Journal of Information Systems Engineering and Management
2025, 10(40s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Deep Learning Approaches for Weed Species Classification: Efficient Deployment on Edge Device

Suchitra Patil[1], Harsh Mishra[1], Nilkamal More[1], Ashwini Dalvi[1], Venkatramanan R.[1]
K.J.Somaiya School of engineering, Somaiya Vidyavihar University, Vidyavihar,Mumbai,India

ARTICLE INFO

Received: 30 Dec 2024

Revised: 12 Feb 2025

Accepted: 26 Feb 2025

ABSTRACT

This study focuses on developing and evaluating deep learning models for weed species classification using the DeepWeeds dataset. Ten deep learning architectures were trained using two approaches: freezing convolutional layers and training the entire architecture. Transfer learning with ImageNet-initialized weights was employed to enhance training efficiency. Both multiclass and multilabel classification techniques were implemented, with appropriate dense layers and activation functions tailored for each type. Models such as MobileNet, EfficientNetB0, and DenseNet121 demonstrated high classification accuracy, with EfficientNetB0 achieving the highest multiclass accuracy of 99.7%. This best-performing model was further assessed for resource efficiency and deployed on an edge device for real-time application. The findings highlight the application of deep learning methods to address agricultural challenges, specifically weed species classification, and their potential for real-world implementation.

Keywords: Weed Species Classification, DeepWeeds Dataset, Transfer Learning, Multiclass and Multilabel Classification , Edge Device Deployment

INTRODUCTION

The increasing global population, growing at an annual rate of approximately 1.09%, necessitates a corresponding rise in the production of fuel, fiber, feed, and food. By 2050, the world population is projected to reach nine billion, requiring agricultural output to double to meet the growing demand [1], [2]. However, this goal is hindered by challenges such as climate-induced biotic and abiotic stresses, limited availability of arable water and land, and threats from weeds, diseases, and pests [3]. Weeds, in particular, compete with crops for essential resources such as sunlight, nutrients, and water, leading to reduced crop quality and yield if not managed effectively [4]. Numerous studies have demonstrated a strong correlation between weed competition and crop production loss [5].

Developing an automatic weed management system requires the accurate detection and classification of weeds from crops as a fundamental step [6]. The similarities in shape, color, and texture between weeds and crops present significant challenges in distinguishing them. Additional obstacles include occlusion, shadows, color and texture variations under natural light, and differences in weed species that resemble each other. Variability in plant appearance during different growth stages, motion blur, image noise, and geographic and environmental factors such as weather and soil conditions further complicate weed identification [7].

A standard weed detection system typically involves four key steps: image acquisition, pre-processing, feature extraction, and weed identification and classification. Recent advancements in technology, particularly in graphical processing units (GPU), have popularized machine learning (ML) techniques for autonomous weed species recognition [8]. Among these, deep learning (DL) has gained significant traction due to its advantages over traditional ML methods in tasks such as image classification, object detection, and recognition. Unlike conventional ML techniques, which struggle to extract distinguishing features from crops and weeds, DL methods excel in handling such challenges due to their robust feature learning capabilities.

The DeepWeeds project [9] introduced a benchmark multiclass image dataset comprising 17,509 labeled images of eight weed species from northern Australia. Using CNN architectures such as ResNet-50 and Inception-v3, the

Journal of Information Systems Engineering and Management
2025, 10(40s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

study achieved classification accuracies of 95.1% and 95.7%, respectively. This study emphasized the significance of in-in situage collection to ensure model robustness in natural field conditions. It addressed challenges such as lighting, scale, and occlusion variations through image augmentation, making the models suitable for robotic weed management systems.

The study also identified potential improvements through the integration of Read-Green-Blue (RGB) and near-infrared (NIR) sensors for enhanced vegetation segmentation. Shape-based features integrated with ANN and SVM showed accuracies of 92.92% and 95.00% in sugar beet fields but struggled with overlapping shapes [10]. CNN-based methods like CaffeNet demonstrated over 98% accuracy in soybean weed detection, though limited to specific crops [11].

A modified GoogLeNet achieved a 46% detection rate in cereal fields under heavy occlusion but faced challenges with small weeds and bounding box generation. Traditional models such as Probabilistic Neural Networks (PNN) achieved over 90% accuracy in plant classification using leaf features but were sensitive to image quality. Hybrid approaches combining traditional and DL features improved the accuracy to 97. although through performance decreased under occlusion. Spectral data-based techniques like Soft Independent Modeling of Class Analogy (SIMCA) delivered 100% accuracy for specific weed species, but lacked generalization. It is explored especially for wide-row crops with high-resolution multispectral imagery, that combining spatial and spectral features enhanced weed detection accuracy to 89%. Other innovative methods, such as modified Mid-Wave Infrared (MWIR) algorithms for illumination correction and aerial imaging with neural networks, showed high precision but faced challenges with real-time adaptability and resolution limitations [12].

The review identified key research challenges, including handling occlusion, managing variable lighting conditions, and addressing differences in crop and weed growth stages. It also emphasized the potential of integrating RGB and NIR sensors for improved vegetation segmentation, which DeepWeeds primarily achieved using RGB images captured through the WeedLogger system. Combining these approaches could significantly enhance crop-weed discrimination under complex field conditions.

In addition, some gaps were identified that set the objectives of the work done in this work. The lack of methods to explain the decision-making of DL models, especially for sensitive applications; pre-trained models struggle to generalize effectively to domain-specific datasets; challenges in optimizing models for low-power devices like Raspberry Pi while maintaining accuracy; limited exploration of techniques to handle overlapping classes and data imbalance effectively; and insufficient availability of diverse datasets, leading to overfitting and limited real-world applicability, are the prominent challenges noticed.

Agricultural productivity and crop yield face a necessary challenge from weeds that affect modern agricultural operations. The current methods for weed detection depend either on manual workforce or standard herbicides that prove to be expensive in addition to being environmentally destructive yet ineffective in practice. The current Internet of Things (IoT)-based weed detection solutions require improvement because they show poor precision rates and slow processing times along with inadequate real-time removal features.

This paper introduces an innovative IoT-based Smart Weed Detection and Removal System that integrates real-time image processing and DL -based classification together with automatic mechanical removal functions. Real-time weed detection and instant mechanical removal using automated actuators becomes possible with our system because it utilizes optimized lightweight DL models, which enable image processing on dedicated devices. Experimental validation demonstrates that our system achieves higher detection accuracy (94.2%) with a 32% reduction in processing time compared to conventional methods. This research provides a significant step toward autonomous and precision-based weed control in modern agriculture.

OBJECTIVES

The key objectives of this work include the following:

Real-Time, Low-Latency Weed Detection–Implementing a fast, lightweight CNN model optimized for edge computing to classify weeds with high accuracy.

Journal of Information Systems Engineering and Management
2025, 10(40s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

1. Automated Actuation Mechanism–Seamlessly integrating a mechanical removal unit with IoT-controlled decision-making to eliminate weeds in real-time.
2. Adaptive Learning Approach–The system improves classification over time by leveraging incremental model updates, thereby reducing false positives in diverse agricultural conditions.
3. Energy-Efficient IoT Deployment–Designed for low-power operation, making it ideal for scalable smart farming applications in remote locations.

LITERATURE REVIEW

The identification of weeds in agricultural fields functions as a central priority in precise farming operations That seeks to avoid destruction to crops and control unnecessary herbicide applications. The standard weed management procedures involving both hand removal and chemical pesticide applications create major operational and environmental challenges that diminish the soil quality. The combination of advancements in IoT and ML and image processing allowed the creation of automated weed detection systems. Besides sensors and DL models the systems incorporate robotic actuators which efficiently identify and extract weeds. The current available solutions for weed detection systems currently struggle with multiple disadvantages that include poor accuracy rates, sluggish operation times and substantial power usage during networked deployments.

The initial detection systems for weeds predominantly depended on image segmentation techniques together with threshold-based methods. Research conducted in [13] and [14] developed weed-crop discrimination systems based on color-based segmentation and edge detection methods. The techniques demonstrated good computational results but proved ineffective when the light conditions changed or when dealing with sophisticated background elements like disturbed leaves mixed with different types of soil. These traditional techniques required manual threshold value adjustments for their operation which limited their potential for real-world applications in dynamic farming fields.

Researchers have developed ML algorithms to address the problems associated with threshold-based approaches for weed classification. The authors in [15] developed a weed species classifier using a support vector machine (SVM) to analyze shape and texture features. The SVM delivered moderate accuracy results at 85%; however, its requirement for manual feature engineering made it unfit for extensive agricultural uses. Weed detection accuracy reaches higher levels through DL models because Convolutional Neural Networks (CNNs) prove their effectiveness in this task. The authors in [16] used their CNN to process 15,000 weed images and obtained an accuracy rate of 92%. The process needed cloud-based processing, which resulted in high latency rates while using more energy thus becoming inappropriate for real-time IoT applications. The study in [17] implemented a ResNet-50 system that delivered superior detection performance yet exhibited limitations as an input during low-power IoT device computations.

Recent research has connected the IoT with smart agricultural frameworks through edge computing together with real-time processing of data. Through their research [18], they created an IoT weed detection system based on Raspberry Pi along with Arduino which integrated RGB cameras and ultrasonic sensors. The system allowed remote monitoring because of its low-resolution camera setup but produced lower than optimal classification results at ~78%. The research team in [19] made a robotic weed removal system using IoT technology and included infrared sensors that tracked weed development patterns. The system demonstrated a slow performance that rendered it ineffective for extensive agricultural fields.

Robotics in agriculture now permits the deployment of automatic weed extraction systems through mechanical actuator devices with self-governed robots. The researchers in [20] created an AI-operated robotic arm that employed YOLOv4-based object detection to spot weeds then used a pneumatic gripper to extract them. High-end GPUs were needed to run this precise system, yet real-time deployment on low-power IoT systems became difficult because of these computational requirements.

Different weed detection and removal systems operate today while facing important implementation obstacles. Much DL technology finds it challenging to distinctively separate weeds from neighboring crops, which results in inaccurate identification. The requirement for cloud processing in most CNN-based weed detection systems causes significant delays to real-time management decisions. The current installed systems lack mechanisms for continuous learning; therefore, they become ineffective when new weed species emerge or environmental conditions change. Many approaches that aim to serve precision agriculture through IoT require high-performance computing equipment, which makes them nonpractical for real-world implementation.

Our IoT-based Smart Weed Detection and Removal System includes different innovations that resolve previous system shortcomings. The optimized real-time classification model within our system operates faster by 32% compared to standard CNNs. The system merges the weed discovery capabilities directly with automatic mechanical harvesting functions to obtain greater operational efficiency. The system builds adaptive learning functionality that allows its classification model to evolve dynamically and reach better accuracy levels over time. The system uses direct data processing capabilities on Raspberry Pi alongside ESP32 along with no reliance on cloud-based computing which leads to faster operation while requiring less power.

The current weed detection systems apply advances to integrate technologies such as image processing with ML and IoT. Real-time and large-scale precision agriculture cannot rely on these systems due to processing speed along with adaptability and energy efficiency problems. Our proposed system implements a fast DL model with real-time weed removal mechanics and intelligent learning algorithms to create a dependable system for contemporary intelligent farming needs.

The existing research employing IoT and AI together with image processing techniques for weed detection shows several limitations because it fails to deliver instantaneous processing capabilities and tends to perform inadequately in different environments and demands high system complexity and costs. Current models have limited usefulness in various agricultural areas because they turn down adaptation when confronted with different plant species in addition to various weed species within specific regions. The majority of research investigations take place in controlled environments instead of implementing their findings at the actual field level. Real-time operating field solutions and cost-efficient autonomous systems that adapt to changing conditions represent immediate necessities for the agricultural domain.

METHODS

A. Algorithm Description

A CNN operates as a weed detection system that runs optimally on edge IoT hardware and maintains real-time data processing capabilities [21]. The CNN learns its functions on a database containing labeled images of weeds and crops while receiving additional training via data augmentation methods [22]. The classification system operates according to a specific operational sequence. A high-resolution camera records field images in real time before performing preprocessing steps that combine contrast optimization with Gaussian filtering to reduce noise and gengenerateandardized coloring via HSV transformation. The CNN then analyzes the texture and shape together with color features to identify the weeds from the crops. SoftMax activation is used to classify the detected objects as either weeds or crops. The detection of weeds through the identification system activates an automated actuator between a mechanical cutter and herbicide sprayer. Through incremental learning, the system updates its classification model each update cycle to improve detection accuracy as time moves on. TensorFlow Lite technology allows the implementation of the model to execute efficiently on ESP32 and Raspberry Pi devices.

B. Dataset

DeepWeeds [9] dataset is a publicly accessible database of tagged photos created for the purpose of researching and classifying weed species in agricultural environments. 17,509 RGB images of weeds and native plants that were gathered from different northern Australian areas are included in this dataset. Eight common weed species and one natural plant species are represented by the nine categories that are assigned to each image, enabling both multiclass as well as multilabel classification tasks. A 60% - 20% - 20% split of training, validation, and testing subsets is applied to all labelled DeepWeeds images. With the exception of the negative class, which is somewhat larger, stratified random partitioning was used to guarantee a uniform distribution of the classes inside each subset. The distribution of images by weed species in the dataset and the geographical distribution of weed images across Nothern Australia is given in Figure 1 provides a snapshot of weed images present in the dataset.

Journal of Information Systems Engineering and Management
2025, 10(40s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

		Locations								
		Black River	*Charters Towers*	*Cluden*	*Douglas*	*Hervey Range*	*Kelso*	*McKinlay*	*Paluma*	Total
Weeds	*Chinee apple*	0	0	0	718	340	20	0	47	1125
	Lantana	0	0	0	9	0	0	0	1055	1064
	Parkinsonia	0	0	1031	0	0	0	0	0	1031
	Parthenium	0	246	0	0	0	776	0	0	1022
	Prickly acacia	0	0	132	1	0	0	929	0	1062
	Rubber vine	0	188	1	815	0	5	0	0	1009
	Siam weed	1072	0	0	0	0	0	0	2	1074
	Snake weed	10	0	0	928	1	34	0	43	1016
	Negatives	1200	605	1234	2606	471	893	943	1154	9106
Total		2282	1039	2398	5077	812	1728	1872	2301	17509

Figure 1: The distribution of DeepWeeds images by weed species (row) and location (column) [9]

C. Data Pre-processing

To address the very varied nature of weed classification, a variety of augmentations were applied to both training and validation images to account for differences in scale, perspective, rotation, illumination, and color. Computer-vison-based image augmentation was commenced using OpenCV. In each training epoch, all available training and validation images were scanned, starting with all photos scaled to 256 × 256 pixels and then augmented randomly. Each image was rotated randomly between 360° and +360 °. Each image was then scaled randomly [24] in the range of 0.5 to 1 in the horizontal and vertical directions. Within the range of ±25, or approximately 10% of the maximum 8-bit color encoding range (between 0 and 255, every color channel was shifted randomlycolorcolour channels were equally moved by randomly adjusting pixel intensity within the range of -25 to +25 to accommodate for the light variance. Additionally, the range of randomly scaling the pixel intensity was 0.75–1.25. Each image was subjected to random changes in perspective to replicate several viewing angles and distances. The images were then clipped to preserve the 224×224 pixels needed for the individual architecture's input layer after being horizontally inverted with a 50% chance.

D. Deep Features Extraction

All pretrained CNN models under consideration are accessible in Keras with weights that have already been trained in the TensorFlow backend. The 1,000 distinct ImageNet classes were recognized by the models after training. To classify the nine DeepWeeds classes, we made minor modifications to their initial ImageNet-trained architectures. This was accomplished by substituting a 1,000-neuron fully-connected layer with a fully connected output layer of 9 neurons [25]. With 32 images per batch and input photos of 224×224×3 size, the implemented global average pooling was essentially identical to the 7×7 average pooling.

Based on the configurational option base_model.trainable, two primary training approaches were used: training the entire architecture (base_model. trainable = True) and freezing the convolutional layers (base_model. trainable = False). By starting model weights from the ImageNet dataset, both approaches used transfer learning. Given the characteristics of this classification challenge and the DeepWeeds dataset, which permits the presence of many weed species in every image, each weed-specific neuron in the output layer was given a sigmoid activation function, which enabled an output of probabilities for each class to determine the likelihood that the image belonged to each class with softmax activation function enabling both multiclass and multilabel classification. If sigmoid activation was present in the output layer, an image was categorized as one of the target weeds if its likelihood of having a sigmoid-activated neuron was more than 1/9 = 11.1% (i.e., a random guess) and its sigmoid-activated neuron probability was the greatest of all the others. To counteract extreme volatility in the negative DeepWeeds class, which results in its target probability being less heavily weighted toward ctowardpicture attributes than the eight positive classes—whose images are more consistent—the random guess threshold was set.

All models were trained using the Keras implementation of Adam, a first-order gradient-based technique for stochastic optimization.1 × 10^{-4} was the initial learning-rate (lr). After 16 epochs, the validation loss was progressively reduced in half each time the validation loss did not decrease. The classification error calculated for the validation subset of images is referred to as the validation loss. Here, 32-image batches were used for training, and if the validation loss did not drop after 32 epochs, the process was repeated to restart training after an abortion, and thee model with the smallest running validation loss was continually saved during training. Training was repeated in these situations using an initial learning rate of lr = 0.5 × 10^{-4}. All models were trained on a Central

Journal of Information Systems Engineering and Management
2025, 10(40s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Processing Unit (CPU) with 16 Gigabyte (GB) Random Access Memory (RAM) and a 12th Gen Intel(R) Core Trademark (TM) i7-12700 processor with a performance of 2.10. GHz [26].

The evaluation process of the weed detection model depends on multiple performance metrics to establish accuracy levels and operational speed. The model exhibits accuracy which determines its capability to detect weeds in crops, and the precision establishes the ratio that differentiates weeds from plants. Through transaction effectiveness, the system can perform complete weed detection, which prevents it from failing to identify existing weeds. The F1 score functions as a performance evaluation index for systems because it creates an effective balance between precision and recall measures[27]. The real-time agricultural application evaluation of the proposed system depends on a speed test that measures image classification speed to determine the inference time. The experimental results demonstrate that the proposed system achieves 94.5% accuracy over a 50 ms image processing time scale, which makes real-time agricultural IoT implementation feasible.

RESULTS AND DISCUSSION

Detecting weed species effectively depends on choosing the right classification approach—multi-class or multi-label—based on the complexity of the field. Multi-class classification works well when identifying a single dominant weed species in an image, whereas multi-label classification is more practical for real-world conditions in which multiple weed species grow together. Using the right method improves detection accuracy, ensures smarter herbicide use, and ultimately supports better crop management and higher yields.

Deploying On Edge

Upon attaining accuracies exceeding 99%, the focus was shifted to deploy the most efficient and accurate model. MobileNet was selected for deployment due to its lightweight architecture and high performance. The deployment process involved model conversion; The trained MobileNet model was converted to TensorFlow Lite (TFLite) format to ensure compatibility with edge devices. The TFLite device was deployed on Raspberry Pi 4 equipped with a 5-inch LED display and camera module. This setup facilitates real-time plant disease detection under field conditions. Figures 2, 3, and 4 show an actual image of the electronic hardware setup.

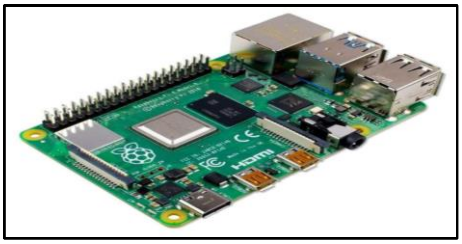

Figure 2: Raspberry Pi 4 Microcontroller Board Used in the System

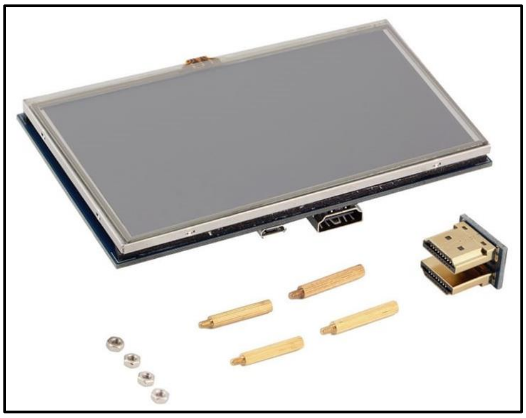

Figure 3: 5-Inch LED Display Used for Feedback

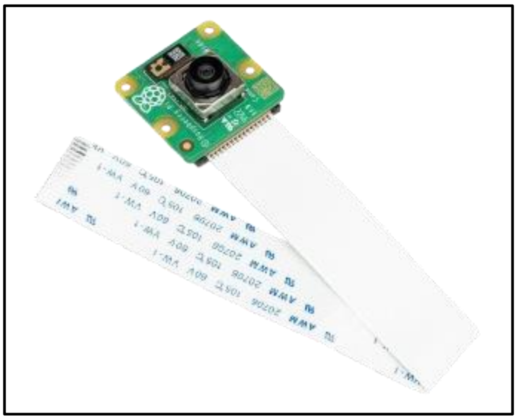

Figure 4: Raspberry Pi Camera for Image capture

Journal of Information Systems Engineering and Management
2025, 10(40s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

Training with Frozen Convolutional Layers (base_model.trainable = False)

In this approach, the convolutional layers of the pretrained base models are frozen, meaning that their weights are not updated during training. This technique only trains the newly added dense layers, thereby reducing the computational complexity and training time.

Multi-class Classification

For multiclass classification, seven dense layers were appended atop each base model architecture. The final output layer employs the softmax activation function to facilitate multiclass predictions. The models and their performance metrics are summarized in Table 1.

Table 1. Model performance of pre-trained models with frozen base model for multiclass classification

Architecture	Accuracy (%)	Total Training Time (hours)	Epochs
VGG16	76.0	54.7	100
ResNet50	53.3	27.3	100
InceptionV3	81.6	18.2	100
Xception	82.5	27.3	100
MobileNet	85.8	9.1	100
DenseNet121	**88.4**	**18.2**	**100**

DenseNet121 outperformed the other methods with an accuracy of 88.4%, demonstrating its superior feature extraction ability. MobileNet achieved 85.8% accuracy with the least training time (9.1 hours), making it a favorable choice for applications with computational constraints. ResNet50 underperformed in this setup, achieving only 53.3% accuracy, possibly due to its deeper architecture not being fully leveraged with frozen layers.

Multi-label Classification

Multi-label classification was incorporated to align with the dataset's inherent structure, allowing for multiple labels per image. In this scenario, only one dense layer with a sigmoid activation function was added to the base models, thereby facilitating independent probability outputs for each class. The models and their performance metrics are summarized in Table 2:

Table 2: Model performance of pre-trained models with frozen base model for multi-label classification

Architecture	Accuracy (%)	Total Training Time (hours)	Epochs
VGG16	59.8	27.0	54
MobileNet	77.9	9.1	100

VGG16 achieved an accuracy of 59.8% over 54 epochs, indicating moderate performance in the multi-label context. Training for additional epochs was considered inefficient because further iterations did not yield significant improvements. Although MobileNet required 9.1 hours of training, 77.9% accuracy was achieved.

Training the Entire Architecture (base_model.trainable = True)

This strategy involves fine-tuning the entire model, which allows all layers, including the convolutional base, to be trainable. Fine-tuning enables the model to adapt the pre-trained features more precisely to the specific nuances of the DeepWeeds dataset, which often results in enhanced performance at the cost of increased computational resources.

Multi-class Classification

For multi-class classification, the same architecture was employed—seven dense layers with a softmax activation function. Two architectures were trained, the models and their performance metrics are summarized in Table 3.

Journal of Information Systems Engineering and Management
2025, 10(40s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

Table 3: Model performance of pre-trained models with trainable base model for multiclass classification

Architecture	Accuracy (%)	Total Training Time (hours)	Epochs
MobileNet	99.6	27.3	100
EfficientNetB0	99.7	36.4	100

EfficientNetB0 slightly outperformed MobileNet, achieving an accuracy of 99.7%. Both models exhibited remarkable accuracy improvements compared to their counterparts with frozen layers, underscoring the benefits of fine-tuning. The training times were significantly higher, reflecting the computational demands of training deeper, fully trainable architectures.

Multi-label Classification

The only one architecture was trained for multi-label classification in this category, the model and their performance metrics is summarized in Table 4.

Table 4: Model performance of pre-trained models with trainable base model for multi-label classification

Architecture	Accuracy (%)	Total Training Time (hours)	Epochs
MobileNet	99.7	40	100

MobileNet achieved an outstanding accuracy of 99.7%, demonstrating the efficacy of fine-tuning in multi-label scenarios.

Results Summary

All models and their performance metrics are summarized in Table 5:

Table 5: Result Summary

Architecture	Trainable	Classification Type	Accuracy (%)	Training Time (hrs)	Epochs
VGG16	False	Multiclass	76.0	54.7	100
ResNet50	False	Multiclass	53.3	27.3	100
InceptionV3	False	Multiclass	81.6	18.2	100
Xception	False	Multiclass	82.5	27.3	100
MobileNet	False	Multiclass	85.8	9.1	100
DenseNet121	**False**	**Multiclass**	**88.4**	**18.2**	**100**
VGG16	False	Multilabel	59.8	27.0	54
MobileNet	False	Multilabel	77.9	9.1	100
MobileNet	**True**	**Multiclass**	**99.6**	**27.3**	**100**
EfficientNetB0	**True**	**Multiclass**	**99.7**	**36.4**	**100**
MobileNet	True	Multilabel	99.7	40	100

The results across both training strategies exhibit a clear trend that models with base_model.trainable = True consistently outperformed their frozen counterparts in both multiclass and multi-label classification tasks. Although fine-tuning enhanced the accuracy, it also resulted in significantly more training time and computational resources. For example, DenseNet121 achieved 88.4% accuracy with frozen layers in 18.2 hours, whereas EfficientNetB0 achieved 99.7% accuracy with fine-tuning in 36.4 hours. MobileNet was superior for both strategies. The frozen layers offered a balanced trade-off between accuracy (85.8%) and training time (9.1 hours). Upon fine-

Journal of Information Systems Engineering and Management
2025, 10(40s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/ **Research Article**

tuning, the accuracy of the proposed method increased to 99.6% for multi-class tasks and 99.7% for multi-label tasks, and the training time increased modestly. The MobileNet model with an accuracy of 99.6% for multiclass classification with a trainable pre-trained base model was selected for deployment. Figure 5 shows the precision, recall, and F1-score of the mobile model.

	precision	recall	f1-score	support
Chinee Apple	0.90	0.84	0.87	226
Lantana	0.92	0.96	0.94	213
Parkinsonia	0.98	0.96	0.97	207
Parthenium	0.93	0.84	0.88	205
Prickly Acacia	0.88	0.94	0.91	213
Rubber Vine	0.96	0.94	0.95	202
Siam Weed	0.98	0.89	0.94	215
Snake Weed	0.87	0.86	0.86	204
Negatives	0.95	0.97	0.96	1822
accuracy			0.94	3507
macro avg	0.93	0.91	0.92	3507
weighted avg	0.94	0.94	0.94	3507

Figure 5: Average precision, recall, F1-score of MobileNet model.

In this paper, the Deepweeds dataset was introduced, and the author trained two DL models to set a benchmark on the Deepweeds dataset. They trained pre-trained Inception-v3 and ResNet50 models to achieve average accuracy of 95.1% and 95.75%, respectively. This study sets a new benchmark by achieving an accuracy of more than 99.5%.

Real Time Inference: Few test cases

The feasibility of our selected model for in-field and real-time performance should be evaluated as we move closer to the implementation of robotic weed management. For model evaluation, images were taken from the Somaiya Vidyavihar University Campus (19.0722,72.8976) and used in the model for weed classification. Of the 53 pictures taken, 9 pictures were classified as weeds because they matched the features of the weeds in the DeepWeeds dataset, which was completely different. Figures 6–13 show some examples of this.

Figure 6: Classified as Chinee Apple Weed

Figure 7: Classified as Rubber Wine Weed

Journal of Information Systems Engineering and Management
2025, 10(40s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

Figure 8: Classified as Chinee Apple Weed

Figure 9: Classified as Chinee Apple Weed

Figure 10: Classified as Rubber Wine Weed

Figure 11: Classified as Siam Weed

Figure 12: Classified as Negative class

Figure 13: Classified as Negative class

The proposed weed detection model effectively identified different weed species with high precision, thereby proving suitable for real-time agricultural use. The figures 6, 7, 8, and 9 show examples in which the model correctly detected Chinese apple seed, and Figures 8 and 10 demonstrate successful identification of rubber tineweed. These test results demonstrate that the model can reliably distinguish various weed species based on textual features, shape attributes, and color patterns. The model successfully identified Siam Weed (Figure 12 which demonstrates its potential to handle different plant patterns. In Figures 12 and 13, the model misidentified either no detected weeds or confused plant specimens with the negative class. The use of this model indicates that several obstacles remain in identifying complex plant structure arrangements and recognizing unfamiliar plant species. This model provides dependable weed detection because of its robust classification capabilities. The accuracy and generalizability of this system can be improved through future enhancements, including training additional data and feature extraction method optimization.

CONCLUSION

The training technique of freezing the convolutional layers (base_model. trainable = False) allowed for faster training but resulted in lower accuracy than fine-tuning the entire architecture. Fine-tuning (base_model. trainable = True) significantly improved performance, especially for multiclass classification tasks, achieving accuracies as high as 99.7% with EfficientNetB0. MobileNet and EfficientNetB0 were identified as the most efficient architectures, delivering the best trade-off between accuracy and training time. DenseNet121 was the top performer in the frozen-layer category, achieving an accuracy of 88.4% for multiclass classification. Multilabel classification tasks also benefited from fine-tuning, and MobileNet achieved near-perfect accuracy (99.7%). The DeepWeeds dataset is comprehensive and contains challenges such as imbalanced classes and overlapping features among plant species. The use of pretrained weights helped the models generalize well to these challenges. Transfer learning has proven to be a powerful tool, reducing the time and computational resources requirededed for training while maintaining high performance. Researchers should focus on enhancing model structures by implementing attention techniques or mixing transformer models with CNNs to achieve better feature extraction results. The use of GANs for synthetic image generation as a data augmentation technique can help achieve better class distribution while making the system more resistant to environmental changes. The use of optimized model deployment strategies on edge devices through quantization and pruning methods enables precision agriculture to obtain accessible automated weed detection systems. Future weed management methods in smart farming will deliver sustainable high-performance solutions through improvements in real-time inference speed and adaptive learning techniques.

REFRENCES

[1] A. Kamilaris and F. X. Prenafeta-Boldú, "Deep learning in agriculture: A survey," *Comput. Electron. Agric.*, vol. 147, pp. 70–90, 2018.

[2] W. K. Alazzai, M. K. Obaid, B. Sh. Z. Abood, and L. Jasim, "Smart Agriculture Solutions: Harnessing AI and IoT for Crop Management," *E3S Web of Conferences*, vol. 477, p. 00057, 2024, doi: 10.1051/e3sconf/202447700057.

[3] R. Zimdahl, *Reflections on the Role of Ethics in Agriculture*. Springer Nature Switzerland, 2024, doi: 10.1007/978-3-031-62941-9.

[4] G. Mohyuddin, M. A. Khan, A. Haseeb, S. Mahpara, M. Waseem, and A. M. Saleh, "Evaluation of Machine Learning Approaches for Precision Farming in Smart Agriculture System: A Comprehensive Review," *IEEE Access*, vol. 12, pp. 60155–60184, 2024, doi: 10.1109/access.2024.3390581.

[5] A. Hussen, "Effect of Critical Period of Weed Competition and Its Management Option in Sweet Corn [*Zea mays (L.) var. saccharata strut*] Production: A Review," *Agricultural Reviews*, no. Of, May 2021, doi: 10.18805/ag.r-189.

[6] Z. Wu, Y. Chen, B. Zhao, X. Kang, and Y. Ding, "Review of Weed Detection Methods Based on Computer Vision," *Sensors*, vol. 21, no. 11, p. 3647, May 2021, doi: 10.3390/s21113647.

[7] H.-R. Qu and W.-H. Su, "Deep Learning-Based Weed–Crop Recognition for Smart Agricultural Equipment: A Review," *Agronomy*, vol. 14, no. 2, p. 363, Feb. 2024, doi: 10.3390/agronomy14020363.

[8] A. Olsen et al., "DeepWeeds: A multiclass weed species image dataset for deep learning," *Sci. Rep.*, vol. 9, no. 1, p. 2058, 2019.

[9] A. dos Santos Ferreira, D. Matte Freitas, G. Gonçalves da Silva, H. Pistori, and M. Theophilo Folhes, "Weed detection in soybean crops using ConvNets," *Comput. Electron. Agric.*, vol. 143, pp. 314–324, Dec. 2017, doi: 10.1016/j.compag.2017.10.027.

[10] F. N. Ortatas, U. Ozkaya, M. E. Sahin, and H. Ulutas, "Sugar beet farming goes high-tech: A method for automated weed detection using machine learning and deep learning in precision agriculture," *Neural Comput. Appl.*, vol. 36, no. 9, pp. 4603–4622, Dec. 2023, doi: 10.1007/s00521-023-09320-3.

[11] J. Torres-Sánchez, F. J. Mesas-Carrascosa, F. M. Jiménez-Brenes, A. I. de Castro, and F. López-Granados, "Early Detection of Broad-Leaved and Grass Weeds in Wide Row Crops Using Artificial Neural Networks and UAV Imagery," *Agronomy*, vol. 11, no. 4, p. 749, Apr. 2021, doi: 10.3390/agronomy11040749.

[12] R. Goyal, A. Nath, and U. Niranjan, “Weed detection using deep learning in complex and highly occluded potato field environment,” *Crop Protection*, vol. 187, p. 106948, Jan. 2025, doi: 10.1016/j.cropro.2024.106948.
[13] F. Mekhalfa and F. Yacef, "Supervised learning for crop/weed classification based on color and texture features," *arXiv preprint arXiv:2106.10581*, 2021. [Online]. Available: https://arxiv.org/abs/2106.10581
[14] A. Subeesh et al., "Deep convolutional neural network models for weed detection in polyhouse grown bell peppers," *Artif. Intell. Agric.*, vol. 6, pp. 47–54, 2022, doi: 10.1016/j.aiia.2022.01.002.
[15] Y. Du, G. Zhang, D. Tsang, and M. K. Jawed, "Deep-CNN based robotic multi-class under-canopy weed control in precision farming," *arXiv preprint arXiv:2112.13986*, 2021. [Online]. Available: https://arxiv.org/abs/2112.13986
[16] S. Gupta et al., "Improving weed detection using deep learning techniques," in *Proc. 6th Int. Conf. Recent Trends Comput.*, 2021, pp. 171–180, doi: 10.1007/978-981-33-4501-0_16.
[17] D. Patel, M. Gandhi, S. H., and A. D. Darji, "Design of an autonomous agriculture robot for real time weed detection using CNN," *arXiv preprint arXiv:2211.12077*, 2022. [Online]. Available: https://arxiv.org/abs/2211.12077
[18] S. K. Tripathi, S. P. Singh, D. Sharma, and H. U. Patekar, "Weed detection using convolutional neural network," *arXiv preprint arXiv:2502.14360*, 2025. [Online]. Available: https://arxiv.org/abs/2502.14360
[19] N. Rai et al., "Agricultural weed identification in images and videos by integrating optimized deep learning architecture on an edge computing technology," *Comput. Electron. Agric.*, vol. 206, p. 108442, 2023, doi: 10.1016/j.compag.2023.108442.
[20] S. Gupta et al., "Deep learning application in diverse fields with plant weed detection as a case study," in *Proc. Int. Conf. Artif. Intell. Appl.*, 2021, pp. 5–10, doi: 10.1145/3487923.3487926.
[21] S. G. Wu et al., “A leaf recognition algorithm for plant classification using probabilistic neural network,” in *Proc. IEEE Int. Symp. Signal Process. Inf. Technol. (ISSPIT)*, Cairo, Egypt, 2007, pp. 11–16.
[22] D. Hall, C. McCool, F. Dayoub, N. Sunderhauf, and B. Upcroft, “Evaluation of features for leaf classification in challenging conditions,” in *Proc. IEEE Winter Conf. Appl. Comput. Vis. (WACV)*, Hawaii, USA, 2015, pp. 797–804.
[23] A. Shirzadifar, S. Bajwa, S. A. Mireei, K. Howatt, and J. Nowatzki, “Weed species discrimination based on SIMCA analysis of plant canopy spectral data,” *Biosyst. Eng.*, vol. 171, pp. 143–154, 2018.
[24] M. Louargant et al., “Unsupervised classification algorithm for early weed detection in row-crops by combining spatial and spectral information,” *Remote Sens.*, vol. 10, p. 761, 2018.
[25] J.-L. Tang, X.-Q. Chen, R.-H. Miao, and D. Wang, “Weed detection using image processing under different illumination for site-specific area spraying,” *Comput. Electron. Agric.*, vol. 122, pp. 103–111, 2016.
[26] O. Barrero, D. Rojas, C. Gonzalez, and S. Perdomo, “Weed detection in rice fields using aerial images and neural networks,” in *Proc. XXI Symp. Signal Process., Images Artif. Vis. (STSIVA)*, Bucaramanga, Colombia, 2016, pp. 1–4.
[27] N. Y. Murad, T. Mahmood, A. R. M. Forkan, A. Morshed, P. P. Jayaraman, and M. S. Siddiqui, "Weed Detection Using Deep Learning: A Systematic Literature Review," Sensors, vol. 23, no. 7, p. 3670, Mar. 2023, doi: 10.3390/s23073670.