Weed identification using Image processing and Deep learning

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Abstract

The agricultural industry increasingly requires sustainable weed management techniques that surpass conventional pesticide methods. While conventional pesticides pose risks to crops and the environment, weeds remain a persistent threat. Fortunately, advancements in smart farming have led to the development of sophisticated methods for accurate weed detection, particularly through image-based approaches using deep learning algorithms. This paper proposes a new method in a contrary way, which combines deep learning and image processing technology. Data was collected from different sources and processed to cover different types of weeds and crops. Model propose includes identification of different weeds and corps, image processing and segmentation methodologies using OpenCV, and the application of Convolutional Neural Networks (CNNs). The proposal reports significant advancements using MobileNetV3_Small which achieved exceptional results, 99.38% accuracy, 0.256 loss, 98.99% precision, 99.76% recall rates, and 99.48% f1score emphasizing the potential of deep learning models in revolutionizing automated weed management systems.

Keywords: Sustainable Weed Management, Deep Learning Algorithms, Image Processing, Convolutional Neural Networks (CNNs), Automated Weed Management Systems.

1. **Introduction**

Vegetable is considered one of the most nutrient-dense food all around the world due to its sufficient vitamins, minerals and antioxidants. Raising living standards boosts the consumption of green vegetables, which makes them a substantial part of our lives and possess great commercial value. Weeds compete with vegetables for water, sunlight and nutrients, leaving them prone to insect and disease infestation [1], [2]. The yield of vegetables decreased by 45%-95% in the case of weed-vegetable competition [3]. Excessive use of chemical herbicides results in over-application in areas of low or no weed infestation and causes environmental impacts including soil and ground water pollution [4]. Moreover, organic production of vegetables requires non-chemical weed control. Thus, hand weeding is still the primary option for weed control in vegetable plantation at present [5]. With the labor cost substantially increased, development of a visual method of discriminating between vegetable and weed is an important and necessary step towards ecologically sustainable weed management.

Sustainable management [6] is a comprehensive approach aimed at meeting the needs of the present without compromising the ability of future generations to meet their own needs. It emphasizes not only boosting income and productivity but also promoting equitable distribution of resources and opportunities. In this context, artificial intelligence (AI) plays a pivotal role by optimizing resource allocation, enhancing productivity through automation [7], and enabling new forms of economic activity, such as precision agriculture.

Artificial intelligence is a transformative tool that enhances the effectiveness of sustainable development initiatives across all these pillars. Its capacity to analyze vast amounts of data, generate actionable insights, and automate complex tasks makes AI indispensable for driving sustainable practices. For instance, AI algorithms can optimize supply chains [7], reduce waste, and improve the efficiency of production processes, leading to cost savings and increased profitability [6]. Additionally, AI fosters innovation by enabling new technologies and business models, such as precision farming techniques that enhance productivity while minimizing environmental impact. In terms of social inclusion, AI improves access to essential services like healthcare and education by providing scalable, personalized solutions that can reach underserved populations. It also helps ensure equitable resource distribution by analyzing demographic and socio-economic data to identify disparities and recommend targeted interventions [7]. For environmental protection, AI facilitates detailed monitoring of environmental parameters, enabling real-time detection and response to pollution and resource depletion. It also supports the implementation of sustainable practices, such as optimizing energy use in buildings, reducing emissions in transportation, and enhancing agricultural sustainability [6]. Within agriculture, weed management poses a critical challenge that demands precise intervention to maximize crop yields [1],[2]. Traditional weed control methods, which rely heavily on extensive chemical herbicide use, have significant environmental and economic drawbacks [4]. Overuse of chemicals degrades soil health, increases production costs, and can harm non-target species.

The main objective of this research is to develop a weed identification algorithm based on deep learning and image processing for robotic weed removal in vegetable plantations. The specific objectives were to

- Extract and segment vegetation, in this case, weeds by image processing utilizing color filter.
- Train a model using a deep learning approach that capable of detecting the bounding boxes of vegetables and weeds.

Paper organization starts with a review of the existing literature on weed detection using machine vision techniques. Following the literature review, the proposed model is presented in detail. Subsequently, the results obtained from the experiments are discussed. The study concludes with a discussion of the findings and a comprehensive list of references.

2. Literature Review

In contemporary agriculture, effective weed detection and management are crucial for optimizing crop yields and reducing labor costs. Advances in technology and machine learning have paved the way for innovative approaches in this domain. This section provides a detailed examination of notable studies that have explored various methodologies and their findings in weed detection, setting the stage for the current research.

Herrera et al. [8] proposed method achieves a classification accuracy of 92% using a dataset comprising 66 outdoor field images captured by an RGB camera. By utilizing shape descriptors such as Hu moments and geometric shape descriptors, the approach effectively distinguishes between monocot and dicot weeds. This methodology is pivotal in precision agriculture for optimizing herbicide application, as it enables targeted treatment based on weed species. However, the method's applicability may face challenges due to varying lighting conditions, occlusions, and the complexity of discriminating between overlapping or differently grown weed species. Further validation and adaptation under diverse field conditions are essential to ascertain its robustness and scalability in practical agricultural applications.

Jialin Yu et al. [9] delves into the use of VGGNet and DetectNet, two types of deep convolutional neural networks (DCNNs), for precise weed management in perennial ryegrass. VGGNet was found to be highly effective, achieving notable recall and F1 scores in identifying specific weed species. The researchers employed a combination of object detection DCNN and single- and multiple-species neural networks for training. They evaluated the results using metrics such as Matthew’s correlation coefficient (MCC), recall, precision, and F1 score. The study also explored the integration of DCNN in smart sprayer machine vision systems for object identification and categorization. However, the study was limited by an uneven training dataset, a small geographic training image set, and the need for a larger and more diverse training dataset. The report also highlighted research gaps, including the need for larger neural networks to cover a wider range of weed species, exploration of the effect of the ratio of negative to positive images on neural network performance, the limited geographical diversity in the current training dataset, and the potential benefits of pixel-wise semantic segmentation for accuracy improvement. The authors also noted that there were no business or financial ties.

M. Vaidhehi et al. [10] proposes a deep learning model for accurately segmenting weeds in paddy fields. The model uses Regional Convolutional Neural Networks (R-CNN) and real-time data from agricultural regions to emphasize the importance of weed removal. The R-CNN model uses a specific architecture for determining the bounding box and deep convolutional layers for extracting features. The process includes preprocessing, segmentation, and dataset collection. The performance evaluation shows an accuracy of 83.33%, which is better than current methods. However, certain limitations need to be addressed, and more research is required in this area to improve weed growth prediction, crop-weed discrimination, and detection techniques.

Xiaojun Jin et al. [11] main goal is to develop a reliable robotic system for removing weeds from vegetable farms using deep learning and image processing. The proposed solution utilizes color index-based segmentation for weed removal and a trained CenterNet model for vegetable detection. This solution has achieved a 0.953% F1 score, a recall of 95.0%, and a precision of 95.6%. Color index segmentation is more efficient and less computationally demanding than ExG index segmentation. However, the research has identified several limitations, such as the need for further investigation into plant identification in in-situ recordings, and the algorithm's inability to detect certain weed species due to occlusion. The model's estimated accuracy rate is 95%. The study has highlighted some gaps in the literature, such as the lack of prior research on weed identification in vegetable plantations, the challenges of dealing with weed mixing and random plant spacing during harvesting, the necessity for a visual weed identification method for sustainable management, and the potential use of robotic weeding. However, the algorithm is not suitable for organic vegetables and does not account for the adverse effects of excessive chemical herbicide use on the ecosystem.

A.Subeesh et al. [12] A study was conducted to assess how effectively deep learning techniques could identify weeds in bell pepper fields, to improve weed control precision and automate agricultural processes. The study found that the InceptionV3 model outperformed other models, such as AlexNet, GoogLeNet, and Xception when analyzing RGB photos from a playhouse. The research involved gathering data, preprocessing, augmenting data, and building training, testing, and validation sets. The model's performance was evaluated using accuracy, precision, and recall metrics. InceptionV3 achieved an impressive 97.7% accuracy after 30 epochs and 16 batches. The study identified research gaps and emphasized the need for further investigation and development of automation and digitization methods for weed identification in farming environments. It also suggested that improvements in deep learning models could enhance the effectiveness and precision of weed identification.

Table 1: Summary of Literature Review

Study	**Date**	**Limitations**	**classes**	**model**	**Accuracy (%)**
Herrera et al. [8]	2014	Small dataset and limited number of weeds only 66 images for each class	2(Weeds, Crops)	Shape descriptors and Fuzzy Decision-Making	92%
Jialin Yu et al. [9]	2019	Uneven training dataset, limited geographic diversity, need for larger neural networks	3 (Weeds, Crops, Soil)	VGGNet, DetectNet	92.9
M. Vaidhehi & C. Malathy [10]	2021	Specific research gaps or limitations not mentioned in the summary.	2 (Weed, No Weed)	Regional Convolutional Neural Networks (R-CNN)	83.33
Xiaojun Jin et al. [11]	2021	Limitations include plant identification in in-situ recordings, inability to detect certain weed species due to occlusion	2 (Weed, No Weed)	CenterNet	95
A. Subeesh et al. [12]	2022	Gaps in automation and digitization for weed identification in farming environments.	2 (Weed, No Weed)	InceptionV3	97.7

The table highlights several limitations in previous studies on weed detection. Herrera et al. (2014) faced constraints due to a small dataset with only 66 images per class. Jialin Yu et al. (2019) dealt with an uneven training dataset and limited geographic diversity, necessitating larger neural networks. M. Vaidhehi & C. Malathy (2021) did not specify research gaps or limitations in their summary. Xiaojun Jin et al. (2021) encountered difficulties in plant identification during in-situ recordings and had trouble detecting certain weed species due to occlusion. A. Subeesh et al. (2022) noted gaps in automation and digitization for weed identification in farming environments.

3. Proposed Model

The proposed model outlines a detailed framework for an automated system designed to identify and spray weeds using an unmanned vehicle equipped with a camera and spraying mechanism. This system aims to enhance precision agriculture by specifically targeting weeds, thereby reducing herbicide usage and promoting efficient weed management. Below is a step-by-step explanation of the model.

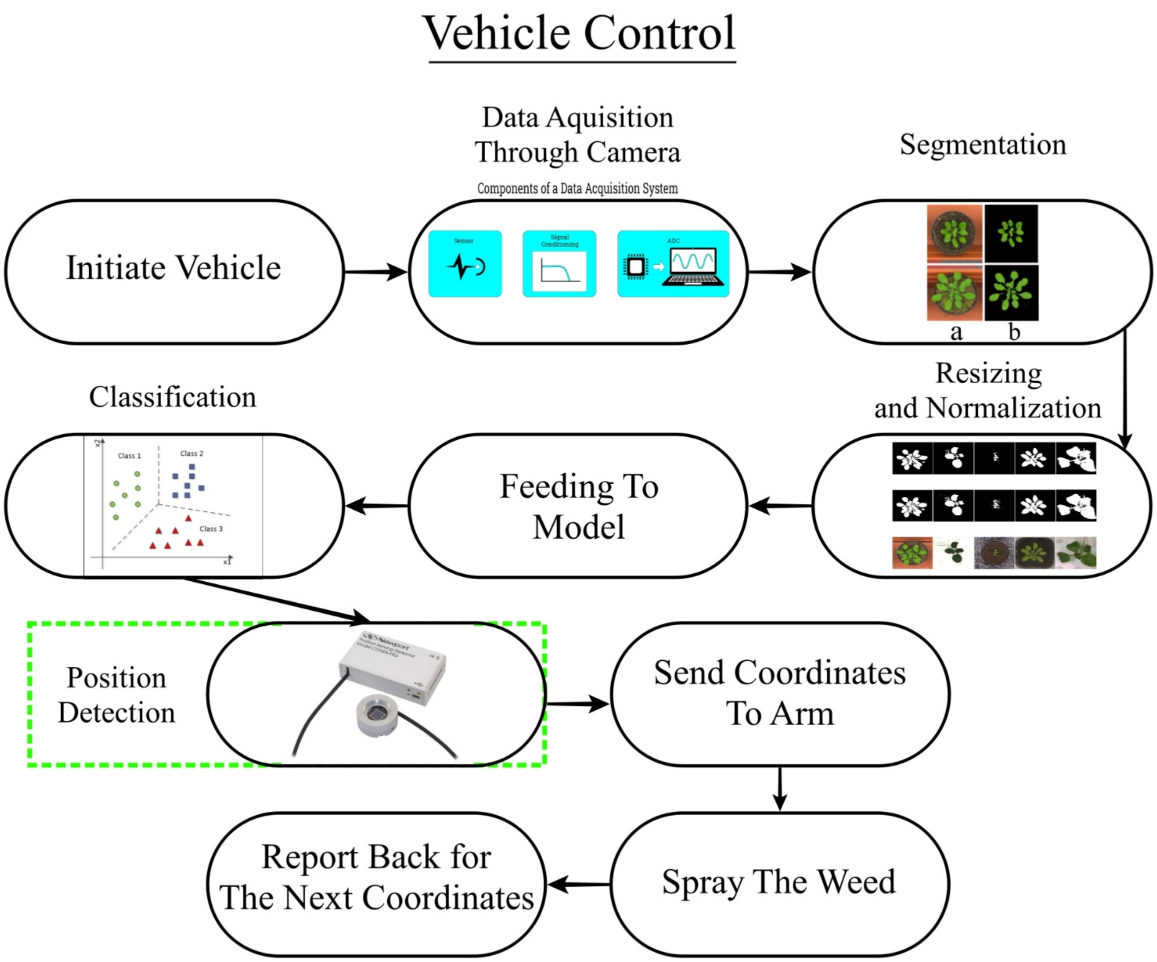


FIGURE 1. Flow diagram for proposed weed detection methodology.

i. **Initiate Vehicle:**
The process begins with the initiation of the vehicle's system, either manually by an operator or autonomously, to start its operation in the field. This step involves setting up the necessary operational parameters and ensuring all systems are functional and ready for data acquisition.

ii. **Data Acquisition through Camera:**
The vehicle captures real-time images of the field using onboard cameras. These images serve as the primary data source for detecting weeds. The

camera system is designed to cover the area efficiently, ensuring comprehensive image acquisition for subsequent processing steps.

iii. **Segmentation:**
The captured images are processed to segment the field into distinct regions. Segmentation isolates areas of interest, such as plant rows, soil, and potential weeds, simplifying the data by breaking down the image into manageable sections for further analysis.

iv. **Resizing and Normalization:**
The segmented images are resized and normalized to standard dimensions and intensity values. Resizing adjusts the images to a consistent size, while normalization scales the pixel values to a uniform range. This preprocessing step ensures the data is in an optimal format for feeding into the machine learning model.

v. **Feeding to Model:**
The preprocessed images are fed into a pre-trained machine-learning model. Typically, a convolutional neural network (CNN) is used to analyze the images and perform complex pattern recognition tasks to identify and classify different elements within the image.

vi. **Classification:**
The model evaluates the processed images and identifies various objects within them, distinguishing between crops and weeds. The classification output includes labels for each detected object, enabling the system to understand which areas contain weeds that require treatment.

vii. **Position Detection:**
After classification, the system determines the precise coordinates of the detected weeds within the field. Position detection is crucial for guiding the vehicle's arm to the exact location where spraying is needed. Accurate positioning ensures the targeted application of herbicides.

viii. **Send Coordinates to Arm:**
The detected weed coordinates are sent to the vehicle's robotic arm, equipped with the spraying mechanism. This communication allows the arm to position itself accurately above the weed, preparing for the spraying action.

ix. **Spray the Weed:**
Upon receiving the coordinates, the robotic arm deploys the spray mechanism to apply herbicide directly onto the identified weed. This precise spraying minimizes herbicide usage and ensures that only the targeted weed is treated, reducing environmental impact and cost.

x. **Report Back for the Next Coordinates:**
After spraying the weed, the system reports back to the main control unit, indicating the completion of the task. This step involves updating the system's log and preparing to acquire data for the next set of coordinates, allowing continuous operation and efficiency in the field.

xi. **Vehicle Control:**

The overall operation of the vehicle is controlled by a central system that coordinates the various steps. Vehicle control encompasses navigation, adjusting speed, and ensuring that the vehicle covers the designated area effectively. This control loop ensures seamless integration between data acquisition and operational execution.

The methodology section details the design and implementation of the proposed model. It is divided into two main parts: Software and Hardware.

3.1. Software

The approach proposed in this research for the identification of weeds is composed of two stages. The first stage is to Process, extract and segment vegetation using OpenCV (CV), in this case, weeds and corps by image processing utilizing color feature. After having clean images for corps, second stage is to train a model using MobileNetV3_Small that will be capable classification of vegetables and weeds efficiently and accurately.

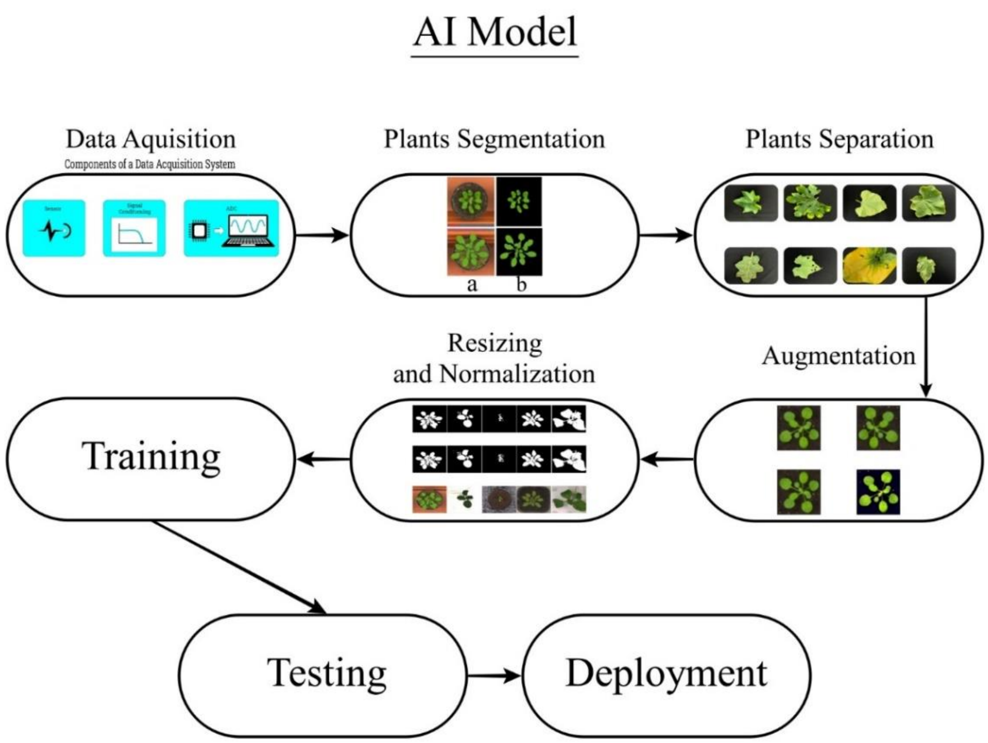


FIGURE 2. Flow diagram for AI model

i. **Data Acquisition and Description**

To detect the presence of weeds in the farmland, a process known as weed identification and detection is used. A collection of different types of weeds and plants is gathered from different sources. Data is structured in the form of folder containing 12 folders (12 classes) each folder have images of the contained class.

Table 2: Summary of gathered Data for crops & weeds

Name	Arabic Name	Type	Number of images	Sources
Cotton	قطن	Crop	3658	[13],[14],[15],[16]
Sesame	سمسم	Crop	1092	[17]
Wheat	قمح	Crop	180	[20]
Sugar beet	بنجر	Crop	642	[20],[21],[22]
Tomato	طماطم	Crop	214	[16], [23],[24]
Corn	ذره	Crop	1016	[17],[18],[19]
Convolvulus Arvensis	العليق	Weed	831	[14],[15], [16]
Euphorbia	ام اللبن	Weed	3882	[28]
Grass	النجيل	Weed	2464	[29]
Lolium multiflorum	الصامة	Weed	2053	[25], [26]
Nutgrass	السعد	Weed	1460	[14], [29]
Purslane	الرجله	Weed	693	[29],[30]

ii. Data Preprocessing and Segmentation

Images are filtered using OpenCV to isolate plants and weeds from the background and crop the image to saturate the image with the plant. Images are then preprocessed by resizing and reshaping to 224x224x3 to get better training efficiency and normalized by dividing them by 255 as shown in FIGURE 3 for demonstration.

FIGURE 3. Before and after Segmentation

iii. Data Augmentation

To balance the data, offline data augmentation techniques are employed, including horizontal flipping, rotation, brightness, contrast, gamma correction, random cropping, and adjustments to hue and saturation values to ensure uniform image distribution across all classes and enhance generalization example in Figure 4.

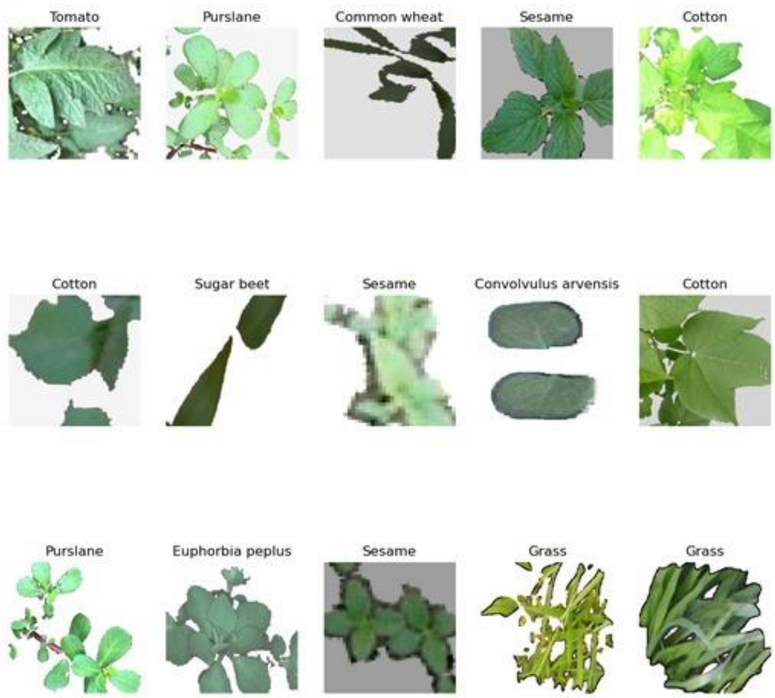


FIGURE 4. Random batch example after augmentation

In summary, data augmentation serves as a critical step in the model training pipeline, transforming a limited and potentially biased dataset into a more comprehensive and balanced representation of the field. This process is crucial for developing a robust weed detection system capable of performing consistently in the varied and dynamic conditions encountered in real-world agricultural applications.

Data augmentation not only increases the dataset size but also enhances its diversity and balance. By fixing the number of images per class to 3,000 presented in Figure 5 and Figure 6, we ensure that our model is trained on an evenly distributed and rich dataset, better preparing it to handle the varied conditions it will encounter in real-world applications.

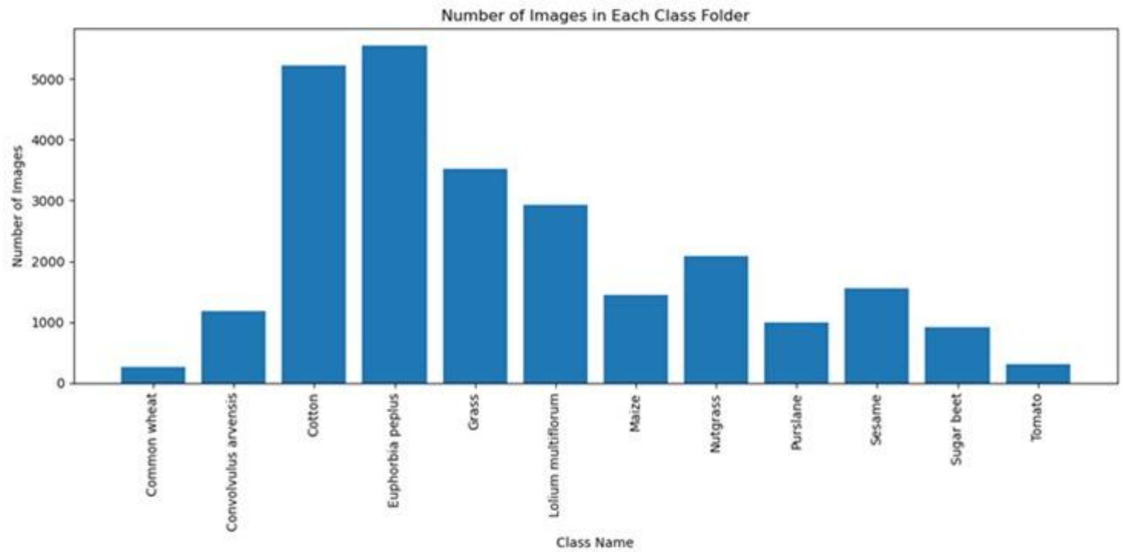


FIGURE 5. Summary for dataset before augmentation

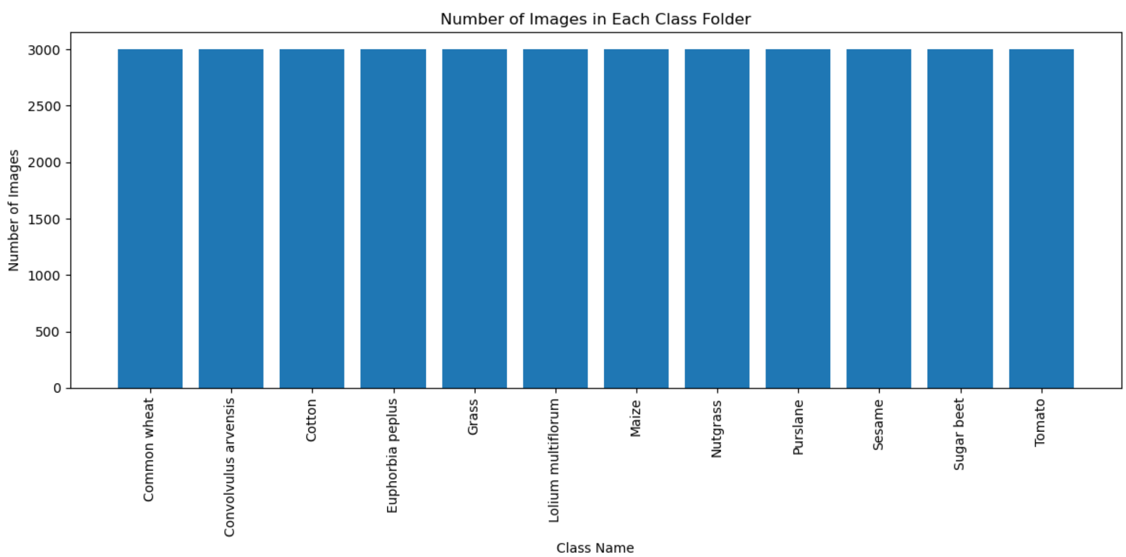


FIGURE 6. Summary for dataset after augmentation

iv. Training and Testing

MobileNetV3_Small is a highly efficient convolutional neural network (CNN) architecture that has been specifically optimized for low-latency and resource-constrained environments, such as mobile and embedded devices. Introduced as part of the MobileNetV3 family, this architecture combines advances from both Neural Architecture Search (NAS) and network pruning to achieve a delicate balance between high performance and low computational cost. This makes MobileNetV3 Small particularly well-suited for tasks that require image classification and object detection on devices with limited hardware capabilities, such as smartphones and IoT devices.

One of the standout features of MobileNetV3 Small is its ability to achieve remarkable performance metrics despite its compact size. The model leverages the Adam optimizer, which is known for its efficiency and effectiveness in training deep learning models and employs batch size of 32, a learning rate of 0.0001 the SoftMax activation function for the final classification layer. This model was further customized to identify 12 different classes, making it versatile for a range of applications.

During the training process, the model was equipped with an early stopping criterion, which helps to prevent overfitting by stopping the training once the performance ceases to improve on a validation set. This approach not only ensures optimal performance but also saves computational resources. In our experiments, the best results were achieved after 35 epochs of training, demonstrating the model's efficiency and effectiveness in learning from the data.

MobileNetV3_Small recorded an accuracy of 99.7%, with a minimal training loss of 0.000154. Additionally, the model achieved a validation accuracy of 99.38% and a validation loss of 0.0256, 98.99% precision, 99.76% recall rates, and 99.48% f1score indicating its robustness in detecting weeds and crops within farmland environments. Despite these promising results, further research is necessary to fully validate the model's effectiveness. This includes testing its capabilities on higher-quality, more professional datasets and under a variety of lighting conditions. Such investigations are crucial to ensure that the MobileNetV3_small model can be reliably applied in diverse and dynamic agricultural settings, thereby enhancing its practical utility and confirming its potential for widespread use.

3.2. Hardware

Deploying a Deep Learning model for weed detection and spraying requires multiple components to work together in real-time. In the pursuit of advancing precision agriculture, the integration of sophisticated hardware components is crucial to complement the capabilities of our software algorithms. The hardware elements are essential for executing the practical tasks of weed detection and management, enabling the system to function autonomously and efficiently in real-world agricultural settings. This section provides an overview of the key hardware components that underpin the functionality of our weed detection and spraying model:

i. **Arduino Microcontroller:**
The Arduino microcontroller serves as the central control unit of the system. It coordinates the operations of all other hardware components, processing inputs from sensors and executing control commands for the actuators. Arduino's versatility, ease of programming, and real-time processing capabilities makes it an ideal choice for managing the system's hardware interactions. It ensures responsive control of the spray pump, movement of the CNC framework, and communication with external devices.

ii. **Bluetooth Module:**
The Bluetooth module facilitates wireless communication between the Arduino and other devices, such as a mobile phone or laptop. This connectivity allows for remote monitoring and control of the system, providing farmers with the flexibility to adjust settings and manage operations without direct physical intervention. The Bluetooth interface enhances the user-friendliness of the system, enabling real-time updates and control adjustments through a mobile application.

iii. **Mobile Phone:**
The mobile phone acts as both a user interface and a supplementary processing unit. It connects to the Arduino via the Bluetooth module and allows the user to monitor system status, adjust parameters, and manually control the system when necessary. Additionally, the phone can be used to capture images of the field, which are then transmitted to the laptop for further computation. This integration extends the system's capabilities, allowing for more complex processing and control tasks to be handled efficiently.

iv. **Spray Pump with 3D Printed Nozzle**
A precision spray pump is employed to deliver herbicides directly to the targeted weeds. The nozzle of the spray pump is custom-designed, and 3D printed to ensure optimal spray patterns and minimize chemical waste. Controlled by the Arduino, the pump precisely dispenses herbicides onto the detected weeds, significantly reducing the overall usage of chemicals and their environmental impact. The design and operation of the spray pump are crucial for achieving precise and efficient weed control.

v. **CNC Build Framework (X and Y Axis)**
The CNC (Computer Numerical Control) build framework provides a robust and precise platform for mounting the spray pump and other components. It allows for accurate movement along the X and Y axes, facilitating precise

targeting of weeds (58). The CNC framework is essential for the system's ability to navigate the field and position the spray nozzle accurately over the weeds, ensuring effective and localized herbicide application.

vi. **DC Motors for Movement**

DC motors drive the movement of the CNC framework and other movable components. These motors are controlled by the Arduino to provide precise and adjustable movements necessary for the system to navigate the field and position the spray pump accurately. The reliability and precision of the DC motors are vital for maintaining the system's operational accuracy and efficiency, especially in varying terrain and field conditions.

vii. **Battery**

A robust battery provides the necessary power to all the system's hardware components. The battery ensures that the system can operate autonomously in the field for extended periods. Its capacity and efficiency are critical for supporting the continuous operation of the Arduino, DC motors, Bluetooth module, and other electronic components. A reliable power supply is essential for maintaining the system's functionality and performance during field operations.

viii. **Mobile Phone Connected with Laptop for Computation**

For computationally intensive tasks, such as image processing and machine learning inference, the mobile phone is connected to a laptop. The phone captures images from the field, which are then processed by the laptop to identify weeds and determine the appropriate actions. This setup leverages the computational power of the laptop to handle complex processing tasks, while the phone serves as an intermediary for data collection and communication. This distributed processing approach enhances the system's capability to handle large datasets and perform sophisticated analyses.

ix. **System Integration and Functionality**

The integration of these hardware components with the software algorithms creates a cohesive and efficient system for precision weed management. The Arduino microcontroller acts as the central hub, orchestrating the activities of all hardware components based on inputs from the software. The system captures real-time data from the field, processes it through advanced algorithms, and executes precise weed detection and spraying actions. This seamless integration ensures that the system operates autonomously and adapts to real-time conditions, significantly improving the efficiency and effectiveness of weed management practices.

The careful selection and integration of hardware components are fundamental to the successful implementation of our weed detection and spraying system. Each component plays a critical role in ensuring the system's precision, efficiency, and reliability, ultimately contributing to more sustainable and productive agricultural practices. This comprehensive hardware setup not only supports the sophisticated functionalities required for precision agriculture but also lays the foundation for future advancements and scalability of the system.

4. Results and discussion

The performance of the proposed MobileNetV3_Small model was benchmarked against several other deep learning architectures commonly used for image classification tasks. MobileNetV3_Small outperformed other models in terms of accuracy and computational efficiency. For instance, it achieved an accuracy of 99.7% with a minimal training loss of 0.000154. In contrast, other models such as ResNet101v2, EfficientNet-B0, and VGG16 in table 3 and table 1 exhibited either lower accuracy or higher computational requirements, highlighting MobileNetV3_Small's suitability for real-time applications in precision agriculture.

The evaluation of the proposed weed detection model, which leverages MobileNetV3_Small, involved extensive experiments to validate its accuracy, efficiency, and robustness. The experiments were conducted using a diverse dataset, consisting of various weed and crop images, preprocessed and augmented to enhance model training. The following subsections provide a comprehensive analysis of the model's performance metrics and the outcomes of different experimental setups.

To evaluate the performance of the MobileNetV3_Small model, several key metrics were utilized, including accuracy, loss, precision, recall, and the F1 score. Accuracy (A) refers to the ratio of correctly predicted instances to the total instances, defined as

$$A = \frac{\text{Number of Correct Predictions}}{\text{Total Number of Predictions}}$$

Loss (L) measures the model's prediction error and is calculated using the formula

$$L = -\sum_{i=1}^{N} y_i \log(\hat{y}_i)$$

where yi is the true label and y^i is the predicted probability for the i'th instance. Precision (P) is the ratio of true positive predictions to the total predicted positives, given by

$$P = \frac{TP}{TP+FP}$$

where TP is the number of true positives and FP is the number of false positives. Recall (R) is the ratio of true positive predictions to the total actual positives, calculated as

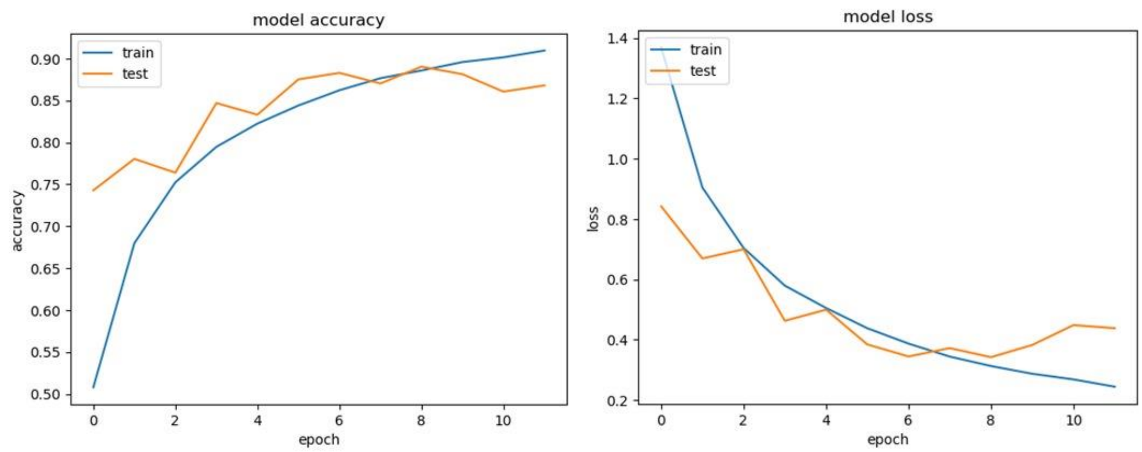
$$R = \frac{TP}{TP+FN}$$

where FN is the number of false negatives. The F1 score (F1) is the harmonic mean of precision and recall, defined as

$$F1 = 2 \cdot \frac{P \cdot R}{P+R}$$

The experiments were conducted in a controlled environment, using the dataset described in the "Data Acquisition and Description" section. The dataset was divided into training, validation, and test sets in a 70/20/10 ratio. Each model was trained using a batch size of 32, a learning rate of 0.0001, the SoftMax activation function, and the Adam optimizer. Early stopping with a patience of five epochs was used to prevent overfitting, and the best model from each epoch was saved based on validation accuracy.

Model Performance the MobileNetV3_Small model demonstrated exceptional performance across all key metrics. With a validation accuracy of 99.38% and a validation loss of 0.0256, it outperformed several more computationally expensive models, such as ResNet101v2 and VGG16, in terms of efficiency and speed. The precision of 98.99%, recall of 99.76%, and F1 of 99.48% underscore its robustness in detecting weeds and crops accurately.



Comparative Analysis MobileNetV3_Small's high performance is notable given its relatively low computational cost, making it an ideal candidate for deployment in resource-constrained environments. While models like ResNet101v2 and VGG16 achieved high accuracy, their substantial computational demands make them less practical for real-time applications in the field.

Error Analysis Despite the high performance, some errors were observed primarily due to factors such as occlusion, where weeds partially covered by crops led to occasional misclassification. Lighting variations also affected the model's accuracy, although augmentation techniques helped mitigate this issue to some extent. Additionally, certain weeds and crops with similar visual characteristics posed challenges for precise classification. Further refinement of the model and the inclusion of additional training data under diverse conditions can help address these issues.

Experiments

To achieve efficiency triaining more than one model to reach the best accuracy for computation requirements. The parameters for all models' training are the same: batch size 32, learning rate of 0.0001, activation function SoftMax, and optimizer Adam. After reaching the best model, we adjust parameters to achieve optimal values. We save the better model only at each epoch and use early stopping with a patience of 5 epochs. EfficientNet-B0 only modified the output layer to 15 classes. The overall model performance is acceptable but did not perform well using transfer learning, and the best results were achieved when all layers were trained. MobileNetV3_large only modified the output layer to 15 classes. The overall model was slightly better in generalization but was computationally more expensive than EfficientNet-B0. MobileNetV3_small only modified the output layer to 15 classes.

Model performance was slightly less than EfficientNet and MobileNetV3_large by a small margin, but it was very efficient, using only 1.54 million parameters and achieving very satisfying results. The ResNet101v2 model had its last layer removed and eight new layers added to tune the model for application purposes. The model was very computationally expensive and did not perform well in both training with all parameters and freezing part of it. VGG16 modified the pre-trained model's last layer and added six new layers to start training and retrained only the new layers and the complete model. The model performance was very good in generalization and can be used if the vehicle is powered with better hardware for heavy use.

TABLE 3: Summary of model experiments

Name	FLOPS X million	Parameters X million	Train acc/ loss	Val acc/ loss
Mobilenetv3_large	27.03	4.02	99.8 0.000139	99.69 0.0199
Mobilenetv3_small	233.57	4.22	99.6 0.000154	99.38 0.0256
Resnet101v2	7866.50	44.61	98.7 0.0628	98.77 1.6311
EffiecentNet b-0	61.47	1.53	99.7 0.0000703	99 0.0486
Vgg16	15365.58	33.65	99.4 0.0628	99.43 0.0402

In this study, MobileNetV3_Small model demonstrated exceptional effectiveness, achieving outstanding performance metrics. It achieved a remarkable accuracy of 99.7%, coupled with a notably low training loss of 0.000154. In addition, the model recorded a validation accuracy of 99.38% and a validation loss of 0.0256, underscoring its robustness in accurately detecting weeds and crops within agricultural fields.

However, despite these impressive results, further research is imperative to comprehensively validate the model's capabilities. This should involve rigorous testing on higher-quality, more diverse datasets and under varying lighting conditions. Such studies are essential to ascertain the model's reliability and effectiveness across different and dynamic agricultural environments. Ensuring these evaluations will enhance the practical applicability of the MobileNetV3_small model and confirm its potential for broad-scale implementation in precision agriculture.

5. Conclusion

In this paper, we have presented a comprehensive framework for precision weed management in agricultural ecosystems, leveraging advanced technologies in plant imaging, machine learning, and hardware integration. The proposed model addresses significant challenges posed by weeds in agriculture, offering innovative solutions that enhance environmental sustainability, crop health, and economic efficiency. Through the development and evaluation of our software components, particularly the MobileNetV3_small model, we demonstrated exceptional accuracy and robustness in detecting weeds and crops within farmland environments. Achieving a remarkable accuracy of 99.7% highlights the efficacy of our approach in minimizing the reliance on indiscriminate spraying methods, thereby reducing chemical usage and environmental impact. Furthermore, the integration of sophisticated hardware components such as the Arduino microcontroller, Bluetooth module, precision spray pump, and CNC build framework ensures precise and efficient weed detection and management. These components enable autonomous operation and real-time data processing, enhancing the system's adaptability to diverse agricultural settings and optimizing herbicide application. Despite the successes observed, challenges remain in optimizing weed detection across varying environmental conditions and enhancing the scalability of the system. Future research should focus on expanding the model's capabilities through rigorous testing on diverse datasets and integrating adaptive algorithms for dynamic field conditions. In conclusion, our integrated approach represents a significant advancement in weed management practices, promising sustainable agricultural solutions that promote environmental stewardship, improve crop productivity, and support the economic viability of farming operations. By harnessing the power of technology and innovation, we aim to empower farmers with effective tools to mitigate the challenges posed by weeds, fostering a more resilient and productive agricultural sector.

6. Future Directions

There are several potential future directions for further research and development in the area weed detection:

Larger and more diverse datasets: While the current dataset used in this study is a good starting point, larger and more diverse datasets could help improve the performance of the model. This could include incorporating data from multiple farms, as well as incorporating images from different types of cameras.

Improving preprocessing techniques: While the current study used several offline data augmentation methods, there may be other techniques that could further improve the performance of the model. For example, using online data augmentation techniques during training could help the model better generalize to new data.

Exploring different architectures: While the MobileNetv3_Small and custom architectures used in this study were effective, there may be other architectures that could perform even better.

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