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Development of a Novel Classification technique for detection of Cowpea Leaves using VGG16 Deep Convolutional Network

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Abstract: This paper is based on CNN-VGG16 network architecture in order to identify the cowpea plants from weed in the cowpea fields. It is done to increase the productivity of the crops. The VGG16 is a basic network of Convolutional Neural Network family and it has quite good classification performance. Implement and modification is quite easy with this model. Here, we have applied pre-trained VGG16 method to the cowpea as well as weed leaves custom dataset. Images of leaves have been taken from standard research farm, ICAR-NBPGR, Pusa campus, New Delhi. The dataset includes 1230 images of two classes. The basic principle of VGG16 network for automatic detection includes, feature extraction from input image, addition of convo layer, pooling layer addition, flatten (fully connected layer), and sigmoid for classifiers. Results from experiments show that the model efficiently classifies the cowpea and weed images. Here, accuracy rate on the training dataset is 97.58%, and that of test dataset set is 90.08%. Such results give hope for achieving agricultural reforms.

Keywords – Deep learning neural network; Binary Classification; Cowpea Legume; VGG16 Model; transfer learning and keras.

INTRODUCTION

In order to remove unwanted plants, there is a common method used in agriculture is known as herbicides which is made by chemicals. When agronomist trying to prevent irrelevant plants for nourishing the crops, then the use of herbicides is the reason for many environmental and health side effects, and weed resistance to herbicides. Hence novel computer vision techniques, like, model developments by using different neural network techniques *viz*., deep learning, convolution neural networks *etc*. play important roles. A camera can be hovered over the field to collect the images and they can be processed with latest techniques of image classifications. In this paper, a novel technique is developed to identify cowpea leaves from weeds. Here, VGG16 algorithm based on convolutional neural network is used for classification purposes. The working of CNN-VGG16 comprises of tedious convo and pooling layers for image classifications. In the network, convo layer deals with many filters inside image to make a matrix, extracting all possible features from the input/images as they conserve contiguous information. Outputs of the convo and pooling layers are applied as inputs to the fully connected layer i.e., dense neural network, in order to produce a final output of classifications. The motivation behind the whole process is automatic features extraction of the images (input) in order to feed to the last layer. Generally, earliest

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layer of convo is only able to extract low features for example lines on image, edges of the images and corners etc. but by using some additional network layers can effectively extract complicated features from its features. Rectified Linear Units (ReLU) activation is used to nerve activation mode. Concisely VGG 16 is type of 3x3 convolution kernels rather than kernels of 7x7 convolution, and duplet kernel of 3x3 convolution are used rather than kernels of 5*5 convolution. When we talk about image classification algorithms, the model VGG16 is being consider as baseline and a successful application of convolutional neural networks. Architecture of VGG 16 CNN Model of Achievements of ImageNet Large Scale Visual Recognition Challenge (ILSVRC) competitions and their neural network depths are proposed by Oxford [1].

LITERATURE SURVEY

Automatic detection of weed (other/ irrelevant) leaves from the relevant plants is very important for the precision agriculture. In this regard, Convolutional Neural Networks found the most suited for image classification problems, because these networks show good results in leaves detection under binary and multiclass classifications [2-4]. In these papers, authors have Deep CNN methodology for classifications. Author Potena et al. clearly shown in [5] how two distinct CNNs models can be used to process both NIR and RGB images in order to recognize crops and weeds accurately. Authors in [6] propose methods for evaluation of accuracy for two weed detection algorithms and images based on UAV. The accuracy of AlexNet in weed detection was around 99%, but ANN shown on the same dataset was low accuracy i.e., 48% so there is big difference in performance. Authors Ramirez et al. in [7] compared with SegNet and U-Net for aerial image weed segmentation model. In [8], an enhanced method called Region based CNN model to extract early harebell seedlings has been presented. The presented method allowed the weeds to be fully identified from the exact input in order to obtain nutrients from the crops. In paper [9], authors presented advanced methodology for segmentation of weed and leaves based on DNNs. It has been observed that the identification accuracy is better as compared to manually extraction of features under traditional ML algorithms. CNN algorithms, such as AlexNet [10],

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ResNet [11,12], CNN-VGG [13], Popular Google [14], and most advanced UNet, and most popular network MobileNets, and fully connected DenseNet [15], are also mostly used in weed automatic detection. Chechli ´nski *et al.* in [15] showed that how to measure distinct plants in various fatten steps under light situations, and their procedural framework by using U-Net, MobileNets, ResNet and DenseNet. Since a decade, FCNs have made great achievements in computer vision explained in details [16] and also remote sensing applications shown in [17,18]. Dyrmann *et. al.* in [19] presented an automatic detection technique of weeds using RGB images and an FCN. Authors in [20] explores rice field research experiments by using UAV based image and they opted for FCN for pixel-level classification. Ma *et. al.* in [21] presented a SegNet semantic segmentation methodology based on FCNs for weed automatic detection in rice fields. For weed control in the early stages, Fu *et. al.* in [22] presented a segmentation followed by FCNs for high-resolution remote

Figure 1: input data sample: (a) is the set of cowpea leaves and (b) is the set of weeds (other) leaves

sensing images. Now according to the VGG16 CNN model, a pretrained FCN have been used to fine-tune the object data. such methodology can also improve the segmentation effect of inside images. Hence, this method can efficiently classify all the pixel without observing the relationship between pixels.

EXPERIMENTAL DESIGN AND PROCEDURE

In our experiments we have considered transfer learning VGG16 architecture of

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```
trdata = ImageDataGenerator()
traindata = trdata.flow_from_directory(directory="/content/drive/MyDrive/CowpeaProperDataset/train",
                                       target_size=(224,224))
tsdata = ImageDataGenerator()
testdata = tsdata.flow_from_directory(directory="/content/drive/MyDrive/CowpeaProperDataset/validation",
                                      target_size=(224,224))
```

```
Found 1011 images belonging to 2 classes.
Found 207 images belonging to 2 classes.
```

Figure 2: Summary of data set after data Pre-processing

CNN for model development. As an input, we have taken leaves of cowpea legume and different weeds, which grow along with cowpea to stop the appropriate growth of the legume. We have adopted this model for automatic detection because its average accuracy is quite high and it performs better on image set of data compared to other algorithms. In this paper we have used images of different leaves (cowpea and weed (others)) of image size (224, 224, 3). Figure 1 is set of sample dataset for our model VGG16 pre-training. We have taken 1011 images for training and 201 for test purposes. All the images of cowpea leave as well as weed (other) leaves have been taken from ICAR-NBPGR, Pusa Campus, New Delhi. VGG 16 can substantially mitigate the model the model on the same dataset. It has been observed that the VGG16 takes lesser computation time compared to other algorithms with good accuracy level. In this case, we have set epoch values of 10 with batch size of 16, steps to the epoch values set. Entire training set is split up into the batch size, each iteration finishes its layers. We have set steps on the test dataset which is the entire verifications sets in the sample again fractionate by the batch size. Then after we have calculated the loss function value to calculate the gradients. Figure 2 depicts the summary of dataset for both the classes. We have opted for Adam optimizer technique with the learning rate to 0.001 and the purpose of being using learning rate is it can mitigate the loss

```
r = model.fit_generator(
    traindata,
    validation_data=testdata,
    epochs=10,
    steps_per_epoch=len(traindata),
    validation_steps=len(testdata)
)
```

```
/usr/local/lib/python3.7/dist-packages/keras/engine/training.py:1972: UserWarning: `Model.fit_generator` is deprecated and will be removed in a future version. Please use `Model.fi
  warnings.warn('`Model.fit_generator` is deprecated and '
Epoch 1/10
32/32 [==============================] - 2264s 70s/step - loss: 1932244.2500 - accuracy: 0.8961 - val_loss: 0.2565 - val_accuracy: 0.9662
Epoch 2/10
32/32 [==============================] - 2158s 67s/step - loss: 0.2485 - accuracy: 0.9565 - val_loss: 0.2952 - val_accuracy: 0.9662
Epoch 3/10
32/32 [==============================] - 2153s 67s/step - loss: 0.0980 - accuracy: 0.9881 - val_loss: 0.1499 - val_accuracy: 0.9662
Epoch 4/10
32/32 [==============================] - 2133s 67s/step - loss: 0.3869 - accuracy: 0.9881 - val_loss: 0.1723 - val_accuracy: 0.9662
Epoch 5/10
32/32 [==============================] - 2141s 67s/step - loss: 0.0842 - accuracy: 0.9881 - val_loss: 0.2037 - val_accuracy: 0.9662
Epoch 6/10
32/32 [==============================] - 2300s 72s/step - loss: 0.0820 - accuracy: 0.9881 - val_loss: 0.1411 - val_accuracy: 0.9662
Epoch 7/10
32/32 [==============================] - 2261s 71s/step - loss: 0.0624 - accuracy: 0.9881 - val_loss: 0.2078 - val_accuracy: 0.9662
Epoch 8/10
32/32 [==============================] - 2271s 71s/step - loss: 0.0837 - accuracy: 0.9881 - val_loss: 0.1320 - val_accuracy: 0.9662
Epoch 9/10
32/32 [==============================] - 2281s 71s/step - loss: 0.0653 - accuracy: 0.9881 - val_loss: 0.1381 - val_accuracy: 0.9662
Epoch 10/10
32/32 [==============================] - 2301s 73s/step - loss: 0.0345 - accuracy: 0.9921 - val_loss: 0.0647 - val_accuracy: 0.9758
```

Figure 3: VGG 16 Network Training process by Keras

training time. We have implemented some different model structure ideas also such as CNN-Inception-V3 and CNN-Densenet121 for training and testing of function slope in between output of the model and the expected outcome. Update on this is obtained in the algorithm. Figure

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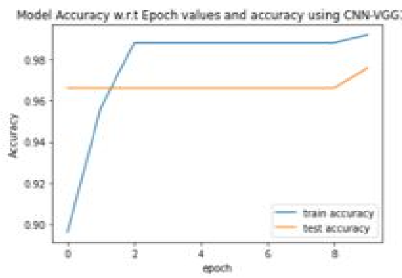
3 shows that the model training process by standard keras

RESULTS AND DISCUSSION

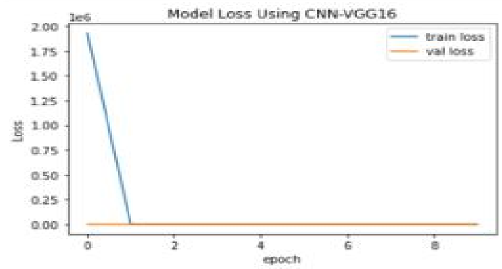
Entire experiments have executed on computer that is having Intel Celeron Processor N3350 With Intel HD Graphics, memory 4GB DDR with operating system Windows 10. We have taken open source flatform (Python) as programming environment. To execute the whole model for the detection of Cowpea leaves we have used the Python programming language. To interpret the actual shape of cowpea leaves on an image we have used OpenCV (Open-Source Computer Vision). To set up the architecture of the learning model for detection of images APIs TensorFlow and Keras have been used. For the graphical interface implementation, the Matplotlib framework has been used. We ran for 10 iteration and to plot the results as the shown in Figure 4 on both the training and the validation set. Figure 4 showing that after 10 epochs round of training on the model, VGG16

```
plt.plot(r.history['accuracy'], label='train accuracy')
plt.plot(r.history['val_accuracy'], label='test accuracy')
plt.xlabel("epoch")
plt.ylabel("Accuracy")
plt.title("Model Accuracy w.r.t Epoch values and accuracy using CNN-VGG16 ")
plt.legend()
plt.show()
plt.savefig('AccVal_acc')
```



(a)

```
import matplotlib.pyplot as plt
plt.plot(r.history['loss'], label='train loss')
plt.plot(r.history['val_loss'], label='val loss')
plt.xlabel('epoch')
plt.ylabel('Loss')
plt.title('Model Loss Using CNN-VGG16')
plt.legend()
plt.show()
plt.savefig('LossVal_loss')
```



(b)

Figure 4: Experimental Results as Accuracy and loss of the VGG 16 Model

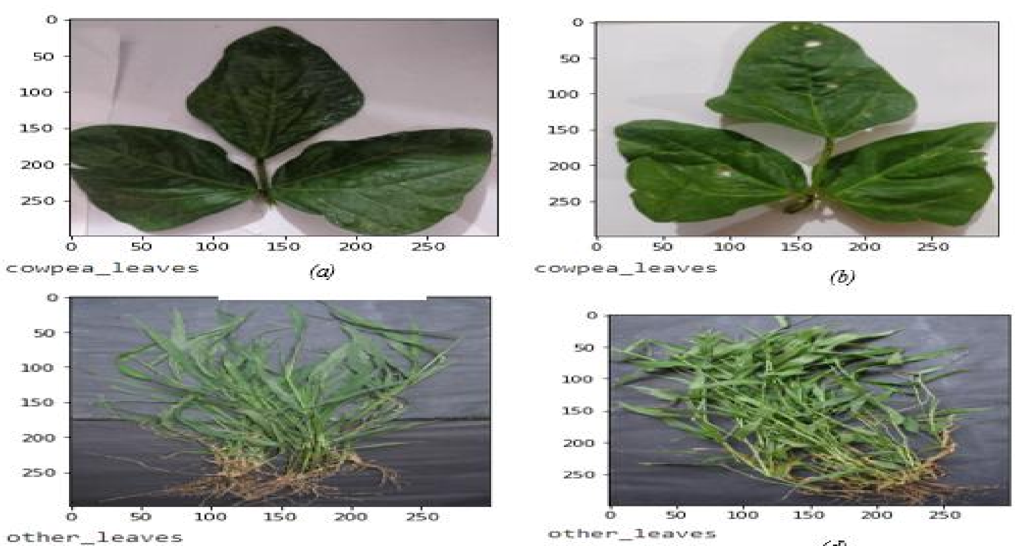


Figure 5: VGG16 Network Binary Classification outcome

performance reaches to 97.58% on the training set and 90% on the test dataset, which is greater than the VGG16 standard accuracy and performs well and can be used for dataset. Figure 4 also depicts that how better VGG16 network worked for the developed model. Figure(a) shows the model accuracy w.r.t epoch values similarly figure 4(b) shows loss of the model. Figure 5 showing the final output of the binary classification model. Figures 5 (a) and (b) is the outcome for value “1” that is cowpea leaves, in other hand Figures (c) and (d) showing the results for values”0” which is weed (other) leaves. For automatic detection of cowpea leaves using CNN-Inception-V3 models, we have taken initially 10 epochs for cowpea leaves dataset using transfer learning techniques and results are explained in detail [23].

CONCLUSION AND FUTURE SCOPE

In this paper, a novel method for classification of leaves is proposed. Two types images are chosen, viz., cowpea and weed leaves. We have considered the binary classification i.e., when it is “0” then cowpea leaves and if it “1” then other (weed) leaves for the dataset of cowpea real field. For our experiments we have opted CNN-VGG16 architecture. We have identified 2 types of images of leaves in order to achieve good performance. With this evaluation it is adorn that our VGG16 technique can recognize both the leaves with the aim to implementation of automatic techniques for agriculture reforms. In this paper, our focus is to increase the level of the model accuracy for automatic detection of the leaves in order to distinguish with relevant plants from its irrelevant ones. This model may be useful to replace the current technique to remove the weed plants which is very harmful for health as well as environment.

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REFERENCES

1) Architecture of VGG 16 CNN Model of Achievements of ILSVRC (ImageNet Large Scale Visual Recognition Challenge) competitions and their neural network depth from Oxford
2) Dyrmann, M.; Karstoft, H.; Midtiby, H. Plant species classification using deep convolutional neural network. Biosyst. Eng. 2016, 151, 72–80
3) Yu, J.; Sharpe, S.; Schumann, A.; Boyd, N. Deep learning for image-based weed detection in turfgrass. Eur. J. Agron. 2019, 104, 78–84
4) Olsen, A.; Konovalov, D.; Philippa, B.; Ridd, P.; Wood, J.; Johns, J.; Banks, W.; Girgenti, B.; Kenny, O.; Whinney, J.; et al. Deepweeds: A multiclass weed species image dataset for deep learning. Sci. Rep. 2019, 9, 2058
5) Potena, C.; Nardi, D.; Pretto, A. Fast and accurate crop and weed identification with summarized train sets for precision agriculture. Intelligent Autonomous Systems 14. IAS 2016. Adv. Intell. Systems Comput. 2017, 531, 105–121.
6) Beeharry, Y.; Bassoo, V. Performance of ANN and AlexNet for weed detection using UAV-based images. In Proceedings of the 2020 3rd International Conference on Emerging Trends in Electrical, Electronic and Communications Engineering (ELECOM), Balaclava, Mauritius, 25–27 November 2020; pp. 163–167
7) Ramirez, W.; Achanccaray, P.; Mendoza, L.; Pacheco, M. Deep Convolutional Neural Networks for Weed Detection in Agricultural Crops using Optical Aerial Images. In Proceedings of the 2020 IEEE Latin American GRSS & ISPRS Remote Sensing Conference (LAGIRS), Santiago, Chile, 22–26 March 2020; pp. 133–137
8) Patidar, S.; Singh, U.; Sharma, S.; Himanshu. Weed Seedling Detection Using Mask Regional Convolutional Neural Network. In Proceedings of the 2020 International Conference on Electronics and Sustainable Communication Systems (ICESC), Coimbatore, India, 2–4 July 2020; pp. 311–316
9) You, J.; Liu, W.; Lee, J. A DNN-based semantic segmentation for detecting weed and crop. Comput. Electron. Agric. 2020, 178, 105750.

10) Ferreira, A.; Freitas, D.; Silva, G.; Pistori, H.; Folhes, M. Weed detection in soybean crops using ConvNets. Comput. Electron. Agric. 2017, 143, 314–324
11) Peteinatos, G.; Reichel, P.; Karouta, J.; Andújar, D.; Gerhards, R. Weed Identification in Maize, Sunflower, and Potatoes with the Aid of Convolutional Neural Networks. Remote Sens. 2020, 12, 4185.
12) Asad, M.; Bais, A. Weed detection in canola fields using maximum likelihood classification and deep convolutional neural network. Inf. Process. Agric. 2020, 7, 535–545.
13) Quan, L.; Feng, H.; Lv, Y.; Wang, Q.; Zhang, C.; Liu, J.; Yuan, Z. Maize seedling detection under different growth stages and complex field environments based on an improved Faster R–CNN. Biosyst. Eng. 2019, 184, 1–23.
14) Suh, H.; IJsselmuiden, J.; Hofstee, J.; Henten, E. Transfer learning for the classification of sugar beet and volunteer potato under field conditions. Biosyst. Eng. 2018, 174, 50–65.
15) Chechli ´nski, Ł.; Siemi ˛atkowska, B.; Majewski, M. A System for Weeds and Crops Identification—Reaching over 10 FPS on Raspberry Pi with the Usage of MobileNets, DenseNet and Custom Modifications. Sensors 2019, 19, 3787.
16) Huang, H.; Lan, Y.; Deng, J.; Yang, A.; Deng, X.; Zhang, L.; Wen, S. A semantic labeling approach for accurate weed mapping of high-resolution UAV Imagery. Sensors 2018, 18, 2113.
17) Peng, C.; Li, Y.; Jiao, L.; Chen, Y.; Shang, R. Densely Based Multi-Scale and Multi-Modal Fully Convolutional Networks for High-Resolution Remote-Sensing Image Semantic Segmentation. IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens. 2019, 12, 2612–2626.
18) Chen, F.; Wang, C.; Gu, M.; Zhao, Y. Spruce Image Segmentation Algorithm Based on Fully Convolutional Networks. Trans. Chin. Soc. Agric. Mach. 2018, 49, 188–194+210
19) Dyrmann, M.; Jørgensen, R.; Midtiby, H. RoboWeedSupport-Detection of weed locations in leaf occluded cereal crops using a fully convolutional neural network. Adv. Anim. Biosci. 2017, 8, 842–847
20) Huang, H.; Deng, J.; Lan, Y.; Yang, A.; Deng, X.; Wen, S.; Zhang, H.; Zhang, Y. Accurate Weed Mapping and Prescription Map Generation Based on Fully Convolutional Networks Using UAV Imagery. Sensors 2018, 18, 3299
21) Ma, X.; Deng, X.; Qi, L.; Jiang, Y.; Li, H.; Wang, Y.; Xing, X. Fully convolutional network for rice seedling and weed image segmentation at the seedling stage in paddy fields. PLoS ONE 2019, 14, e0215676
22) Fu, X.; Qu, H. Research on Semantic Segmentation of High-resolution Remote Sensing Image Based on Full Convolutional Neural Network. In Proceedings of the 2018 12th International Symposium on Antennas, Propagation and EM Theory (ISAPE), Hangzhou, China, 3–6 December 2018; pp. 1–4.
23) V. Choudhary, P. Guha, S. Mishra, K. Tripathi "Automatic Detection of Cowpea leaves Using Image Processing and Perception V3 Model of Deep Learning” 6th IEEE International Conference on Signal Processing, Computing and Control (ISPCC 2K21)