Deep Convolutional Neural Network Architecture for Plant Seedling Classification

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Abstract-Weed control is essential in agriculture since weeds reduce yields, increase production cost, impede harvesting, and degrade product quality. As a result, it is indeed critical to recognize weeds early in their vegetation cycle to evade negative impacts to crop growth. Earlier traditional methods used machine learning to determine crops along with weed species, but they had issues with weed detection efficiency at early growth stages. The current work proposes the implementation of a deep learning method that provides accurate results for precise weed recognition. Two different deep convolution neural networks have been used for our classification framework, namely Efficient Net B2 and Efficient Net B4. The plant seedlings dataset is utilized to investigate the proposed work. The evaluation metrics average accuracy, precision, recall, and F1-score were used. The findings demonstrate that the proposed approach is capable of differentiating between 12 species of a plant seedling dataset which contains 3 crops and 9 weeds. The average classification accuracy and F1 score are 99.00% for our Efficient Net B4 model and 97.00% for the Efficient Net B2. In addition, the proposed Efficient Net-B4 model performance is compared to the one of existing models on the plant seedlings dataset and the results showed that the proposed model Efficient Net B4 has superior performance. We intend to detect diseases in the identified plant species in our future research.

Keywords-deep learning; efficient net; machine learning; plant seedling classification; weed recognition; deep convolutional neural networks

I. INTRODUCTION

Weed control is one of the most challenging aspects of precision farming. Weeds harm the plant seedlings and take up the space and nutrients required for the crops reducing crop growth, while exercising herbicides over the crops would spoil the unexpected crops. It is important to identify plant seedlings because doing so can aid in identifying various plant species. When using machine learning algorithms to monitor plant state and even model climate change, a thorough knowledge of appearances, leaflet, and leaf classes in addition to the complete plant is crucial. Weed control should begin as soon as crop germination is complete. As a result, optimal weed control is recommended during the seedling stage. Automated plant seedling classification using machine learning methods has emerged as an important and encouraging field of research for enhancing agricultural results. Modern academics have developed numerous agricultural applications using cutting-edge deep learning algorithms. At the early stages of growth the weeds and crops look similar in appearances when the images of plant seedlings are collected during various lighting conditions, the CNN methods achieved high classification performance. The goal of the current research is to develop a model for a crop-weed discrimination system that employs deep Convolution Neural Networks (CNNs) to classify 12 crops and weed plant species.

A generic image database with plant seedling classification benchmarks was acquired with the use of a conditional camera. The dataset consists of 12 species at early growth stages [1]. Authors in [2] implemented techniques using binary image conversion and SVM to differentiate between crop and weed and obtained an accuracy of around 50%. A review work was done in [3] in the introduction of artificial intelligence for crop and weed management. Authors in [4] used deep learning architectures, namely Resnet, VGG16, and InceptionV3 for banana disease detection. Authors in [5] utilized prediction models on CNN, SVM, and KNN for apple classification and recognition. Authors in [6] conducted research regarding plant image classification tasks, for instance classifying maize plants and weeds by utilizing segmented images at initial stages of growth, with a training accuracy of 97.00%. Image processing and identification have been the subjects of [7-8]. Weed identification is challenging to ambiguous crop constraints and differing rocky or sandy identities, and long established classification techniques are most likely to fail in this task [9]. Authors in [10] proposed a classification model for plant seedlings. The authors attempted to improve classification efficiency by combining seedling and individual leaf classification. Bayes belief integration was used for classification design.

A deep encoder-decoder CNN was updated with a 14-channel image containing vegetation index values for segmentation to solve crop-weed classification consisting of sugar beet plants and weeds in [11]. In [12], a CNN network was able to determine unsupervised feature characterizations from 44 different plant species with high accuracy. In [13], instance segmentation was utilized to identify crops and weeds.

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The authors were able to classify crops and weeds with an accuracy of 60%. For a large dataset to obtain good accuracy we need graphical processing units, in addition, during the training operation, continuous modifications of the training parameters are needed in order to obtain a balanced output [14]. An image classifier model using deep CNNs was used to determine the accuracy of CNN, SVM, and KNN in [15]. Author in [16] proposed a CNN framework for classifying plant seedlings. The main topic of the endeavor involves classifying young plant seedlings using a CNN while monitoring accuracy and precision metrics. A hybrid architecture using Alex Net and VGG Net was implemented to determine the model accuracy and F1 score for a plant seedlings dataset with 94.38% average accuracy. In [17], in order to classify images of crop and weed seedlings, 5 pre-trained convolution network techniques were used, i.e. ResNet50, Xception, MobileNetV2, VGG16, and VGG19. ResNet50 architecture produced the best results scoring 95.23% testing accuracy [17]. Weeds and crops were classified using Residual Network 101 in [18], obtaining an overall accuracy rate of 98.47% on the validation set and 96.04% on the test set. CNN frameworks for plant seedlings classification by using ResNet50V2, MobileNetV2, and Efficient Net B0 architectures were implemented in [19]. The Efficient Net B0 method provided an average F1-Score of 96.26% and an accuracy of 96.52%. A limitation of this work is that the authors would have added more layers by increasing depth or resolution to obtain maximum accuracy.

In this paper, a novel method that fully trains a network is presented. The Proposed Efficient Net B4 model is used to provide better accuracy for image classification by compound scaling the dimension of network width, depth and resolution. For this experiment, we have used an i7 processor with Nvidia RTX 3080 Ti GPU and other supporting frameworks such as Keras and Tensor flow for the classification and analysis of the images of plant seedlings.

II. MATERIALS AND METHODS

A. Dataset

The plant seedling dataset for training, validation, and testing is described in this section. The dataset was obtained from Computer Vision and Biosystems Signal Processing group, Aarhus University, an open-source website which contains plant seedling images. The dataset contains 5541 plant seedling images, namely 833 test images, 833 validation images, and 3875 training images were acquired, each representing a different stage of growth for all the 12 considered species [1, 19].

B. Dataset Distribution

The plant seedling dataset is split into 3 sections: testing (15%), validation (15%), and training (70%). The testing set is used in evaluating the performance of the trained model. We made sure that testing and validation sets had no duplicates. The plant seedling dataset distribution is displayed in Table I and the test set of 12 plant seedling species is shown in Figure 1.

TABLE I. PLANT SEEDLING DATASET WITH CLASS WISE DISTRIBUTION

Class	Species	Training	Validation	Testing	Total
1	Black grass	217	46	46	309
2	Charlock	316	68	68	452
3	Cleavers	235	50	50	335
4	Chickweed	497	108	108	713
5	Common wheat	177	38	38	253
6	Fat hen	376	81	81	538
7	Loose silky-bent	532	115	115	762
8	Maize	179	39	39	257
9	Scentless mayweed	425	91	91	607
10	Shepherd's purse	192	41	41	274
11	Small-flowered cranesbill	404	87	87	578
12	Sugar beet	325	69	69	463
Total Images		3875	833	833	5541

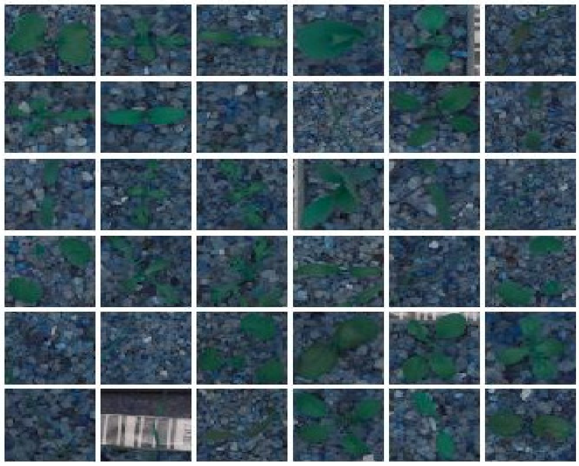

Fig. 1. Test set of the 12 plant seedling species.

C. Test Data Set

The motivation of our research work was to investigate the Efficient Net [19, 27] architecture because this model outperforms other CNN models in terms of accuracy and efficiency. The Efficient Net model has received little attention when considering datasets of plant seedlings. In this paper, a new mobile-size baseline is established. Efficient Net, compound scaling, and neural architecture are used. Efficient Models introduced a new baseline network (B0-B7) to provide better accuracy for image classification by compound scaling size (e.g. depth, width, and resolution) of the network by having a balanced output for the above parameters. A compound scaling technique is suggested in [19] that consistently scales width, depth, and resolution according to a set of guiding principles. They suggest the following formula:

$$s.t. \alpha . \beta^2 . \gamma^2 \approx 2$$

$$\alpha \geq 1, \beta \geq 1, \gamma \geq 1$$

where depth: $d = \alpha^{\phi}$, width: $w = \beta^{\phi}$, resolution: $r = \gamma^{\phi}$, ϕ is a user-defined coefficient that regulates the resources (e.g. FLOPs, or floating point operations) available for model scaling, and α, β, γ allocate resources according to depth, width, and resolution. A convolution operation uses a certain amount of FLOPS in relation to d, w^2 and r^2. In the equation above, this information is reflected. For each new ϕ, the number of required FLOPs increases by 2^{ϕ}. The authors scaled it up using the following method starting with EfficientNet-B0:

- Fix $\phi = 1$. We assume that the resource is twice as available at any given scaling step as it was at the one before.
- Perform a quick grid search across α, β, and γ to ensure that the restriction in the above equation is not violated.
- The authors discovered that the values α=1.2, β=1.1, and γ=1.15 perform optimally.
- Fix α, β, and γ, then scale up the EfficientNet-B0 with various ϕ to get recent scaled networks, i.e. Efficient Net B0-B7 [27].

TABLE II. MODIFICATIONS IN NETWORK ARCHITECTURE

Layer (type)	Output shape	Parameters
Efficient Net B4 (Functional)	(None,7,7,1792)	17673823
global_max_pooling2d_5 (Global Max Pooling2D)	(None,1792)	0
flatten_6(Flatten)	(None,1792)	0
dense_12(Dense)	(None,1024)	1836032
batch_normalization_4 (Batch Normalization)	(None,1024)	4096
dropout_5(Dropout)	(None,1024)	0
dense_13(Dense)	(None,512)	524800
batch_normalization_5 (Batch Normalization)	(None,512)	2048
dropout_6(Dropout)	(None,512)	0
dense_14(Dense)	(None,128)	65664
batch_normalization_6 (Batch Normalization)	(None,128)	512
dropout_7(Dropout)	(None,128)	0
dense_15(Dense)	(None,12)	1548
Total Parameters		20,108,523
Trainable Parameters		3,237,772
Non- Trainable Parameters		16,870,751

D. *The Proposed Methodology*

In the proposed methodology, the first step is to obtain a plant seedling data set. Once we acquire the image dataset, the next step is to pre-process the raw images in order to keep only relevant information. The preprocessing steps consist of resizing the image into 380×380 resolution for Efficient Net B4 and 280×280 resolution for Efficient Net B2 model, sharpening the image to highlight fine details by removing blurring and highlighting edges, and applying segmentation to the objects of interest, which are the leaves of the plant, and finally applying masking. After preprocessing we split the dataset into training, validation, and testing parts with ratio of 70:15:15 and passed it into a custom designed model using the Efficient Net B4 as the base model. The Modified Efficient Net B4 can be used in many different ways:

- Training the whole Efficient Net architecture.
- Applying transfer learning paradigm to extract features from the pre-trained Efficient Net on plant seedling dataset.
- Applying the transfer learning paradigm along with fine-tuning of the architecture by adding a few more layers like pooling, flattening, and normalization followed by a few dense layers and a final layer with softmax activation function.

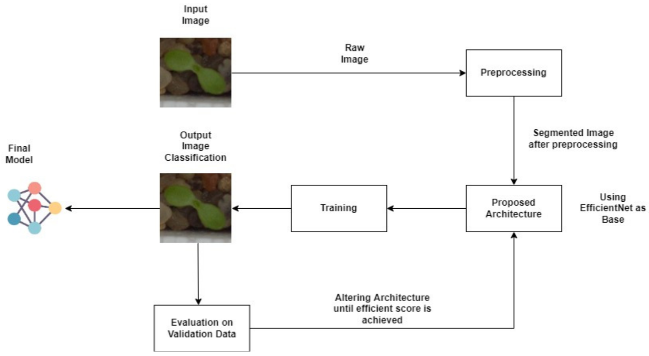

Fig. 2. The proposed methodology.

E. *Pipeline for Image-Processing*

For training, each image in the plant seedlings dataset was scaled to 380×380 (resolution scaling) for Efficient Net B4 and 280×280 for Efficient Net B2. We synthetically increased the dataset size by using image augmentation through rotating, zooming, and horizontal and vertical flipping. Gaussian filter was first used to smooth the image. As can be seen, the background of the plant images has numerous pointless rock-formed borders. Because these edges would only provide background noise, we converted the values of the discontinuous pixels into continuous ones. Our next step was to identify the relevant information in the image and remove any unnecessary background. To classify an object, a binary image that we wish to represent must be created. We will just need to look at the beneficial object's shape, making the classification procedure considerably simpler. To accomplish this, we converted the RGB image to the much more useful HSV format, which makes it much easier to discriminate between colors. There is now no overlap because the object can be easily distinguished from the background, but still there is some noise and flaws in the image, so as a follow-up, we slightly eroded it. We rescaled all images, created a mask for every image and then applied segmentation on each sample. Each image in the dataset was subjected to the processing pipe line by a function that we defined which outputs the processed dataset. Figure 3 shows the pre-processed images of the training model.

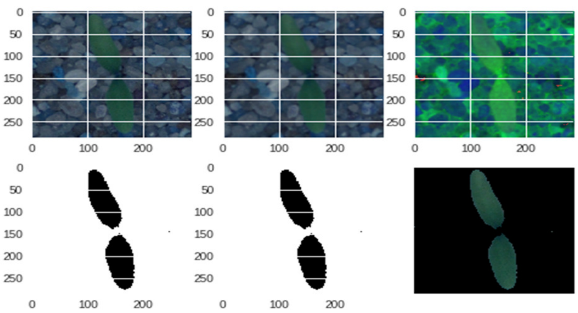

Fig. 3. Pre-processed images of plant seedlings.

F. Transfer Learning

In order to complete tasks that are related to one another, transfer learning is another used high-level concept. We could not directly apply the pre-trained weights for interpretation and expect excellent performance due to the different fields of the dataset images. As a result, we carried out refinement to customize towards the original domain of the images. For an Efficient Net B4 model, few more layers were added and minor parameter adjustments to the trained model were made in this step. There are numerous approaches to fine tuning. These incorporate the use of a pre-trained design for feature extractors out of which features were fed to each classifier, for fine adjustment to all or a few parameters at the last number of layers in the pre-trained modeling.

III. IMPLEMENTATION

We cover the implementation and training of Efficient Net B4 and Efficient Net B2 in this section to ensure reproducibility.

A. Learning Rate Change

The learning rate is classified by the best significant hyper-parameters to obtain quick and reliable training for neural networks. A large range of the loss gradient is applied to the latest parameters in order to alter them in the orientation of the reduced loss. In order to do this, the network's learning rate was linearly increased in a certain range of values after each network had been trained for a few epochs. We observed the change in validation loss by decreasing the learning rate from 0.01 to 0.001. After this change, the validation loss is considerable. The final plot of the validation loss against epoch is displayed in Figure 4.

B. Fine Tuning Efficient Net B2

All layers in the Efficient Net B2 were trained using gradient updates and a learning rate of 0.001. We applied Stochastic Gradient Descent optimizer for custom dense layers and a default decay rate for this implementation.

C. Fine Tuning Efficient Net B4

Since training was unstable, we have added a few more layers for Efficient Net B4. Based on multiple runs with hyper parameter tuning as well as grid search techniques, we found the best parameters suitable for our problem for Efficient Net B4 architecture with a learning rate of 0.001, RHO value of 0.9, epsilon of 1e-08 and default decay values. We applied Adam Optimizer for the custom dense layers.

D. Performance Evaluation Metrics

The effectiveness of any classification model cannot be assessed with common criteria. The performance metrics considered for each model are accuracy, precision, recall, F1 score, support, and confusion matrices.

E. Confusion Matrix

The confusion matrix provides details about the classifier's errors, including the kinds of errors that are occurring. The performance of a classification model's predicting power was compiled in an N×N table (N represents the number of classes). It is a matrix that shows the relationship between the model's categorization and its real label (predicted label). A correct estimation of an image's class is referred to as a True Positive (TP). When the model suggests an image's class incorrectly, it produces a False Positive (FP). Whenever the model correctly estimates a negative class of the image, it produces a True Negative (TN). False Negative (FN) will occur when it incorrectly predicts a negative class of an image. The accuracy score is applied to assess our model's performance wherein TPc, FPc and FNc signify True Positives, False Positives and False Negatives. Pc indicates a class' specific precision metric that says, out of all points that are predicted to be positive, how many are actually positive. Rc represents a class specific recall metric that says, out of all positive points, how many are actually positive. N represents the overall collection of images, whereas Nc denotes the overall collection of images of class c and C denotes the overall collection with regard to classes. S denotes the mean of average weighted (F1) over all cross validation folds.

$$\mathrm{P_c} = \frac{\mathrm{TP_c}}{\mathrm{TP_c+FP_c}} \quad (1)$$

$$\mathrm{R_c} = \frac{\mathrm{TP_c}}{\mathrm{TP_c+FN_c}} \quad (2)$$

$$\mathrm{f_{1,c}} = 2\,\frac{\mathrm{P_cR_c}}{\mathrm{P_c+R_c}} \quad (3)$$

$$avg_{weighted}(f_1) = \sum_{c=1}^{C} \frac{N_c}{N} . f_{1,c} \quad (4)$$

$$S = \frac{1}{N_{fold}} \sum_{i=1}^{N_{fold}} avg_{weighted}(f_1) \quad (5)$$

IV. RESULTS AND DISCUSSION

We used (1) to (4) to evaluate the performance. The topmost validation accuracy obtained on Efficient Net B4 model is 99% whereas for Efficient Net B2 is 97%. Figures 4 and 5 show the accuracy and loss curves of training and validation sets for Efficient Net B4 and Efficient Net B2 respectively.

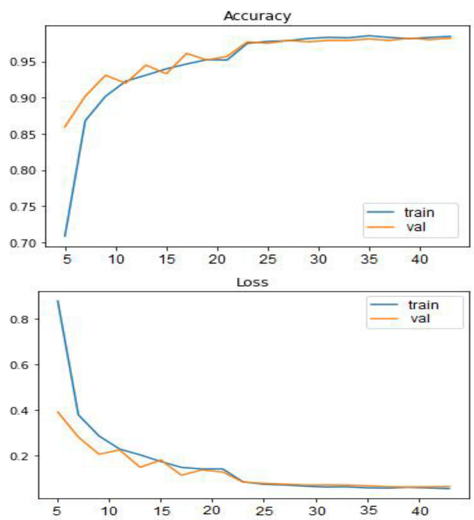

Fig. 4. Efficient Net B4 model performance.

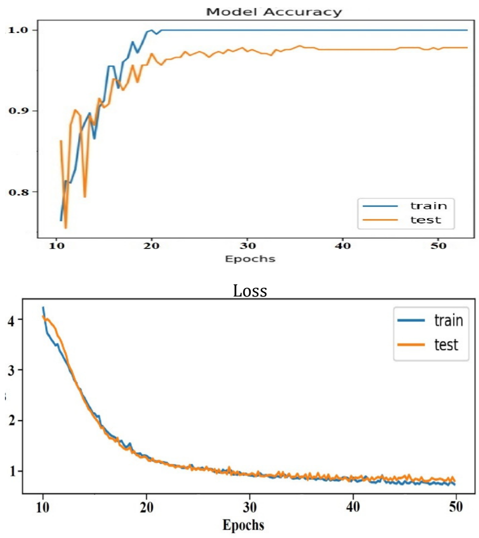

Fig. 5. Efficient Net B2 model performance.

(a)

	precision	recall	f1-score	support
Black-grass	0.87	0.89	0.88	46
Charlock	1.00	1.00	1.00	68
Cleavers	1.00	1.00	1.00	50
Common Chickweed	1.00	1.00	1.00	108
Common wheat	1.00	1.00	1.00	38
Fat Hen	1.00	1.00	1.00	81
Loose Silky-bent	0.96	0.95	0.95	115
Maize	1.00	1.00	1.00	39
Scentless Mayweed	1.00	1.00	1.00	91
Shepherds Purse	1.00	1.00	1.00	41
Small-flowered Cranesbill	1.00	1.00	1.00	87
Sugar beet	1.00	1.00	1.00	69
accuracy			0.99	833
macro avg	0.99	0.99	0.99	833
weighted avg	0.99	0.99	0.99	833

(b)

	precision	recall	f1-score	support
Black-grass	0.80	0.89	0.85	46
Charlock	1.00	1.00	1.00	68
Cleavers	1.00	1.00	1.00	50
Common Chickweed	1.00	1.00	1.00	108
Common wheat	1.00	0.79	0.88	38
Fat Hen	0.95	1.00	0.98	81
Loose Silky-bent	0.92	0.95	0.94	115
Maize	1.00	1.00	1.00	39
Scentless Mayweed	1.00	1.00	1.00	91
Shepherds Purse	1.00	1.00	1.00	41
Small-flowered Cranesbill	1.00	1.00	1.00	87
Sugar beet	1.00	0.94	0.97	69
accuracy			0.97	833
macro avg	0.97	0.96	0.97	833
weighted avg	0.97	0.97	0.97	833

Fig. 6. Plant seedlings classification report of (a) Efficient Net B4 and (b) Efficient Net B2 on the test data set.

The performance metrics on the test dataset for precision, recall, F1-score, and support are depicted in Figure 6. The average weighted accuracy of the Efficient B4 model is 99% whereas the Efficient Net B2 model has 97%. For Efficient Net B4, classes black grass and loose silky bent have F1-score equal to 0.88 and 0.95. For the remaining plant species the F1-score is 1 indicating that all the plants are correctly classified. For the Efficient Net B2 model, classes black grass, common wheat, fat-hen, loose silky bent, and sugar beet have F1-score of 0.85, 0.88, 0.98, 0.94, and 0.97 while the remaining plant species are correctly classified. Figures 7 and 8 demonstrate the confusion matrix for the test data set in support of the 12-class configuration of the plant seedlings dataset during testing. The plant seedling dataset consists of 12 species representing 12 rows and 12 columns of the matrix, which analyzes correct classification using 833 test images. In the confusion matrix, the rows indicate the current classification, while the columns indicate the predicted score. From the confusion matrix of the Efficient Net B4 model we can infer that 6 images of black grass and 5 images of loose silky bent are misclassified while the remaining plant species are predicted correctly. For the Efficient Net B2 model, 5 images of black-grass, 4 images of common wheat, 6 images of loose silky bent, and 4 images of sugar beet are incorrectly classified and the remaining are classified correctly. The conclusion is that the Efficient Net B4 model performed better than the B2 model.

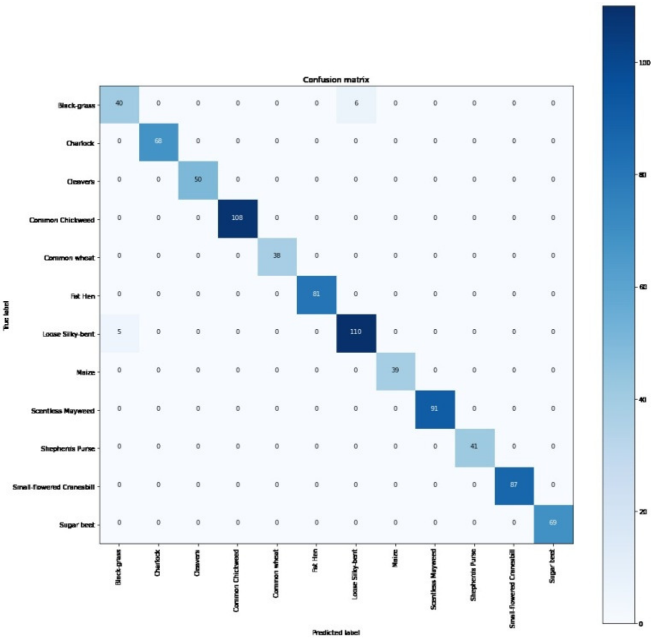

Fig. 7. Confusion matrix of the plant seedling test dataset of Efficient Net B4.

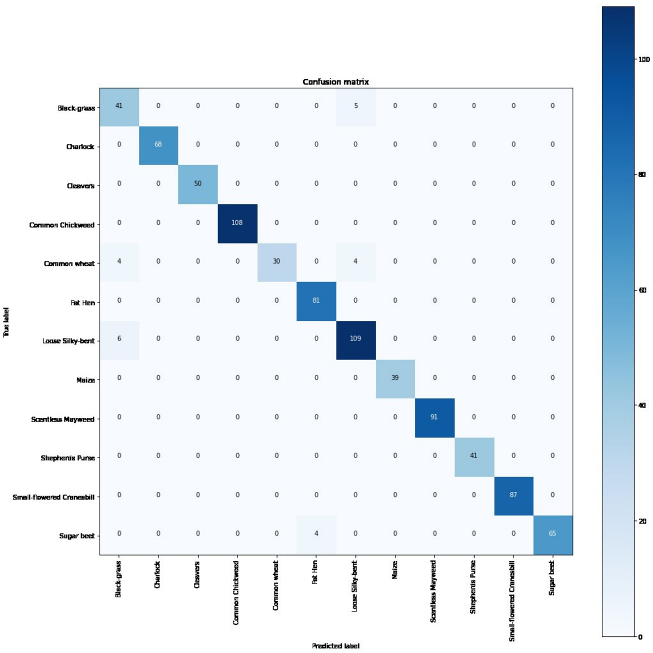

Fig. 8. Confusion matrix of the plant seedling test dataset of Efficient Net B2.

The proposed Efficient Net B2 and Efficient Net B4 methods were compared with existing methods [16-19] for the plant seedlings dataset and the results are shown in Table III. We can see that the proposed Efficient Net B4 method outperforms the latest competitive approaches in terms of accuracy and F1-score.

TABLE III. METHOD COMPARISON ON THE PLANT SEEDLING DATASET

Ref.	Method	Accuracy (%)	F1-score (%)
[16]	Alexnet + VGGNet	94.38	93.57
[17]	Resnet 50	95.23	95.00
[18]	Residual Network 101	98.47	95.72
[19]	Efficient Net B0	96.52	96.26
Proposed	Efficient Net B2	97.00	97.00
	Efficient Net B4	99.00	99.00

Figure 9 depicts examples of charlock and sugar beet images of the test set that are correctly classified with the proposed Efficient Net B4 model.

(a)

(b)

Fig. 9. Correctly classified charlock and sugar-beet images.

Figure 10 depicts loose silky-bent and black-grass, images which are misclassified plant seedling images of weed species, because they almost look similar. Black grass class contains 6 images and loose silky bent class contains 5 images which are misclassified.

(a)

(b)

Fig. 10. Incorrectly classified loose silky bent and black grass images.

V. CONCLUSION

In this paper, deep convolution neural networks were investigated for identifying plant species at early growth stages. The proposed Efficient Net B4 model for plant seedling classification dataset which contains 12 species of crops and weed achieved a high level of accuracy and average F1-score rate, precision, and recall of 99.00%. When compared with other known methods, the proposed model shows a significant increase in accuracy in the considered plant seedlings dataset. Nevertheless, throughout our investigations, we discovered that images from two specific groups, black-grass and loose silky-bent, had been incorrectly classified. There are some limitations in distinguishing crops and weeds during the seedling stage: (a) image resolution is insufficient to allow differentiation among susceptible soil, plant seedlings, and weeds, (b) there are spectral and apparent similarities in the initial stages, as there is a competition among weeds and useful crops, and (c) the detection method and the soil background reflectance overlap. The proposed model can be further extended and improved with the use of a larger dataset.

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