Automatic Weed Detection using CNN

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Abstract Weeds are becoming a serious threat to the agricultural sector, which is acknowledged as the foundation of the Indian economy but is currently experiencing production issues. Plants that grow in inappropriate places are known as weeds, and they compete with crops for vital resources like water, light, nutrients, and space. This competition lowers crop yields and uses machinery inefficiently, which lowers agricultural productivity as a whole. Traditional weed control techniques include applying herbicide widely across the field or removing weeds by hand, which takes a lot of work. The latter approach, on the other hand, is considered ineffective since it pollutes the environment and offers little assistance in controlling weeds. There are financial and environmental issues associated with the widespread use of agricultural chemicals, such as fertilizers and herbicides. As a result, farmers are looking for alternatives more and more to reduce their reliance on chemicals in farming operations. Creative weed management strategies are becoming more and more necessary in response to these difficulties. The main goal is to distinguish between crops and weeds to provide a focused and effective weed management strategy. The agricultural industry may be able to increase productivity while lowering its impact on the environment and relying less on chemical solutions by implementing cutting-edge technologies for accurate weed identification and targeted eradication. The transition in weed control techniques towards technology-based and sustainable approaches is indicative of a wider movement in the agriculture sector to investigate environmentally friendly substitutes for a future that is more robust and fruitful.

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1 Introduction

The cornerstone of the Indian economy undeniably rests upon agriculture, a sector that sustains livelihoods for nearly half of the country's population. Given its paramount importance, ensuring the efficiency and productivity of agricultural practices becomes imperative. Thus, there arises a critical need to embrace cutting-edge cultivation techniques that not only optimize resources but also maximize crop yields. One of the primary challenges faced by farmers in this endeavor is the meticulous task of discerning weeds from the cultivated crop during the rinsing process. This seemingly mundane yet crucial aspect can significantly impact crop quality and quantity, underscoring the significance of innovative solutions and technologies in modern agricultural practices. Among a group of cultivated crops, weeds are extraneous plants that compete with the desired plants for nutrients, light, water, and space. The weeds can absorb the nutrients needed for crop growth. The yield may significantly decrease or be delayed in such a scenario. Therefore, it is necessary to prevent weed growth as much as possible. Furthermore, weeds will likely grow faster than crops. This is because the weed's seed or root is already in the ground and is just waiting for the right circumstances to sprout. This necessitates routine and frequent weed removal. When done by hand, this is a labor-and time-intensive process[1]. Identifying crops and weeds manually is a time-consuming task, requiring considerable labor to complete. The process involves distinguishing between desirable crops and unwanted weeds, a task that has become increasingly challenging in recent times. Traditionally, techniques for agricultural weed identification focused primarily on recognizing the weed species itself. However, as agricultural practices evolve and weed populations become more diverse and widespread, the complexity of accurately identifying and distinguishing weeds from crops has intensified. This heightened difficulty necessitates the development of more sophisticated and efficient methods for weed identification in plants, ensuring optimal management and maintenance of agricultural fields.

2 Literature Review

There has been a lot of work done to classify crops and weeds. Classification of crops and weeds has been a lengthy process. [2] concluded that only few percentage of fertilizers are reached to the root of plants which is very less effective. Authors of [3] have identified that most research is targeted towards unsupervised learning.

Authors of [4] identified three classes: apple scab, carpetweed, and crabgrass (weeds) by using the histogram based on color indices and tested with methods viz CNN with an accuracy of 93% respectively. Other models like GoogLeNet are also available, AlexNet has also been tested and are very accurate with a high f1 score of more than 95% for the detection of weeds. In addition, research has been carried out with the implementation of CNN for weed detection in unsupervised training data collection [3]. Research has been carried out on the detection of broad leaf weed in pasture using CNN models with an accuracy of 90%. The authors present CNN models for the classification of 16 plant species, including weeds, with a precision of 94%. In the case of weed species with an accuracy of 80%, similar work has been proposed to predict the growth stage [5]. The authors investigated the use of CNNs and obtained more than 90% accuracy with an average between all images above 85% to detect carpetweed and grass weeds in the soil. In this paper, traditional machine learning algorithms and deep learning models have been compared for the classification of seeds. By performing background segmentation, a good accuracy of 93.8% was achieved. For 16 different plant species with high precision, the authors have shown that CNNs are very effective in learning useful feature representations. Various approaches and systems for the classification of crops and weeds have been suggested to be introduced into the literature. The authors have tried to solve the problem using the CNN model Detection of weeds Agriculture has always been vital to human existence [6]. Agriculture has begun to mechanize and digitize throughout the past century, and more specifically over the last 15 years. As a result of this development and automation, labor flow has become virtually entirely standardized. The data will be used for the prediction of the weed from the crop in the Convolutional Neural Networks (CNN) and deep learning base model to find out the unwanted weeds and then suggest some herbicides. A machine vision technique may detect crops for weed management. Its characteristics, such as size, shape, spectral reflection, and texture, have detected weeds in agricultural fields. In this document, they have demonstrated the detection of weed by its size. Crop and weed detection using texture and size characteristics, as well as the automatic spraying of herbicides" They've been developing an image processing algorithm for crop discovery and weed management. 'Computer vision application for detecting undesirable weeds in early stage crops' Computer vision application for detection of undesirable weeds from one area which has an impact on agriculture. An Image To achieve the region of interest, processing has been developed, which has been completed throughout neural networks.

3 Methodology

3.1 Trend in recent year

Deep learning algorithms have been helpful in recent years for effectively analyzing text, picture, and spectrum data. Artificial intelligence uses a variety of deep learning methods to make it easier to identify weeds in photos. These algorithms are effective in analyzing data and identifying distinctive characteristics. Each digital image can be recognized as a 2D array of values, where each value corresponds to a greyscale code between 0 and 255. The convolutional, pooling, and dense layers get these pixel values after which they are fed [7].Throughout this process, weights are adjusted in accordance with how much the output and true label differ from one another. The methodologies employed in this investigation will be covered in the parts that follow.

3.2 Deep Neural Networks

Weed detection is the primary goal of the suggested methodology. The convolutional neural network is proposed for weed detection. Figure 1 depicts the architecture of the suggested methodology. We tried to use CNN with a few conv2d layers, dropout, max_pooling, and dense layers. Deep Learning (DL) is a type of machine learning algorithm characterized by sequential layers [8]. Unlike traditional machine learning methods that necessitate manual feature extraction, DL automatically selects features. A popular DL model known as Convolutional Neural Network (CNN) efficiently extracts features from input data, particularly in image analysis tasks. CNN's layered architecture allows it to identify and classify elements/pixels with minimal preprocessing. Typically, a CNN model consists of four main layers: convolutional, activation function, pooling, and fully connected layers (FCN) for classification purposes [9].

3.3 Procedure

In this part we will understand the characterization process for weeds into all the classes that we considered, we performed image processing on the dataset; images in the dataset are in RGB color code and have various dimensions (width and heights) [4]. AlexNet and GoogleNet models use three input channels corresponding to red, green, and blue color codes, input dimensions for GoogleNet are (224 x 224) and AlexNet is (227 x 227) [7].

We performed image processing in two steps. In the first step, all images are resized to conform to the input layer dimensions of AlexNet and GooleNet, and in the second step original image is duplicated three times for input channels (Red, Green, and Blue). We have used a transfer learning model to extract important information from the dataset images by identifying key details. Our models involve numerous convolutional neural networks (CNNs) stacked over each other. We have used two pre-trained models AlexNet and GoogleNet, we have replaced the bottom layers of the model with three fully connected layers which helps in uniting data extracted by previous layers. Used a softmax layer to convert a vector of real values into probability distribution with k- k-potential outcomes and we used a softmax layer to normalize the output. Table 1 below lists the hyper-parameters that were utilized during training [10].

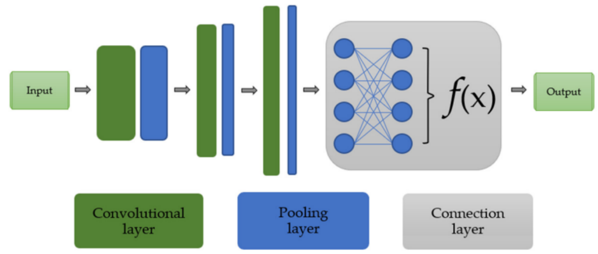

Fig. 1 The basic structure of a CNN models.

4 Dataset

For our experimental setup, we utilized a dataset sourced from the Kaggle website, consisting of approximately 6268 plant images, which are all in PNG format [11]. A training set and a validate set were created from this dataset, with a validate size ratio of 0.2.

Species	Training	Testing
Apple___Apple_scab	630	126
Apple___Black_rot	621	124
Apple___Cedar_apple_rust	275	55
Apple___healthy	786	157
Carpetweeds	763	152
Crabgrass	111	22
Goosegrass	216	43
Grape___Black_rot	1000	200
Grape___Esca_(Black_Measles)	1000	200
Grape___healthy	423	85
Tomato_Bacterial_Spot	96	19
Tomato_Early_Blight	46	9
Tomato_Healthy	73	15
Tomato_Leaf_mold	44	9
Tomato_Septorial_Leaf_Spot	82	16
Tomato_Yellow_Leaf_Curl_Virus	102	20

Fig. 2 Different classes used in our model.

[12] divided the dataset for training and testing of the model in which 20% part was used in training and the remaining used for testing the model. Subsequently, the training set consists of 5015 images, while the test set comprises 1253 images, totaling the initial 6268 images in the dataset. Our model was trained using the training set with 5015 images over 30 epochs, resulting in a comprehensive training process encompassing the entirety of the available image samples.

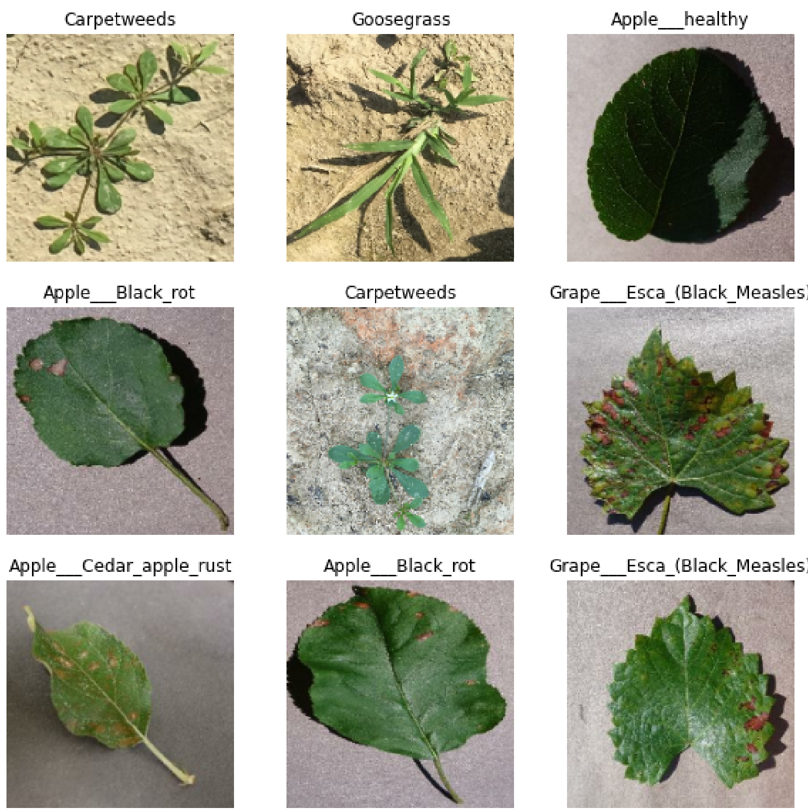

Fig. 3 Sample pictures from dataset.

5 Performance Analysis

To assess the efficacy and efficiency of various CNN designs in weed identification in agricultural contexts, a performance analysis of automatic weed detection using CNNs was carried out [13]. The primary focus of the test was on metrics such as accuracy, precision, recall, F1-score, and computing efficiency.

1. **Accuracy**:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

where:

$$TP = \text{True Positives (correctly identified weeds)}$$
$$TN = \text{True Negatives (correctly identified non-weeds)}$$
$$FP = \text{False Positives (incorrectly identified as weeds)}$$
$$FN = \text{False Negatives (missed identification of weeds)}$$

2. **Precision**:

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

3. **Recall**:

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

4. **F1-score**:

$$F1 - score = \frac{2 \times Precision \times Recall}{Precision + Recall}$$

6 Result

The research paper concludes with a thorough investigation of machine learning-based automatic weed detection, emphasizing the effectiveness of various models on a particular dataset. Initial test accuracy of only 84% was obtained using an AlexNet CNN model and 90% was obtained using GoogleNet, which produced less-than-ideal results. There was no overfitting or underfitting observed in our model [7]. Fig. 6 displays the confusion matrices for weed identification using the chosen deep-learning models. Fig. 5 presents a comparison of all the models' precision, recall, and F1 scores using the best-performing set, trained over 30 epochs, and a 16-batch size. The obtained results demonstrate that the model can accurately and confidently identify weeds in crops.

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Classification Report:
                              precision    recall  f1-score   support

           Apple___Apple_scab       0.93      0.95      0.94        95
            Apple___Black_rot       0.95      0.98      0.96        94
     Apple___Cedar_apple_rust       0.90      0.90      0.90        42
              Apple___healthy       0.96      0.95      0.95       119
                  Carpetweeds       1.00      0.97      0.98        89
                    Crabgrass       0.78      0.78      0.78        18
                   Goosegrass       0.83      0.91      0.87        33
            Grape___Black_rot       0.94      0.97      0.96       153
 Grape___Esca_(Black_Measles)       0.97      0.93      0.95       151
              Grape___healthy       1.00      0.98      0.99        64
        Tomato_Bacterial_Spot       0.79      0.73      0.76        15
          Tomato_Early_Blight       0.60      0.38      0.46         8
               Tomato_Healthy       0.90      0.75      0.82        12
             Tomato_Leaf_mold       0.88      0.88      0.88         8
   Tomato_Septorial_Leaf_Spot       0.80      0.62      0.70        13
Tomato_Yellow_Leaf_Curl_Virus       0.64      0.88      0.74        16

                     accuracy                           0.93       930
                    macro avg       0.87      0.85      0.85       930
                 weighted avg       0.93      0.93      0.93       930

Accuracy: 0.932258064516129
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Fig. 4 Accuracy of each class

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Confusion Matrix:
[[ 90   0   1   3   0   0   0   0   0   0   0   0   0   0   0   1]
 [  1  92   0   1   0   0   0   0   0   0   0   0   0   0   0   0]
 [  1   3  38   0   0   0   0   0   0   0   0   0   0   0   0   0]
 [  4   1   1 113   0   0   0   0   0   0   0   0   0   0   0   0]
 [  0   0   0   0  86   1   2   0   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0  14   4   0   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0   3  30   0   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0 149   4   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0  10 140   0   0   0   0   0   0   1]
 [  0   0   0   1   0   0   0   0   0  63   0   0   0   0   0   0]
 [  0   0   1   0   0   0   0   0   0   0  11   1   0   0   0   2]
 [  0   0   0   0   0   0   0   0   0   0   1   3   1   0   2   1]
 [  0   1   1   0   0   0   0   0   0   0   0   0   9   0   0   1]
 [  0   0   0   0   0   0   0   0   0   0   1   0   0   7   0   0]
 [  0   0   0   0   0   0   0   0   0   0   1   1   0   1   8   2]
 [  1   0   0   0   0   0   0   0   1   0   0   0   0   0   0  14]]
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Fig. 5 Confusion Matrix of our model

7 Conclusion

Weed detection using convolutional neural networks is a promising technique that facilitates agricultural operations automation. This study illustrated CNN models' applicability in the field of weed detection. Two machine learning models (Alexnet, GoogLeNet) have been used in this work to identify weeds that are present in the field. Real-time crop and weed detection based on the CNN models' decisions is one area of possible future investigation.

Our model's accuracy in the experiment was 93.2%. We concluded that our suggested approach might more accurately and swiftly predict weeds than the manual method. This demonstrates the great potential of deep learning in the agricultural sector. You will be able to identify weeds much more quickly by employing this strategy. Future research in the deep learning sector of agriculture may benefit from this approach.

We have created a user-friendly web interface, especially for farmers as part of our creative project. Farmers are empowered by this interface, which makes it easy for them to choose photos from a gallery and upload them to the platform. After the photos are uploaded, the interface's built-in algorithms examine them and, astonishingly, identify any weeds. Farmers greatly benefit from this feature, which makes it possible for them to quickly locate and eradicate weed infestations in their fields. To further promote agricultural efficiency, we've included a helpful resource: a link to comprehensive guidelines on practical weed-removal techniques. This resource gives farmers the skills and information they need to successfully manage weed growth, maximizing crop yield and guaranteeing the success of their farming endeavors.

8 Future Scope

Convolutional Neural Networks (CNN) models, such as AlexNet and GoogLeNet, provide great promise for automatic weed detection in a variety of agricultural and environmental management applications.

Precision Agriculture: Using CNN models to identify weeds can improve methods of precision agriculture. Farmers can administer targeted herbicide treatments, limiting chemical usage and environmental impact while maximizing crop production, by properly recognizing and localizing weeds within crops.

Crop management: By differentiating between undesirable weeds and crops, weed detection CNN models can help monitor the health of crops. By using this data, crop management practices can be optimized by timely interventions like selective harvesting and irrigation modifications.

Environmental Conservation: By reducing the environmental impact of pesticide use, accurate weed detection using CNN models promotes sustainable agriculture methods. These systems support soil health, biodiversity, and overall ecosystem resilience by lowering chemical inputs.

All things considered, the future of automatic weed detection with CNN models such as AlexNet and GoogLeNet resides in its many applications in scientific research, environmental management, and agriculture, providing creative answers for effective and sustainable weed management techniques.

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