Exploring Novel CNN Architectures for Weed Seedling Recognition in Precision Agriculture

Monisha R[a*], Tamilselvan KS [b], Vaishnavi T [c], Sharmila A [d]

[a]Department of ECE, KPR Institute of Engineering and Technology, Coimbatore, Tamil Nadu, India – 641 407.

e-mail id: 21ftec004@kpriet.ac.in

ORCID ID: 0000-0002-4591-897X

[b]Department of ECE, KPR Institute of Engineering and Technology, Coimbatore, Tamil Nadu, India – 641 407.

e-mail id: tamilselvan@kpriet.ac.in

ORCID ID: 0000-0001-8364-0596

[c]Department of IT, Kongu Engineering College, Erode, Tamil Nadu, India – 638 060.

e-mail id: vaishnavi.it@kongu.edu

[d]Department of ECE, Bannari Amman Institute of Technology, Coimbatore, Tamil Nadu, India – 638 401.

e-mail id: sharmilaa@bitsathy.ac.in

ORCID ID: 0000-0002-6029-4376

*Corresponding author –Monisha R.

Abstract

Precision agriculture (PA) aims to maximize crop yields while minimizing inputs like water, fertilizer, and pesticides. To achieve this, PA relies on advanced technologies such as sensors, drones, and satellite imagery to monitor crops and optimize inputs. However, weeds pose a significant challenge, competing with crops for vital resources and thereby reducing production output. For weeds to be managed and controlled effectively, they must be categorized accurately. Effective weed management requires understanding each weed's characteristics, which can be challenging with traditional methods. In our research, a comprehensive investigation of 14 hybrid ResNets and 2 SqueezeNets architectures to classify multiclass weed seedlings was conducted. They include ResNet(18, 34, 50, and 101), XResNet(18, 34, 50, and 101), XSEResNet(18, 34, 50, and 101), SqueezeNet (1.0, 1.1). The results demonstrate that the ResNet 101 model achieves superior performance with 90% accuracy, surpassing other architectures. It is a deep architecture that can capture more complicated associations in data, which explain its greater performance. Moreover, it was observed that the XSEResNets exhibit a smoother loss curve, which could be attributed to its channel weighting mechanism. This comprehensive analysis establishes ResNet 101 as the most effective pre-trained CNN model within the Fast.ai library for weed seedling classification in PA applications, provided sufficient computational resources are available.

Keywords: Fast.ai, Precision agriculture, ResNet, SqueezeNet, Weeds.

1. Introduction

By 2050, there will be 9.7 billion people on the earth, according to the United Nations [1]. Food consumption has increased owing to the rapidly expanding human populace. This population growth, coupled with increasing urbanization and changing dietary habits, will put significant pressure on the agricultural sector to produce more food while minimizing environmental impact. There is an urgent need for application of non-invasive modern technologies to better meet the food demand in the upcoming future. To sustain and improve agricultural production, the sector must embrace ingenious technological advancements like Computer Vision, Internet of Things (IoT), etc.

Since the past few years, there have been numerous contributions integrating cutting edge technologies into Precision Agriculture (PA). PA is often defined as the highest degree of exactness considering multiple aspects of crop cultivation [2]. It is an approach that combines various techniques for acquiring and examining field data, processing and utilizing it appropriately for the task at requirement [3]. Nowadays, Artificial Intelligence (AI) and machine learning algorithms are being coalesced with sensors, drones, etc for real-time deployment in farming sites for a variety of applications to maximize plant yield. Raw information like soil moisture, water content, leaf health, and nutrient values, etc can be obtained through these appliances and they can be processed to make timely decisions. The precise crop management leads to reduced utilization of fertilizers and pesticides and is cost-effective. Precision agriculture focuses on enhancing crop yield thereby creating a sustainable environment in the long term.

Weed management, through which the hindrances produced by these risky crops are removed, is one of the main aspects covered by PA. Weeds contend with crops for water, nutrition, and sunlight and tend to overgrow them [4 and 5]. They affect plant growth slowly and steadily, where its damages can be incurable in the latter stages. Moreover, consumption of certain species of weeds by animals results in an unfavorable odor in their milk. In addition, some weed species are toxic to cattle, therefore it's critical to handle them cautiously to protect both people and animals. They also impose additional costs on farmers, primarily in terms of the labor and time required to control them, as well as the economic losses caused by diminished harvest rates and standards. Small-scale farmers may find it especially difficult to manage weeds effectively because they lack the tools, resources, and technology needed. By changing the quality of the soil, upsetting native plant populations, and causing erosion, they can also have an effect on the ecology and the surrounding environment.

These situations emphasize the necessity for early weed and crop distinction. Earlier mechanical methods including hand weeding and tillage were used for curbing the weed growth. Later gardening strategies like cover cropping and crop rotation, and chemical methods like herbicides and pesticides were undertaken. Every method has its own shortcomings when not used appropriately. Although cultural and mechanical weed management techniques have their uses, they can also have certain drawbacks in real-world applications, such as being labor-intensive and ineffective [6]. Additionally, because weeds swiftly regenerate from tiny fragments or root systems, they can lessen the efficiency of mechanical and cultural weed control measures [7]. Tilling and other mechanical weed-control techniques can reduce soil fertility and porosity, impede water infiltration, and increase the risk of water pollution by causing soil erosion and compaction.

Chemical treatments, such as herbicide application, are designed particularly to eliminate or manage weeds. It can be used broadly to control a wide range of weeds or narrowly to target specific weed species. Herbicides, when used correctly, can be a helpful tool for farmers to manage weeds more effectively and efficiently than they could with alternative methods. However, herbicides have the potential to contaminate soil and water, harming unintentional plants and animals and hastening the degradation of the ecosystem. There are worries about the potential health risks that agricultural workers and farmers may face from chemical exposure. Moreover, herbicide-resistant weeds might arise due to misuse or improper application, making long-term suppression of weeds more difficult.

AI is more desirable than conventional weed-control methods in many ways. First, analyzing vast volumes of data and pinpointing particular locations where weeds are growing may offer accurate and focused weed control. This lowers the quantity of chemicals used and the possibility that crops may be harmed by herbicide applications made only when necessary by farmers. Second, weed control can be achieved more effectively and economically using AI-powered devices since they can operate more quickly and constantly than conventional mechanical approaches. By doing this, farmers can safeguard their crops from weed infestations and save time and money. Thirdly, they limit the usage of chemicals, which may have negative environmental consequences, and encourage sustainability in agriculture. Farmers can embrace a more economic and ecologically responsible approach to agriculture by utilizing AI-powered weed management techniques. Finally, these systems can adjust to shifting environmental factors like crop development phases, soil moisture content, and weather patterns. This implies that the system can optimize weed management techniques in real-time, improving overall outcomes and increasing the farmer's yield.

In a nutshell Deep Learning, or DL for short, is a subset of Machine Learning (ML) that uses neural networks to learn from data. This approach works especially well for tasks like speech recognition, image identification, natural language processing, and predictive modeling, where a lot of data can be used to train the network to identify patterns and make precise predictions. As the big data age has grown, DL has developed more complex network structures, powerful feature learning, and expressiveness than traditional ML techniques. Since its inception, the models trained by the DL algorithms have excelled in numerous challenging identification tasks in computer vision [8]. Convolutional Neural Networks (CNNs), for example, have recently acquired popularity in activities involving identification and categorization due to their reliance on automatic extraction of features [9-11]. Additionally, DL methods have made important strides that have led to challenges and competitions in picture classification tasks [12-14]. Providing an all-inclusive method for weed detection that is both early and automatic is the driving force behind the current work. Fast AI, one of the most well-known open-source DL libraries that aims to democratize AI by making DL accessible to everyone, regardless of their background or

expertise [15]. It is important for weed classification as it provides a powerful and accessible platform for developing DL models that can accurately and efficiently classify different weed species.
Prior research in weed classification primarily employed traditional convolutional neural network (CNN) architectures [16-25]. This study investigates the application of more recent and potentially superior CNN models, particularly those that can be compared against compact architectures when dealing with limited datasets. While the performance of these models has been explored in various computer vision tasks, their application in weed classification remains relatively underexplored. To address this gap, we conduct a comprehensive evaluation of 14 state-of-the-art CNN models on a multiclass weed seedling image dataset. The investigated models encompass ResNet (18, 34, 50, and 101), XResNet (18, 34, 50, and 101), XSEResNet (18, 34, 50, and 101), SqueezeNet (1.0, 1.1). A rigorous comparison by analyzing their parameters, outputs, and performance metrics including loss curves, confusion matrices, and classification reports was implemented.

2. Background

Crop and weed discrimination are still an exigent issue to deal with. Several researchers classified weed species in natural corn fields using shallow and DL models [16-17]. In [16], images of weeds were captured at distinct stages of growth from the fields. They acquired the region of interest from the images during processing and categorized the narrow and wide leaves by employing proposed models. It was inferred that CNNs outperformed the shallow networks with an accuracy of 97%. In [17], the authors incorporated a range of ML and DL approaches for weed classification. They discussed the challenges involved while processing in terms of dataset size, variability in images, and inter-class similarity. The review highlighted that CNN has shown remarkable success in weed classification, but they require large datasets and computational resources. Classification of weeds on the site amid cultivable crops is a notable area of research in agriculture. In [18], the suggested method classified the weeds concerning color and texture by employing VGG16 and support vector machine classifiers. The Relief algorithm extracted the attributes and the classifiers were able to predict the four distinct weeds from six different species of crops. In [19], the authors analyzed 35 state-of-the-art CNN methods for weeds grown in cotton fields. They classified a weed dataset with 5187 images and introduced a new cosine similarity metric to evaluate the performance of the 35 models. ResNext 101 had a good F1 score with 10 models achieving an F1 score above 98%. Identifying the appropriate weed as an individual or in a cluster and treating it with non-toxic substances is the precise weed treatment technique [20]. Spotting distinct weeds and treating the weeds on the variety is proposed in [21]. Certain types of weeds respond to particular herbicides alone. Despite utilizing the same herbicide, the weed-specific spraying of herbicides proffers acceptable results in the treatment of weeds. For this, the authors have deployed a SAMBot, an autonomous weed detection robot using MobileNetv2 model for classification with the shortest decision making time. In [22], an active learning method based on dissimilarity for integrated weed identification using a dataset of images of crop fields with weeds and crops was presented. A small initial set of labeled images was employed for training a classifier, and then the classifier selected the unlabeled images with the most information for annotation by an expert. The selected images were then labeled and added to the training set, and the revised training set was used to retrain the classifier. [22] outperformed traditional active learning and random sampling approaches in weed identification, achieving high accuracy rates with fewer labeled images. The trained model was transferred to NVIDIA Jetson nano for real-time weed detection. [23] employed a model that indicated the weeds of appropriate species in the input feeds and forecasting them. The system outperformed the existing models in predicting the presence of solitary weeds. DL models inclusive of VGG 16, ResNet, DenseNet proffered efficacy in distinguishing the weeds of numerous species. [24] employed a random forest classification approach, where the study extracted features such as texture, shape, and spectral information from the images and used them to train the classifier [24]. The study also reported low commission and omission errors, indicating that the method can accurately detect alligator weed in the images. Another leap was weed localization and segmentation using a single-stage object detection DL module was deployed with an inference speed of 1.25x on a hardware device [25].

3. Materials and Methods

3.1 Dataset

The comparative analysis was performed on a subset of the publicly available V2 Plant Seedlings Dataset from Kaggle [26]. The utilized subset encompasses six classes of weeds in their seedling stage with RGB images. The class contains some of the most commonly occurring weeds in large arable lands. Figure 1 gives the image samples of each crop included in the dataset.

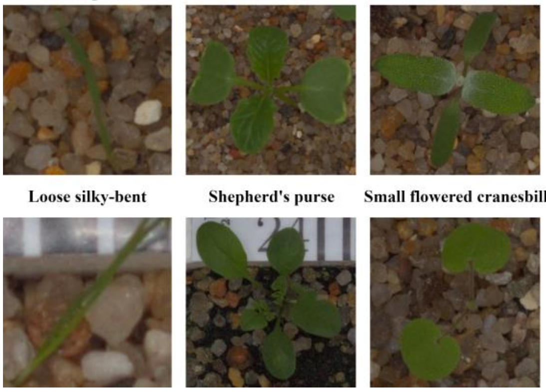

Fig 1 Samples of weed seedlings in the dataset

The dataset comprised 2,911 images with an uneven number of samples in every class, thus making it an imbalanced dataset. The class distribution and leaf characteristic appearance of every weed species member are given in Table 1. Google Colab in a laptop with Microsoft Windows 10 Pro and an Intel Core i7 processor was used to implement the architectures.

Table 1 Weed characteristics and class distribution.

Class	Scientific name	Leaf Characteristics	Total images
Black grass	*Alopecurus myosuroides*	Short, flat, bluish-green, and hairless. typically rolled, rough, and having a clearly discernible keel	309
Charlock	*Alopecurus myosuroides*	a wide, rounded tip with shallow ridges running around its edges	452
Fat hen	*Chenopodium album*	toothed borders, which are comparatively wide	538
Loose silky-bent	*Apera spica-venti*	Sharp, slender, coarse, and hairless. rolled.	762
Shepherd's-Purse	*Capsella bursa-pastoris*	The earliest true leaves are whole; later leaves are severely lobed or sliced, lance-shaped, and silvery in appearance.	274
Small-flowered cranesbill	*Geranium pusillum*	The leaves are opposite and have deeply and rather thinly cut hairs on the stalks; each solitary leaf lobe frequently has three smaller lobes.	576

3.2 Proposed models

In this study, the performance efficacy of 14 recent CNN-based models for the identification and classification of weeds has been investigated. The models utilized in the study are either variants of ResNet with certain tweaks or hybrid ResNets. Along with that SqueezeNet, a heavily compressed lightweight model is also studied. The following section delves into the method structures.

3.2.1 ResNet

Generally, in deep learning, it is said that the deeper the network, the higher the accuracy. As such DL networks designed focused on stacking layers and complicating the model. However, it was seen that the network performance diminished when a certain threshold for layering was reached. The problem is attributed to the gradients becoming zero after complex computations and thus having nothing to learn more from the data. Thus, to avoid the vanishing gradient problem, the authors of ResNet introduced residual blocks with skip connections [28]. The main idea behind ResNet is to use residual connections, which allow information to stream from one layer to another, without passing through all the intermediate layers. To connect layer activations to later layers, the skip connection skips over some intermediate levels as shown in Fig 2. Thus, a leftover block is produced. To build resnets, these leftover blocks are piled. ResNet's 34-layer simple network architecture is inspired by VGG-19, and the shortcut connection is added after that.

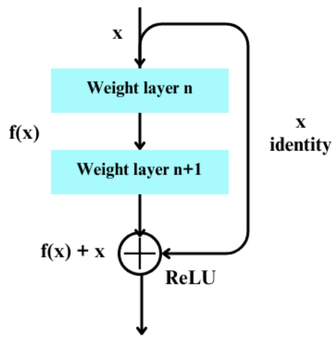

Fig 2 Residual block

ResNet makes it possible to train neural networks with hundreds of layers that are incredibly deep while still maintaining good accuracy. In the ResNet architecture, a convolutional layer processes the image input first, followed by several blocks with residuals. A shortcut link that adds the original input to the convolutional layers' output follows each residual block's two or more convolutional layers. This allows the network to learn the residual mapping—the difference between the block's input and output.

To create the final output for classification, ResNet also employs a fully connected layer at the end and an overall pooling layer. In general, as the number of layers increases, the network becomes deeper and more complex, allowing it to learn complex features and achieve good performance on tasks such as image classification.

3.2.2 XResNets

The ResNet model was tweaked as XResNets, which incorporated slight modifications, each variant focusing on different layers of the base architecture [29]. These modifications, often referred to as ResNet-B, ResNet-C, and ResNet-D, address different aspects of the architecture as shown in Fig 3. ResNet-B and ResNet-D concentrate more on retaining more data whereas ResNet-C concentrates on reducing the computational complexity. The former has alterations in the downsampling block by changing the strides for the convolution operation. The latter replaced the 7x7 convolution with three 3x3 convolutions. Though the variants underperform in accuracy when compared to the base model, they highlight the importance of random points in layer selections that could affect the overall efficacy.

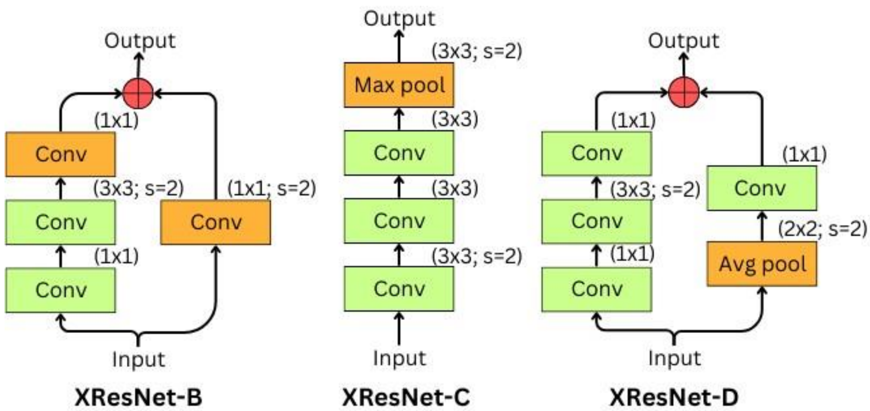

Fig 3 XResNets

3.2.3 SE-ResNets

SE-Nets, squeeze and excitation networks, introduced a method to weigh each channel instead of assigning equal weights to all input channels [30]. Basically in CNN's multi-channel architecture, the top layers are responsible for high-level feature extraction whereas the bottom layers extract simple features like edges. To avoid sharing the same weights across all input channels, SE-Nets perform the weighing by parameterizing the weights at the end of the block. They take in a residual convolutional feature map as input and then apply average pooling, which results in reduced dimensions. Later two fully connected layers are used for non-linear representation using bottleneck parametrization. The first FC layer is followed by ReLU and the second by the sigmoid activation function. The output of these layers is used to calculate the weights of each channel in a neural network.

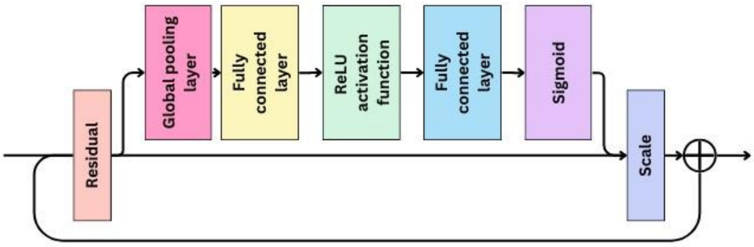

Fig 4 SE-Net

3.2.4 SqueezeNet

SqueezeNets were developed to design a network that can be deployed in any edge device or computer network [31]. They have fewer trainable parameters thus rendering a small network with minimal processing time and memory. The two methodologies of the SqueezeNet model are built upon the AlexNet; one with heavy compression and the other with a hybrid compression technique. AlexNet has five convolutional layers in combination with a pair of max pooling and ReLU layers and three final dense layers. The entire network consisted of 61 million parameters. SqueezeNet with its base as AlexNet, is made up of two convolutional layers, eight fire modules, three max-pooling layers, and one global average pooling layer as shown in Fig 5. In the fire block, an expand layer with a combination of 1x1 and 3x3 convolution filters receives input from a squeeze convolution layer, which only has 1x1 filters.

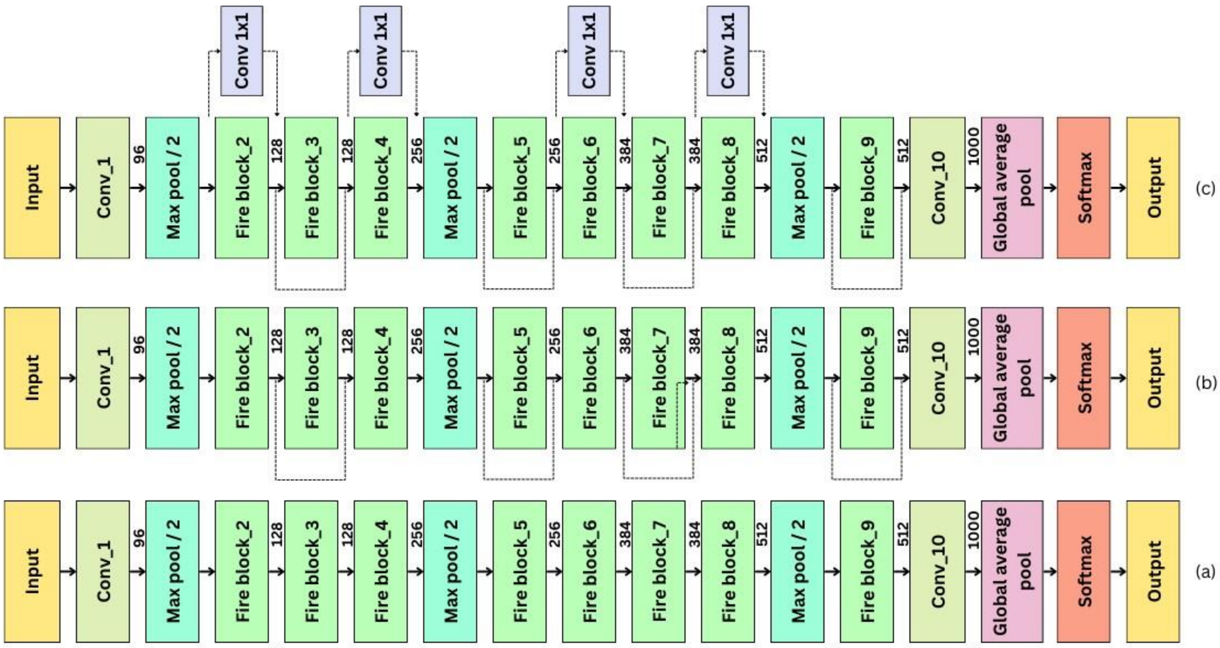

Fig 5 (a) SqueezeNet module; (b) with bypass; (c) with complicated bypass

The fire block consists of three hyperparameters:

The number of filters (all 1x1) in the squeeze layer is denoted by s_{1x1}. The expand layer's number of 1x1 filters is denoted by $e_{1(1}$, and the number of 3x3 filters is denoted by $e_{3(3}$. The sum of these filters is $s_{1(1}<(e_{1(1}+e_{3(3})$. To reduce the amount of input channels for the 3x3 filters, the squeeze layer is used. Here, concat has been used to link many layers to improve expressiveness (expressiveness in this context refers to the earlier portions' extraction of features and spatial information from the images). Furthermore, no fully connected layer exists. This yields a vector that has been flattened and whose dimension is equal to the number of classes. This vector is then supplied to the SoftMax layer. The number of parameters is significantly reduced when FC layers are absent.

3.3 Overall methodology

Fig 6 shows our proposed methodology. First, the training data was pre-processed using various augmentation techniques, such as random flipping, and resizing. These pre-processing steps increased the diversity of the training data, making the model more robust and resistant to overfitting. Next, the CNN models' architecture was used for feature extraction and classification, which is commonly used for pre-training applications in computer vision. This pre-training step enabled the model to learn features that are useful for classifying the seedlings.

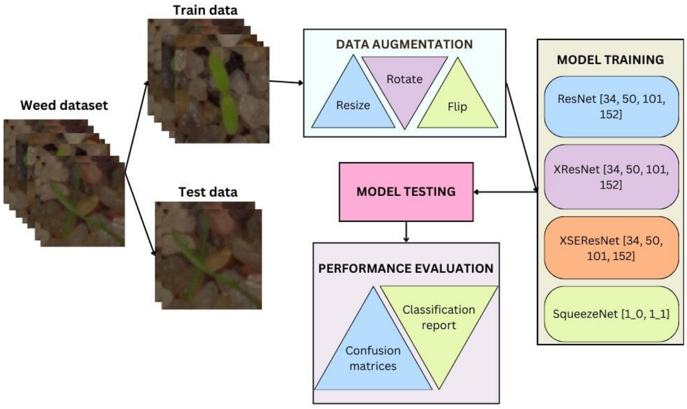

Fig 6 Overall flow of the proposed model

During training, the weights of the new layer were updated using backpropagation and gradient descent, optimizing the model for the classification task. Afterward, 14 CNN models were deployed and their accuracy alongside loss values was tested on the test dataset. Finally, their results have been compared in terms of classification reports and confusion matrices. Throughout the training process, the model was evaluated on a validation set to ensure that it is not overfitting to the training data. After the model had been trained and validated, it was used to predict the class labels of new images. This process involves passing the image through the newly trained model, which extracts the features from the image, and then passing these features through the new layer to obtain the predicted class label. The hyperparameters used for all models are discussed in Table 2.

Table 2 Hyperparameters

Parameters	Values
Loss function	Categorical cross-entropy
Optimizer	Adam
Learning rate	0.001
Epochs	50
Image size	64×64
Batch size	60
Library	Fast.ai

4 Performance Evaluation Metrics

A range of performance evaluation criteria have been utilized to appraise the efficacy of the implemented models. These include loss curves, confusion matrices, and classification reports. The training curves in Figure 9 show how the models' classification performance has increased with increasing epochs. Loss curves that reach the local minima, have a smoother form, and exhibit the least amount of zigzag or fluctuation are assumed to yield the best results. The anticipated category labels and the actual label are compared using a two-dimensional array known as the confusion matrix. As Table 3 illustrates, a confusion matrix consists of four sectors, or quadrants. This facilitates tracking the number of images that the models accurately and inaccurately categorize. Figure 10 displays the CNN models' Precision, Recall, and F1 score values from the classification report. An illustration of a confusion matrix that can be obtained from a binary classification task is shown below:

Table 3 Confusion matrix

		Predicted	
Actual		*Positive*	*Negative*
	Positive	TP	FN
	Negative	FP	TN

$$Precision = \frac{TP}{(TP+FP)} \quad \text{---(1)}$$

$$Recall = \frac{TP}{(TP+FN)} \quad \text{---(2)}$$

$$F1\ Score = \frac{2*(Precision*Recall)}{(Precision+Recall)} \quad \text{---(3)}$$

True Positive (TP): The model accurately estimates a positive class.
False Positive (FP): The model misidentifies a positive class.
True Negative (TN): The model accurately predicts a negative class.
False Negative (FN): The model mistakenly forecasts a negative class.

5 Results and Discussion

In this study, we used a multiclass dataset to compare the performance of 14 cutting-edge CNN models for weed seedling classification. The models tested were ResNet (18, 34, 50, and 101), XResNet (18, 34, 50, and 101), XSEResNet (18, 34, 50, and 101), and SqueezeNet (1.0, 1.1). The accuracy scores and loss curves provide information on each model's correctness and training stability.

5.1.1. Accuracy Scores and Loss Curves

The model accuracies obtained after training are given in Table 4. Among all of the investigated CNNs, the ResNet architectures fared the best, with ResNet 101 having the maximum overall accuracy (90%). ResNet 50 came in close behind with an accuracy of 88%, demonstrating that deeper networks with more layers perform better on this classification challenge. In contrast, the XSEResNet models, despite their consistent training procedure, had the lowest accuracy ratings. XSEResNet 50 had the lowest accuracy of 77%, indicating that these models may need longer training periods or more intensive hyperparameter tuning to realize their full potential. The XSEResNet models, while promising because of their continuous drop in loss and constant gain in accuracy, require additional research to improve their performance. The SqueezeNet models had juxtaposing results. SqueezeNet 1.0 did well reasonably, with an accuracy of 88%; however, SqueezeNet 1.1, a more compact version, achieved just 81%. This performance gap can be explained by SqueezeNet 1.1's considerable reduction in parameters and processing time, which may limit its capacity to generalize effectively.

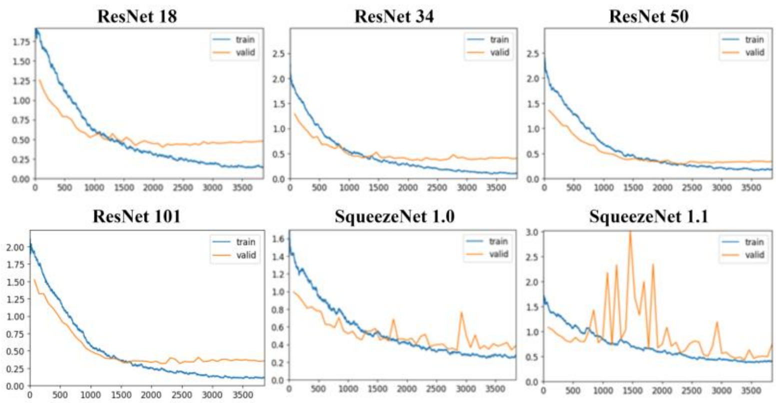

Fig 7 Learning curves for ResNets and SqueezeNets

The loss curves for all the proposed 14 models were plotted after training and are shown in Fig 7 and Fig 8. The XSEResNet models had the cleanest loss curves, with few variations or spikes, indicating a consistent training procedure. These models demonstrated a gradual decrease in loss and a trend towards a plateau, indicating the possibility of improved performance with additional training. In contrast, SqueezeNet variations showed large fluctuations in their loss curves, while SqueezeNet 1.0 outperformed SqueezeNet 1.1. SqueezeNet 1.1's compact architecture, which was supposed to cut computation time by 2.4 times over SqueezeNet 1.0, is likely to contribute to its instability during training and validation. The ResNet models showed significant convergence in their training and validation curves. This convergence implies that these models can effectively learn from the dataset, capturing the complex properties required for accurate classification. The performance gain from ResNet 18 to ResNet 101 implies that deeper architectures are better suited for this kind of classification since they can use more layers to understand complicated patterns in the data.

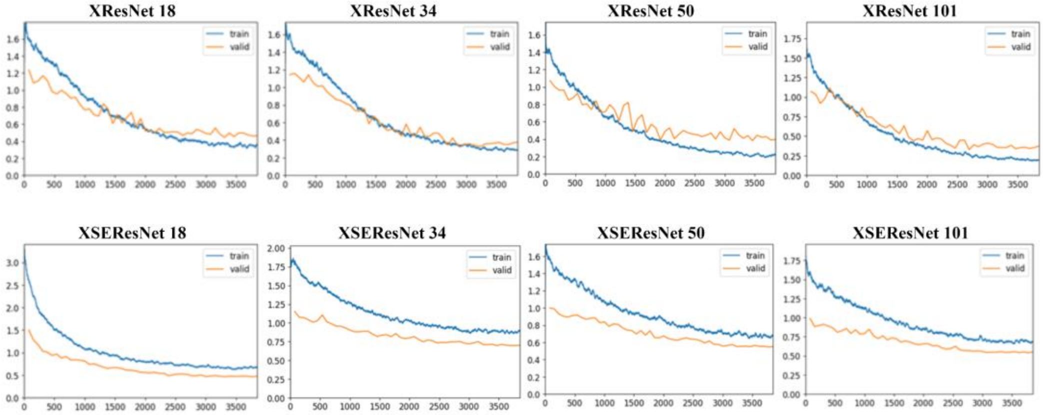

Fig 8 Learning curves for XResNets and XSEResNets

5.1.2. Classification report

Deeper architectures, such ResNet 101 and XResNet 101, are more effective for classifying weed seedlings, offering higher accuracy, better precision, and better recall across most classes, according to the classification results for the CNN models. Even with their training stability, the XSEResNet models still need to be further optimised in order to improve accuracy. The trade-off between model compactness and performance is obvious in the SqueezeNet models, with SqueezeNet 1.0 beating its more compact version, SqueezeNet 1.1. These results highlight how crucial it is to strike a balance between model depth, training stability, and compactness in order to get the best results possible for precision agriculture applications.

Black grass has the lowest precision and recall scores among the others. XSEResNet 18 showed the least precision value for black grass with 0.48 followed by XResNet 18 with 0.49. The precision values reach as high as 1.00 in Shepherd's purse for all XResNet variants and ResNet 50. The recall showed the lowest value 37 for XSEResNet 64 and SqueezeNet 1.1 models indicating the high number of FN which may be due to the unbalanced classes. Except for black grass all the F1-scores were above 0.60 for each class. While evaluating the model based on F1 score, it can be seen that this score balances the precision and recall metrics, since both the metrics could result in a less overall accuracy score. Overall it can be seen that the models performance were affected due to the absence of fine-tuning the hyperparameters and an uneven number of images in each class in the dataset.

5.1.3. Confusion Matrices

It's interesting to see that different models display efficiency across various classes. The confusion matrices for all 14 models are displayed in Fig 9 and Fig 10. They are used for telling the properly classified and misclassified items apart in each class. For all the models it can be seen that there is a confusion between Black grass and Loose silky-bent. Apart from them, Shepherd's purse is miscalculated as Small flowered cranesbill in all the models. The dataset has the least amount of images from Shepherd's purse compared to others making this an unbalanced dataset. In SqueezeNet 1.1 Shepherd's purse is confused with 9 images each with Fat hen and Small flowered cranesbill. XSEResNet models misidentifies the most of Shepherd's purse as Small flowered cranesbill with the minimum being 9 images. The third pair that gets most confused is the fat hen and charlock resulting in less precision and recall for many models.

Table 4 Model accuracy

Model	Accuracy	Model	Accuracy
ResNet 18	87	XResNet 101	87
ResNet 34	87	XSEResNet 18	80
ResNet 50	88	XSEResNet 34	81
ResNet 101	90	XSEResNet 50	77
XResNet 18	82	XSEResNet 101	78
XResNet 34	85	SqueezeNet 1.0	87
XResNet 50	85	SqueezeNet 1.1	81

Finally, the superior performance of the ResNet architecture provides us with an understanding of the importance of complicated architectures for extracting complex features. To put it briefly, the leftover connection blocks greatly facilitate the layers' acquisition of identity functions. Consequently, ResNet reduces the percentage of test errors while increasing the efficiency of deep neural networks with more neural layers. The accuracy of residual neural networks was found to be higher than that of traditional deep neural networks in a number of benchmark datasets. Due to the skip connections, vanishing gradients are avoided and gradients can flow through the model more directly, resulting in faster convergence. Additionally, this results in quicker training and cheaper resource usage. ResNets' structure allows these models to learn broader patterns in the data rather than concentrating on attributes unique to a certain dataset. As a result, the model is more broadly applicable and produces superior outcomes with unknown data.

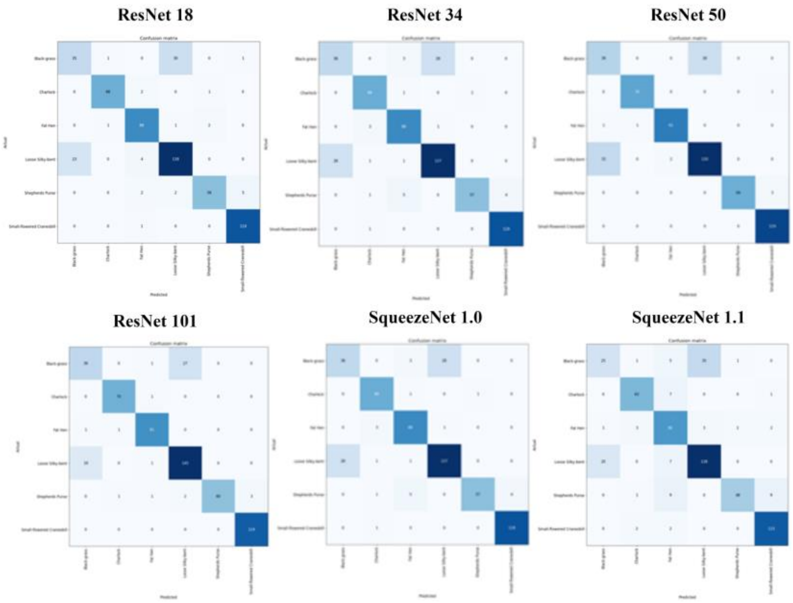

Fig 9 Confusion matrices for ResNets and SqueezeNets

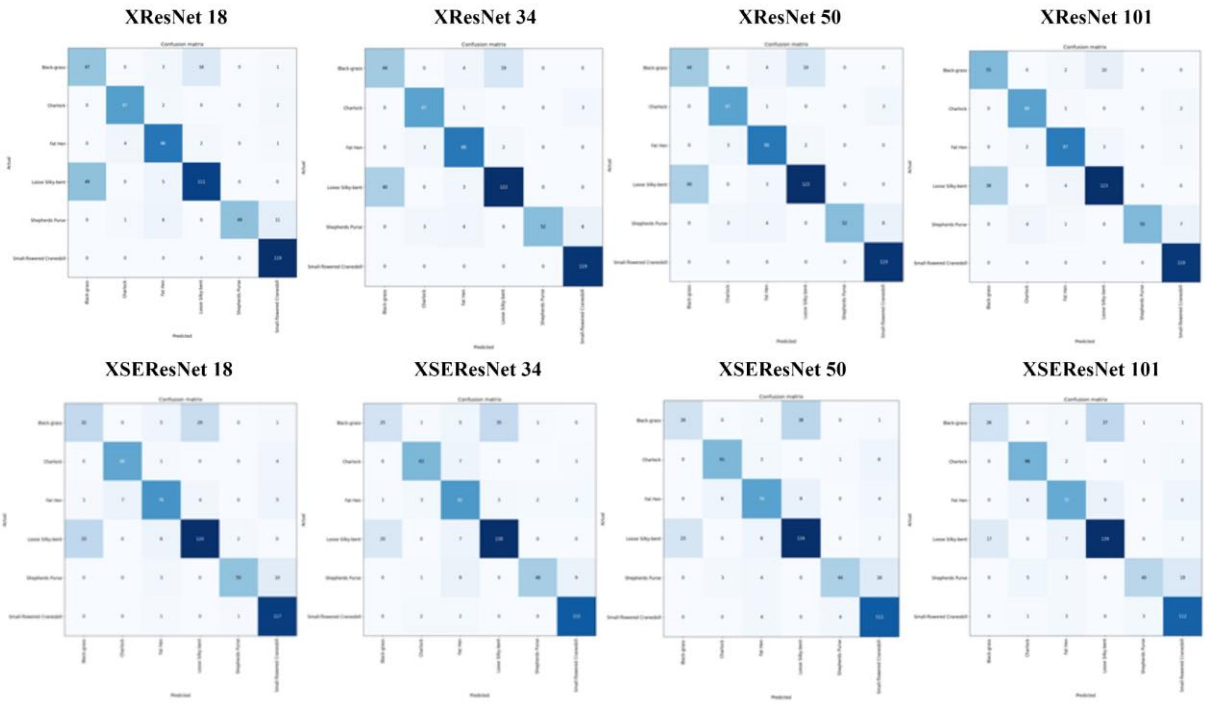

Fig 10 Confusion matrices for XResNets and XSEResNets

6 Conclusion

The study conducted in this research demonstrated the effectiveness of the proposed 14 approaches using ResNet and SqueezeNet for weed identification. The overall accuracy for ResNet was found to be 88%, which was the highest among other models tested. The easiest approach, which doesn't require a specialist, is to observe the field for the emergence of weeds in a computerized manner and use those images to automatically identify the sort of response. Hence, a study on novel CNN architectures on a weed dataset with 2911 images was conducted. from the results obtained, the ResNet 101 architecture performed the best with 90% accuracy. These tests were conducted only for 50 epochs, whereas there is a high potential that there will be an improvement in accuracy and other metrics if the experiments were performed for longer epochs. After inferring the potential of these networks for weed eradication, they can also be applied to other applications such as disease detection, yield prediction, etc. Future works will be focused on increasing the efficiency of the XSEResNet models without comprising the compact structures. The models used in this study are primarily based on the default architectures; no special adjustments have been made to take into consideration the dataset that has been obtained. Perhaps by improving the current models and making a few more architectural modifications even higher scores could be attained. It is also possible to test the model's deployment on edge devices. These are all jobs that will be included in future work.

The authors of this publication declare there are no competing interests.

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors. Funding for this research was covered by the author(s) of the article

The data used in this work is publically available at Kaggle website: https://www.kaggle.com/datasets/vbookshelf/v2-plant-seedlings-dataset .

References:

1. United Nations. (2019). World population projected to reach 9.7 billion by 2050. Retrieved from https://www.un.org/development/desa/en/news/population/world-population-prospects-2019.html.
2. Pierce FJ, Nowak P. Aspects of precision agriculture. Advances in agronomy. 1999 Jan 1;67:1-85.
3. Pathak HS, Brown P, Best T. A systematic literature review of the factors affecting the precision agriculture adoption process. Precision Agriculture. 2019 Dec;20:1292-316.
4. Zimdahl RL. Weed-crop competition: a review.
5. Verma SK, Singh SB, Meena RN, Prasad SK, Meena RS. A review of weed management in India: the need for new directions for sustainable agriculture. The Bioscan. 2015;10(1 Supplement):253-63.
6. Liebman. Integration of soil, crop and weed management in low-external-input farming systems. Weed research. 2000 Feb;40(1):27-47.
7. Slaughter DC, Giles DK, Downey D. Autonomous robotic weed control systems: A review. Computers and electronics in agriculture. 2008 Apr 1;61(1):63-78.https://doi.org/10.1016/j.compag.2007.05.008.
8. Der Yang M, Tseng HH, Hsu YC, Tseng WC. Real-time crop classification using edge computing and deep learning. In2020 IEEE 17th Annual Consumer Communications & Networking Conference (CCNC) 2020 Jan 10 (pp. 1-4). IEEE. https://doi.org/10.1109/CCNC46108.2020.9045498.
9. Dash S, Verma S, Kavita, Khan MS, Wozniak M, Shafi J, Ijaz MF. A hybrid method to enhance thick and thin vessels for blood vessel segmentation. Diagnostics. 2021 Oct 30;11(11):2017.https://doi.org/10.3390/diagnostics11112017.
10. Abas FS, Gokozan HN, Goksel B, Otero JJ, Gurcan MN. Intraoperative neuropathology of glioma recurrence: cell detection and classification. InMedical Imaging 2016: Digital Pathology 2016 Mar 23 (Vol. 9791, pp. 59-68). SPIE. https://doi.org/10.1117/12.2216448.
11. Valkonen M, Kartasalo K, Liimatainen K, Nykter M, Latonen L, Ruusuvuori P. Metastasis detection from whole slide images using local features and random forests. Cytometry Part A. 2017 Jun;91(6):555-65. https://doi.org/10.1002/cyto.a.23089.
12. Lo SC, Lou SL, Lin JS, Freedman MT, Chien MV, Mun SK. Artificial convolution neural network techniques and applications for lung nodule detection. IEEE transactions on medical imaging. 1995 Dec;14(4):711-8. https://doi.org/10.1109/42.476112.
13. Luis R, Sucar LE, Morales EF. Inductive transfer for learning Bayesian networks. Machine learning. 2010 May; 79:227-55. https://doi.org/10.1007/s10994-009-5160-4.
14. Zhuang F, Qi Z, Duan K, Xi D, Zhu Y, Zhu H, Xiong H, He Q. A comprehensive survey on transfer learning. Proceedings of the IEEE. 2020 Jul 7;109(1):43-76. https://doi.org/10.1109/JPROC.2020.3004555.
15. Howard J, Gugger S. Fastai: A layered API for deep learning. Information. 2020 Feb 16;11(2):108. https://doi.org/10.3390/info11020108.

16. 1. Garibaldi-Márquez F, Flores G, Mercado-Ravell DA, Ramírez-Pedraza A, Valentín-Coronado LM. Weed Classification from Natural Corn Field-Multi-Plant Images Based on Shallow and Deep Learning. Sensors. 2022; 22(8):3021. https://doi.org/10.3390/s22083021.
17. Al-Badri AH, Ismail NA, Al-Dulaimi K, Salman GA, Khan AR, Al-Sabaawi A, Salam MS. Classification of weed using machine learning techniques: a review—challenges, current and future potential techniques. Journal of Plant Diseases and Protection. 2022 Aug;129(4):745-68. https://doi.org/10.1007/s41348-022-00612-9.
18. Sunil GC, Zhang Y, Koparan C, Ahmed MR, Howatt K, Sun X. Weed and crop species classification using computer vision and deep learning technologies in greenhouse conditions. Journal of Agriculture and Food Research. 2022 Sep 1; 9:100325. https://doi.org/10.1016/j.jafr.2022.100325.
19. Chen D, Lu Y, Li Z, Young S. Performance evaluation of deep transfer learning on multi-class identification of common weed species in cotton production systems. Computers and Electronics in Agriculture. 2022 Jul 1; 198:107091. https://doi.org/10.1016/j.compag.2022.107091.
20. Ajayi OG, Ashi J. Effect of varying training epochs of a Faster Region-Based Convolutional Neural Network on the Accuracy of an Automatic Weed Classification Scheme. Smart Agricultural Technology. 2023 Feb 1; 3:100128. https://doi.org/10.1016/j.atech.2022.100128.
21. Du Y, Zhang G, Tsang D, Jawed MK. Deep-cnn based robotic multi-class under-canopy weed control in precision farming. In2022 International Conference on Robotics and Automation (ICRA) 2022 May 23 (pp. 2273-2279). IEEE. https://doi.org/10.1109/ICRA46639.2022.9812240.
22. Yang Y, Li Y, Yang J, Wen J. Dissimilarity-based active learning for embedded weed identification. Turkish Journal of Agriculture and Forestry. 2022;46(3):390-401. https://doi.org/10.55730/1300-011X.3011.
23. Jin X, Bagavathiannan M, McCullough PE, Chen Y, Yu J. A deep learning-based method for classification, detection, and localization of weeds in turfgrass. Pest Management Science. 2022 Nov;78(11):4809-21. https://doi.org/10.1002/ps.7102.
24. Sheffield KJ, Clements D, Clune DJ, Constantine A, Dugdale TM. Detection of aquatic alligator weed (Alternanthera philoxeroides) from aerial imagery using random forest classification. Remote Sensing. 2022 Jun 2;14(11):2674. https://doi.org/10.3390/rs14112674.
25. Rai N, Sun X. WeedVision: A single-stage deep learning architecture to perform weed detection and segmentation using drone-acquired images. Computers and Electronics in Agriculture. 2024 Apr 1;219:108792.
26. VBOOKSHELF, dec 13 2018, V2 Plant Seedlings Dataset, version 1, https://www.kaggle.com/datasets/vbookshelf/v2-plant-seedlings-dataset.
27. LeCun Y, Bottou L, Bengio Y, Haffner P. Gradient-based learning applied to document recognition. Proceedings of the IEEE. 1998 Nov;86(11):2278-324. https://doi.org/10.1109/5.726791.
28. He K, Zhang X, Ren S, Sun J. Deep residual learning for image recognition. InProceedings of the IEEE conference on computer vision and pattern recognition 2016 (pp. 770-778).
29. He T, Zhang Z, Zhang H, Zhang Z, Xie J, Li M. Bag of tricks for image classification with convolutional neural networks. InProceedings of the IEEE/CVF conference on computer vision and pattern recognition 2019 (pp. 558-567).
30. Hu J, Shen L, Sun G. Squeeze-and-excitation networks. InProceedings of the IEEE conference on computer vision and pattern recognition 2018 (pp. 7132-7141).
31. Iandola FN, Han S, Moskewicz MW, Ashraf K, Dally WJ, Keutzer K. SqueezeNet: AlexNet-level accuracy with 50x fewer parameters and< 0.5 MB model size. arXiv preprint arXiv:1602.07360. 2016 Feb 24.