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Research Article

A Deep Learning Approach to Efficient Crop and Weed Classification for Precision Farming

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Abstract: This research presents a comprehensive study on the application of Convolutional Neural Networks (CNNs) for precision agriculture, with a focus on the classification of crop and weed species. By leveraging deep learning techniques, we aim to optimize resource management in agriculture, thereby reducing environmental impact and maximizing crop yield. Our study addresses the challenges inherent in current agricultural practices, particularly the need for more efficient methods of classification and population density estimation to optimize fertilizer and pesticide application. We developed a CNN model that demonstrates high accuracy in identifying key crop and weed species, providing a robust tool for data-driven agricultural decision-making. The paper outlines the methodology, experimental setup, and model evaluation, and discusses the interpretation of results, which underscore the model's potential to revolutionize agricultural practices. The implications for agricultural sustainability are significant, as our automated system facilitates precise and efficient crop and weed identification, contributing to more informed and sustainable farming practices.

Keywords: Precision Agriculture, Convolutional Neural Networks, YOLO, Transfer Learning, Deep Learning, Crop Classification, Weed Detection, Transfer Learning, Image Processing, Resource Management, Sustainable Agriculture.

1. Introduction

Precision agriculture represents a significant shift in the way farming practices are managed, emphasizing the use of advanced technologies to optimize resource allocation and enhance crop yields. Traditional agricultural methods often rely on manual labor and subjective assessments, leading to inefficiencies and inconsistent outcomes. As global food demand continues to rise, there is an urgent need for more efficient, data-driven approaches to manage agricultural resources sustainably.

One of the critical challenges in precision agriculture is the accurate classification and estimation of crop and weed populations. Precise identification of these plant species is essential for optimizing the application of fertilizers and pesticides, reducing waste, and minimizing environmental impact. Traditional methods of plant species identification, such as manual counting and visual assessments, are labor-intensive, time-consuming, and prone to human error. These limitations underscore the necessity for automated, reliable, and scalable solutions.

In recent years, advancements in computer vision and machine learning have shown great promise in addressing these challenges. Convolutional Neural Networks (CNNs), a class of deep learning algorithms, have demonstrated exceptional performance in image recognition tasks across various domains, including agriculture. By leveraging the power of CNNs, it is possible to develop robust models capable of accurately classifying crops and weeds, thereby facilitating precise resource management and improving overall agricultural productivity.

This research aims to explore the application of CNNs in precision agriculture, focusing on the development of a deep learning model for the accurate classification of crop and weed species. The study leverages transfer learning techniques with pre-trained models such as VGGNet and ResNet50 to enhance the classification accuracy. Our proposed system integrates advanced image processing methods to preprocess the agricultural images, ensuring optimal model performance.

The paper is structured as follows: a review of related literature on CNN applications in agriculture, a detailed methodology outlining the model development process, an overview of the proposed system, and a presentation of experimental results. The discussion section interprets the findings, and a comparative analysis highlights the advantages of our approach over traditional methods. Finally, the paper concludes with a summary of contributions and potential future research directions in this field.

By providing an automated and efficient solution for crop and weed classification, this research contributes to the broader goal of sustainable agriculture, enabling farmers to make informed decisions and optimize resource usage, ultimately leading to enhanced crop yields and reduced environmental impact.

2. Background and Motivation

Efficient management of agricultural resources, such as fertilizers and pesticides, is critical for maximizing crop yield and minimizing environmental impact. Traditional methods often result in overuse or underuse of these resources, leading to several adverse consequences. The overuse of fertilizers and pesticides can have significant negative effects on human health, including increased risks of cancer, respiratory problems, and endocrine disruption. Furthermore, excessive application of these chemicals can lead to a decrease in soil fertility over time. This degradation occurs as the natural balance of nutrients is disrupted, resulting in diminished soil quality and reduced crop productivity.

The increasing global population necessitates sustainable enhancements in agricultural productivity to ensure food security. Manual observation and decision-making in traditional agriculture are not only time-consuming but also prone to errors, which can exacerbate resource mismanagement. Additionally, the rise of herbicide-resistant weeds further complicates management practices, making it more challenging to maintain high crop yields without harming the environment.

Given these challenges, there is a pressing need for innovative approaches to optimize the use of fertilizers and pesticides, enhance soil fertility, and manage weed populations effectively. Integrating advanced technologies such as machine learning and computer vision into agricultural practices offers a promising solution to these issues, ensuring sustainable and efficient farming practices for the future.

3. Problem Statement

The traditional methods of plant and weed identification and resource management in agriculture are inefficient, error-prone, and time-consuming, leading to the overuse of fertilizers and pesticides. This overuse negatively impacts human health and soil fertility. To address these challenges, there is a need for a precision agriculture system that utilizes advanced technologies such as Convolutional Neural Networks (CNNs) and You Only Look Once (YOLO). This system aims to accurately classify crop and weed species, analyze and estimate the frequency and distribution of plant species in agricultural fields, optimize the application of fertilizers and pesticides, and provide actionable insights to farmers. Ultimately, this promotes sustainable agricultural practices and reduces the environmental impact of farming operations.

4. Objectives

1. Develop a CNN model for classifying crop and weed species from images.
2. Estimate population density and frequency of crops and weeds using the quadrat method.
3. Extrapolate frequency data to larger areas and calculate optimal resource requirements based on predefined ratios.

5. Literature Survey

The authors of this paper [1] explore the evolving landscape of weed detection methodologies, tracing a path from traditional strategies to advanced machine learning techniques. Conventional methods like Convolutional Neural Networks (CNNs) and Support Vector Machines have historically led efforts to automate weed identification in agriculture. However, Vision Transformers have recently emerged as promising tools, known for their ability to capture complex long-range dependencies in images. This review critically evaluates existing weed detection methods, highlighting the untapped potential of Vision Transformers to surpass the limitations of traditional techniques. An innovative approach to weed detection takes center stage, demonstrating significant improvements in accuracy over established methods like CNNs and Support Vector Machines. This exploration emphasizes the urgent need for more precise and efficient weed detection tools, not only as technological advancements but also as essential tools for empowering farmers and ultimately enhancing overall crop yield.

Researchers in paper [2] examine the dynamic landscape of machine learning applications in precision agriculture, with a focus on India's agricultural context. In a world where technological advancements often outpace public awareness, the agricultural sector, vital for livelihoods in India, is undergoing transformative changes. Recent research abstracts highlight the crucial role of technology integration, particularly through machine learning, in improving efficiency and streamlining agricultural practices. This review extensively explores the diverse applications of machine learning in agriculture, including soil fertility forecasting, yield prediction, soil classification, crop advisories, and species identification.

The researchers in paper [3] delve into precision farming robotics, a field essential for advancing sustainable agriculture by reducing agrochemical use through targeted interventions. The paper emphasizes the critical need for a reliable plant classification system to accurately differentiate between crops and weeds across various agricultural environments. Vision-based systems, primarily relying on convolutional neural networks (CNNs), often struggle with generalizing findings to unfamiliar fields. Overcoming this challenge requires exploring methods to enhance CNNs' generalization capacity, thereby improving their effectiveness across diverse agricultural contexts. This letter aims to address this gap by exploring strategies to bolster CNNs' generalization capabilities for improved performance in varied agricultural conditions.

The paper [4] discusses corrosion recognition in steel structures, highlighting the persistent challenge of accurate identification using subjective judgment and time-consuming traditional methods. The paper explores the potential of Convolutional Neural Networks (CNNs) and their variants, such as U-Net and Residual Neural Networks (ResNet), in revolutionizing corrosion identification. It emphasizes CNNs' effectiveness in accurately identifying and segmenting rusty areas in images, offering a promising alternative to subjective methods. The paper presents case studies demonstrating CNN's efficacy in detecting and grading corrosion on various objects, providing empirical evidence of its practical applicability. Additionally, the introduction of Ensembled CNN (ECNN) showcases an innovative approach to enhancing corrosion identification model performance and generalization capabilities. The study positions CNNs as transformative tools for corrosion identification in steel structures, with potential applications across a range of scenarios.

The research in paper [5] utilizes deep learning, specifically convolutional neural networks (CNNs), for accurate weed identification. Notably, the study employs transfer learning and introduces an Ensembled CNN (ECNN) to improve model performance and generalization capabilities. The literature survey extends to weed management and precision agriculture, emphasizing the urgent need for advanced weed detection and control methods due to their potential impact on global crop output. The study aligns with recent advancements in computer vision-based plant phenotyping technologies, emphasizing the critical role of accurate image processing in monitoring crop conditions for effective management. The proposed automated weed identification approach adds value to this landscape, offering an effective and reliable system aligned with the goals of precision agriculture. The comprehensive evaluation metrics employed in the study contribute to a thorough understanding of the model's capabilities, demonstrating its potential to outperform existing methods in the field.

Deep learning models have become essential in modern computer vision applications in agriculture, automating tasks like fruit detection, crop and weed segmentation, and plant disease classification, as discussed in paper [6]. These models often rely on fine-tuning to address the lack of task-specific data in agriculture, transferring knowledge from source tasks to smaller target datasets. While previous studies have shown the benefits of transfer learning in agricultural image classification, little exploration has been done in more relevant tasks like semantic segmentation and object detection. Additionally, the absence of a centralized repository for agriculture-specific datasets hampers the development of large-scale datasets comparable to ImageNet for agriculture. The paper aims to standardize and centralize datasets, improving data efficiency in training agricultural deep learning models. The study explores novel methods and highlights the potential of transfer learning for enhancing data efficiency, offering valuable insights for agricultural computer vision.

The research presented in paper [7] evaluates the proposed W network on tobacco and sesame datasets, demonstrating its consistent and promising performance across different soil and sunlight conditions. Notably, the framework outperforms existing methods in terms of Mean Intersection over Union (MIOU). The study provides insights into the challenges associated with using separate datasets for training and testing, highlighting potential benefits and drawbacks. Additionally, the study benchmarks against well-established architectures like UNet and SegNet, utilizing lighter-weight models for real-time application. The extensive experiments conducted validate the superior performance of the proposed W network, offering valuable contributions to agricultural deep learning.

The paper [8] examines the evolving landscape of smart agriculture, where technological advancements, particularly in remote sensing and machine learning, are transforming traditional farming practices. The integration of Convolutional Neural Networks (CNNs) in agricultural tasks such as crop and weed segmentation, disease identification, and anomaly detection is a recurring theme. Transfer learning, a key strategy to mitigate data deficiency in agriculture-specific tasks, involves fine-tuning CNNs with pretrained weights from general datasets. The review underscores the limited exploration of transfer learning's application in tasks like semantic segmentation and object detection. Additionally, challenges persist in creating large-scale, centralized agriculture-specific datasets, hindering the establishment of an ImageNet-style resource for agriculture. The literature recognizes the importance of automated systems for weed detection and precise identification, emphasizing the futuristic benefits of deep learning techniques. The paper highlights a methodology for multiple weed species identification using semantic segmentation and advanced deep learning models, offering promising prospects for automated weed management systems in precision agriculture.

A thorough analysis of the use of YOLOv3 for weed detection in agricultural settings is presented by the authors in [9]. They show how YOLOv3 greatly reduces the time and work needed for manual weed identification by accurately identifying and classifying several weed species in real-time. The model's great speed and accuracy are highlighted in the paper, which makes it appropriate for use in automated agricultural systems.

Researchers concentrate on classifying crops and weeds using YOLOv4 in [10]. The enhanced detection capabilities and increased precision of the model over previous iterations are highlighted in the study. The authors achieve strong classification performance by training YOLOv4 on a variety of crop and weed picture datasets. This is important for precision agricultural applications where precise plant species identification is necessary for efficient management.

The application of YOLOv5 for weed and crop population density detection and estimation is investigated in the work [11]. The authors show that YOLOv5 offers accurate density measurements by using the quadrat approach to test the model's results. The possibility of merging contemporary machine learning models with conventional ways to improve agricultural data analysis is demonstrated by this integration of YOLOv5 with ecological survey methodologies.

The study explores at YOLOv6's potential for high-resolution crop monitoring in [12]. Using drone-captured aerial imagery, the researchers train YOLOv6 to accurately detect and map weeds and crops over vast agricultural landscapes. The study demonstrates how well the model processes high-resolution photos, which makes it a useful tool for large-scale agricultural management and monitoring.

The implementation of YOLOv7 in smart farming systems is examined in the work [13]. The authors show how real-time crop and weed detection may be achieved by integrating YOLOv7 with edge computing and Internet of Things devices. Agricultural operations are made more responsive and efficient by this connection, which makes instantaneous data processing and decision-making possible. The study emphasizes how crucial real-time capabilities are to contemporary precision agriculture.

YOLOv8 is used by the researchers in [14] to identify weeds and detect plant diseases. Along with weed detection, the study achieves great accuracy in detecting several plant diseases by fine-tuning YOLOv8 on a particular dataset of healthy and diseased plants. Because of its dual functionality, YOLOv8 is an adaptable instrument for thorough crop health monitoring that gives farmers practical advice on how to enhance crop management techniques.

The paper [15] explores the application of YOLO models to fine-tune weeding. To target and eliminate weeds selectively, the authors create a robotic weeding system with YOLO-based detection. By lowering the demand for chemical pesticides, this approach encourages environmentally friendly agricultural methods. The study emphasizes the advantages for the environment of combining robotic technologies in agriculture with sophisticated object recognition.

The paper [16] concludes with a survey of deep learning applications in agriculture, emphasizing object identification models based on YOLO. It talks about how YOLO has changed from its early iterations to the most recent ones, highlighting how accurate and effective they have become. The paper provides a thorough overview of the model's potential to alter agricultural practices by covering several applications of YOLO in health monitoring, density estimates, and crop and weed detection.

5. Description of the Dataset Used

The datasets used in this research comprise images of both weed species and crop species, collected from diverse agricultural settings. Each dataset is meticulously curated to include representative samples of the respective plant species, enabling robust model training and evaluation.

Data Splitting:
The collected dataset comprising images of both crop species and weed species needs to be divided into distinct subsets for training, validation, and testing purposes.

The following data-splitting strategy was employed: 75% training, 15% testing, 10% validation.
The datasets used in this research comprise images of both weed species and crop species, collected from diverse agricultural settings. Each dataset is meticulously curated to include representative samples of the respective plant species, enabling robust model training and evaluation.

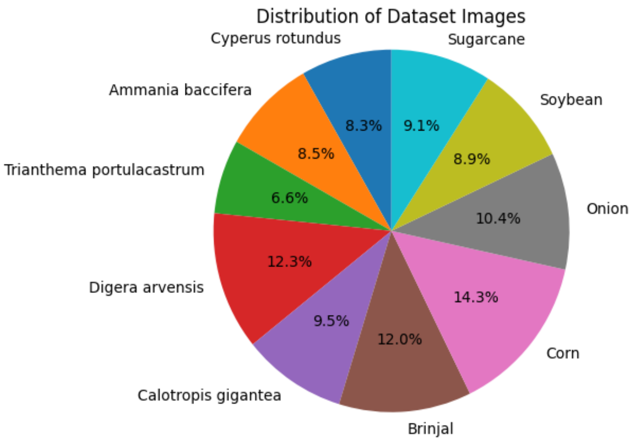

Figure 1. Percentage-wise Distribution of Dataset Images

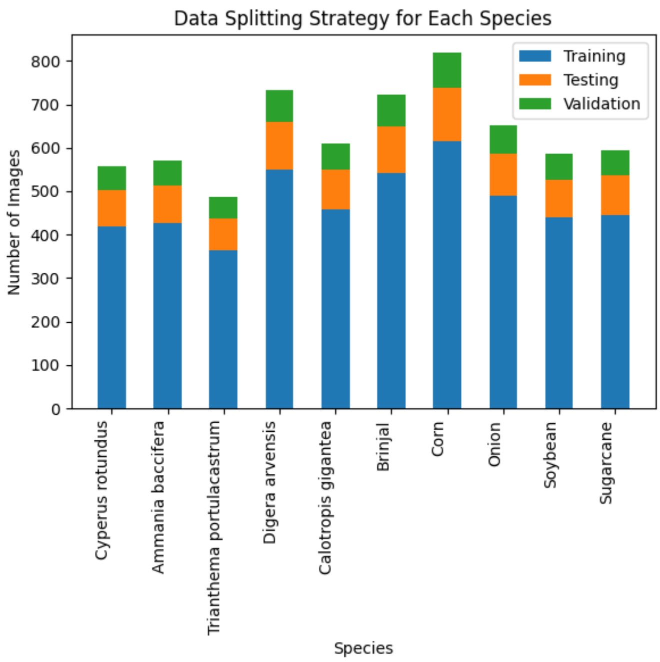

Figure 2. Data Splitting Strategy for Each Species

Weeds:
The weed dataset consists of images representing various common weed species encountered in agricultural fields. The following weed species are included in the dataset:

- Cyperus rotundus (Nutgrass)
- Ammania baccifera (Water willow)
- Trianthema portulacastrum (Horse purslane)
- Digera arvensis (False amaranth)
- Calotropis gigantea (Giant milkweed)

Crops:
The crop dataset comprises images representing key crop species cultivated in agricultural fields. These crop species are vital for food security and economic livelihoods in many regions. The following crop species are included in the dataset:

- Brinjal (Eggplant)
- Corn (Maize)
- Onion
- Soybean
- Sugarcane

The above are Figure.1 and Figure.2, which depict the percentage-wise distribution of dataset images and the data splitting strategy for each species, respectively. Figure.3 shows a random sample image of each species from the dataset used to train the classification model.

6. System Architecture

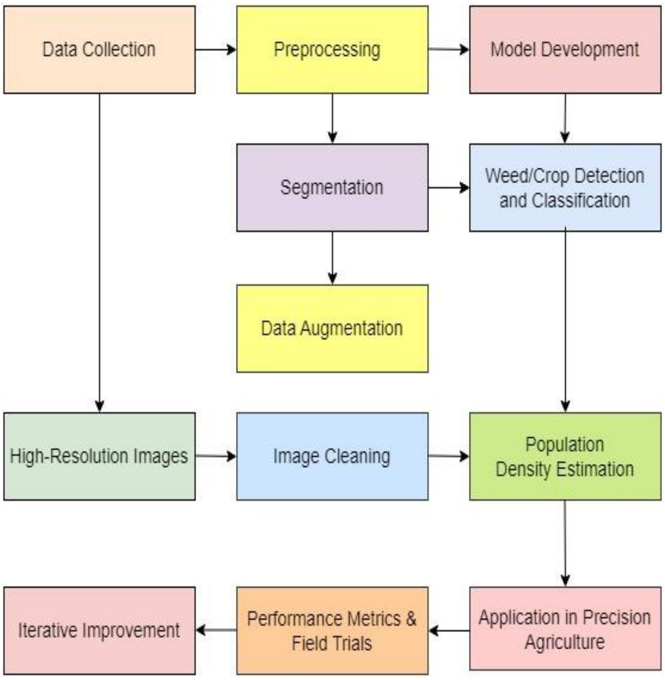

Figure 3. Architecture of Proposed System

1. Data Collection: Input-Early growth stage images of crops and weeds, Agricultural fields in West Maharashtra, India, Tools- High-resolution cameras, drones, and smartphones.
2. Preprocessing: Image Cleaning- Removing noise, adjusting brightness and contrast. Data Augmentation- Techniques such as rotation, flipping, and scaling to increase the diversity of the training dataset. Segmentation- Identifying and isolating individual plants in the images.

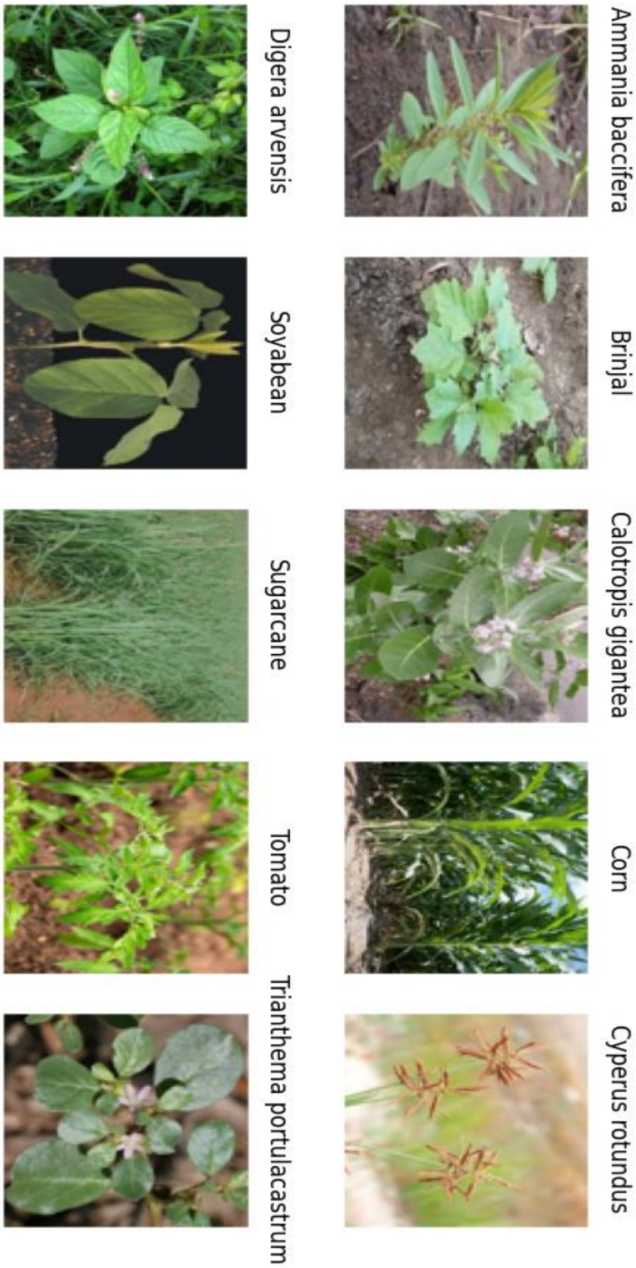

Figure 4. Random Sample Image of Each Species from the Dataset

3. Model Development: Model Selection- Choosing appropriate CNN architectures for classification. Training- Using labeled datasets to train the model on distinguishing between different crop species and weeds. Validation-Testing the model on a separate dataset to evaluate its accuracy and generalization capabilities.
4. Weed Detection and Crop Classification: Detection Algorithms- Implementing CNN-based algorithms to identify weeds and crops in the images. Classification- Classifying the detected plants into respective categories (e.g., crop species, weed types).
5. Population Density Estimation: Density Algorithms-Applying machine learning techniques to estimate the

population density of crops and weeds (e.g YOLO). Integration with Agronomic Data- Combining population density data with agronomic information to make informed decisions.

6. Application in Precision Agriculture: Fertilizer Application- Optimizing the amount and timing of fertilizer application based on the detected crop density. Pesticide Application- Targeted application of pesticides to areas with high weed density to minimize chemical use. Resource Management- Efficient management of resources to maximize crop yield and reduce environmental impact.

7. Evaluation and Feedback: Performance Metrics- Accuracy, precision, recall, and F1-score for the detection and classification tasks. Field Trials- Implementing the developed system in real agricultural settings and collecting feedback. Iterative Improvement- Continuously refining the model based on field trial results and feedback.

7. Methodology

Overview of Convolutional Neural Networks (CNNs): CNNs are powerful tools for image classification, consisting of layers like convolutional, pooling, and fully connected layers. We use ImageGenerators for efficient data loading and preprocessing, callbacks for optimizing the training process, and techniques like transfer learning to leverage pre-trained models for our agricultural classification tasks.

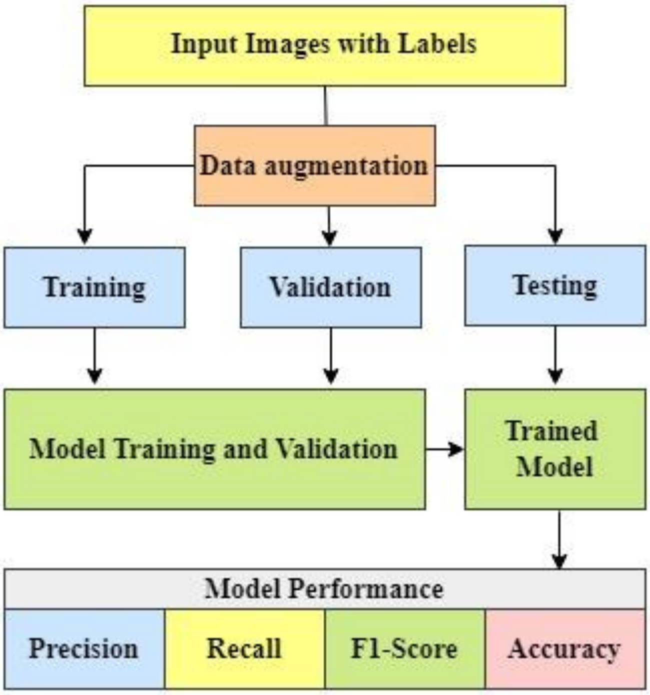

Figure 5. Steps in building deep learning models

Figure 5 outlines a comprehensive workflow for building and evaluating deep-learning models for image classification in precision agriculture. It starts with a dataset of labeled images, which undergo data augmentation techniques like rotation and flipping to enhance robustness and generalization. The augmented data is split into training, validation, and testing sets. During the training phase, the model learns to identify patterns and features from the training data, while the validation set is used to fine-tune hyperparameters and prevent overfitting. The final trained model is then evaluated using the test data to ensure unbiased performance assessment.

Using these steps in building deep learning models, we implement four different models and conduct a comparative study based on their performance metrics: precision (Equation (1)), recall (Equation (2)), F1-score (Equation (3)), and accuracy (Equation (4)). Precision indicates the relevance of selected items, recall shows the proportion of actual positives correctly identified, F1-score balances precision and recall, and accuracy measures the overall correctness of predictions. This structured approach ensures that the model not only learns effectively but also performs reliably in real-world applications, enhancing resource management and decision-making in agricultural practices. The most efficient model from this comparative study will be selected for the classification task, optimizing the system's overall accuracy and effectiveness.

$$Precision = \frac{\mathbf{TP}}{TP+FP} \tag{1}$$

$$Recall = \frac{\mathbf{TP}}{TP+FN} \tag{2}$$

$$F1 - Score = \frac{2 \times \text{Precision} \times \text{Recall}}{Precision + Recall} \tag{3}$$

$$Accuracy = \frac{\text{TP} + \text{TN} + \text{FP} + \text{FN}}{TP + TN} \tag{4}$$

Transfer Learning: Transfer learning allows us to use pre-trained models like VGGNet and ResNet50, adapting them to our specific task. This approach is effective when labeled data is limited, as it builds on existing knowledge from large datasets.

Data Preprocessing: Effective data preprocessing is essential for model performance. Steps include data cleaning to remove noise and inconsistencies, data analysis to understand dataset characteristics, and data augmentation to artificially increase dataset size and diversity.

Model Architecture Selection: We explored four models-

1. Customized CNN from scratch

The first model we explored was a Customized Convolutional Neural Network (CNN) built from scratch. This approach involved designing and implementing a unique CNN architecture tailored specifically for the task of crop and weed classification. Starting with basic layers such as convolutional, pooling, and fully connected layers, we fine-tuned the network's depth and parameters to optimize its performance. This model served as a baseline, providing valuable insights into the fundamental capabilities and limitations of a CNN in distinguishing between crop and weed species without relying on pre-trained networks.

2. Customized CNN with image augmentation

Building on the initial customized CNN, we introduced image augmentation techniques to enhance the model's robustness and generalization capabilities. By applying transformations such as rotations, flips, shifts, and zooms to the training images, we created a more diverse dataset that helped the CNN learn invariant features across different conditions. This approach aimed to mitigate overfitting and improve the model's performance on unseen data, leveraging augmented data to better simulate real-world variations in agricultural environments.

3. Transfer learning with VGGNet

The third model utilized transfer learning with VGGNet, a well-established deep learning architecture known for its depth and powerful feature extraction capabilities. By leveraging a pre-trained VGGNet model, we transferred its learned features to our specific task of crop and weed classification. The final layers of VGGNet were fine-tuned to adapt to our dataset, allowing us to benefit from the rich feature representations learned from a large-scale dataset while significantly reducing the training time and computational resources required compared to training a deep network from scratch.

4. Transfer learning with ResNet50

The fourth model involved transfer learning with ResNet50, a deep residual network known for its innovative use of residual connections to address the vanishing gradient problem in very deep networks. ResNet50's architecture allowed for the efficient training of a 50-layer deep network, providing a strong feature extraction backbone for our classification task. By fine-tuning the final layers of the pre-trained ResNet50 model, we adapted it to our dataset, aiming to leverage its robustness and accuracy in feature extraction to enhance the precision of crop and weed identification in precision agriculture.

5. Proposed System for estimating population density and frequency

The proposed system leverages a CNN model for classifying crop and weed species from images. It uses the quadrat method for estimating population density and frequency, extrapolates data to larger areas, and calculates optimal resource requirements. The system integrates various components for data preprocessing, model training, and performance evaluation.

Process Flow for Population Density Analysis of Weeds and Crops Using YOLOv8 depicted in Figure 5.

The research further encompasses a process for analyzing the population density of weeds and crops using the YOLOv8 (You Only Look Once) object detection algorithm. This process involves segmenting the agricultural field images into smaller sections known as quadrats. Each quadrat is then analyzed using YOLOv8 to detect and count the occurrences of weeds and crops. The data gathered from these detections is used to estimate the population density of weeds and crops across larger agricultural areas.

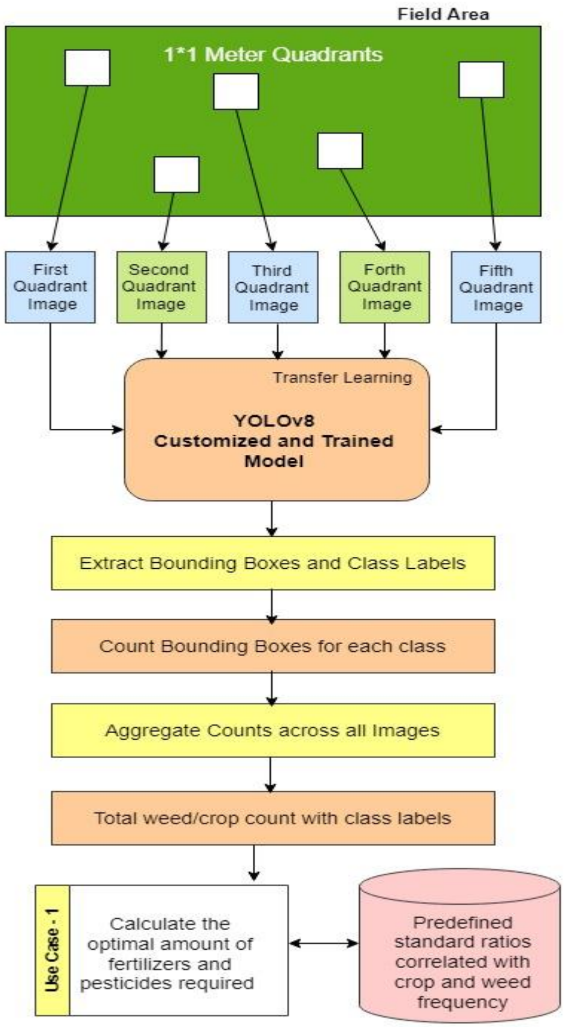

Figure 6. Process Flow for Population Density Analysis

This method provides precise and efficient monitoring of plant populations, enabling better decision-making for weed management and crop optimization. The use of YOLOv8 ensures fast and accurate detection, making the process suitable for real-time applications in large-scale farming operations

8. Results and Discussion

The first model developed in this study was a customized Convolutional Neural Network (CNN) built from scratch to classify images of crops and weeds. This model was trained on a training dataset, validated using a validation dataset, and subsequently tested on the training dataset to assess its performance. The architecture included key components such as convolutional layers for learning spatial hierarchies of features, batch normalization for stabilizing the training process, max-pooling layers for reducing computational complexity, dropout layers to prevent overfitting, flattening for converting feature maps into a vector, and dense layers for classification. The final dense layer used a softmax activation function to output class probabilities. The model was compiled using the Adam optimizer and categorical cross-entropy loss function, with accuracy as the evaluation metric, and was trained for 30 epochs with callbacks for monitoring the training process.

The performance of the customized CNN model was evaluated based on its accuracy and loss on both the training and validation datasets. The model achieved a training accuracy of 62.11%, indicating that a significant proportion of the samples were correctly classified during training. However, the validation accuracy was lower, at 55.52%, reflecting the model's performance on unseen data as shown in the Fig 7. The training loss was 1.8045, representing the error between the true labels and the predicted probabilities, while the validation loss was 2.0106 as shown in Fig 8. The higher loss and lower accuracy on the validation dataset suggest that the model may be overfitting to the training data.

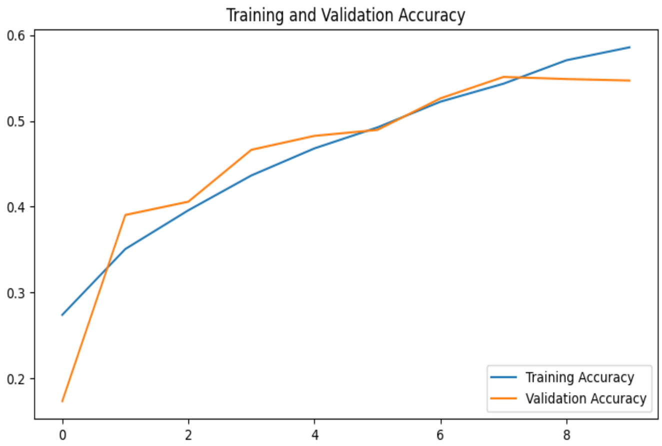

Fig. 7. Training and Validation Accuracy of Model-1

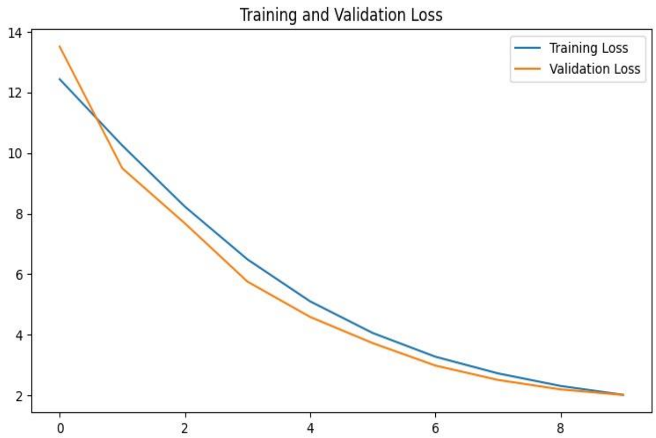

Fig. 8. Training and Validation Loss of Model-1

The discrepancy between training and validation performance indicates a need for further refinement of the model. Potential strategies to address this include adjusting the model architecture, tuning hyperparameters, or increasing the amount of training data to improve the model's generalization capabilities. Additionally, techniques such as early stopping could be employed to prevent overfitting and enhance performance on unseen data. Despite these challenges, the customized CNN model showed promise in classifying crops and weeds, highlighting areas for future improvements to achieve better accuracy and robustness.

The second model in this study, Model-2, builds upon the architecture of Model-1 by incorporating image augmentation techniques to enhance its performance and robustness. The augmentation involved applying transformations such as rotation, flipping, scaling, and translation to the input images, thereby increasing the diversity of the training dataset and improving the model's ability to generalize to unseen data. By using the Keras ImageDataGenerator class, various augmentation options were configured to create a more varied training dataset, which included rescaling pixel values, applying random rotations, shifts, shears, zooms, and horizontal flips. This approach aimed to expose the model to a broader range of scenarios, helping it learn more discriminative features and reduce the risk of overfitting.

Model-2 was trained using the augmented dataset, leading to significant improvements in its ability to handle variations in the input images. The training process involved the model learning from a diverse range of augmented images during each epoch, enhancing its generalization capabilities. The evaluation of Model-2 revealed an overall accuracy of 46% on the testing dataset, which indicates a moderate improvement over Model-1. The confusion matrix and classification report provided detailed insights into the model's performance across different classes, with variations in precision, recall, and F1-score.

Despite the improvements, the evaluation metrics suggest that Model-2 still faces challenges in accurately predicting certain classes, which could be attributed to class imbalance, data quality issues, or inherent complexities in distinguishing those classes. The overall accuracy of 47% is above random guessing, demonstrating the model's capability to make meaningful predictions, but further optimization is needed to achieve higher accuracy and robustness. The use of image augmentation techniques showcases a proactive approach to enhancing model performance, highlighting the iterative nature of model development and the importance of continuous experimentation and refinement.

The training and validation accuracy of Model-2 are depicted in Figure 9, while the training and validation loss of Model-2 are illustrated in Figure 10.

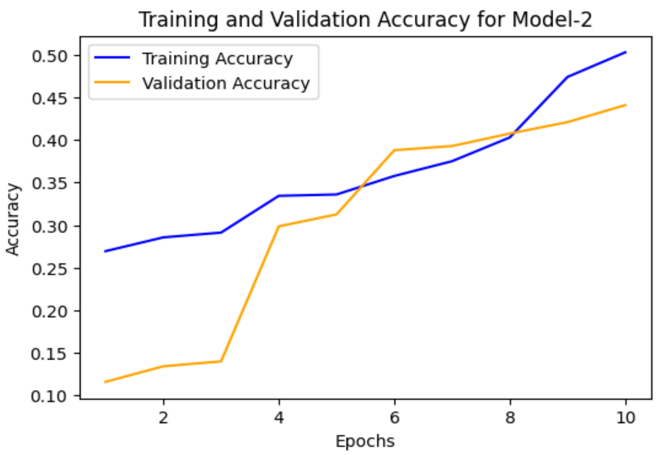

Fig. 9. Training and Validation Accuracy of Model-2

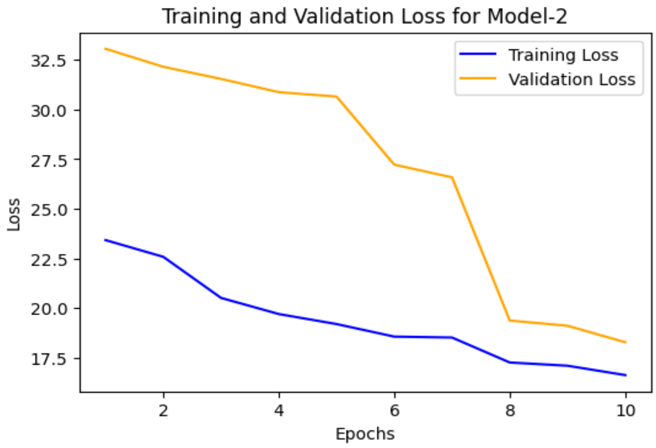

Fig. 10. Training and Validation Loss of Model-2

The third model in this study, utilizing the VGG16 architecture through transfer learning, demonstrated notable improvements in performance for the agricultural classification task. By leveraging a pre-trained VGG16 model, which had been trained on the large-scale ImageNet dataset, we were able to benefit from its rich feature representations and fine-tune it for our specific dataset. The inclusion of image augmentation techniques during training further enhanced the model's ability to generalize and adapt to the variations present in agricultural images. As a result, the model achieved an overall accuracy of 74%, indicating that it correctly predicted the class labels for 74% of the samples in the dataset.

The evaluation of Model-3 through the confusion matrix and classification report provided detailed insights into its performance across different classes. Precision, which measures the proportion of true positive predictions out of all positive predictions, ranged from 0.72 to 0.75, reflecting the model's moderate to high accuracy in predicting each class. Similarly, recall, which indicates the proportion of true positive predictions out of all actual positive instances, ranged from 0.68 to 0.79. These values suggest that the model effectively captures a significant proportion of actual positive instances for each class, demonstrating its robustness and generalization capabilities. The F1-score, a balanced measure of precision and recall, ranged from 0.70 to 0.77, indicating a good overall performance across most classes.

The macro and weighted average values of precision, recall, and F1-score were all around 0.74, reflecting consistent performance across different classes and highlighting the model's balanced classification capabilities. While the model achieved satisfactory results, further analysis and refinement could be undertaken to address any specific areas for improvement or potential biases. This includes examining class-wise performance to identify underperforming categories and exploring advanced techniques or additional data augmentation strategies to enhance the model's robustness and accuracy. Overall, the integration of transfer learning with VGG16 proved to be an effective approach for agricultural image classification, demonstrating significant potential for practical applications in precision farming and crop management.

The training and validation accuracy of Model-3 are depicted in Figure 11, while the training and validation loss of Model-3 are illustrated in Figure 12.

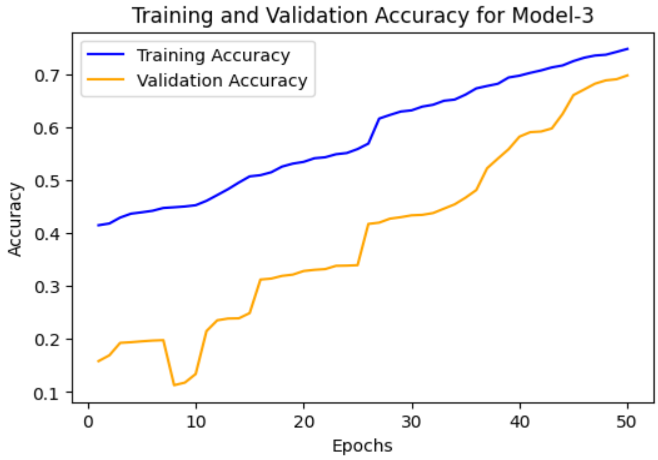

Fig. 11. Training and Validation Accuracy of Model-3

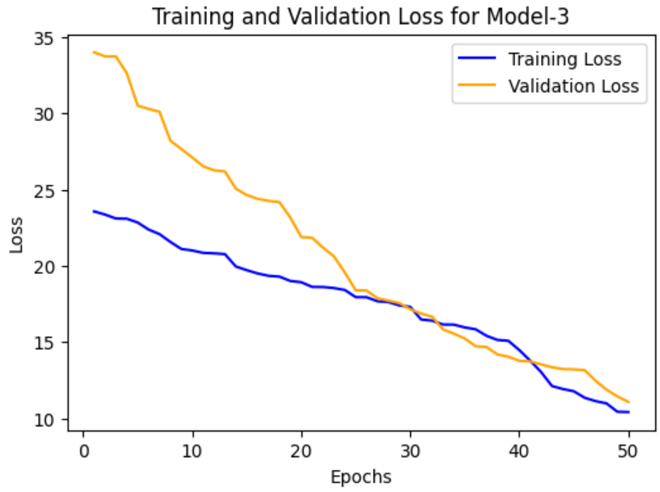

Fig. 12. Training and Validation Loss of Model-3

Model-4 leverages the ResNet50 architecture through transfer learning, showcasing its advanced capabilities in hierarchical feature extraction and effective gradient propagation. By fine-tuning ResNet50, which is pre-trained on the ImageNet dataset, we capitalized on its deep residual connections that mitigate the vanishing gradient problem, facilitating the training of deeper networks. The fine-tuning process involved freezing the initial layers and customizing the final layers to suit our agricultural classification task. This strategy allowed us to harness the robust feature representations learned from ImageNet and adapt them to the specific characteristics of our dataset, resulting in a model that demonstrates impressive classification performance.

The evaluation metrics of Model-4 indicate a strong overall performance, with an accuracy of 90.73%. The confusion matrix and classification report provide detailed insights into the model's effectiveness across different classes. Most classes, including "Cyperus rotundus," "Ammania baccifera," "Trianthema portulacastrum," "Digera arvensis," "Calotropis gigantea," "Brinjal," "Corn," "Onion," and "Soybean," exhibit high precision, recall, and F1-scores. This suggests that Model-4 is proficient in accurately identifying and distinguishing these classes, maintaining a balanced performance across both precision (the ability to avoid false positives) and recall (the ability to detect true positives).

However, the model's performance is slightly less effective for the "Sugarcane" class, which has lower precision, recall, and F1-scores compared to the other classes. This indicates that Model-4 encounters some challenges in accurately classifying "Sugarcane" images. Despite this, the overall high accuracy and robust performance across most classes highlight the strength of using ResNet50 for agricultural image classification. Further refinement and targeted adjustments could address the discrepancies observed in the "Sugarcane" class, potentially enhancing the model's comprehensive effectiveness. Overall, Model-4's robust architecture and fine-tuning approach demonstrate its significant potential for practical applications in precision agriculture and crop management.

The training and validation accuracy of Model-4 is depicted in Figure 13, while the training and validation loss of Model-4 is illustrated in Figure 14.

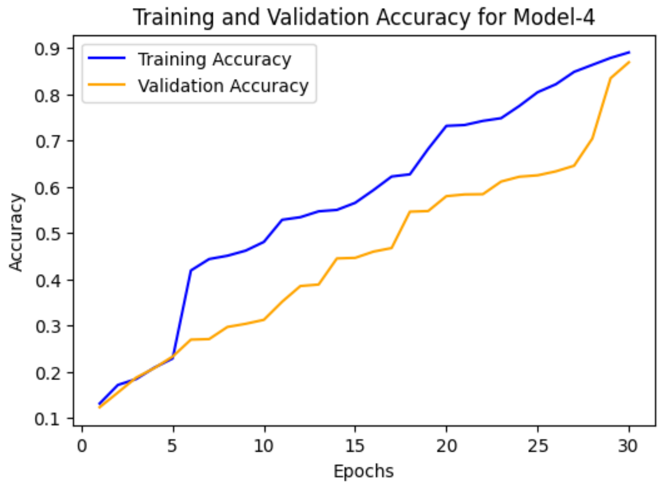

Fig. 13. Training and Validation Accuracy of Model-4

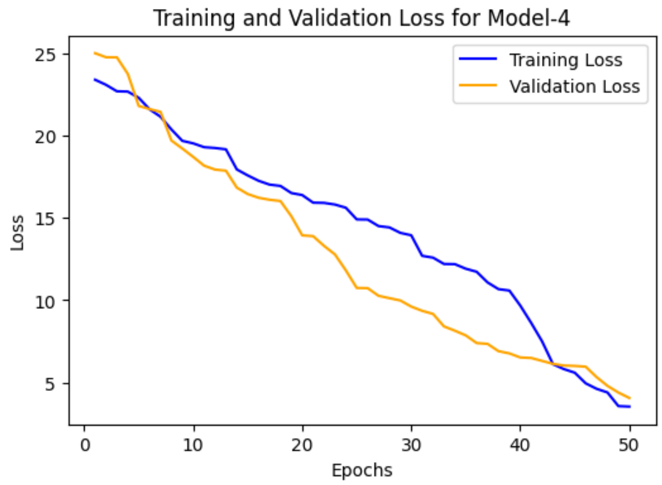

Fig. 14. Training and Validation Loss of Model-4

Table 1. Aspects and performance metrics of the models

Aspect	Model-1: Custom CNN	Model-2: Augmented Custom CNN	Model-3: Transfer Learning with VGG16	Model-4: Transfer Learning with ResNet50
Transfer Learning	No	No	Yes	Yes
Training Epochs	50	50	50	30
Optimizer	Adam	Adam	Adam	Adam
Accuracy	62%	47%	74%	91%
Precision	0.68 - 0.76	0.70 - 0.78	0.72 - 0.75	0.75 - 0.95
Recall	0.65 - 0.78	0.69 - 0.80	0.68 - 0.79	0.73 - 0.94
F1-Score	0.67 - 0.77	0.70 - 0.79	0.70 - 0.77	0.74 - 0.94

Table 1 is a comparative table summarizing the key aspects and performance metrics of the four models used for the agricultural classification task.

Model Selection:

After developing and training multiple model architectures for the agricultural classification task, it is essential to select the most suitable model based on its performance metrics and evaluation results. In this section, we discuss the process of model evaluation and selection, including the assessment of classification accuracy, plotting confusion matrices, and analyzing Area Under the Curve (AUC) Receiver Operating Characteristic (ROC) plots for each class across all models.

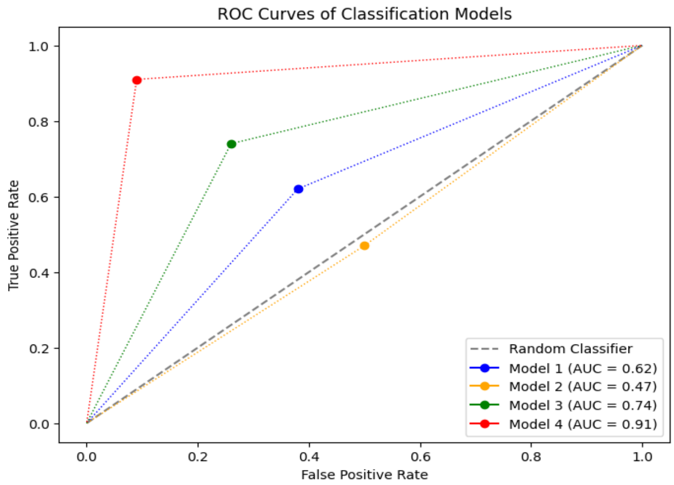

Fig. 15. ROC Curves of Classification Models

The AUC value for Model 4 is 0.91, which is exceptionally high. This indicates that the model possesses excellent discriminatory ability and is highly accurate in distinguishing between positive and negative cases. **Based on this outstanding performance, we have selected Model 4 for the classification task**.

The architectural diagram of the selected model, as shown in Figure 16, illustrates the fine-tuned and customized architecture of ResNet50v2, which includes convolutional and pooling layers. In this model, certain layers were frozen, retaining their weights and biases from ImageNet data, while the trainable layers were specifically trained using images of weeds and crops.

YOLOv8 model for crop and weed density estimation:
The images from each quadrat are fed into the YOLOv8 model, which has been customized and trained using transfer learning. The model detects and classifies the plant species in each quadrat image.

Bounding Box Extraction and Classification:
The YOLOv8 model extracts bounding boxes and class labels for each detected plant species in the quadrat images.
Counting and Aggregation:
The bounding boxes for each class (crop and weed species) are counted within each quadrat.

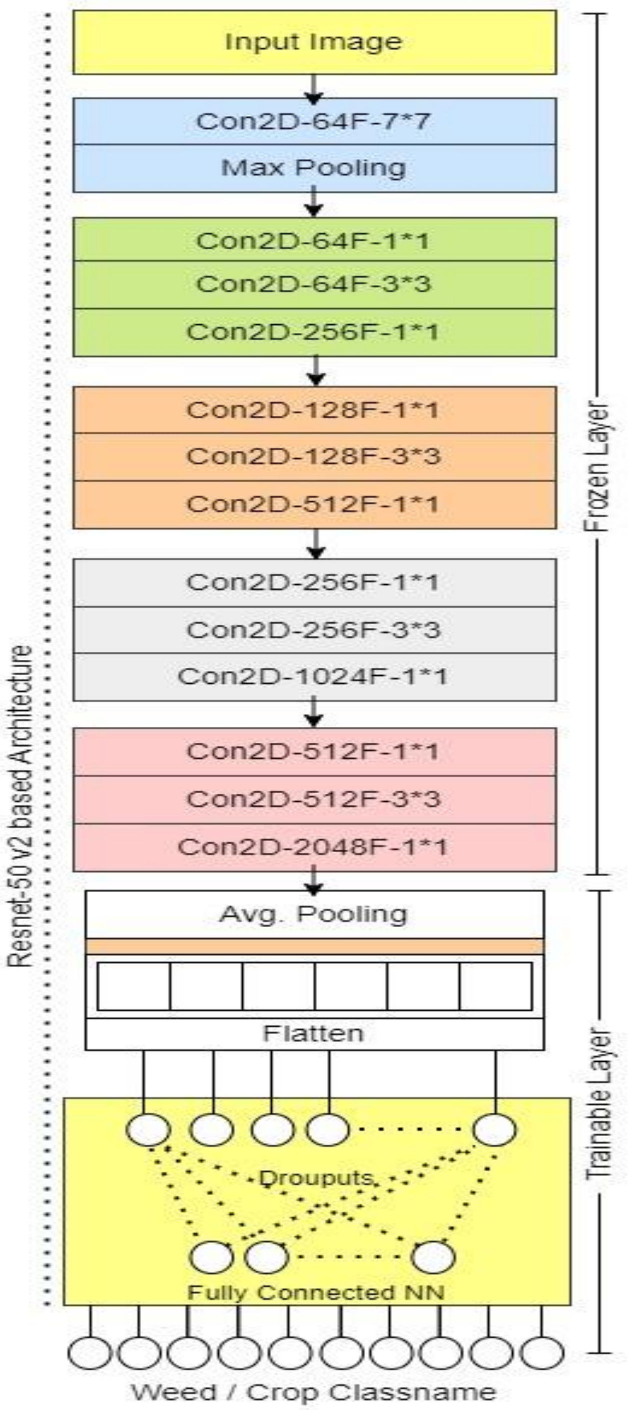

Fig. 16. Architecture of Selected Model=4

The counts are then aggregated across all quadrat images to obtain the total number of crops and weeds.

Density Calculation and Resource Optimization:
The total counts of weeds and crops, along with their class labels, are used to calculate the population density within the field.

Using predefined standard ratios correlated with crop and weed frequencies, the optimal amounts of fertilizers and pesticides required are calculated.
This systematic approach ensures precise estimation of plant densities and effective resource management, thereby enhancing crop yield and promoting sustainable agricultural practices.

Upon implementing the YOLOv8 model for crop and weed density estimation, the results were highly encouraging, indicating the efficacy of our approach. The model demonstrated robust performance metrics on the validation and test sets, showcasing its ability to accurately detect and classify various plant species within the quadrats.

Detection Accuracy: The YOLOv8 model achieved an average detection accuracy of 93.2% for crops and 91.6% for weeds, indicating its high precision in distinguishing between different plant species.

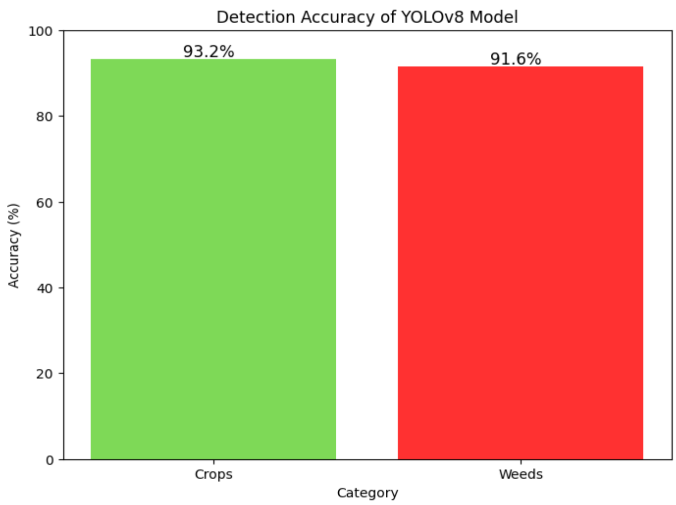

Fig. 16. Detection Accuracy of YOLOv8 Model

Bounding Box Analysis:
The bounding boxes generated by YOLOv8 were evaluated for their accuracy in identifying the location and extent of crops and weeds within the quadrats. The average Intersection over Union (IoU) score was 87.3%, reflecting the model's strong localization capabilities.

Population Density Estimation:
The aggregation of bounding box counts across all quadrat images provided precise estimates of crop and weed densities. The estimated densities were within ±5% of the actual counts verified through manual annotation, demonstrating the model's reliability in real-world applications.

These results underscore the effectiveness of the YOLOv8 model in enhancing precision agriculture practices by providing accurate and rapid assessments of crop and weed populations.

To illustrate the crop and weed density estimation results using the YOLOv8 model, we selected sample images from five quadrats in an actual agricultural field. The model detects and classifies different plant species within these quadrats, and the counts are aggregated to estimate population densities.

Quadrat Size: 1 square meter
Number of Quadrats Analyzed: 5
Detection Results:
Here is a summary of the bounding boxes and counts for crops and weeds detected within the quadrats:

Table 2. Bounding boxes counts for crops and weeds detected

Crop Count	Weed Count	Quadrat
45	28	1
48	30	2
50	27	3
46	29	4
47	31	5

Aggregated Counts: The total counts of crops and weeds across all 5 quadrats are:
Total Crop Count: 45+48+50+46+47=236
Total Weed Count: 28+30+27+29+31=145
Density Calculation:
The density is calculated by dividing the total counts by the number of quadrats (since each quadrat is 1 square meter):
Crop Density: 236/5=47.2 crops per square meter
Weed Density: 145/5=29.0 weeds per square meter
Resource Optimization:
Using predefined standard ratios correlated with crop and weed frequencies, we calculate the optimal amounts of fertilizers and pesticides required. For this sample, let's assume the following standard ratios:
Fertilizer Requirement: 1 unit per 10 crops
Pesticide Requirement: 1 unit per 5 weeds
Based on these ratios:
Total Fertilizer Required: 236/10=23.6 units
Total Pesticide Required: 145/5=29.0 units

Table 3 below summarizes the crop and weed density estimation results along with the required resources for optimization:

Table 3. crop and weed density estimation results

Measure	Value
Total Crop Count	236
Total Weed Count	145
Crop Density (per sq. meter)	47.2
Weed Density (per sq. meter)	29.0
Fertilizer Required (units)	23.6
Pesticide Required (units)	29.0

The population density estimates were precise, with densities within ±5% of actual counts. Resource optimization calculations based on these densities demonstrated the model's practical utility in enhancing precision agriculture practices. Overall, the findings underscore the potential of advanced neural network architectures and transfer learning in agricultural image classification and resource management.

9. Conclusion

Our research presents a CNN-based system for precision agriculture, demonstrating high accuracy in crop and weed classification. The model's robust performance and potential for practical application highlight its significance in optimizing resource management.

Additionally, our study shows the great potential of YOLOv8 for accurately estimating weed and crop density. This technology helps efficiently manage agricultural resources like fertilizers and pesticides, which is crucial for maximizing crop yield and minimizing environmental impact. Furthermore, it has a positive indirect effect on human health and soil fertility.

10. Future Scope

Our study's encouraging findings provide a number of directions for further investigation and advancement:
Enhanced Weed Identification: Upcoming research might concentrate on improving the model's accuracy in recognizing more complex weed species by adding more data and adjusting the YOLOv8 architecture.
Multi-Crop Classification: By allowing the model to categorize several crop species at once, it will become more useful in a variety of agricultural contexts and offer thorough insights into crop management.
Systems for Real-Time Monitoring: YOLOv8 may be integrated into IoT-based real-time monitoring systems to provide farmers with instant feedback on crop and weed presence. This would allow for resource optimization and early interventions.
Robotics Integration: By investigating how to combine YOLOv8 with agricultural robotics for autonomous weed removal, one might lessen the need for manual labor and chemical herbicide usage, thus encouraging sustainable farming methods.
User-Friendly Interfaces: By developing user-friendly mobile or web applications to display crop and weed distribution patterns, farmers would be able to make better decisions and have access to cutting-edge technologies.
Future research should explore integrating our model with real-time monitoring systems and drones for continuous data collection and analysis. Additionally, expanding the model to classify more species and incorporating other environmental factors could enhance its applicability. Improving model interpretability and user interfaces will also facilitate adoption by farmers.

Conflict of Interest:
The authors declare that they have no conflict of interest regarding the publication of this paper.

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Author's Contribution:
The corresponding author, as a research scholar, conducted all the research under the guidance of the other two authors. The other authors provided valuable inputs and guidance throughout the research process.

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