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Weeds Detection using Deep Learning Methods and Dataset Balancing

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Abstract – Weeds have detrimental effects on agriculture and prove costly for farmers because they can quickly spread to fertile areas and reduce the fertility of the soil. Therefore, weed control is crucial for sustainable agriculture, and by detecting weeds and removing them from agricultural lands, we can transfer the limited resources we have to the plants to be grown, which would be a major step forward in sustainable agriculture. This article explores the feasibility of weed detection methods using deep learning architectures. Architectures used in the research are as follows: ResNet152V2, DenseNet121, MobileNetV2, EfficientNetB1 and EfficientNetB7. The F1-Score of EfficientNetB1 is 94.17\%, which is the highest score among those of all architectures. Among all architectures, EfficientNetB1 has the least number of parameters after MobileNetV2. In this research, data augmentation was done using horizontal flip, rotation, width shift, height shift, and zoom.

Keywords *– deep learning, weeds detection, EfficientNetB1, balanced dataset, sustainable agriculture*

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I. Introduction

Weeds are difficult and expensive to control, and their presence threatens agricultural fields. On the other hand, weeds compete with useful plant species on agricultural lands. They also negatively affect the growers' harvest yields and reduce their incomes. Using herbicides to eliminate weeds is not only costly but also harmful to the environment and human health.

Herbicides are widely used against weeds to minimize their detrimental effects. However, these substances do not easily degrade in nature and their effects under various environmental conditions are still not clearly known (Ustuner, al Sakran, Almhemed[1]).

Deep learning is a type of machine learning that imitates the learning ability of the human brain, and it is one of the most preferred technologies by researchers today. Having led to the emergence of many intelligent systems, deep learning models are frequently used in various fields, especially in smart and sustainable agriculture.

Agriculture is becoming more important with each passing day due to many factors, including global warming, the decrease in freshwater resources, and rapid population growth. Therefore, studies in the field of agriculture are gaining momentum.

In their study, Selvi, Subramanian, and Ramachandran [2] pointed out three key points:

- Accurate classification using CNN for overlapping crops and weeds.
- For real-time classification, the model should be reliable and more robust.
- Reducing the rate of misclassification.

Mowla and Gok [3] studied weed detection with VGG16, VGG19, MobileNetV2, Xception, and DenseNet201 using transfer learning. The architectures used in this study and the relevant statistical information are provided below:

Singh, Rawat, and Ashu [5] used image processing and deep learning methods to detect weeds in agricultural crops. After obtaining the images with FarmBot, they pre-processed and trained them using Artificial Neural Network, and analyzed the results. This study made use of image segmentation, unlike other studies, and a total of 54 photographs. The accuracy is not 100\% according to the results of the study which, although, has shown that the plant species used in architectural education can be distinguished well enough.

- MobileNetV2: 2,257,984 parameters used / 88.27% test accuracy
- VGG16: 14,714,688 parameters used / 89.17% test accuracy
- VGG19: 20,024,384 parameters used / 87% test accuracy
- Xception: 20,861,480 parameters used / 88.27% test accuracy
- DenseNet201: 18,321,984 parameters used / 92.42% test accuracy

- CovWNET (created in the experiment): 3,087,966 parameters used / 90.7% test accuracy

DenseNet201 gave the best results in this study.

Jabir, Noureddine, Sarih and Tannouche [4] investigated the weed status in sugar beet fields. They used 9,260,230 parameters in the CNN architectures they developed, and obtained a validation accuracy value of 73%, which they increased to 82% by optimizing the architecture and increasing the amount of data.

Singh, Rawat, and Ashu [5] used image processing and deep learning methods to detect weeds in agricultural crops. After obtaining the images with FarmBot, they pre-processed and trained them using Artificial Neural Network, and analyzed the results. This study made use of image segmentation, unlike other studies, and a total of 54 photographs. The accuracy is not 100% according to the results of the study which, although, has shown that the plant species used in architectural education can be distinguished well enough.

In a study conducted by Diaz, Castaneda, and Vassallo [6] on plant classification in precision agriculture, accuracy values were compared using deep learning architectures. In the study, pre-trained models such as InceptionV3, VGG16 and Xception were preferred. With a runtime of around 741 seconds and an accuracy score of 86.21%, Xception proved to be more efficient than other models.

Conducted to find an answer to the question "Which pre-trained model is more accurate on the balanced dataset for plant identification?", the research is divided into 5 sections. The section numbers and their contents are as follows:

- Section 2: characteristics of the data set
- Section 3: the method used in the research
- Section 4: results
- Section 5: conclusion

II. Materials and Method

A. Dataset Description

According to the literature review, Giselsson et al. [7] used the "Plant Seedlings Dataset", which is an open data source. This dataset consists of 12 different species and 960 unique weeds found in Denmark. It also contains 5539 photos in total, which are RGB photos with a resolution of 10 pixels per mm. The plants were grown in a laboratory environment and photographed at regular intervals. Styrofoam boxes were used to enlarge the samples, images were created at intervals of 2 to 3 days, starting a few days after the plants emerged, over a total period of 20 days, and a fixed dSLR camera (Canon 600D) was used to photograph the plants.

In this study, the dataset named "Plant Seedlings Dataset" was chosen to be used, and since some images in the first version of the dataset contained more than one plant, the second version was preferred. In order to balance the dataset, we both increased the amount of data using the data augmentation method for the types with missing data, and also reduced the amount of data by deleting the data from the types with large amounts of data. The image shapes of the data created by data augmentation are set to be (66,66,3). The batch size of these photos is 40. Horizontal flip was applied to the photographs in the training and validation dataset created by data augmentation. Rotation range was chosen as 20, width and height shift range and zoom range as 0.2. In addition, photos were reduced by deleting the data from types with a large amount of data.

Table 1. V2 Plant Seedlings Categories[7]

Plants	Original	Balanced
Black-grass	309	500
Charlock	452	500
Cleavers	335	500
Common Chickweed	713	500
Common wheat	253	500
Fat Hen	538	500
Loose Silky-bent	762	500
Maize	257	500
Scentless Mayweed	607	500
Shepherd's Purse	274	525
Small-flowed Cranesbill	576	500
Sugar beet	463	500

B. Method

For our experiment, we used the online community called Kaggle, and chose the aforementioned dataset because it was available for use in the competition and also user friendly. On this website, we first loaded the dataset in our own notebook and subsequently balanced our dataset as shown in Figure 1 and Figure 2, after which the training/testing split ratio was 90:10 and the validation ratio was 10. We divided the dataset into train, test and validation, and we had 5422 data in train set, 485 data in test set and 603 data in validation set. Then, we added the model we plan to use to the system. We used deep learning models such as ResNet152V2, MobileNetV2, DenseNet121, EfficientNetB1, EfficientNetB7. The sizes and parameters of the architectures used are shown in Table 2.

Fig. 1. Dataset before balanced

Shepherd's Purse	525
Sugar beet	500
Charlock	500
Black-grass	500
Loose Silky-bent	500
Cleavers	500
Common wheat	500
Maize	500
Common Chickweed	500
Small-flowered Cranesbill	500
Scentless Mayweed	500
Fat Hen	500

Fig. 2. Dataset after balanced

Table 2. Features of architectures[8]

Model	Size(MB)	Parameters(M)
ResNet152V2	232	60.4
MobileNetV2	14	3.5
DenseNet121	33	8.1
EfficientNetB1	31	7.9
EfficientNetB7	256	66.7

In addition to using many parameters (for optimization purposes) for the models and making sure that these parameters were the same for each model, we also chose the weight used in the models as 'imagenet' and set the models' metric as accuracy. Furthermore, we set the dropout value as 45% and also chose softmax because in this activation function, there is multiple classification in outputs. We initially thought of it as 40 epochs and decided to stop the training when more than 3 epochs fell. We chose the Learning Rate as 0.001 and preferred to reduce it according to the state of the training, during which we observed the loss and accuracy parameters. At the end of the training, we had the values plotted on the chart, and finally prepared the model's confusion matrix and classification report.

III. Results

In Table 3 and Table 4, EfficientNetB1[9] delivered great performance as the 2nd architecture with the lowest size and parameter among the architectures.

In this research, we aimed for maximum f1-score and accuracy among the selected architectures on the balanced dataset. In Table 4, the highest values occurred in the EfficientNetB1 model.

Table 3. Unbalanced Dataset Comparison Based on Accuracy, F1-Score, Precision and Recall

Model	Accuracy	F1-Score	Precision	Recall
ResNet152V2	89.35%	87.83%	88.58%	87.25%
MobileNetV2	88.27%	85.83%	86.92%	85.50%
DenseNet121	92.06%	90.17%	92.08%	89.25%
EfficientNetB1	**93.32%**	**92.17%**	**93.08%**	**91.50%**
EfficientNetB7	90.25%	89.50%	90.83%	88.67%

Table 4. Balanced Dataset Comparison Based on Accuracy, F1-Score, Precision and Recall

Model	Accuracy	F1-Score	Precision	Recall
ResNet152V2	91.34%	90.42%	90.50%	90.42%
MobileNetV2	90.52%	90.08%	90.50%	89.58%
DenseNet121	93.61%	93.17%	93.50%	93.33%
EfficientNetB1	**94.85%**	**94.17%**	**94.42%**	**94.08%**
EfficientNetB7	93.40%	93.42%	94.08%	93.00%

In Table 3 and Table 4, the use of balanced dataset seems to give better results in models. An average of 2% increase can be seen in the EfficientNetB1 model, which has the highest accuracy and f1-score value. There is an increase in other models as well.

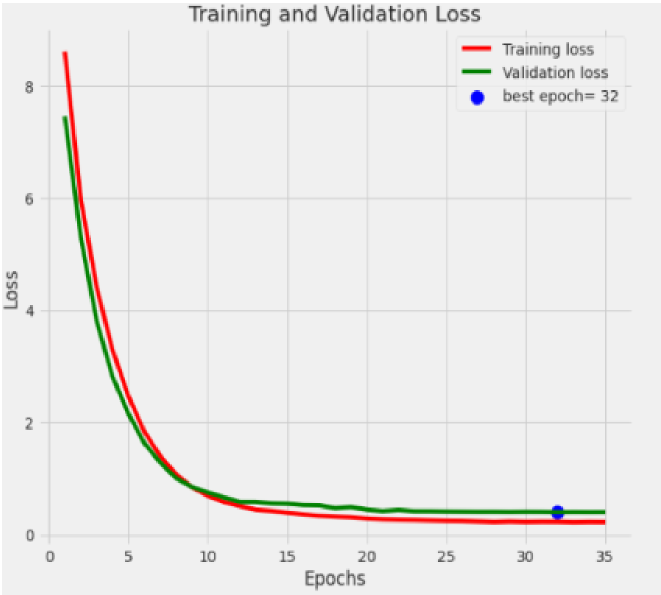

Fig. 3. Train and Validation Loss of EfficientNetB1

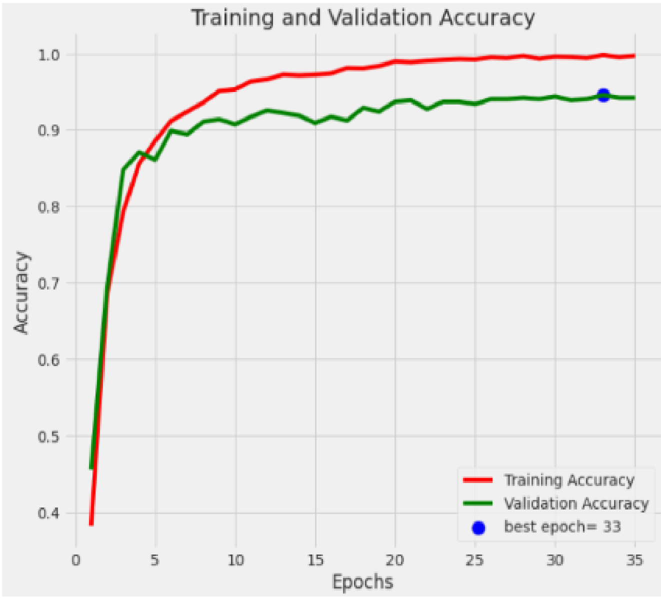

Fig. 4. Train and Validation Accuracy of EfficientNetB1

In Figure 3, the loss value of EfficientNetB1 has decreased continuously and remained at a low value, constantly approaching zero, while in Figure 4, the accuracy value of EfficientNetB1 has increased continuously despite its fluctuating behaviour. They have reached a balanced state over time without any inconsistency between train and validation accuracy values.

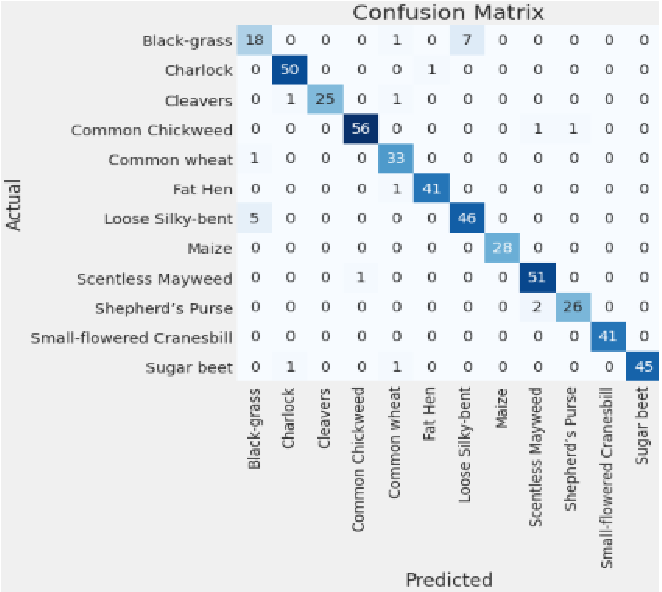

Fig. 5. Confusion Matrix of EfficientNetB1

The values of EfficientNetB1 in the confusion matrix are provided in Figure 5, and it can be observed that Black-Grass is the type with the highest number of errors, and it misclassified 8 photos.

Classification Report:

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	precision	recall	f1-score	support
Black-grass	0.75	0.69	0.72	26
Charlock	0.96	0.98	0.97	51
Cleavers	1.00	0.93	0.96	27
Common Chickweed	0.98	0.97	0.97	58
Common wheat	0.89	0.97	0.93	34
Fat Hen	0.98	0.98	0.98	42
Loose Silky-bent	0.87	0.90	0.88	51
Maize	1.00	1.00	1.00	28
Scentless Mayweed	0.94	0.98	0.96	52
Shepherd's Purse	0.96	0.93	0.95	28
Small-flowered Cranesbill	1.00	1.00	1.00	41
Sugar beet	1.00	0.96	0.98	47
accuracy			0.95	485
macro avg	0.94	0.94	0.94	485
weighted avg	0.95	0.95	0.95	485

Fig. 6. Classification Report of EfficientNetB1

In Figure 6, precision, recall and f1-score values of each plant species for the EfficientNetB1 model are shown. Black-grass has the lowest Precision value, and the lowest f1-score.

IV. CONCLUSION

Weed detection is of vital importance to precision agriculture, and our aim in this article was to show that weed detection can be conducted with high accuracy using deep learning architectures on a balanced dataset. The models used in our study are pre-trained models and they are available in the Keras library [8].

Among these models, EfficientNetB1 got the highest results with 94.85% accuracy and 94.17% f1-score. It has not been fully optimized to avoid confusion in comparing models. We think that EfficientNetB1 can be useful for mobile applications due to the number and size of its parameters, and that studies can be conducted on robots working with higher accuracy by using different datasets and models. It is crucial that these datasets are from nature because it is necessary to observe how the model that is used behaves in real-time in the natural environment. Robots can be used for this purpose, and the technical aspects of weed detection methods can be improved. In conclusion, it is our understanding that deep learning applications will increase productivity in agriculture, making it possible to produce more crops using fewer natural resources.

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