Classification of plant seedlings using deep convolutional neural network architectures

Namratha Makanapura, Sujatha C, Prakash R Patil and Padmashree Desai
School of Computer Science and Engineering, KLE Technological University, Hubballi, India
makanapursm@gmail.com, sujata_c@kletech.ac.in, prakashpatil@kletech.ac.in and padmashri@kletech.ac.in

Abstract. Weed management has a vital role in applications of agriculture domain. One of the key tasks is to identify the weeds after few days of plant germination which helps the farmers to perform early-stage weed management to reduce the contrary impacts on crop growth. Thus, we aim to classify the seedlings of crop and weed species. In this work, we propose a plant seedlings classification using the benchmark plant seedlings dataset. The dataset contains the images of 12 different species where three belongs to plant species and the other nine belongs to weed species. We implement the classification framework using three different deep convolutional neural network architectures, namely ResNet50V2, MobileNetV2 and EfficientNetB0. We train the models using transfer learning and compare the performance of each model on a test dataset of 833 images. We compare the three models and demonstrate that the EfficientNetB0 performs better with an average F1-Score of 96.26% and an accuracy of 96.52%.

1. Introduction

Precision farming is the revolution of traditional agriculture which focuses on crop production with controlled quality using evolving technologies. It focuses on the usage of drones, autonomous vehicles, robots and information technologies to achieve structured, sustainable, environment-friendly and cost-effective agriculture. Weed management is one of the key challenges of precision farming. Weeds are non-targeted plants that do not yield any profit to the farmers still compete for space and nutrients with the target crops which intern degrades the plant growth. Managing the weeds by human laborers is time-consuming and expensive. Even applying the herbicides uniformly across the farms will harm the unintended crops. Identifying and managing weeds based on their location and density helps to overcome the disadvantages of earlier approaches. Nowadays researchers have used the state-of-art algorithms of deep learning to implement many agricultural applications. Even we have used the deep CNNs to implement the plant seedlings classification.

Many researchers have proposed frameworks for weeds and plant seedlings classification using a transfer learning approach and CNNs. Authors in [1] have implemented maize and weed classification using LeNet, AlexNet, cNET and sNET architectures and used outperformed cNET for real-time implementation. Authors in [2] have implemented a framework to classify weeds of Australian rangelands using pre-trained ResNet50 and InceptionV3 architectures and proposed a real-time robotic weed control system using outperformed pre-trained ResNet50. Authors in [3] have proposed the Philippine Indigenous plant seedlings classification frameworks by fine-tuning pre-trained AlexNet,
GoogleNet and ResNet50 architectures. ResNet50 performs better over the other two architectures. Authors in [4] have implemented a carrot and weed classifier using the CNN. Authors in [5] have introduced a robotic weed control system using two CNNs serially.

Authors in [6] have collected the benchmark plant seedlings dataset and made it publicly available to ease the work of researchers. Authors in [7] used the same dataset and designed a CNN to classify the plants and weeds. It has achieved an average accuracy of 94.38%. Authors in [8] used the same dataset to propose plant seedlings classification frameworks using five different CNNs. They compared the performance of convolutional neural networks using three different training approaches, namely training the architectures from scratch, training the pre-trained architecture with fixed feature extractor and fine-tuning the models during training. Out of five architectures, ResNet152V2 achieved the highest accuracy of 92.93% with fine-tuning less than half of the network. Authors in [9] used the same dataset and proposed framework to classify plant seedlings using transfer learning and compared the performance of ResNet50, VGG16, VGG19, Xception and MobileNetV2 architectures. ResNet50 performed better over other models with an accuracy of 95.23%. Authors in [10] used the same dataset to train the LeNet5, VGG16, DenseNet121 and ResNet50 architectures to classify the plant seedlings. The comparative study results that ResNet50 performed better over other models with the highest accuracy. Authors in [11] used the same dataset and compared the performance of the CNN and VGG16. The VGG16 model performed better over CNN. Authors in [12] used the same dataset to implement the crop and weed seedlings classification using transfer learning. Authors in [13] have used the segmented plant seedlings dataset to classify the plant seedlings using VGG16 architecture. They have used three different training approaches, among them fine-tuning VGG16 model exhibits the highest accuracy which has trained using balanced dataset.

In this paper, we present a framework for plant seedlings classification using deep convolutional neural networks. The main contributions towards the proposed work are: Fine-tuning the pre-trained models, namely ResNet50V2, MobileNetV2 and EfficientNetB0 using a transfer learning approach. Comparing the performance of fine-tuned models using a test set to get the better performing architecture and comparing the proposed framework with existing methods to showcase the improvement in accuracy and F1-Score.

In section 2, we describe an overview of the plant seedlings classification framework. In Section 3, we present the result analysis. At last, we conclude in section 4.

2. Framework for plant seedlings classification

2.1. Overview of plant seedlings classification framework
The proposed framework classifies the weeds from target plants at the early-stage of plant growth. The CNN (we used fine-tuned ResNet50V2, MobileNetV2 and EfficientNetB0) takes the preprocessed RGB images as an input and predicted class label as the output. The overview of plant seedlings classification framework is as shown in figure 1, which contains preprocessing stage, automated feature extraction using fine-tuned pre-trained deep CNNs and classifier to output the predicted labels. A comprehensive explanation of the proposed framework is provided below.

2.2. Preprocessing
In the preprocessing step images are resized to (224,224) to ensure the same aspect ratio and images are normalized to maintain the uniform data distribution [8]. Different data augmentation techniques like rescaling, zooming and horizontal flip are applied to increase the data as well as to avoid the overfitting problem.

2.3. Convolutional neural network
It mainly includes feature extraction and classification to learn specific patterns from the given input image. We have used three pre-trained convolutional neural networks, namely ResNet50V2,
MobileNetV2 and EfficientNetB0 for feature extraction by fine-tuning from scratch using ImageNet weights.

![Figure 1. Framework of plant seedlings classification.](image)

Overview of the three convolutional neural networks is as follows: Residual Networks [14] are the very deep neural networks with residual connections. Usually increasing the depth of network causes the problem of vanishing gradient which influences the performance degradation. In residual networks, this challenge is addressed with residual connections. ResNet50v2 [15] is improved in the propagation formulations of residual blocks over the other earlier proposed architectures. We fine-tune 23,519,360 trainable parameters and extract 2048 features with each of 7x7 kernel size. MobileNetV2 [16] is the light-weight neural network that encourages embedding deep learning models in low computing devices. MobileNetV2 contains blocks with stride 1 and stride 2. Blocks with stride 1 contain inverted residuals and blocks with stride 2 are used for downsizing. Both the blocks contain depthwise separable convolution [17] which is the key point of success in MobileNetV1. ReLU6 activation is removed at the last convolutional layer of each block to improve the accuracy. We fine-tune 2,223,872 trainable parameters and extract 1280 features with each of 7x7 kernel size. EfficientNets [18] introduces a method of uniformly scaling width, height and resolution of the network with compound coefficient. This family contains models from EfficientNetB0 to EfficientNetB7 which are built by scaling width, height and resolutions using a baseline network. EfficientNetB0 is the first introduced model of the EfficientNets family. We fine-tune 4,007,548 trainable parameters and extract 1280 features with each of 7x7 kernel size.

The classifier of the convolutional neural network contains pooling layer, fully connected layer and output layer. In the pooling layer, global average pooling is applied over all the feature maps to get the averaged single value for each feature map. This layer helps in avoiding the overfitting. A fully connected layer contains 512 nodes with ReLU activation. It helps to learn more specific features from the input data to improve the model performance. Finally, the output layer contains 12 output nodes with softmax activation. It results label with the highest probability as an output.

For this experiment, we have used google colab with GPU and for programming, the keras library is used with tensorflow backend. The plant seedlings dataset is divided in the ratio of 70% for training, 15% for validation and 15% for testing. Models are trained for 50 epochs with a 0.00001 learning rate. Images are batched with a batch size of 32. Categorical crossentropy loss function is used to calculate the loss and Adam optimizer is used to optimize the loss by updating the weights during back propagation while training the models.
3. Results and Discussions
Models are evaluated with the benchmark performance metrics, namely F1-Score, precision, recall and accuracy. Precision calculates the plant seedling that is classified correctly. Precision is the ratio of plant seedling classified correctly (TP (true positive)) over the total number of plant seedling actually classified by the model (sum of TP (true positive) and FP (false positive)). Pc denotes the class specific precision.

\[ P_c = \frac{TP}{TP + FP} \]  

Recall calculates the plant seedling that is correctly classified by the model. Recall is the ratio of total number of plant seedling classified correctly by the model (TP (true positive)) over the sum of all the actual plant seedling (sum of TP (true positive) and FN (false negative)). Rc denotes the class specific recall.

\[ R_c = \frac{TP}{TP + FN} \]  

F1-Score includes both recall and precision instead of focusing on only one metric. Good value of f1-Score indicates the good value of both recall and precision of the model. F1-Score is the ratio of twice the product of precision (Pc) and recall (Rc) over the sum of precision (Pc) and recall (Rc). F1c denotes the class specific F1-Score. Pc and Rc are computed using the equations (1) and (2).

\[ F1_c = \frac{2 \times P_c \times R_c}{P_c + R_c} \]  

Accuracy is the ratio of total count of correctly classified plant seedlings (sum of TP (true positive) and TN (true negative)) over the total count of instances classified by the model (N designates the total instance count in the dataset).

\[ Accuracy = \frac{(TP + TN)}{N} \]  

Weighted average values of F1-Score, precision and recall are computed using the equations given below. C designates the total count of species (classes), Nc designates the total count of instances in class c and N designates the total instance count in the dataset. Pc, Rc and F1c are computed using equations (1) to (3).

\[ avg_{weighted}(F1) = \sum_{c=1}^{C} \frac{N_c}{N} \times F1_c \]  

\[ avg_{weighted}(P) = \sum_{c=1}^{C} \frac{N_c}{N} \times P_c \]  

\[ avg_{weighted}(R) = \sum_{c=1}^{C} \frac{N_c}{N} \times R_c \]  

3.1. Dataset description
Plant seedlings dataset [6] contains RGB images of 960 distinct plants belonging to 12 different species. The images are collected over 20 days at the early-stage of plant growth to achieve early weed management. We are using the V2 Plant seedling dataset which contains 5541 RGB images. Few sample images are shown in figure 2. The dataset contains 3 plant species and 9 weed species. Three plant species are Common wheat (253 images), Maize (257 images) and Sugar beet (463 images). Nine weed species are Black-grass (309 images), Common chickweed (715 images), Cleavers (335 images), Scentless mayweed (607 images), Small-flowered cranesbill (576 images), Charlock (452 images), Loose silky-bent (762 images) Fat hen (538 images) and Shepherd’s purse (274 images).

The dataset is divided in the ratio of 70% for training, 15% for validation and 15% for testing. The data distribution of the test set is tabulated in table 1. It contains 833 images where common wheat
species contains the least number of image samples (38 images) and loose silky-bent contains the highest number of image samples (115 images).

![Sample images of plant seedlings dataset](image)

**Figure 2.** Sample images of plant seedlings dataset. Class labels of sample images from top left to bottom right are Cleavers, Common chickweed, Black-grass, Charlock, Loose silky-bent, Maize, Common wheat, Fat hen, Small-flowered cranesbill, Sugar beet, Shepherd’s purse and Scentless mayweed.

| Class | Species                        | Test set samples |
|-------|--------------------------------|------------------|
| 1     | Black-grass                    | 46               |
| 2     | Charlock                       | 68               |
| 3     | Cleavers                       | 50               |
| 4     | Common chickweed               | 108              |
| 5     | Common wheat                   | 38               |
| 6     | Sugar beet                     | 69               |
| 7     | Loose silky-bent               | 115              |
| 8     | Scentless mayweed              | 91               |
| 9     | Maize                          | 39               |
| 10    | Small-flowered cranesbill      | 87               |
| 11    | Shepherd’s purse               | 41               |
| 12    | Fat hen                        | 81               |

**Table 1.** Description of test set images.

3.2. **Evaluation metrics for models validation**

The proposed plant seedlings classification framework is evaluated using the test set with fine-tuned ResNet50V2, MobileNetV2 and EfficientNetB0 models. We evaluate the performance metric using the equations (4) to (7). Accuracy and average weighted F1-Score for all the three models are above
95%. EfficientNetB0 performs better over ResNet50V2, MobileNetV2 as tabulated in table 2 with 96.52% accuracy and 96.26% average weighted F1-Score. The highest validation accuracy of EfficientNetB0 was 96.64%. Training accuracy and loss curves of EfficientNetB0 are very smooth compared to the other two models as shown in figure 3 and figure 4. The accuracy curves and loss curves for training and validation sets are presented in figures 3 and 4 respectively.

![Figure 3. Training and validation accuracy curves for the dataset.](image)

![Figure 4. Training and validation loss curves for the dataset.](image)

| Model           | Accuracy | F1-Score | Precision | Recall |
|-----------------|----------|----------|-----------|--------|
| ResNet50V2      | 95.68%   | 95.61%   | 95.72%    | 95.76% |
| MobileNetV2     | 96.04%   | 96.00%   | 96.29%    | 96.14% |
| EfficientNetB0  | **96.52%** | **96.26%** | **96.46%** | **96.59%** |

The proposed method is also compared with the model proposed in [10]. We compare the accuracy and F1-Score of the models as tabulated in table 3.

| Method          | Model      | Accuracy | F1-Score |
|-----------------|------------|----------|----------|
| [10]            | ResNet50   | 96.21%   | 95.42%   |
| Proposed framework | EfficientNetB0 | **96.52%** | **96.26%** |

3.3. Sample results of plant seedlings classification
Few Sample results of the test set classified using EfficientNetB0 are presented in figures 5 and 6 respectively. Figure 5 contains the samples that are correctly classified by the model. Predicted correct
labels are written on top of each sample in blue color. Figure 6 contains the samples that are misclassified by the model. Predicted incorrect labels and also true labels are written on top of each sample. Regardless of the model, loose silky-bent and black-grass are the two most misclassified weed species which impact the accuracy and F1-Score. This misclassification is due to their same physical appearance.

![Common Chickweed, Cleavers, Loose Silky-Bent](image1)

Figure 5. Correctly classified sample images using EfficientNetB0.

![Shepherd Purse, Black-Grass, Scentless Mayweed](image2)

Figure 6. Incorrectly classified sample images using EfficientNetB0.

4. Conclusion
We proposed a plant seedlings classification framework using ResNet50V2, MobileNetV2 and EfficientNetB0 architectures. The models are validated using the benchmark plant seedlings dataset, which contains 12 different species where three belong to plant species and the other nine belongs to weed species. We compared the models and demonstrated that the EfficientNetB0 model outperformed with an average F1-Score of 96.26% and an accuracy of 96.52%.

References
[1] C. Andrea, B. B. Mauricio Daniel and J. B. José Misael 2017 Precise weed and maize classification through convolutional neuronal networks IEEE 2nd Ecuador Technical Chapters Meeting (ETCM) pp 1-6
[2] Olsen, A., Konovalov, D.A., Philippa, B.et al 2019 DeepWeeds: A Multiclass Weed Species Image Dataset for Deep Learning Sci Rep 9, 2058
[3] J. A. Villaruz, J. A. A. Salido, D. M. Barrios and R. L. Felizardo 2018 Philippine Indigenous Plant Seedlings Classification Using Deep Learning IEEE 10th Int. Conf. on Humanoid, Nanotechnology, Information Technology, Communication and Control, Environment and Management (HNICEM) pp 1-5
[4] F. Miao, S. Zheng and B. Tao 2019 Crop Weed Identification System Based on Convolutional Neural Network IEEE 2nd Int. Conf. on Electronic Information and Communication Technology (ICEICT) pp 595-598

[5] M. Fawakherji, A. Youssef, D. Bloisi, A. Pretto and D. Nardi 2019 Crop and Weeds Classification for Precision Agriculture Using Context-Independent Pixel-Wise Segmentation 3rd IEEE Int. Conf. on Robotic Computing (IRC) pp 146-152

[6] T. M. Giselsson, R. N. Jørgeensen, P. K. Jensen, M. Dyrmann and H. S. Midtiby 2017 A Public Image Database for Benchmark of Plant Seedling Classification Algorithms arXiv:1711.05458 [cs.CV]

[7] H. A. Elnemr 2019 Convolutional Neural Network for Plant Seedling Classification Int. Journal of Advanced Computer Science and Applications 10 319–325

[8] Ofori, Martinson & El-Gayar and Omar 2020 Towards Deep Learning for Weed Detection: Deep Convolutional Neural Network Architectures for Plant Seedling Classification Americas Conf. on Information Systems (AMCIS)

[9] K. Gupta, R. Rani and N. K. Bahia 2020 Plant-Seedling Classification Using Transfer Learning-Based Deep Convolutional Neural Networks Int. Journal of Agriculture and Environmental Information Systems 11 25-40

[10] N. R. Rahman, M. A. M. Hasan and J. Shin 2020 Performance Comparison of Different Convolutional Neural Network Architectures for Plant Seedling Classification 2nd Int. Conf. on Advanced Information and Communication Technology (ICAICT) pp 146-150

[11] S. Malliga, S. V. Kogilavani, Jaivignesh.D and Jeevananth.S 2020 Classification of Plant Seedlings using Deep Learning architectures Int. Journal of Advanced Science and Technology 29 1024 – 1030

[12] Abdel-Aziz Binguitcha-Fare, Prince Sharma 2019 Crops and weeds classification using Convolutional Neural Networks via optimization of transfer learning parameters Int. Journal of Engineering and Advanced Technology (IJAT) 8 2284-2294

[13] B. A. M. Ashqar, B. S. Abu-Nasser and S. S. Abu-Naser 2019 Plant Seedlings Classification Using Deep Learning Int. Journal of Academic Information Systems Research 3 7-14

[14] K. He, X. Zhang, S. Ren and J. Sun 2016 Deep Residual Learning for Image Recognition IEEE Conf. on Computer Vision and Pattern Recognition (CVPR) pp 770-778

[15] K. He, X. Zhang, S. Ren and J. Sun 2016 Identity Mappings in Deep Residual Networks arXiv:1603.05027 [cs.CV]

[16] M. Sandler, A. Howard, M. Zhu, A. Zhmoginov and L. Chen 2018 MobileNetV2: Inverted Residuals and Linear Bottlenecks IEEE/CVF Conf. on Computer Vision and Pattern Recognition pp 4510-4520

[17] A. G. Howard, M. Zhu, B. Chen, D. Kalenichenko, W.wang, T. Weyand, M. Andreetto and H. Adam 2017 MobileNets: Efficient Convolutional Neural Networks for Mobile Vision arXiv:1704.04861 [cs.CV]

[18] M. Tan and Q. V. Le 2019 EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks Int. Conf. on Machine Learning arXiv:1905.11946 [cs.LG]