Weed Classification in Agriculture by employing Deep Learning Algorithms

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Abstract. In this study, we look at the state of the art in deep learning model and methods for weed detection and weed classifications to enhance the sustainability of crop production. We compare performance metrics like recall rate, accuracy rate (F1-Score), and precision. We also look at the adoption of attention mechanisms, Single-stage detection mechanism, and lightweight models to improve the performance of the model. Deep learning for weed detection and weed classification has the potential to increase crop yields and reduce the negative effects of agriculture on the environment. Reducing the use of herbicides can prevent water pollution, food pollution, land pollution, and ecosystem pollution. It can also prevent weeds from developing resistance to chemicals. By reducing the impact of agriculture on climate change mitigation and adaptation, we can minimize the environmental impact of agriculture and improve sustainability in the agricultural sector. The abstract presents a comprehensive exploration of the role of machine learning algorithms and convolutional neural networks (CNNs), in weed categorization within the context of precision agriculture. The study investigates various deep learning algorithms and methodologies, including supervised, unsupervised, and transfer learning, in the classification of weed species. Results indicate CNN's consistent supe-riority in accuracy, recall, precision, and F1-score over other algorithms, such as SVM and Random Forest, particularly in distinguishing between different weed and crop species. This demonstrates how well deep learning techniques handle complicated image datasets and points to possible future possibilities for this field of study.

Keywords: Deep Learning, Feature Selection, Machine Learning, Precision Agriculture, Weed Classification, and CNN.

1 Introduction

Weed classification is a critical task in precision agriculture, wherein farmers must detect and remove undesired plants (weeds) from their crops to maximize production and decrease pesticide use. Traditional weed categorization methods rely on physical labor, which is both time-consuming and costly. Consequently, there is a growing interest in employing machine-learning techniques to develop automated methods for weed classification. Convolutional neural networks (CNNs), for example, have shown considerable promise for automated weed categorization. These approaches can automatically learn complicated features from photos of crops and weeds and categorize them with high accuracy. Numerous research conducted in the last few years have shown how well CNNs classify weed. These studies have shown that CNNs can accurately classify different weed species and growth stages, enabling farmers to optimize their crop yields while reducing their use of herbicides. Various approaches for weed classification utilizing deep learning techniques, such as supervised, unsupervised, and transfer learning, have been proposed in literature. Despite great progress, some issues remain to be tackled in this discipline. For example, annotated databases that accurately depict the diversity of weed species and growth stages are scarce. Furthermore, developing efficient and dependable deep learning models that can operate in real-world scenarios is a difficult undertaking. This study paper intends to provide an in-depth analysis of cutting-edge deep learning algorithms for weed classification in this environment. The paper will examine the most recent advances in the field and will emphasize the benefits and drawbacks of utilizing deep learning techniques for weed classification. We will also explore the evaluation measures that are routinely employed in this sector and identify potential future research directions.

2 Literature Survey

Weed categorization is a crucial aspect of modern agriculture, particularly in the pursuit of eco-friendly and sustainable farming practices. This literature review synthesizes recent advancements in deep learning applications for weed categorization, highlighting significant studies and their contributions to this field. Qu H-R and Su W-H emphasize the importance of deep learning in smart agriculture, particularly its role in distinguishing between crops and weeds. They advocate for innovative solutions to weed management challenges, citing the rising demand for organic products and the need for precision agriculture techniques. Smart agricultural equipment, including robots and drones, is identified as effective tools in addressing weed-related issues, provided accurate detection facilitated by deep learning algorithms. The study conducted by Li et al. (2019) demonstrates the efficacy of deep neural networks (DNNs) in weed species classification. Utilizing a DNN with three hidden layers, they achieved an impressive classification accuracy of 92.2% across 16 weed species. Additionally, they found that convolutional neural networks (CNNs) outperformed other feature extraction methods, highlighting the superiority of deep learning techniques.

Milioto et al. (2019) focus on real-time semantic segmentation of crops and weeds using CNN-based approaches. Their study, employing a dataset of 13 crop and weed types, achieved an average segmentation accuracy of 87%. Notably, they discovered that incorporating background knowledge improved segmentation accuracy, underscoring the importance of contextual information in deep learning models.

Kavak et al. (2019) proposed a stacked auto encoder-based feature learning technique for weed classification, achieving a classification accuracy of 91.6% across eight weed species. Their approach demonstrated resilience to changes in lighting and leaf orientation, indicating its robustness in real-world agricultural settings. Mohanty et al. (2016) investigated CNN-based techniques for weed species classification and attained an accuracy of 96.49% across six weed species. They also examined the impact of CNN architecture on performance, noting that models with larger kernel sizes yielded better results. In order to classify weed and crop species, Sunil G. C. et al. (2022) compared deep learning-based visual group geometry (VGG) classification with support vector machine (SVM)-based classification. VGG16 classifiers outperformed SVM classifiers in terms of accuracy and F1-score across a variety of crop varieties, according to their study's encouraging results.

In conclusion, deep learning approaches, such as CNNs and DNNs, offer significant potential in weed categorization within precision agriculture. These techniques exhibit high accuracy and robustness, especially when combined with prior knowledge integration, suitable feature extraction methods, and appropriate dataset selection. Continued research in this area holds promise for further advancements in sustainable farming practices and weed management strategies.

3 Research Methodology

3.1 Data Collection and Preprocessing

To effectively utilize Convolutional Neural Networks (CNNs) for classifying weeds, the data collection process is pivotal. The dataset assembled must be comprehensive, inclusive, and reflective of the targeted domain, starting with identifying the specific weed species to be classified. Gathering diverse images encompassing various parts of the weed, such as leaves, blooms, seeds, and stems, is crucial, capturing them from different angles and lighting conditions. The dataset's size plays a pivotal role; a larger dataset enhances the CNN model's ability to learn and generalize features, thereby improving classification accuracy. Image quality is paramount, necessitating sharp, well-lit, high-resolution photographs devoid of blurriness, shadows, or artifacts. Diverse weed species from different sources and environments, across seasons and geographic locations, should be included to ensure robust learning of relevant features. Annotation of the dataset is essential for accurate categorization, whether performed manually or with automated tools. Resizing images to a consistent size while maintaining aspect ratio is necessary for model compatibility. Cropping extracts relevant regions, aiding in background removal and computational efficiency. Normalization adjusts pixel values for consistent scaling, while standardization ensures uniformity. Data augmentation artificially enhances dataset diversity through random image alterations, crucial for improving generalization. Finally, preprocessing steps must be validated to ensure data integrity and suitability for the CNN model, including thorough inspection for faults or inconsistencies and analysis of pixel value distributions.

3.2 Dataset Analysis

Images of various weed species taken at various development stages, from various perspectives, and in various lighting situations are included in the dataset. This will help the model learn robust features that can distinguish between different weed species [Table 1].

Table 1. Different Weed Species

				
Horseweed	Kochia	Ragweed	Water hemp	Black Bean
				
Canola	Corn weed	Sugar beets	Soya been	Flax Weed

3.3 Data Augmentation and Model Selection

Data augmentation is a technique used to artificially expand the dataset size by applying random changes to images, aiming to enhance the CNN model's generalization ability through increased dataset variety. Various transformations such as horizontal and vertical flipping, rotation by specific angles, scaling, adjusting brightness and contrast, introducing random noise, random cropping, and perspective modifications are employed to create diverse versions of the same image, simulating real-world scenarios. The input layer of the CNN model must be configured to accommodate pre-processed images, with an input shape matching the dataset image size. The dataset utilized in constructing the deep learning model consists of 3029 samples representing 10 distinct weed species, each subjected to data augmentation techniques to enrich the dataset [Table 2].

Table 2. Weed Dataset.

Weeds	Training Dataset	Testing Dataset	Total
Horseweed	435	109	544
Kochia	301	75	376
Ragweed	430	108	538

Water hemp	285	71	356
Black Bean	180	45	225
Canola	215	53	268
Corn	142	35	177
Flax	131	33	164
Soybean	175	44	219
Sugar beets	130	32	162
Total	**2424**	**605**	**3029**

4 Proposed Work

During the model-training phase, several strategies can be used to the pre-processed dataset. The modified photos are utilised to train the CNN model, resulting in a more diversified dataset that aids in model performance improvement. However, while using data augmentation approaches, it is vital to exercise caution because some changes may not be appropriate for the given classification task. Flipping or twisting an image of a weed, for example, may alter the orientation of the leaves or stem, making it impossible for the CNN model to correctly classify the weed species. As a result, it is critical to select the suitable data augmentation approaches for the specific weed classification task.

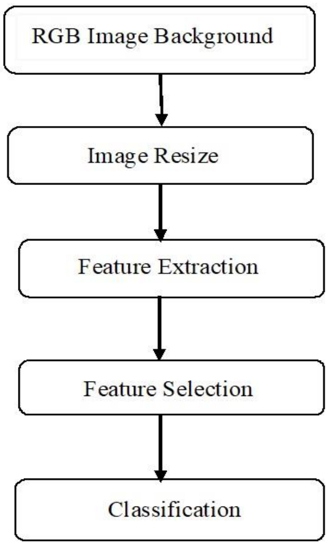

Fig. 1. Image Preprocessing and Feature Extraction

Figure 1 illustrates the sequential process of image preprocessing and feature extraction. Initially, the Excess Green (ExG) algorithm is employed to eliminate background noise from the RGB input images. Subsequently, the images undergo resizing and grayscale conversion. Following this, features are extracted, selected, and classified in a step-by-step manner.

4.1 Training and validation

Overall, for training and validating a weed classification using CNN, the process begins with gathering and pre-processing data, which involves tasks like data cleaning, image resizing, and creating training and validation sets. CNNs, comprising convolutional layers, pooling layers, and fully connected layers, require defining the number and type of network layers, along with setting the optimizer, loss function, and metrics for training. The model is trained on the training set using the fit method in Keras or Tensor Flow, with continuous monitoring of loss and accuracy. Evaluation of the model's performance on the validation set is done using the evaluate method, focusing on loss and accuracy metrics. Based on validation set performance, adjustments to the model's hyper parameters, such as learning rate or number of epochs, may be necessary. This rigorous process of data preparation, model architecture selection, and hyper parameter optimization may require multiple iterations to achieve satisfactory results.

Additionally, Fig. 2 illustrates the steps of CNN model training and testing, including feature selection, division of input data into train and test sets, and utilization of train data for model training.

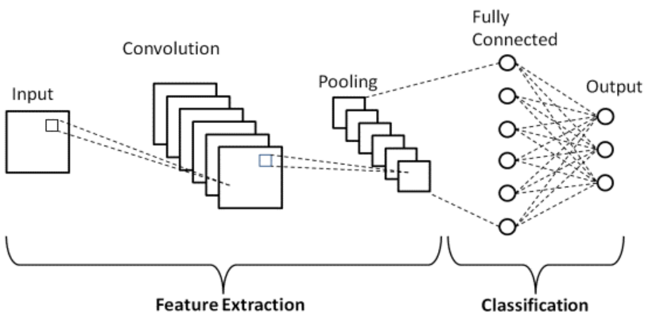

Fig. 1. CNN Architecture and Pooling Layers.

4.2 Model Testing

The algorithm's performance was assessed using the f1-score, kappa score, accuracy, precision, and recall metrics. The ratio of accurately predicted observations to total observations is known as accuracy (Eq. 1). Predicted observation, correctly expressed, is the total of true positives (TP) and true negatives (TN). True positives (TP), true negatives (TN), false positives (FP), and false negatives (FN) add up to total observation. According to Equation 2, precision is defined as the ratio of accurately predicted positive observations to all expected observations. The ratio of accurately anticipated positive observations to all observations made during the actual class is known as the recall (Eq. 3). The harmonic means of recall and precision is the F1-Score (Eq. 4).

$$\text{Accuracy} = TP + TN / TP + TN + FP + FN \quad (1)$$
$$\text{Precision} = TP / TP + FP \quad (2)$$
$$\text{Recall} = TP / TP + FN \quad (3)$$
$$F1 - \text{Score} = 2*\text{precision}*\text{recall} / \text{precision} + \text{recall} \quad (4)$$

5 Result and Discussion

This study used seven distinct types of CNN and classifiers to show how model performance could differ for the same weed species under eight different agricultural production strategies To avoid model-overfitting problems and lower memory usage during CNN model classifier computation, the feature selection strategy is used. The CNN model classifier is constructed utilizing a transfer learning approach and data augmentation because of the minimal amount of data. With its ability to extract self-features, deep learning holds significant potential for solving crop and weed classification issues involving the development of two or three weed seeds and their leaf interaction. With an accuracy of 97.52%, the Weeds-Corn classifier based on deep learning had the best performance. For experimentation, the dataset is divided into training and testing sets. Metrics like accuracy, recall, precision, and F1-score are used to assess the performance of seven distinct machine learning (ML) and deep learning (DL) algorithms, including SVM, Random Forest, KNN, Decision Tree, ANN, and CNN, on both training and testing samples from the weeds and crops dataset.

Table 3. Results from different algorithms for Training Samples

Algorithms	**Accuracy**	**Recall**	**Precision**	**F1-score**
SVM	0.9490	0.9373	0.9580	0.9475
Random Forest	0.9689	0.9632	0.9739	0.9685
KNN	0.9587	0.9521	0.9657	0.9588
Decision Tree	0.9640	0.9568	0.9709	0.9638
ANN	0.9672	0.9617	0.9723	0.9669
CNN	**0.9816**	**0.9761**	**0.9842**	**0.9801**

Table 4. Results from different algorithms for Testing Samples

Algorithms	**Accuracy**	**Recall**	**Precision**	**F1-score**
SVM	0.9256	0.9172	0.9320	0.9245
Random Forest	0.9553	0.9384	0.9728	0.9553
KNN	0.9355	0.9272	0.9428	0.9349
Decision Tree	0.9421	0.9305	0.9510	0.9406
ANN	0.9503	0.9238	0.9748	0.9485
CNN	**0.9752**	**0.9702**	**0.9832**	**0.9767**

The results indicate that the CNN algorithm consistently outperforms other algorithms in terms of accuracy, recall, precision, and F1-score for both training and testing samples [Table 3, 4]. SVM and Random Forest also demonstrate robust performance across the metrics evaluated. However, the CNN model exhibits superior discriminative power, particularly in distinguishing between different weed and crop species [Figure 1]. This underscores the effectiveness of deep learning approaches, such as CNN, in handling complex image datasets like the one used in this study.

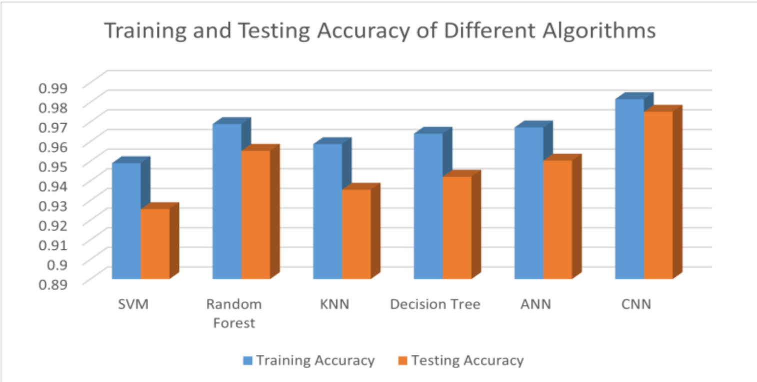

Fig. 3. Training and Testing accuracy of different algorithms for weeds species

6 Conclusion

This study has demonstrated the efficacy of employing convolutional neural networks (CNN) and classifiers in addressing the challenges associated with weed categorization across various agricultural production systems. The utilization of seven distinct CNN models, coupled with feature selection techniques, not only highlighted fluctuations in model performance but also mitigated over fitting concerns and memory requirements. Nonetheless, the field of weed classification through deep learning methodologies faces obstacles, primarily stemming from the necessity of extensive and diverse datasets for robust model training and testing. The significance of data augmentation and transfer learning strategies becomes apparent in dealing with limited data availability, as demonstrated in this research. Deep learning presents a promising avenue for overcoming complexities in weed and crop classification, particularly in scenarios where multiple weed species intermingle. The development of the Weeds-Corn classifier, with its superior performance metrics, underscores the potential of CNN models in discerning between various weed and crop species. While support vector machines (SVM) and random forest algorithms exhibit commendable performance, CNN consistently outperforms them, highlighting its superiority in handling intricate image datasets. Moving forward, optimizing the architecture and parameters of deep learning models remains crucial for enhancing efficiency and accuracy in weed classification endeavours.

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