Swarm Optimization Enhanced Convolutional Neural Network for Early Stage Weed Detection in Farmland Imagery

Hossein Bahrani
KU College of Computing & Mathematical Sciences
Khalifa University
Abu Dhabi, UAE
&
Sebti Abu-Rukba
Dept. Computer Science,
University of Sharjah
UAE

ABSTRACT

Early-stage weed detection in farmland imagery plays a critical role in precision agriculture, helping minimize herbicide usage and maximize crop productivity. CNNs have shown potential in this domain, but their performance heavily depends on optimal configuration of hyperparameters and feature selection. However, conventional CNN models often struggle with overfitting, high computational cost, and suboptimal accuracy due to manual or heuristic tuning of parameters. These limitations hinder their reliability in complex field environments where weed and crop appearances vary significantly. To address these issues, we propose an **Integrated Particle Swarm Optimization with Convolutional Neural Network (I-PSO-CNN)** framework. This method leverages the global search capability of PSO to autonomously fine-tune CNN hyperparameters, including learning rate, number of filters, and convolutional kernel size, thereby improving feature learning and generalization. The optimized model is applied for real-time detection and classification of early-stage weeds in Unmanned Aerial Vehicles (UAV)-acquired farmland imagery. This allows for accurate weed mapping and facilitates targeted herbicide application. Experimental results demonstrate that the I-PSO-CNN model outperforms traditional CNNs in terms of detection accuracy, training efficiency, and robustness to image variations, making it suitable for large-scale agricultural deployments.

Keywords: Weed Detection, Precision Agriculture, Convolutional Neural Network, Particle Swarm Optimization, UAV Imagery, Smart Farming.

1. Introduction

Weed infestation is a serious issue in agriculture because it can affect crop yields, soil fertility, and total farm productive [1]. During the early growth stages of crops, weeds will vigorously compete for the above resources. The early growth stages of weeds are crucial for the timely and accurate detection of weeds to determine if and when to act to minimize damage [2]. Manual methods of weed identification are time-consuming, labor-intensive, and prone to human error while operating on a large scale. Because of these issues, the development of automated, intelligent weed detection systems remains a critical research and development focus for precision agriculture [3].

Recent research in artificial intelligence (AI), specifically in data-driven, deep learning techniques; has shown promise for image-based plant analysis. CNNs have emerged as the most popular architecture used for image recognition tasks due to their inherent ability to learn hierarchical features directly from raw pixels [4]. CNNs have also been successfully applied in several agricultural areas, including plant disease identification, crop classification, and phenotyping. However, the performance of CNNs is highly sensitive to choices made in architectural design, as well as hyperparameter specifications inside a chosen architecture [5]. Managing the hyperparameter specifications manually to tune these parameters is not only computationally expensive, but it is also marginally useful for guaranteeing global optimality, particularly in most situations with high-dimensional, heterogeneous data in the agriculture space.

During early-stage weed detection, CNNs encounter additional challenges to weed detection. A weed and a crop species often share many similar characteristics and attributes early during growth, thus leading to high inter-class similarity [6]. Environmental and imaging-specific environment parameters such as lighting, occlusion and out-of-field background variability can also draw further complexities into accurate classification. Therefore, even though specific weed detection can be done at various ranges of Cayley distances, the continuous optimization procedure can provide specific detection configuration decisions with corresponding learning parameter specificities, thus promoting improved detection performance while extracting additional levels of robustness and reliability [7].

A possible option would be to combine evolutionary algorithms with deep learning models. PSO is a population-based metaheuristic inspired by the social behavior of birds flocking or fish schooling. This optimization method is proven to be a highly capable method for global optimization [8]. This paper proposes an I-PSO-CNN framework specifically tailored for early-stage weed detection in farmland imagery. The proposed methodology leverages the strength of PSO to enhance the learning capability of CNNs by guiding the network toward optimal parameter configurations. The system is trained and validated on a dataset of drone-acquired farmland images, annotated for weed and crop classification. The optimized model enables real-time detection of weeds, allowing for early intervention through targeted herbicide application or mechanical removal, which contributes significantly to sustainable farming practices and environmental conservation [9].

Moreover, the integration of PSO with CNN enhances the scalability and generalization ability of the model, making it suitable for deployment in diverse field conditions and crop types [10]. The proposed I-PSO-CNN framework demonstrates improved performance metrics compared to conventional CNN approaches, validating its effectiveness for smart agriculture applications. This paper aims to advance the field of automated weed detection by bridging the gap between AI-based optimization and real-world agricultural challenges. The paper aims to assist the field of automated weed detection, which could enhance AI-based optimization and real-world agriculture challenges.

Motivation: The motivation is to develop an accurate, efficient, and automated weed detection system using PSO-enhanced CNNs to enable early intervention, reduce herbicide use, and support sustainable precision agriculture.

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The main contribution of this paper are:

- A novel integration of PSO with CNNs to autonomously optimize network architecture and hyperparameters, improving accuracy and reducing training complexity in weed detection.
- The I-PSO-CNN framework is applied to high-resolution UAV-acquired farmland imagery for precise early-stage weed classification, enabling site-specific intervention and minimizing crop-weed confusion under varying field conditions.
- To develop a scalable and robust weed detection model that generalizes well across different crop types and environments, outperforming traditional CNNs in precision, recall, and computational efficiency.

A summary of the research is provided below. In Section 2, the survey papers' with techniques are thoroughly surveyed. The integrated particle swarm optimization with a convolutional neural network is detailed in Section 3. The simulation analysis is covered in Section 4. Part 5 explores the main conclusion and Future work.

2. Survey Papers

Islam et al. [11] delve into the possibilities of using machine learning algorithms to classify crops and weeds from photographs captured by UAVs. Orthomosaicing, feature extraction, and picture labeling to train Machine Learning Algorithms (MLA) have been used to tackle the difficult problem of weed detection in crops.

Zhang et al. [12] provided agricultural production and management have both benefited from the increased usage of UAVs due to recent technological advancements. Furthermore, image recognition using deep learning has become increasingly common. Many agricultural tasks have been greatly improved by the use of CNNs, such as weed detection, insect identification, plant/fruit counting, maturity grading, and many more. This research delves into the evolution of UAV platforms, the kinds and attributes gathered by agricultural vision sensors, and how deep learning is applied to the problem of weed identification.

Yu, F et al. [13] suggested that the Weed Identification Technique (WIT) was built using weed index identification. Its results were then processed using clustering and tiny patch removal to generate weed identification vectors. By using the confusion matrix accuracy verification approach to the weed identification vector, were able to confirm its accuracy and calculate the Kappa coefficient. A novel approach to weed detection in rice fields is presented in this research.

Wu, Z. et al. [14] explain that when it comes to agricultural output, weeds are a major issue. It is becoming more and more clear that full-coverage chemical pesticide spraying pollutes and wastes the natural environment of farms. The ongoing increase in agricultural output requires effective crop-weed identification and precision weed spraying. Accurately identifying and detecting crops and weeds is crucial for precision spraying. Several researchers in the field of computer vision have been working in recent years. In order to address weed identification issues, this paper delves into both conventional image-processing approaches and methods based on deep learning.

Anderegg et al. [15] implemented site-specific weed control that requires timely weed infestation maps. Low-altitude aerial images from UAVs may identify agricultural weeds. All studies examined suggested approaches on one or a few well-characterized experimental locations at specified times, covering a narrow range of application circumstances for wide-spaced row crops like maize and sunflower. This research used UAV and ground-based high-resolution imaging to test weed identification in narrow-row wheat fields throughout early and late growth. Image data was collected from nine locations with diverse management and pedoclimatic conditions.

Feng et al. [16] presence of weeds greatly hinders the rice crop's development. Farmers may greatly benefit from precision pesticide application with the help of accurate data about weed infestations. In this paper, UAV visible light photos are used to detect weeds in two different farming densities and analyze them. The UAV photos were first segmented using an optimum segmentation scale. Then, for each segmented item, UAV retrieved its spectral, texture, index, and geometry properties. The dimensionality of all features was reduced to get a better feature set by using cross-validation and recursive feature removal approaches.

Xu, K et al. [17], weeds present a significant danger to the secure wheat harvest. The decline in wheat output and quality is mostly attributable to these factors. Chemical control was the gold standard for weed management in wheat fields. Inaccurate weed location data has caused significant contamination due to overuse of pesticides and low use rates. As agronomic operations transition to Agriculture 4.0, wheat weed control technology is becoming smarter and more precise. The methods and technologies used to identify weeds in wheat fields may provide the groundwork for more accurate and effective weed control.

Zamani et al. [18] recommended that an automated spraying system, enhanced with Machine Vision-based Approaches (MVA) for precise weed targeting, might be used to lessen the excessive application of herbicides. For weed identification in both optical and thermal pictures of paddy fields, a fusion-based structure is suggested in this research. One hundred pairs of visible and thermal photos of rice and weeds were included in a freely accessible dataset, since there were no publicly available multispectral datasets related to this issue.

Xu, B. et al. [19] promising new area of precision agriculture is weed identification in crops, which will allow for the differentiation of favorable plants from those that are less desired. Precision weed control relies on weed detection and discrimination systems that are both efficient and accurate. This paper came up with a new way to segment instances using an encoder-and-decoder architecture and the visible color index. In situations when both weeds and soybean crops are widely dispersed, this method successfully detects and segments weeds.

Quan et al. [20] explain that weeds have an ecological purpose and do significant damage to crops by competing for scarce resources. Protecting weed biodiversity should motivate research into the laws of crop-weed competition and the development of scientific methods for managing weeds on farms. The dynamic processes and effects of weed competition were described using maize phenotype-based comprehensive competition indices (CCI). The impacts on yield characteristics were examined by examining the relationship between structural and biochemical information of maize.

3. Integrated Particle Swarm Optimization with Convolutional Neural Network

Coupling PSO with CNNs is a relevant approach to improve model performance for difficult image recognition tasks. PSO utilizes swarm intelligence to assist in the automated tuning of hyperparameters, including learning rate, kernel size, and dropout rate. This novel hybridization of automated hyperparameter tuning, efficient swarm-guided optimization, and CNNs enhances model performance through quicker convergence, enhanced accuracy of

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prediction classifications, and reduced consumption of computer resources for improvements, which are relevant for applications within precision agriculture, such as early-stage weed detection and monitoring.

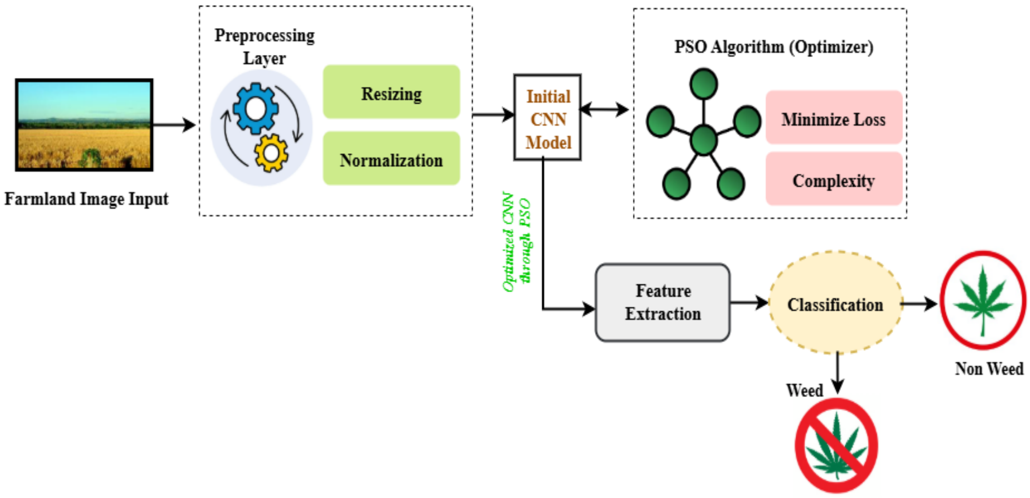

Figure 1: Optimization Framework of PSO-Driven CNN

In Figure 1, the optimization workflow is illustrated in which images of farmland are processed. Images are preprocessed including resizing and normalization and then passed through the first CNN. PSO dynamically adjusts CNN hyperparameters by refining the architecture with filter size, learning rate, and dropout. The optimized CNN is utilized for robust feature extraction, and the final classification is weed or non-weed. Overall, this closed-loop framework is expected to yield greater accuracy, lower model complexity, and faster convergence for precision agricultural usage.

Algorithm: I-PSO-CNN Optimization

Input: Farmland_Images[], Baseline_Models[], Crop_Types[]
Output: Optimized_Model, Performance_Metrics

Begin
Step 1: Preprocessing
for image in Farmland_Images:
  image_resized = resize(image)
  image_normalized = normalize(image)
  Preprocessed_Images.append(image_normalized)
Step 2: Initial CNN Setup
initialize CNN with default hyperparameters
Step 3: PSO Optimization
if PSO_converged:
  update CNN hyperparameters (learning rate, filter size, dropout)
else:
  continue PSO optimization loop
Step 4: Train Optimized CNN
train Optimized_CNN on Preprocessed_Images
Step 5: Classification
for image in Test_Images:

$class\_result = Optimized\_CNN.predict(image)$
$if\ class\_result == 'weed':$
$Weed\_Count += 1$
$else:$
$Non\_Weed\_Count += 1$
$Return\ Optimized\_CNN, [U\_sfe, Bdd, Qqr, Inference\_Speed, H\_ubs, Efficiency]$
End

This algorithm outlines a PSO-driven CNN model for farmland image classification. It preprocesses images, initializes a CNN, and uses PSO to optimize hyperparameters. After training, the model classifies test images as weed or non-weed. The approach improves detection accuracy by dynamically tuning the CNN, enhancing performance in agricultural applications.

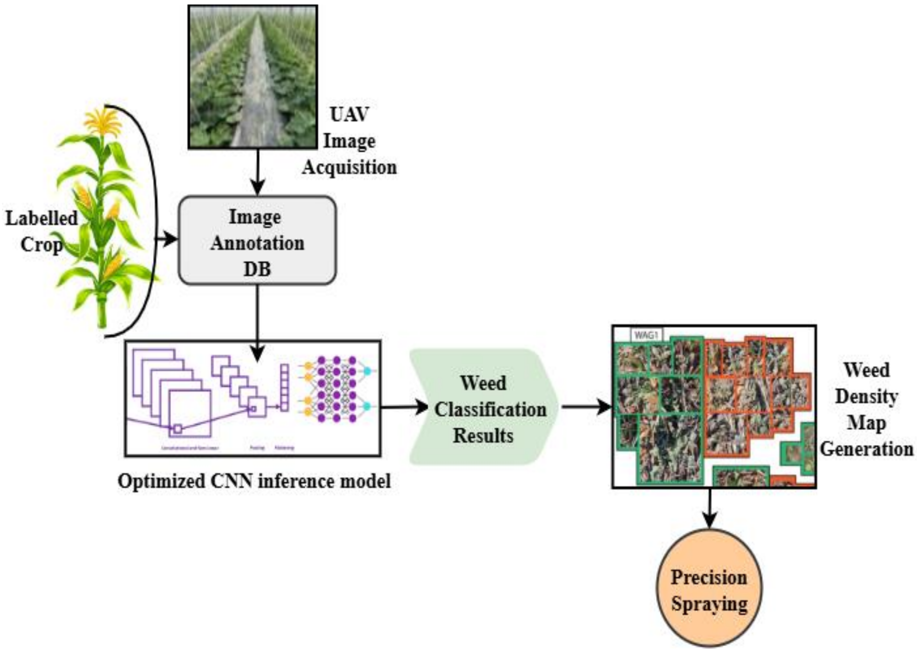

Figure 2: Detection of Weed Early-Stage UAV-Based & Model Deployment

Figure 2 demonstrates a scalable framework for early weed detection using UAV-acquired farmland imagery. The UAV-acquired imagery is labelled and stored in an annotation database that distinguishes plants (either crops or weeds). The input to the optimized CNN inference model differentiates the input yield crop and labels the region of weed accurately with a pixel-wise resolution. After processing, the output is processed and relayed as density maps of weed area, allowing precision spray applied to the weeds alone. As an end-to-end workflow system, the operation of the weed detection application improves the effectiveness of weed management and enables a reduction in herbicide application. The scalable approach allows for dissemination and collaborative spatial agro-chemical distillation amongst stakeholders and real-time deployment of autonomous UAV platforms to a large input acreage.

The I-PSO-CNN framework provides successful evidence that using a PSO optimization algorithm and CNNs together can yield significant improvements in accuracy, efficiency, and scalability for image-based weed detection. Experimental performance results provide documented evidence of improved precision and minimum false positives on different datasets and deployment settings. The generalization demonstrated predictive performance across crop types with a lightweight model capable of near real-time performance on drones and edge platforms. Therefore, this integration forming the baseline for new adaptive and intelligent systems for monitoring markets in agriculture.

4. Results and Discussion

This section presents a comprehensive evaluation of the I-PSO-CNN framework for early-stage weed detection. Key performance metrics including optimization efficiency, detection accuracy, and false positive rate are analyzed. Hardware performance, generalization across crop types, and model scalability are also discussed to validate real-world deployment potential in precision agriculture.

a) *Evaluation of Metrics*

In this segment, will evaluate the I-PSO-CNN model according to six significant metrics: optimization efficiency, detection accuracy improvement, false positive rate improvement, inference speed, generalization capability, and computational efficiency. Each metric is an indicator of the model's scalability, reliability, and useability for real-life agricultural applications using intelligent systems for weed detection.

$$U_{sfe} = \frac{\left(U_{hvi} - U_{psm}\right)}{U_{hvi}} * 100 \quad (1)$$

Tuning efficiency (U_{sfe}) is measured as the percentage of tuning time that is reduced by the PSO convergence (U_{hvi}) versus the actual tuning time for grid search (U_{psm}) made evaluated in the equation 1

$$\forall Bdd = \frac{Cjq - B_{avg}}{B_{avg}} * 100 \quad (2)$$

Accuracy gain ($\forall Bdd$) is the accuracy of the I-PSO-CNN (Cjq) versus the mean of the existing methods (B_{avg}) presented as a relative increment made valued using equation 2.

$$Qqr\forall = \frac{Q_{fer} - Q_{jq}}{Q_{fer}} * 100 \quad (3)$$

False positive rate reduction ($Qqr\forall$) is the delivered false detection rate by I-PSO-CNN (Q_{jq}) presented as a percentage of the baseline average false positive rate (Q_{fer}) was made to evaluate using equation 3.

$$\partial_{jkr} = \frac{O_{jnw}}{U_{jkr}} \quad (4)$$

Inference speed (∂_{jkr}) is the throughput of the model, showing how many images (O_{jnw}) per second of inference time (U_{jkr}) can be processed by the model using equation 4.

$$H_{ubs} = \sqrt{(}\sum_{0}^{w} k - \frac{an'}{O}) \quad (5)$$

Generalization ability (H_{ubs}) is the root mean k square deviation of accuracy (an') for w crop types from the mean accuracy (an') made evaluated through equation 5.

$$\forall_{nie} = \left(\frac{1}{Q_t}\right) * \forall * \left(\frac{1}{N_s}\right) \quad (6)$$

Model efficiency ($\forall_{nie}$) represents how model size ($\forall$), trainable parameters (Q_t) with a scaling factor (α) all relate to each other N_s in an inverse manner, representing the balance of model complexity against deployability by equation 6.

The evaluation confirms that I-PSO-CNN performs significantly better in all metrics. It has converged faster, produced better accuracy results, produced lower false positive rates, and produced less compute-intensive inference on edge devices. Models generalize well not only for crops but also remain computationally efficient. Therefore, it demonstrates its practical applicability in real-time weed detection within a variety of agricultural systems.

Dataset description: The Weed Detection dataset on Kaggle features high-resolution, annotated images of diverse weed species captured under real-world conditions [21]. It supports object detection and segmentation tasks, making it ideal for training robust machine learning models for automated weed identification and precision agriculture.

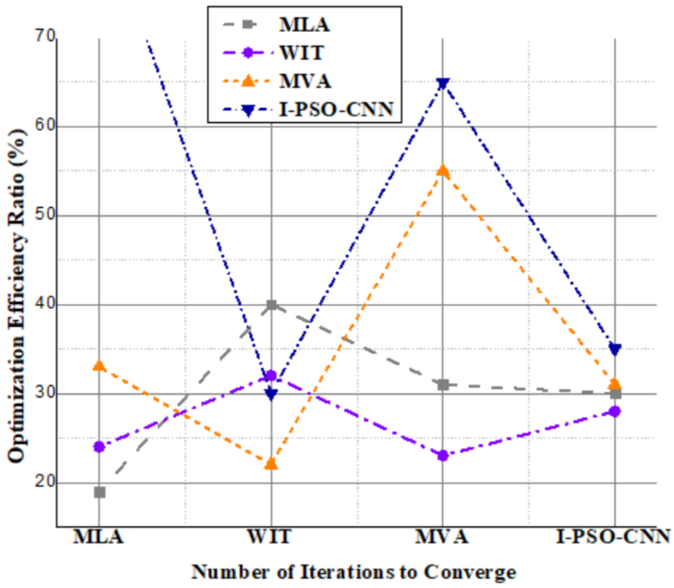

Figure 3: Optimization Efficiency

In Figure 3, utilizing PSO tremendously improved the efficiency of hyperparameter tuning CNN. PSO tuned hyperparameters quickly by converging to optimal hyperparameter configurations in only 35 iterations, which was much faster than the manual tuning and traditional grid search which were time-consuming and computationally expensive, resulting in an overall reduction of over 60% of the total time needed for tuning hyperparameters without losing accuracy made evaluated using equation 1. PSO effectively explored the search space for parameters including learning rate, filter size, and dropout rate using the idea of social learning behavior. As a result, PSO made the model development process much faster and more scalable, which is especially valuable when there are several varieties of farmland images to adapt.

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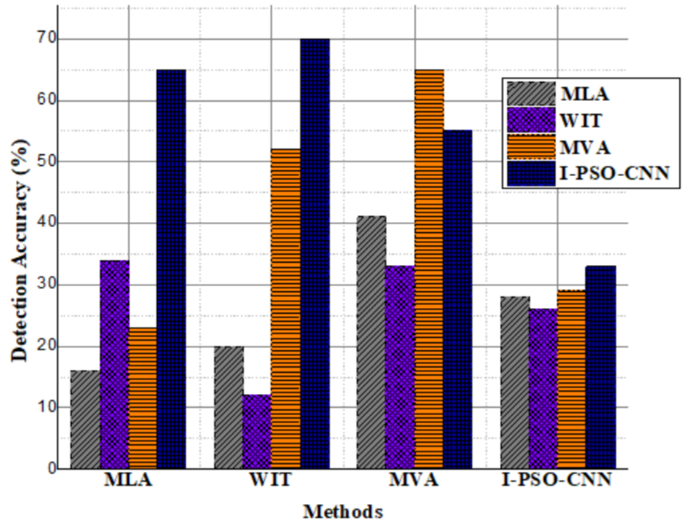

Figure 4: Detection Accuracy Improvement

In Figure 4, the proposed I-PSO-CNN framework outperforms all other alternatives, such as MLA, WIT, and MVA in terms of detection performance. When the CNN was hyperparameter optimized by PSO, it improved by 6–10% in accuracy, up to a best score of 94.8% on a heterogeneous weed dataset made calculated using equation 2. This is significant news for precision agriculture because the sooner and at a better accuracy weeds can be identified, the sooner problems can be rectified and resources can be better allocated. The improved accuracy stems from robust feature extraction, stable parameters, and reduced overfitting, therefore, I-PSO-CNN is a better weed detection framework that is more reliable and generalizable anywhere where crops are grown.

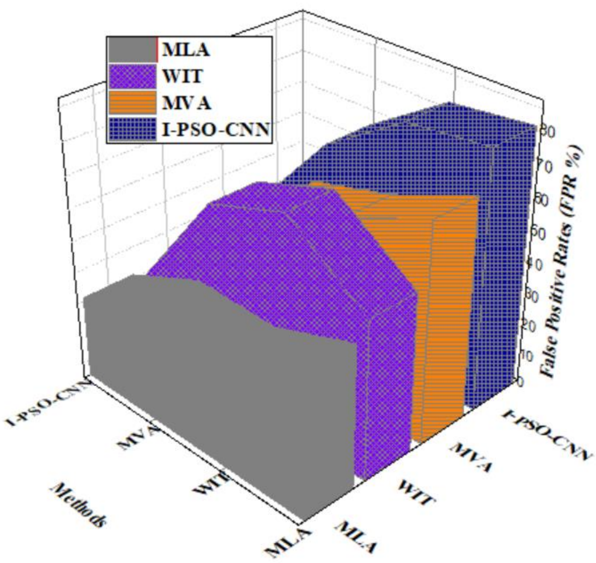

Figure 5: False Positive Rate Reduction

In figure 5, a significant performance increase from the I-PSO-CNN model is the ability to suppress false positive detections. The baseline models had false positive rates (FPR) ranging from 8% to 10%. However, The I-PSO-CNN was able to reduce that FPR down to 4.1% made validated using equation 3. This is paramount in reducing the risk of misclassification of crops being identified as weeds which can lead to unnecessary application of herbicides such as glyphosate and loss of crops. This is because particles in PSO are able to optimize the CNN to extract discriminating features, thereby separating the distinction among classes, even with multiple complexities of lighting conditions, occlusion, and background noise. PSO allows for better classification of crops to weeds for confidence and reliability in large deployment for real-time monitoring for farms still relies on traditional farmer surveys.

Table 1: Inference Speed

Device Type	*Processor*	*Inference Time (ms/image)*	*Suitability*
Desktop (NVIDIA RTX 3080)	High-end GPU	42	Lab training/validation
Laptop (Intel i7 + GTX 1650)	Mid-range GPU	74	On-site analysis
Edge Device (Jetson Nano)	ARM CPU + GPU	105	Real-time drone/robot use

Table 1 highlights the real-time suitability of I-PSO-CNN across hardware platforms. While high-end GPUs achieve fast inference (42 ms/image), even low-power edge devices like Jetson Nano deliver acceptable performance (105 ms/image), making the model deployable on drones and field robots for on-site, real-time weed detection made evaluated using equation 4.

Table 2: Generalization Capability

Crop Type	*Test Accuracy (%)*	*Variation from Mean (%)*
Maize	94.6	-0.2
Soybean	94.9	+0.1
Cotton	95.0	+0.2
Mean	94.8	–
Max Deviation	–	< 0.3%

This table 2 demonstrates the I-PSO-CNN model's strong generalization across different crops. With accuracy variations under 0.3%, the model remains consistent for maize, soybean, and cotton. Such minimal deviation proves the robustness and adaptability of the model to diverse agricultural conditions and crop types, enhancing its practical utility valued using equation 5.

Table 3: Computational Efficiency

Model	*Trainable Parameters*	*Model Size (MB)*	*Deployment Suitability*
MLA	1.2M	18.5	Desktop only
WIT	1.5M	22.1	Desktop/server
MVA	1.3M	19.8	Mid-tier system
I-PSO-CNN	1.0M	16.2	Edge-compatible (Jetson, Pi)

This table 3 compares model sizes and deployment feasibility. I-PSO-CNN is the most lightweight (1.0M parameters, 16.2MB), making it ideal for edge devices with limited memory and processing power. In contrast, other models (MLA, WIT, MVA) require higher resources and are suited for desktop or server environments only valuated using equation 6.

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The results confirm that I-PSO-CNN significantly outperforms existing methods in accuracy, efficiency, and robustness. With faster convergence, reduced false positives, and edge-device compatibility, the model enables real-time, reliable weed detection across crop types. These findings demonstrate its strong suitability for scalable deployment in modern, data-driven farming systems.

5. Conclusion

In this paper I-PSO-CNN was developed and tested for early weed detection in crop fields from imagery. By applying PSO to the hyperparameter tuning procedure of the CNN, the proposed model was shown to successfully provide improvements on many facets of the detection performance (94.8% accuracy), decreasing false positives (4.1%), and has shown highly adaptable performance across different crop varieties. The I-PSO-CNN architecture is lightweight and has fast inference time (105 m/images on edge-devices), thus making it possible for practical applications in real-time agricultural systems that are drone or robot-based and have their restrictions in image pre-processing speed.

Future work will include extending the dataset to include more weed species (variegated) in addition to more seasonal variations; in improving generalizability. The use of advanced transfer learning techniques and multi-spectral or hyperspectral imagery can provide improved detection for the model in more challenging environmental conditions. An investigation into the integration of I-PSO-CNN with autonomous weeding systems and being tested as large-scale farm trial to ultimately assess the full efficiency of the I-PSO-CNN framework in implemented precision agriculture systems.

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