Development of Modified CNN Algorithm for Agriculture Product: A Research Review

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ABSTRACT

Now a day, with the increase in world population, the demand for agricultural products is also increased. Modern days electronic technologies combined with machine vision techniques have become a good resource for precise weed and crop detection in the field. It is becoming prominent in precision agriculture and also supporting site-specific weed management. By reviewing as there are so many different kinds of weed detection algorithms that were already used in the weed removal process or in agriculture. By the comparative study of research papers on weed detection. In this paper, we have suggested advanced and improved algorithms which take care of most of the limitations of previous work. The main goal of this review is to study the different types of algorithms used to detect weeds present in crops for automated systems in agriculture. This paper used a method that is based on a convolutional neural network model, VGG16, to identify images of weeds. As the basic network, VGG16 has very good classification performance, and it is relatively easy to modify. Download the weed dataset. This image dataset has 15336 segments, being 3249 of soil, 7376 soybeans, 3520 grass, and 1191 broadleaf weeds. Our model fixes the first 16 layers of VGG16 parameters for layer-by-layer automatic extraction of features, adding an average pooling layer, convolution layer, Dropout layer, fully connected layer, and softmax for classifiers. The results show that the final model performs well in the classification effect of 4 classes. The accuracy is 97.76 %. We will compare our result with the CNN model. It provides an accurate and reliable judgment basis for quantitative chemical pesticide spraying. The results of this study can provide an overview of the use of CNN-based techniques for weed detection.

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1. INTRODUCTION

Weed detection and removal were done by hiring some men for that task. When any unwanted plant is found, that is the weed plant, just pluck it manually with hands or simple tools that were available at that time. Later, there were many improvements and advancements in agricultural technologies. Nowadays, farmers started using herbicides to destroy the weeds. But still, in many places, to remove the weed plants, manpower is used. Crop and weed discrimination is a major requirement to realize such systems for precision weed control [9]. The weed plant competes for water and other nutrients during the growth of the crop; this causes losses to the crop productivity [40], and weed is the main reason for getting less production in the agriculture field [15]. Detecting such unwanted plants in the field is referred to as weed detection [25]. Therefore, weed detection is important because weed control is essential in agricultural productivity as weeds act as a pest to crops [29]. Weeds usually grow faster than crop plants and thus absorb nutrients earlier, resulting in a lack of nutrients for the growth of plants [8], [28].

In the past few years, so many algorithms have been developed for weed detection. Modern agriculture introduces machine vision technologies in weed detection [23]. They have contributed a lot to weed and crop classification in the weed detection process. There are a number of papers on weed detection. We have listed some papers here with their works and limitations. In 2019, Hea Choon Ngo et al. proposed weed detection using CNN [1], [31]. The limitation of this work is the unspecific direction of spraying herbicide, causing a harmful effect on the crop. In 2018, Sadia Murawwat et al. proposed weed detection using SVMs [2]. The drawback of the support vector machine (SVM) algorithm is not suitable for large data sets. In 2018, S. Umamaheswari, R. Arjun, and D. Meganathan proposed weed detection using image processing [3]. The limitation in the proposed system is that the predicted bounding boxes can partly overlap with crops due to very close proximity. In 2018, S. S. Durugkar, P. S. Jadhav, S. S. Zade, and V. S. Bhong proposed weed detection using image processing [4]. In this, they used thresholding-based segmentation, edge base segmentation, Color-based segmentation, and watershed segmentation. The limitation of this process is if a small weed is present separately in the field means, not in a group, then it cannot be detected because it cannot meet the threshold condition. In 2018, A. Bakhshipoura and A. Jafarib proposed weed detection using SVM and ANN [18], [5]. In this study, two substantial methods of nonlinear pattern recognition, i.e., ANN and SVM, were employed to discriminate the weeds from sugar beet plants based on shape features. Both ANN and SVM were able to reasonably recognize the shape-based patterns and classify the plants with overall accuracies up to 92.67% and 93.33%, respectively. But SVM is not suitable for large datasets [13]. In 2019 F.Miao, S.Zheng, and B.Tao proposed weed and crop identification using a convolutional neural network [6]. The limitation of this work is the recognition accuracy needs to be improved.

In this paper, we suggested VGG16 [7].model is inspired by the CNN, which is pre-trained on almost 1.2 million images having over a thousand classes from the ImageNet dataset. Certain elements have been fine-tuned in the VGG16 model to create this novel model. In the VGG16 design, there are thirteen convolution layers, five max-pooling levels, and three dense layers. The parameters can't be changed because the first few levels are frozen. The model was fine-tuned with the addition of a sequential network with a dense layer. The research contribution is to analyze these two models and improve their accuracy.

2. METHOD

The weed detection process depends upon segmentation and feature extraction in order to minimize the limitations revealed in the literature review for weed detection in agriculture. We suggest an improved approach that is CNN and VGG16 [39] architecture which will take care of parameters. The proposed idea includes the designing of an efficient technique for weed detection based on a convolutional neural network (CNN), VGG16 model [24] to classify the images to separate weeds from crops, and it's aimed to give good image classification.

2.1 Convolutional Neural Network

The Convolutional Neural Network (CNN) consists of repeated convolutional and pooled layers and is widely used for image recognition. It can be used as a highly-accurate method for image classification [17]. The convolution layer slides multiple filters across the image to generate a matrix and the pooling layer samples from the convolutional layer [20]. Convolutional Neural Networks (CNN) constitute a class of deep, feed-forward ANN [27]. CNN is especially useful when extracting features from images because it preserves spatial information. The output of the convolution and pooling layers feeds into a dense neural network, producing the final output.

A convolutional neural network is a feedforward neural network. It is more suitable for image recognition and classification than traditional neural networks [22]. A convolutional neural network consists of an input layer, an output layer, and multiple hidden layers. The hidden layer also includes a convolutional layer, a pooled layer, a fully connected layer, and a canonical layer [14]. We enter the extracted image blocks into the convolutional layer of the convolutional neural network. The convolutional neural network algorithm computes image features on predefined image blocks that cover the entire image. In general, the input picture matrix and the following weight matrix are square arrays. Convolution of a single weight matrix produces a single depth dimension of the convolution output. In most cases, multiple filters with the same dimensions are applied [16]. The output of each filter is stacked together to form the depth dimension of the convolution image [6]. The advantage of using CNN for image classification is that they have the ability to learn features describing complex non-linear relations between dependent and independent variables by themselves when given enough data [32].

2.2 VGG16

VGG16 is a convolutional neural network model proposed by K. Simonyan and A. Zisserman from the University of Oxford in the paper "Very Deep Convolutional Networks for Large-Scale Image Recognition." The model achieves 92.7% top-5 test accuracy in ImageNet [33], which is a dataset of over 14 million images belonging to 1000 classes. It was one of the famous models submitted to ILSVRC-2014. It makes the improvement over AlexNet by replacing large kernel-sized filters (11 and 5 in the first and second convolutional layer, respectively) with multiple 3×3 kernel-sized filters one after another. VGG16 was trained for weeks and was using NVIDIA Titan Black GPUs [21].

VGG 16 has 16 weight layers containing two sets of two convolution layers with max-pooling, two sets of three convolution layers with max-pooling, followed by three fully connected layers [37]. The input to cov1 layer is of fixed size 224 x 224 RGB image. The image is passed through a stack of convolutional (Conv.) layers, where the filters were used with a very small receptive field: 3×3 (which is the smallest size to capture the notion of left/right, up/down, center) [35]. One of the configurations also utilizes 1×1 convolution filters, which can be seen as a linear transformation of the input channels (followed by non-linearity). The convolution stride is fixed to 1 pixel; the spatial padding of Conv. layer input is such that the spatial resolution is preserved after convolution, i.e., the padding is 1 pixel for 3×3 Conv. Layers [36]. Spatial pooling is carried out by five max-pooling layers, which follow some of the Conv. layers (not all the Conv. layers are followed by maxpooling).

Max-pooling is performed over a 2×2 pixel window, with stride 2 [12]. Three Fully-Connected (FC) layers follow a stack of convolutional layers (which have different depths in different architectures): the first two have 4096 channels each, and the third performs 1000-way ILSVRC classification and thus contains 1000 channels (one for each class). The final layer is the soft-max layer. The configuration of the fully connected layers is the same in all networks. All hidden layers are equipped with rectification (ReLU) non-linearity. It is also noted that none of the networks (except for one) contain Local Response Normalisation (LRN). Such normalization does not improve the performance of the ILSVRC dataset but leads to increased memory consumption and computation time [11], [26]. The VGG16 architecture is shown in Fig. 1.

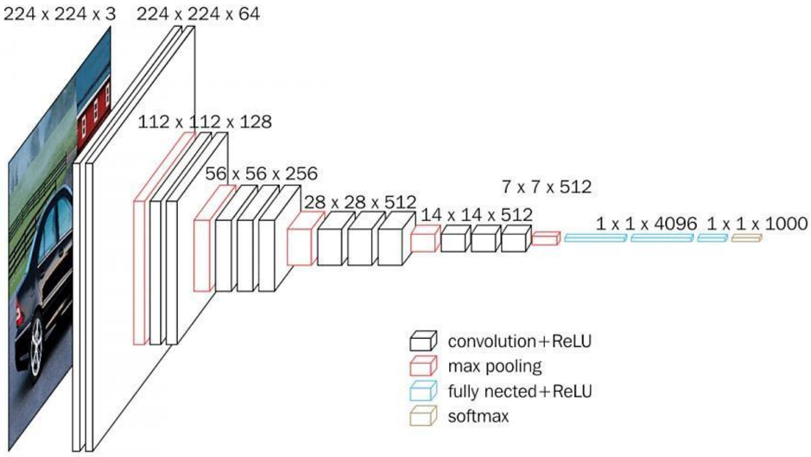

Fig. 1. The architecture of the VGG16 Model [10]

The transitions from the first layer $a^{[0]}$ to the second layer $a^{[1]}$ were simply a weight matrix multiplication, the addition of a bias, and the element-wise application of the ReLU function.

$$a^{[1]} = g(W^{[1]}a^{[0]} + b^{[1]}) \tag{1}$$

Where $a^{[0]}$ is the first layer, and $a^{[1]}$ is the second layer.

For VGG-16, the only difference is replacing the general matrix multiplication with a convolution instead of a 2-D weight matrix and using a 3-D filter tensor.

- In order to make the final transition from fully connected to the softmax layer, there is use the softmax function. Softmax Layer $a^{[16]}$ and preceding Fully Connected Layer a $a^{[15]}$ highlighted.
- The transition from the fully connected layer $a^{[15]}$ to the softmax layer $a^{[16]}$ starts off as any fully connected layer usually does. We apply a matrix multiplication using $W^{[16]}$ and add a bias $b^{[16]}$ to attain $z^{[16]}$.
- Fourteen and fifteen layers are fully connected hidden layers of 4096 units, followed by a softmax output layer (Sixteenth layer) of 1000 units [38]. $W^{[16]}$ has dimensions (1000, 4096), and $b^{[16]}$ has

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dimensions (100, 1), which makes sense since $a^{[15]}$ is a row vector with dimensions (4096, 1) and $z^{[15]}$ is a row vector with dimensions (1000, 1).

$$z^{[16]} = W^{[16]}\, a^{[15]} + b^{[16]} \tag{2}$$

Where $z^{[16]}$ is the row vector and $a^{[15]}$ is the 16th layer

Now, we would normally use a ReLU function to introduce nonlinearity. Instead, we are going to use the softmax function. Softmax as the final layer of the neural network that has a value of either 0 or 1 [30]. This is similar to when we used the sigmoid function to produce the last fully connected layer. We'll denote the softmax function with (σ) [34]. We compute the ith element in $a^{[16]}$.

$$a_{i,1}^{[16]} = \sigma_{(i,1)}\left(z^{[16]}\right)z \tag{3}$$

Where σ is the softmax function

$$a_{i,1}^{[16]} = \frac{e^{z_{i,1}^{[16]}}}{\sum_j^{1000} e^{z_{i,1}^{[16]}}} \tag{4}$$

After applying the softmax activation function, we have a vector of probabilities that sum to 1. Softmax activation function provided effective results in major classification problems. This Softmax activation function is used for building a multi-class classifier. Fig. 2 represents the process flow chart to be carried out for the weed detection process.

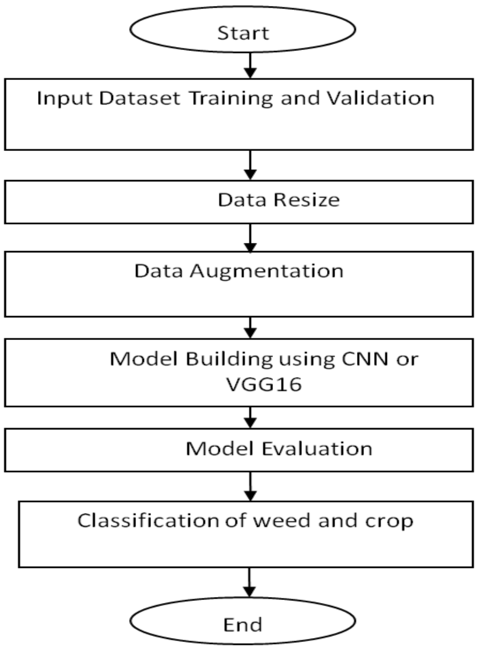

Fig. 2. Flow Chart of Proposed Work

To carry out the proposed plan of research work on the development of designing of our model, the following methodological steps will be adopted:

- Collecting the dataset of images of different types of weed and preprocessing the images using convolutional layer, flattening layers, and pooling.
- Splitting the dataset into train and test sets, training the model with the help of the training set, and then testing the required model with the trained test set.
- Performance Evaluation, like Accuracy, is the most common metric used to evaluate the performance of a model.
- A comparative analysis of the proposed technique with other techniques.

Dataset Collection

Dataset for the proposed system comes from the online, different categories of images, of which some of the data is randomly divided into training sets, and some of the data is divided into testing sets. The various preprocessing operations are performed to preprocess the image.

Dataset Augmentation

Data augmentation is a powerful tool in image processing systems. It avoids overfitting by creating a diversity of objects, also increasing the size of the dataset.

The training dataset was artificially enlarged to reduce overfitting. The data set has been enlarged using an augmentation strategy so that results can be improved.

3. RESULTS AND DISCUSSION

This study uses a 3-channel color dataset, namely Red, Green, and Blue, with the size of each data being 150×150. The model will perform the identification of weeds in relation to soybean and soil and classification of them in the grass and broadleaf data.

We tuned the batch size and epoch parameters to see the accuracy values for training and validation. Table 1 shows the experimental results, and Table 2 shows the accuracy results matching data testing with CNN and VGG16.

Table 1. Experiments in the training data

Model	Val Loss	ValAcc.	Loss
CNN	0.2083	0.9198	0.1777
VGG16	0.1066	0.9808	0.1296

Table 2. The accuracy results matching data testing with CNN and VGG16

Model	Accuracy
CNN	93.36 %
VGG16	97.76 %

Fig. 3 shows that VGG16 improves the accuracy. Future research can continue to calculate processingtime when using video data as testing data. The results of this study were better than previous studies [1]. In other words, the accuracy increased.

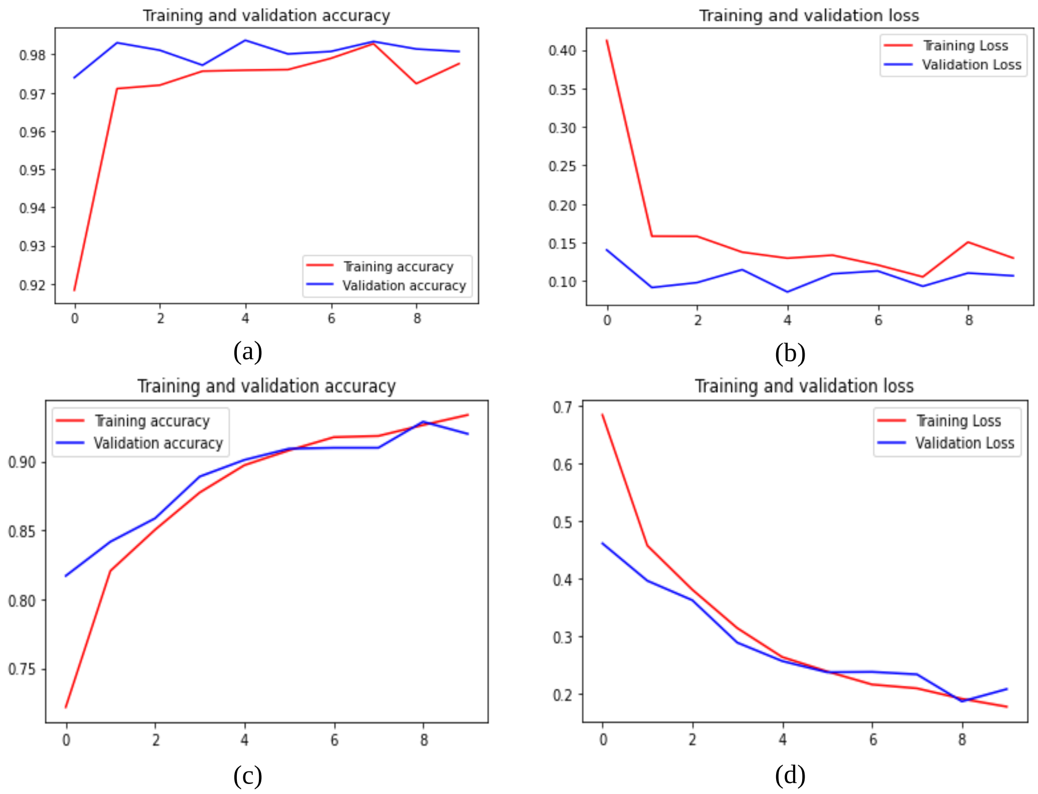

Fig. 3. The result of training data, (a), (b) CNN, (c), (d) VGG16

4. CONCLUSION

The goal of this paper is to detect weeds using a VGG16 model and evaluate accuracy in an efficient way. This paper has reviewed that there are many different algorithms or techniques for weed detection. Also, this is an era of intelligent algorithms and using machine learning which is developing day in and day out. So, this paper will be helpful in the agriculture area. The main aim of this research work is to remove the problems which are arising in previous research work and give out the best accuracy using the proposed model. In this paper, we have provided an overview of the current status of the area of the automatic weed detection technique.

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