For object detection tasks.

Semantic Segmentation Masks: For precise pixel-level classification.

Stem Position Annotations: For stem localization tasks.

Environmental Meta-Annotations: Including time of day, moisture level, soil texture, lighting conditions, and GPS coordinates [9].

The annotation process involved:

Initial automatic soil/vegetation pre-segmentation using color thresholding and CNN-based models.

Manual refinement of bounding boxes and segmentation masks.

Voting-based review among annotators for ambiguous cases [9].

Species Coverage: The dataset includes **74 plant classes**, specifically:

16 crop species (e.g., Maize, Sugar beet, Pea, Sunflower, Soybean, Potato, Pumpkin)

58 weed species (e.g., Goosefoot, Amaranth, Knotweed, Chickweed, Thistle) [9].

In addition, instances too small to classify (< 162 pixels) are labeled under the generic class **Vegetation**, providing a fallback for ambiguous or tiny samples.

Dataset Statistics: The breakdown of the dataset is as follows:

Sessions Recorded: 2,101 sessions

Images Captured: 43,814 images

Images Annotated: 8,034 images

Instances Annotated: 111,953 plant instances [9].

Data acquisition emphasized non-redundant collection by maintaining at least a 3-meter distance between sampled locations. Images include a wide range of soil types, lighting variations (e.g., cloudy, sunny, shadowed), and diverse plant combinations.

Dataset Variants for Specific Tasks*:* To adapt to various precision agriculture tasks, multiple dataset variants were introduced:

Fine24: 24 classes (8 crops + 16 weeds) with detailed species categorization.

CropsOrWeed9: 9 classes combining crops individually and all weeds into a single class.

CropOrWeed2: Simple binary classification (crops vs. weeds).

Coarse1: Binary classification (vegetation vs. soil) [9].

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XIV, Issue IV, April 2025

Additionally, specific mappings allow for tailored model training by combining rare classes or merging similar species based on botanical taxonomy or visual similarity.

Advantages over Previous Datasets: Compared to earlier datasets such as Plant Seedlings and Crop and Weep, the CropAndWeed dataset offers:

Higher diversity of species and environmental conditions.

Simultaneous multi-modal annotations (bounding boxes, segmentation masks, stem locations).

Representation of early growth stages critical for weed intervention.

Inclusion of negative samples (e.g., bare soil, rocks, straw) to increase model robustness.

Therefore, the CropAndWeed Dataset establishes a strong foundation for advanced machine learning tasks in precision agriculture, ensuring robust, accurate, and scalable solutions for automated crop and weed management.

Dataset Annotation and Setup: The CropAndWeed dataset provides detailed multi-modal annotations organized into several directories for each variant ().

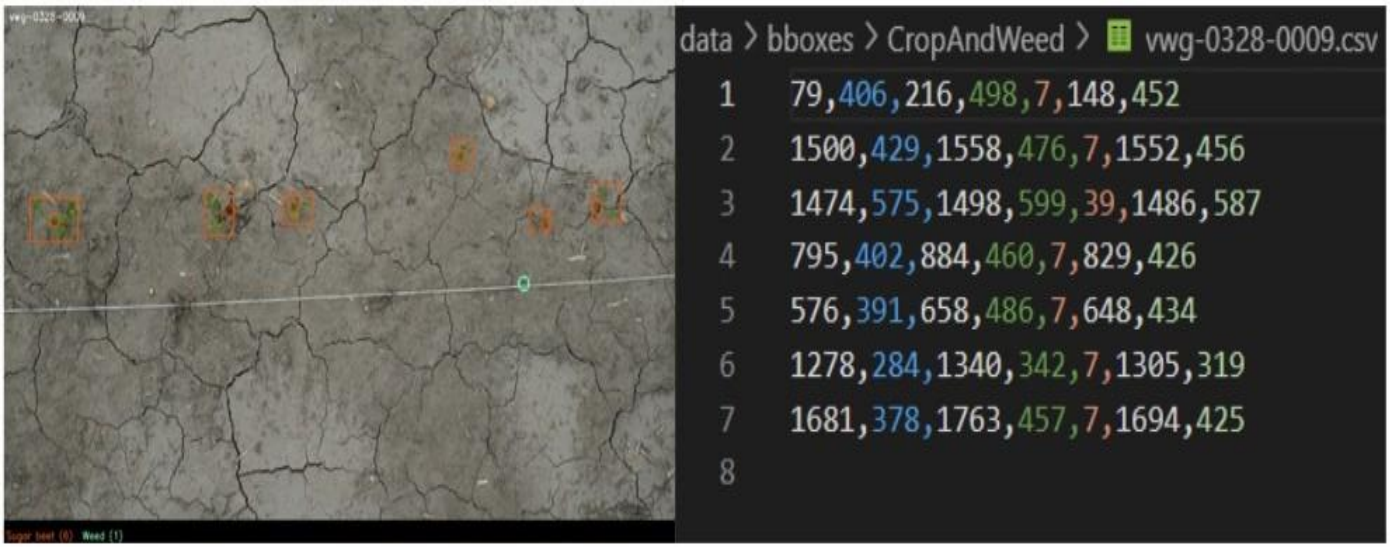


Fig. 2. Annotated bounding boxes and corresponding label data for crop and weed instances

The bboxes directory is where you'll find CSV files for each image. Each row in these files outlines an object instance, detailing columns like Left, Top, Right, Bottom, Label ID, Stem X, and Stem Y. Meanwhile, the labelIds directory holds the semantic masks for every image, and the params directory keeps track of extra parameters for each image. These include moisture levels (0 for dry, 1 for medium, and 2 for wet), soil types (0 for fine, 1 for medium, and 2 for coarse), lighting conditions (0 for sunny and 1 for diffuse), and separability (0 for easy, 1 for medium, and 2 for hard). You can find the mapping of label IDs for various dataset versions in the datasets.py file. The files are prefixed with either ave or vwg, which represent the Application and Experimental Sets, respectively. The naming convention follows a 4-digit recording session code, followed by a 4-digit image ID [9].

The Fine24 dataset is a specially curated version of the original CropAndWeed dataset, tailored for precision agricul- ture tasks. It simplifies the 74 original plant categories into 24 essential classes—featuring 8 crop classes and 16 weed classes—to find a sweet spot between detailed classification and real-world usability. This dataset comes with multi-modal annotations, including bounding boxes for object detection, semantic segmentation masks for pixel-level analysis, and accurate stem locations to help with targeted weed removal and crop protection [9].

Soil Data Collection and Integration

Soil data is of significant importance in the generation of crop advice and in the determination of soil health within AgroVision. To provide ease of access to farmers, the platform allows for the collection of soil data in a basic, manual entry format [3]. Farmers can provide the following values:

pH level (as collected using color strip-based soil pH test kits),

Moisture content (read using low-cost handheld moisture meters),

Nutrient levels (estimated by using simple soil test kits or outside laboratory reports).

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XIV, Issue IV, April 2025

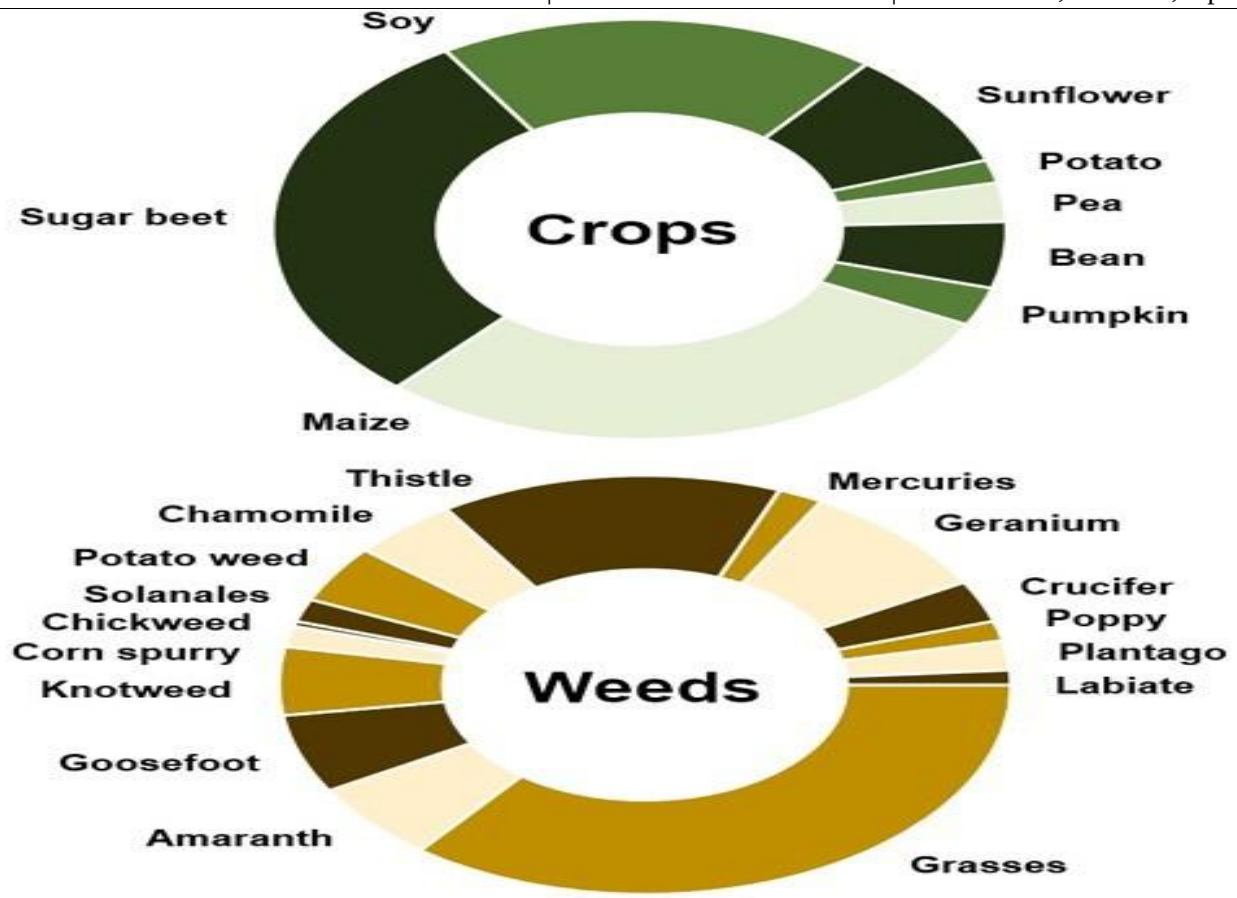


Figure 4. Distribution of crop and weed classes in the *Fine24* dataset variant.

Fig. 3. Distribution of crop and weed classes in the Fine24 dataset variant. [9]

The mobile app offers a simple interface that assists users in entering data, such as instructions and reference charts to assist with interpreting physical test results. This method makes the system usable even in regions with no advanced sensors or automated data collection systems [3]b12.

Upon submission, the soil information is processed by the back-end machine learning algorithms, which map the environmental factors to crop suitability scores. The output is a dynamic and customized crop suggestion based on local soil conditions [3]. Future development will include the integration of IoT-based soil sensors for automated data capture and Bluetooth connectivity to minimize human input errors and enhance real-time responsiveness. YOLOv8, which stands for You Only Look Once, Version 8, is an advanced object detection model that strikes a great balance between accuracy and efficiency. When it comes to agricultural uses, especially within the AgroVision framework, YOLOv8 is crucial for the real-time detection and classification of crops and weeds.

Algorithm

YOLOv8 Detection Flowchart: YOLOv8, which stands for You Only Look Once, Version 8, is an advanced object detection model that strikes a great balance between accuracy and efficiency. When it comes to agricultural uses, especially within the AgroVision framework, YOLOv8 is crucial for the real-time detection and classification of crops and weeds.

The detection process kicks off when a farmer snaps a picture of their field using either a smartphone or a drone. These images usually show a mix of crops and weeds, making it essential for the model to identify and differentiate between them accurately. They are first preprocessed through:

Resizing: Standardizing input images (e.g., 640×640 pixels) to ensure uniformity.

Normalization: Scaling pixel intensities to improve model stability and performance.

The preprocessed image is then passed into YOLOv8, where a Convolutional Neural Network (CNN) backbone extracts high-level visual features such as color, texture, size, and shape [5]. The model divides the image into a grid and, for each grid cell, predicts multiple bounding boxes and their corresponding class probabilities—identifying whether the object is a *crop* or a *weed*.

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XIV, Issue IV, April 2025

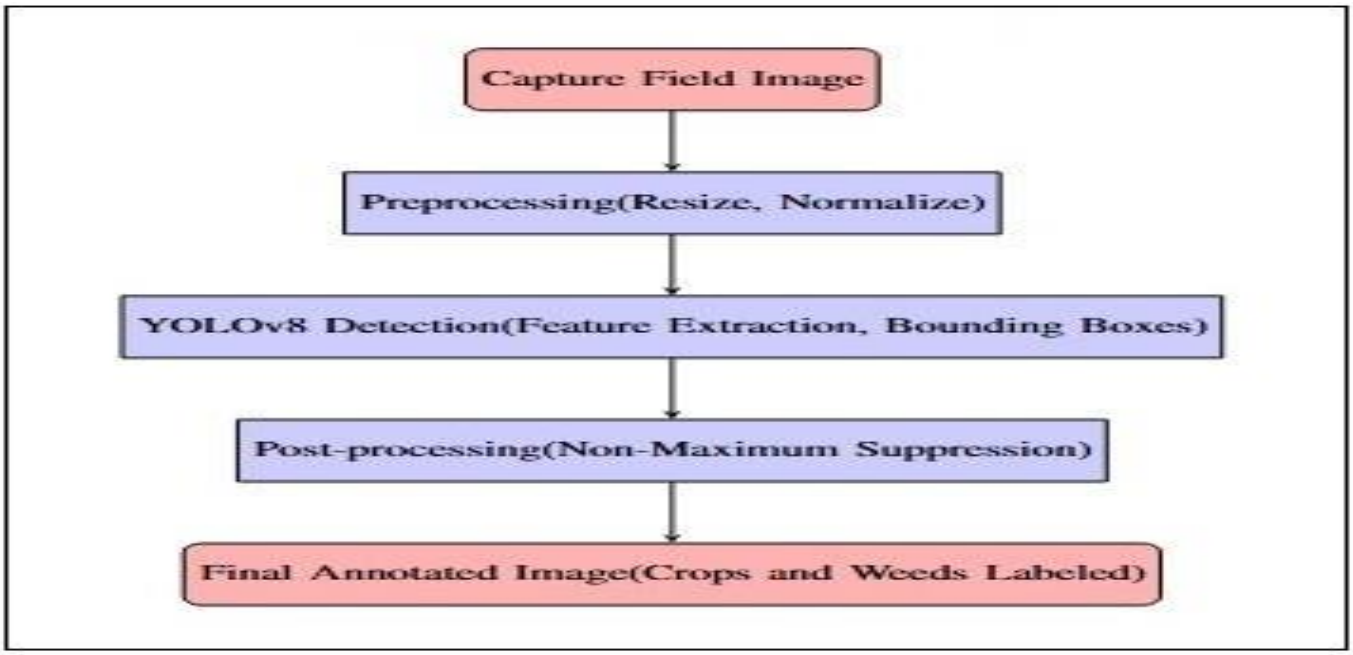


Fig. 4. YOLOV8 Flowchart

In a tomato field, for instance, YOLOv8 can spot tomato plants with green bounding boxes and identify weeds with red ones. To fine-tune these detections, YOLOv8 uses something called **Non-Maximum Suppression (NMS)**,, which helps eliminate overlapping and redundant detections by keeping only the bounding box that has the highest confidence score. The end result is an annotated image where every crop and weed is clearly labeled, counted, and visualized, giving farmers instant feedback. For example, a drone image of a 1- acre brinjal field might show **120 brinjal plants** and **30 weeds** scattered throughout the area.

Research, like that conducted by A. Thakur et al. [5], has demonstrated that YOLO-based models can achieve im- pressive detection accuracy while maintaining low inference times, making them perfect for real-time agricultural tasks such as weed management. Additionally, Steininger et al. [9] showed that training lightweight models like YOLO on spe- cific datasets, such as the CropAndWeed dataset, significantly boosts model efficiency, paving the way for scalable drone- based farming solutions.

So, in AgroVision, YOLOv8 serves not just as a detec- tion tool but also as a real-time decision-making assistant, equipping farmers with actionable insights for sustainable and precision farming practices.

Results

The AgroVision system was built on the YOLOv8 ar- chitecture, utilizing the CropAndWeed dataset to create a solid object detection framework tailored for agricultural use. During the training phase, images were prepped by resizing them to 640×640 pixels and normalizing the pixel values to maintain consistency. The results showed that the model could effectively pinpoint and identify both crops and weeds in actual farmland images [5], [9].

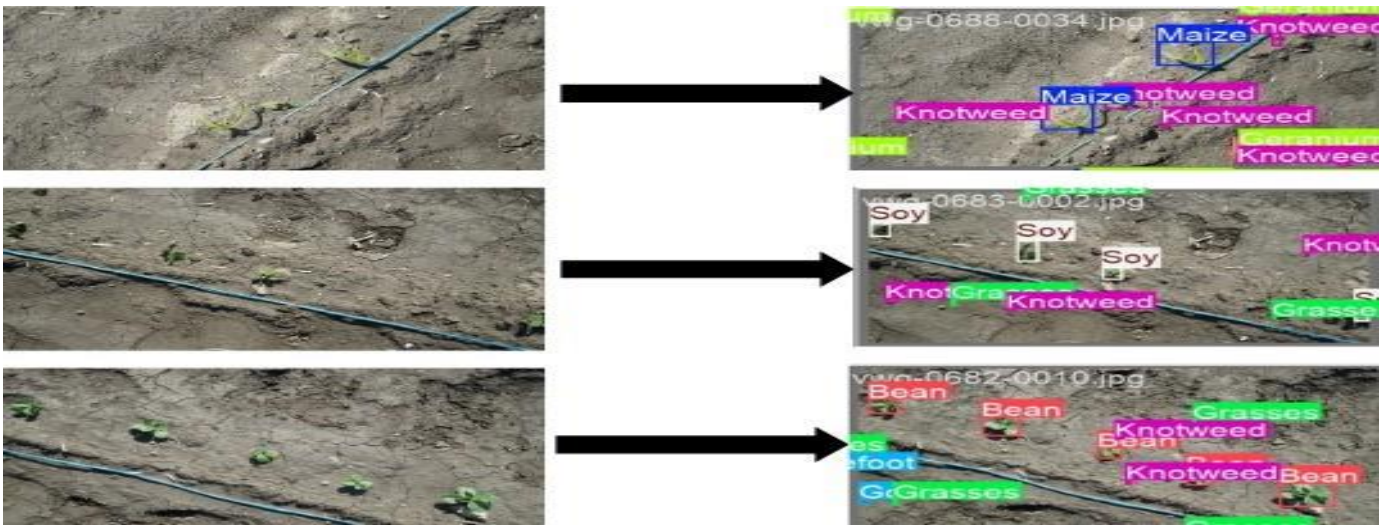


Fig. 5. YOLOv8 Crop and Weed Detection Output

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XIV, Issue IV, April 2025

The visual outputs really showcased how effective the detection pipeline was. We processed input images taken with drones or mobile devices through the trained YOLOv8 model, and the results were impressive—clearly annotated images with bounding boxes around the detected objects. Crops like maize, soy, and beans were easily identified with green bounding boxes, while various weed species, such as knotweed and grasses, were marked with different colors. The model consistently delivered strong performance, regardless of planting densities and soil conditions, proving its reliability in a variety of agricultural settings [9].

The performance metrics of the model further highlighted its effectiveness. During the training phase, we observed key loss functions—box regression loss, classification loss, and distribution focal loss—showing a steady decline, which indicated that the model was learning and converging well. Likewise, during validation, these loss metrics kept decreasing, suggesting that the model was generalizing well and avoiding overfitting. The precision and recall curves improved steadily throughout the training epochs, demonstrating an increasingly balanced ability to reduce both false positives and false nega- tives [5].

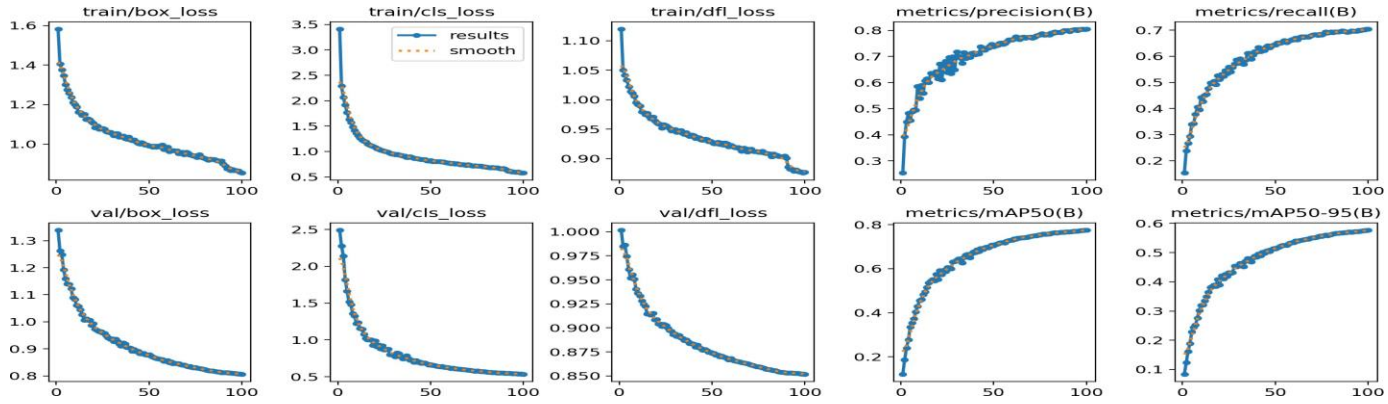


Fig. 6. Results for Crop and Weed Detection

When it comes to quantitative evaluation, the system achieved a mean Average Precision (mAP) of around 80% at an IoU threshold of 0.5 (mAP50) and roughly 58% across a range of IoU thresholds from 0.5 to 0.95 (mAP50–95). These impressive mAP figures show that the model not only identifies objects but also pinpoints their locations accurately, even in different field conditions [6], [9].

In summary, the results confirm that the YOLOv8-based AgroVision system is quite capable of handling real-time agricultural detection tasks. The trained model offers farmers quick and detailed insights into the number and location of crops and weeds, allowing for targeted actions like selective herbicide application. This kind of precision promotes sus- tainable farming practices by minimizing chemical use and enhancing crop health [7], ultimately leading to smarter and more eco-friendly agricultural management.

Although the YOLOv8-based AgroVision system has demonstrated excellent detection performance and high ac- curacy across various agricultural contexts, some restrictions were noted when testing. The model performed below average in the following instances:

Extreme Lighting Conditions: In pictures taken under extreme sunlight or deep shadow, detection accuracy decreased as a result of insufficient contrast or overex- posure.

Dense Plant Overlap: Where crops and weeds were densely overlapped or occluded, the model sometimes misrecognized or failed to identify certain plant species.

Device Constraints: Inference time was longer and re- sponsiveness was lower on less powerful smartphones, which could impact real-time use in the field.

To further assess the performance of the AgroVision system, baseline models like YOLOv5 were compared first. Though YOLOv5 had competitive accuracy, YOLOv8 was more supe- rior with both mean Average Precision (mAP) and inference speed, and hence suitable for real-time agricultural use cases. In addition to this, a pilot survey was carried out with ten rural farmers who implemented the AgroVision application under field conditions. Responses obtained through guided interviews reflected high levels of satisfaction with the ac- curacy of detection and the quality of visual output. Users also proposed improving the layout of the interface, language support, and offline capabilities. This feedback will play a critical role in informing future versions of the system to more closely meet user expectations and operational realities in farm environments.

CONCLUSION

AgroVision represents a major leap forward in harnessing artificial intelligence and deep learning to boost agricultural yields. By shifting from a web-based platform to an Android app, it greatly enhances accessibility, particularly for farmers who may not be very tech-savvy. The app comes packed with essential features like crop and weed identification, tailored crop suggestions, predictions for fertilizers and pesticides, and soil health assessments—empowering farmers to make smart, data-informed choices.

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XIV, Issue IV, April 2025

Plus, with extras like real-time weather updates via the OpenWeather API and an AI-driven chatbot powered by Google Gemini, user interaction and engagement are taken to the next level. AgroVision not only meets the cur- rent needs of farmers but also promotes sustainable practices by providing solutions tailored to specific conditions. While the system shows great potential, further work on improving model accuracy, adding support for regional languages, and refining the user interface will be vital. AgroVision has the potential to truly empower farmers and foster the development of smart, sustainable agriculture.

ACKNOWLEDGMENT

I want to take a moment to sincerely thank everyone who has been essential to the successful completion of the AgroVision project. First off, a huge shoutout to our Guide, Prof. Shreeya Palkar, whose steadfast support, expertise, and encouragement have been crucial every step of the way. I'm also incredibly grateful to P.E.S Modern College of Engineer- ing for offering the resources and a supportive atmosphere. A special thanks goes to Dr. Shraddha Pandit, Head of the AI and Data Science Department, and Prof. Shreeya Palkar for their invaluable insights and assistance that made this project a reality. I can't forget to mention my peers and family, whose unwavering encouragement and motivation kept me focused and driven. This achievement truly wouldn't have been possible without their support.

REFERENCES

1. G L, N. V and S. U, "A Review on Prediction of Crop Yield using Machine Learning Techniques," 2022 IEEE Region 10 Sympo- sium (TENSYMP), Mumbai, India, 2022, pp. 1-5, doi: 10.1109/TEN- SYMP54529.2022.9864482.
2. S. Mohammed, R. Malhotra, M. D. Shamout, B. Pithadiya, S. Patil and S. M. Sangve, "High-Accuracy Crop Yield Estimation Through IoT and Remote Sensing," 2023 IEEE International Conference on Paradigm Shift in Information Technologies with Innovative Applications in Global Scenario (ICPSITIAGS), Indore, India, 2023, pp. 225-230, doi: 10.1109/ICPSITIAGS59213.2023.10527721.
3. Bhatt and S. Varma, "Recommendation System for Crops Integrating with Specific soil parameters by Machine Learning Techniques," 2023 IEEE International Students' Conference on Electrical, Electronics and Computer Science (SCEECS), Bhopal, India, 2023, pp. 1-8, doi: 10.1109/SCEECS57921.2023.10063029.
4. D. Pujari, R. Yakkundimath and A. S. Byadgi, "Identification and clas- sification of fungal disease affected on agriculture/horticulture crops us- ing image processing techniques," 2014 IEEE International Conference on Computational Intelligence and Computing Research, Coimbatore, India, 2014, pp. 1-4, doi: 10.1109/ICCIC.2014.7238283.
5. Thakur, Sonu and R. Kumar, "Object Detection approach for Crop and Weed Identification based on Deep Learning," 2024 IEEE International Students' Conference on Electrical, Electronics and Computer Science (SCEECS), Bhopal, India, 2024, pp. 1-6, doi:10.1109/SCEECS61402.2024.10482324.
6. Jin et al., "An Improved Mask R-CNN Method for Weed Seg- mentation," 2022 IEEE 17th Conference on Industrial Electronics and Applications (ICIEA), Chengdu, China, 2022, pp. 1430-1435, doi: 10.1109/ICIEA54703.2022.10006300.
7. Sethia, H. K. S. Guragol, S. Sandhya, J. Shruthi and N. Rashmi, "Automated Computer Vision based Weed Removal Bot," 2020 IEEE International Conference on Electronics, Computing and Communica- tion Technologies (CONECCT), Bangalore, India, 2020, pp. 1-6, doi: 10.1109/CONECCT50063.2020.9198515.
8. Celikkan, M. Saberioon, M. Herold and N. Klein, "Semantic Segmen- tation of Crops and Weeds with Probabilistic Modeling and Uncertainty Quantification," 2023 IEEE/CVF International Conference on Computer Vision Workshops (ICCVW), Paris, France, 2023, pp. 582-592, doi: 10.1109/ICCVW60793.2023.00065.
9. Steininger, Daniel and Trondl, Andreas and Croonen, Gerardus and Simon, Julia and Widhalm, Verena. (2023). The CropAndWeed Dataset: a Multi-Modal Learning Approach for Efficient Crop and Weed Manip- ulation. 3718-3727. 10.1109/WACV56688.2023.00372.
10. Suma, T., Kumar, S. V., and Sandhya, B. R. (2022). Classification of soil and prediction of fertilizer for specific crop cultivation using machine learning technique. International Journal of Health Sciences, 6(S8), 5468–5473.
11. Tulaskar, V., Dhoble, R., Bawane, D., Virmuttu, S., Ambagade, K., and Dhutonde, A. (2023). Soil classification and crop suggestion using ML. International Research Journal of Modernization in Engineering, Technology and Science, 5(6), 940.
12. Gaikwad, S., Aiwale, A., Rekade, V., and Kalunge, V. (2022). Soil classification and crop suggestion using machine learning techniques. International Journal for Research in Applied Science and Engineering Technology (IJRASET), 10(V), 4984.
13. Barvin, P. and Sampradeepraj, T.. (2023). Crop Recommendation Sys- tems Based on Soil and Environmental Factors Using Graph Convolution Neural Network: A Systematic Literature Review. 97. 10.3390/ecsa-10- 16010.

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XIV, Issue IV, April 2025

14. Hao-Ran Qu and Wen-Hao Su. (2024). Deep Learning-Based Weed–Crop Recognition for Smart Agricultural Equipment: A Review. Agronomy. 14. 363. 10.3390/agronomy14020363.

15. Hu, Kun and Wang, Zhiyong and Coleman, Guy and Bender, Asher and Yao, Tingting and Zeng, Shan and Song, Dezhen and Schumann, Arnold and Walsh, Michael. (2023). Deep learning techniques for in-crop weed recognition in large-scale grain production systems: a review. Precision Agriculture. 25. 1-29. 10.1007/s11119-023-10073-1.

16. K. More, C. Asodekar, V. Ghonghade, S. Mandlik, and S. Palkar, "Agrovision: Smart Solutions for Modern Farming," *Journal of Emerg- ing Technologies and Innovative Research (JETIR)*, vol. 12, no. 1, pp. d343–d348, Jan. 2025.