Deep Learning Model for Early Weed Detection in Agriculture Application

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Abstract

One of the current issues in agriculture is the lack of mechanized weed management, which is why weed detection technologies are so crucial. Detecting weeds is useful because it may lead to the elimination of pesticide usage, which in turn improves the surroundings, human health, and the sustainability of agriculture. As novel algorithms are developed and computer capacity increases, deep learning-based approaches are gradually replacing classic machine learning methods for real-time weed detection. Mixed machine learning designs, which combine the best features of existing approaches, are becoming more popular. So, the goal of this study, present the CNN model for early weed detection. The CNN model is applied to the weed dataset. The CNN model achieved 96% accuracy.

Keywords: Weed Detection; Deep Learning; Agriculture; CNN; Machine Learning.

1. Introduction

The agricultural industry is under great pressure to enhance the quantity as well as the quality of food generated as a result of the world's rapidly expanding population and the effects of climate change. By 2050, the United Nations projects, the world's population would have reached nine billion, requiring a doubling of food production. Plant diseases, pests, and weed infestation are all on the rise, posing serious problems for the agricultural industry. Crops' food, fiber, and biofuel potential is diminished due to weed infestations, pests, and illnesses. Catastrophic or persistent losses may occur, although on average they account for 42 percent of harvests of a few crucial crops. Weeds are unwanted plants that are spread by seeds or rhizomes and fight with desirable plants for resources such as space, light, water, and soil nutrients[1]–[3].

The thorns and burrs they create, as well as the poison they carry, make them a nuisance in crop management. Because of this, landowners invest billions of dollars in weed management, which frequently fails to provide sufficient weed control or suitable technical assistance, resulting in lower crop yields. Since insufficient weed control results in lower yields and worse product quality, it is clear that weed care is an essential part of horticulture crop management. When not properly handled, pharmacological and social forms of control may have serious consequences for the natural world[4], [5]. More efficient and long-term methods of weed control will benefit from the availability of a low-cost instrument for early-stage weed detection and mapping. Early weed management helps decrease the appearance of diseases and pests in crops, and it may avert a loss of crop output of up to 34%. There are a variety of methods for weed control, and most of them take into account the state of the environment today[6]–[8].

Automatic weeding relies on a series of intermediate steps, the first of which is weed detection. There is significant potential for lowering financial and ecological costs while preserving a high degree of weed management via the use of tractor-mounted real-time weed identification and control technologies and automated weeds in farming regions.

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The effectiveness and dependability of employing various light spectra and basic image processing methods were the subjects of several early experiments[9], [10].

Detecting objects in a picture and returning bounding boxes that completely contain them is one of the most widely researched topics in computer vision. Recent developments in the world of deep learning have led to significant progress on this problem during the last two years[11], [12].

Using a sliding window technique, Overfeat applies two convolutional neural networks (CNN) architectures over different picture sizes. The first one determines whether or not a given window includes an item, whereas the second one estimates where that object's bounding box is. The final collection of object detections is generated by combining dense category and position forecasts using a greedy approach[13], [14]. The objective of this study is to obtain the CNN model for early weed detection. The CNN model will be applied to 1300 images. The steps of the CNN model are discussed.

2. Background

This section pressed some related work in weed detection in agriculture. For example, using image analysis and machine learning, the scientists hoped to identify weeds in a chilli crop [15]. Pre-processing image analysis methods were used for the UAV data obtained from a chilli plantation in Australia. The photos were processed such that characteristics could be retrieved to tell weeds and crops apart. Using those characteristics, three different models (RF, SVM, and KNN) were evaluated. RF outperformed the other categories in accuracy and other measures of performance, as shown by the experiments.

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The authors in [17] developed a method for variable-rate pesticide spraying based on real-time computer vision identification of crops and weeds. The random forest classification algorithm was used for both weed identification and crop categorization. We used our data to train the categorization algorithm offline before taking it for a spin in the real world. With the help of a vision-based feedback system, agrochemicals were sprayed using application equipment that included a PWM-based fluid flow control system. Multiple experiments conducted in the field corroborate the real-time efficacy of the suggested vision-based pesticide spraying architecture.

The authors in [18] presented a real-time weed identification technique that employs stereo-vision for 3D crop modeling and machine learning for recognizing weeds in crops. A 3D point cloud of agricultural property is created using the structure-from-motion approach applied to a video of the farm. The algorithm for machine learning is taught using data from two crops, cucumbers and onions, that were both produced by hand. The machine learning algorithms are trained using Convolutional Neural Networks (CNNs) and the ResNet-50 method. ResNet-50 works better than CNN, as can be observed. Overall, the ResNet-50 algorithm achieves a precision of 84.6% on the cucumber sample and 90% on the onion crop dataset.

Classical K-Nearest Neighbors, Random Forest (RF), and Decision Tree algorithms, in addition to a YOLOv5 neural network, were offered by the authors in [19] as part of a program for agricultural pest detection. Images of the weeds obtained from different regions of the nation were used to create an exclusive database with more than a thousand examples of every category. Scientists used machine learning techniques, CNN, and deep algorithm development to create methods for recognizing, classifying, and differentiating weeds. The study's findings led to the creation of a weed identification system using the YOLOv5 architecture and the estimation of the quality of the aforementioned algorithms. The evaluation found that the K-Nearest Neighbors classifier had an accuracy of 83.3%, the RF algorithm had an accuracy of 87.5%, and the Decision Tree predictor had an accuracy of 80% when it came to weed identification.

3. CNN Model

This section discusses the steps of the CNN model which are used in this paper[20]. We built a CNN algorithm with an accuracy of 96%. An in-depth examination of the model is the focus of this research. Figure 1 displays the study's developed CNN algorithm. When a picture is read, a 224x224x3 pixels sample is taken at random and then transformed using vibration, distortion, flip, or spin. Stride widths (the gap between filter/mask placements), mask

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size, and the number of convolution and pooling stages may all be adjusted. To do pooling, a mask is first applied to every pixel, and then a single value (such as the highest) is selected.

Multiple iterations of convolution and pooling constitute the mixing phases seen in Figure 1. The weights of the model are trained with the help of a gradient optimizer by putting the final result into a SoftMax operator. The algorithm can effortlessly acquire the decision limits necessary for classifying pictures into one of two classes by adding non-linearities using a ReLU activation function and random dropouts while training. To train for and recognize identical characteristics with varied scaling, the network's filtering and outputs change size (becoming lower as the input progresses through the network). CNNs are invariant when dealing with transformations like rotation and translation since convolution filters are used for whole pictures for training data. In addition, the CNNs' tolerance for abnormalities in the parameters is greatly increased by the pooling layers.

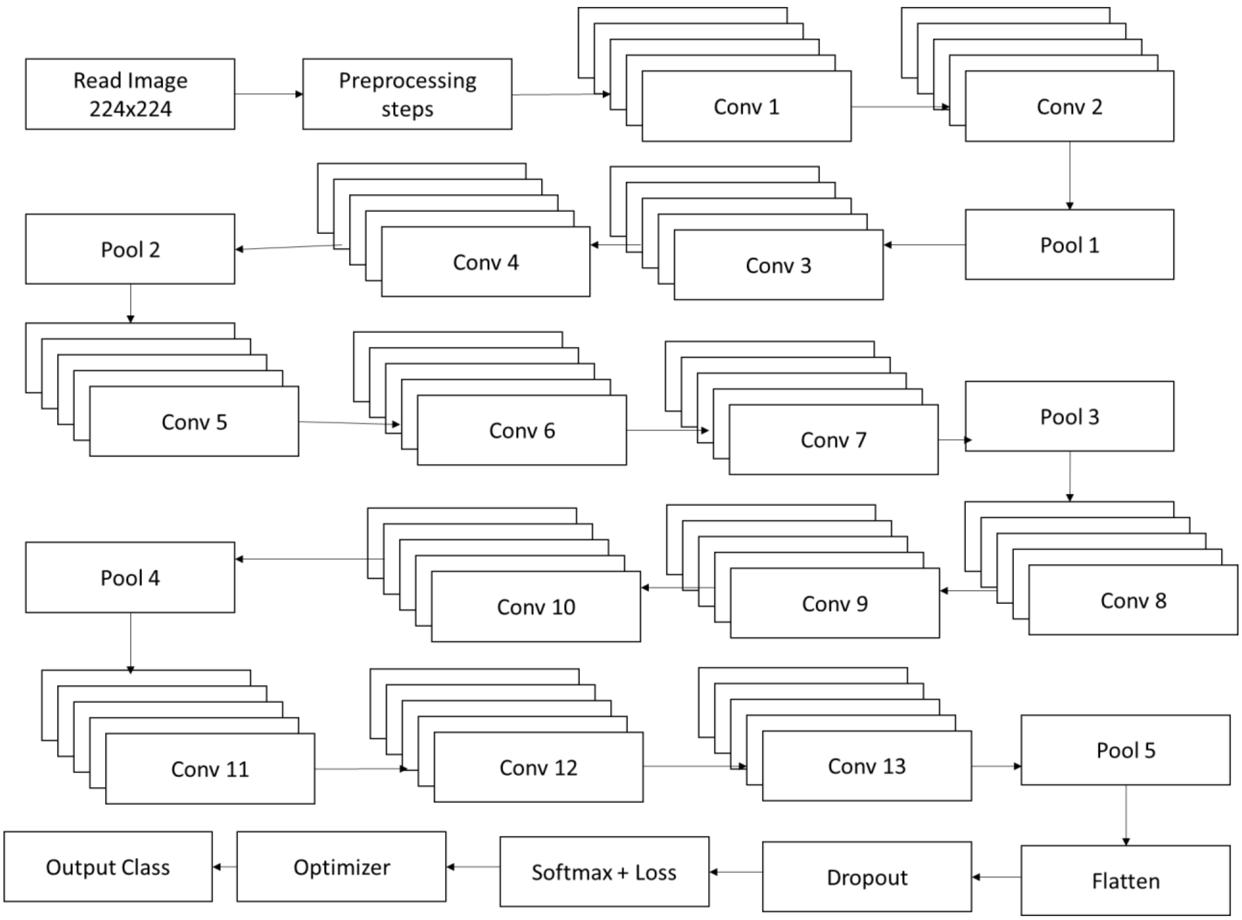

Figure 1: The CNN model was used in this study.

4. Application

The amount of money it makes is significantly affected by weeding. Here we show you the whole process of weed detection. Here, we demonstrate how to use deep learning to automatically identify weeds by partitioning input photos into 224 by 224 squares.

One thousand three hundred RGB digital photos were gathered. As an input dataset, all photos are reduced in size to 224 by 224 for simpler training and quicker implementation. Figure 2 shows a sample of these images.

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Figure 2: The sample of the dataset.

We applied the CNN model to a collected dataset. The summary of the CNN model is presented in Table 1.

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Table 1: The model summary of this study

Layer	Shape
Input	224x224x3
Conv 1	224x224x64
Conv 2	224x224x64
Max Pooling 1	112x112x64
Conv 3	112x112x128
Cove 4	112x112x128
Max Pooling 2	56x56x128
Conv 5	56x56x256
Conv 6	56x56x256
Conv 7	56x56x256
Max Pooling 3	28x28x256
Conv 8	28x28x512
Conv 9	28x28x512
Conv 10	28x28x512
Max Pooling 4	14x14x512
Conv 11	14x14x512
Conv 12	14x14x512
Conv 13	14x14x512
Max Pooling 5	7x7x512
Flatten	25088
Dense 1	4096
Dropout 1	4096
Dense 2	4096
Dropout 2	4096
Output 3	3

The confusion matrix of the results CNN model is presented in Figure 2.

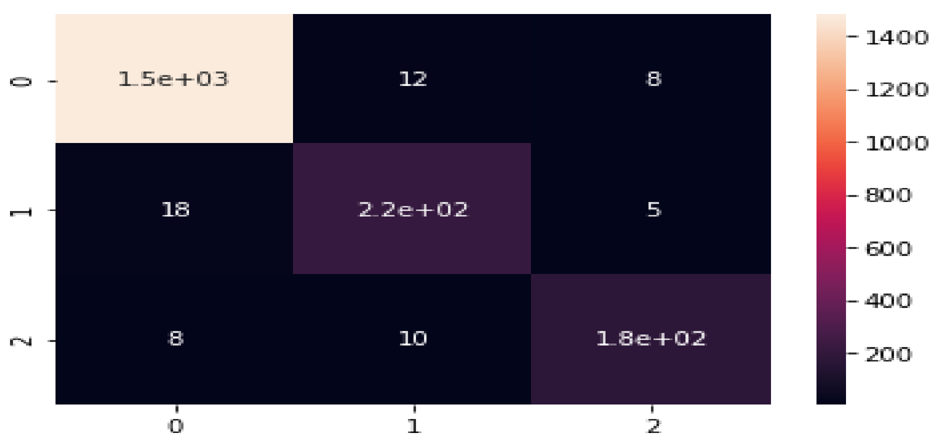

Figure 3: The confusion matrix by the CNN model.

The CNN model obtained 96% accuracy in this study.

5. Conclusion

Weed control techniques, including electrical, magnetic, or heat welding, need accurate weed identification in croplands. The previous parts of this article have covered two types of weed-detecting technology. It proved that conventional machine learning methods are being phased out in favor of those based on deep neural networks. When used as feature extractors, deep CNN designs provide greater accuracy and allow for faster creation of applications.

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The future is likely to hold more hybrid models that combine deep learning with more traditional forms of processing images. We collected 1300 images for weed detection. The CNN model is applied to these images. The CNN model achieved 96% accuracy.

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