IDENTIFICATION OF COMMON WEED SPECIES USING EfficientNetv2B0

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Abstract: *One of the main threats to agriculture and biodiversity is weeds; also, the management of this issue will become more difficult as a result of climate change. The variety of weed species would alter and some weeds may spread further. Owing to their irregular spatial distribution, a ground or aerial robot is utilized to perform targeted herbicide spraying. This application of herbicides relies completely on computer vision algorithms that aid in identifying weeds in the field before the spot spraying occurs. In this study, we aimed to develop a robust system for site-specific weed control in fields by utilizing color images and a deep learning approach to distinguish four common weeds: kochia, horseweed, ragweed, and redroot pigweed. This study uses a weed dataset collected from four locations in North Dakota, which includes 3,424 digital images showing four types of weeds. The results of using the EfficientNetv2B0 method for identifying these weeds were measured using important statistics like accuracy, marco average of precision, recall, and F1- score, which result in 99.5%, 100%, 100%, and 100% respectively. The findings show that EfficientNetv2B0 performs better than other classification methods like InceptionResNetV2, NASNetMobile, DenseNet121, Xception, and EfficientNetB0 as 97.8%, 95.9%, 98.5%, 97.3%, 99.1% respectively. Also, the study investigated the model's performance in terms of total parameters, model size, and inference time. The EffcientNetv2B0 is faster, lightweight, and computationally efficient (both during training and inference).*

Keywords: *Weed classification, Deep learning, EfficientNetv2B0, Transfer learning*

1. Introduction

Agriculture plays a critical role in the global economy, as it contributes significantly to the economic prosperity of developed nations and plays an active role in the economy of developing countries as well. The population is expected to increase to 9.2 billion in 2050[1]. This means that agricultural productivity efficiency will increase by 25% [2], taking into account the restricted resources of land, water, and labor. Many factors effect crop yield and quality; for example, insects, weeds, fungi, viruses, and bacteria. Among these factors, weeds are the most impactful problem, causing 40–60% [3] remarkable yield loss worldwide. Because they compete with the crops for sunshine, water, and nutrients [4]. Chemical treatment is currently the most widely utilized approach globally for eliminating weeds from agricultural areas [5] owing to its practicality and efficacy. When this approach is sprayed evenly throughout crop fields without discrimination of crops or weeds, it is seriously polluting the environment by contaminating the groundwater and soil. Thus, applying an herbicide to the

area of weeds only could save costs and reduce environmental issues while also increasing the yield and quality of the crop[6].

A critical initial step in developing an autonomous weed management system is the ability to correctly detect and recognize weeds [7]. Weed detection in crops is challenging, as crop and weed plants often have similar colours, textures, and shapes. This is a common challenge in the classification and detection of crops and weeds. Noise and motion blur in the image also make it harder to identify plants. A significant amount of research has been conducted on the use of computer vision algorithms for weed detection [8] and classification.

Weed recognition and classification are important steps toward site-specific weed management. Currently, traditional machine learning (ML) and deep learning techniques enable weed categorization on the basis of leaf images [9-10]. Several machine learning (ML) techniques have been applied based on images, including decision tree [11], support vector machine (SVM) [12] and K-nearest neighbor (KNN) classifiers [13]. Vi Nguyen Thanh Leet al. [14] classified three crops, namely, Zea mays (maize/corn), Brassica napus (canola), and radish, by SVM and extracted textural features using local binary pattern (LBP) operators with an accuracy of 91.85%. Pauline Ong et al. [15] used machine learning algorithms, specifically convolutional Neural Network (CNN) and random forest (RF), for weed classification in the Chinese cabbage field. The authors achieved classification accuracies of 92.41% and 86.18% for CNN and RF, respectively. This study uses machine learning to combine texture and the shape of a plant at the level of individual features for weed classification [16]. The various features include Fourier descriptors, shape features, Hu moment invariants, shape curvature local binary patterns and gray-level co-occurrence matrices in weed images. Finally, the classifiers applied are the K-nearest neighbor, support vector machine, naïve Bayes and multilayer perceptron with 10-fold cross-validation. When the texture and shape features are trained together, the SVM classifier performs better than the other classifiers do, reaching a classification accuracy of 99.33%.

In these techniques, weed image color, texture, and shape spectrum, as well as other properties, should be extracted manually. Hence, if the extraction of weed images was not complete or if there were obscured features, it would be impossible to differentiate between similar weed species. In 2006, Hinton et al. [17] presented the idea of deep learning (DL). DL techniques are highly effective in addressing computer vision challenges related to weed classification. These techniques are able to automatically extract more intricate characteristics from images of weeds [18], and work on large datasets. For this reason, deep learning techniques are robust and highly accurate for weed image classification.A. Subeesh et al. [19] used deep learning-based transfer learning techniques (AlexNet, InceptionV3, GoogLeNet, Xception) to classify weeds in the bell pepper field. InceptionV3 performance achieved a high accuracy of 97.7% at 30 epochs and 16-batch size batches.

Sunil G C et al. [20] studied the impact of the image background in training deep learning (DL) algorithms. A total of 6356 crop samples and weed images were taken from the greenhouse, including uniform and non-uniform backgrounds.The residual network (ResNet50), visual group geometry (VGG16), and convolutional neural network (CNN) models were used to identify six weed species (Waterhemp, Palmer Amaranth, Ragweed, Kochia, Redroot Pigweed, and Horseweed) and two crop species (Sugarsugar beet and Canola). The average

f1-scores of ResNet50 and VGG16 on three cases were non-uniform, uniform, and combined with two scenarios datasets background were 75%, 82.75%, 68.4%, 77.5%, 99% and 92%, respectively. Akshay Dheeraj and Satish Chand [21] applied and MobileNetV2 and DenseNet169 on 5544 images, including three crop species: sugar beet, common wheat, maize and nine weed species. The results revealed accuracies of 97.14% and 94.92%, respectively.Ancy Stephen et al. [22] applied several of pretraining models, i.e. GoogLeNet, ResNet18, MobileNetV3 Large and InceptionV3, on cotton crop to classify eleven distinct plant regions. MobileNetLarge offers a high accuracy of 93.9%.

In this paper, DL technique based on transfer learning was used to categorize weed species into many categories by fine-tuning the pretrained EfficientNetv2B0 model. The rest of the paper is categorized into four sections: Materials and methods, experimental setup, results and discussion, and conclusion. The details of the dataset and proposed methodology are covered in Section 2. Section 3 explains the system and software requirements, hyper-parameter settings, and evaluation measures. Section 4 presents the obtained results and their discussion. Finally, the paper concludes with a conclusion and suggestions for future work in section 5.

2. Materials and methods
2.1. Dataset

The study utilized a publicly accessible collection of weed images dataset [23-24]. The dataset was collected from late May to late June 2021, mid-July to late August of 2021, and mid-August to late September 2022 by aerial images and a handheld Canon 90D camera at three geographical locations in North Dakota: Carrington Research Extension Center (47° 22′ 25.7556″ N, 99° 12′ 8.5032″ W), Agronomy Seed Farm in Casselton (46° 54′ 1.8″ N, 97° 12′ 40.896″ W) and Greenhouse (NDSU-Main Campus) (46° 53′ 39.156″ N, 96° 48′ 30.816″ W). Each collection location was recognized to contain expansive pervasions of particular weed species. The final dataset contained 3,424 multiclass images, such as redroot pigweed, kochia, horseweed and ragweed showing in Fig.1.
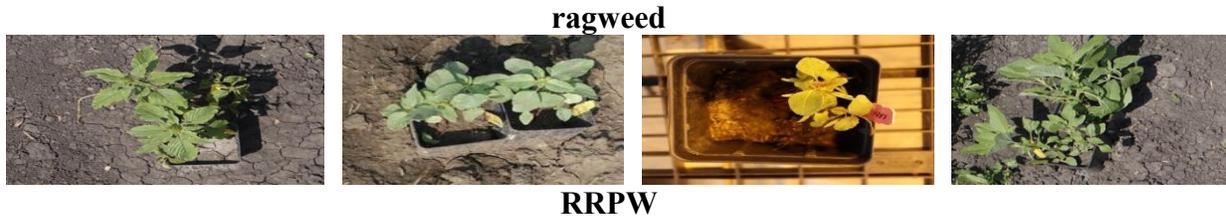

horseweed

kochia

ragweed

RRPW

Fig 1. Sample images of weeds dataset were added. APIs from Keras

2.2 Augmenatation data

Dataset extracted from aerial images with JPG images, which featured a variety of in-field conditions. It was taken with a resolution of 5,472 × 3,648 pixels. Additionally, to offer variety to the training set, a number of greenhouse photos taken with a handheld Canon 90D camera Image data generator were applied to execute numerous augmentation types, including horizontal flip, rotate, shear and zoom range as Fig 2.

Original   horizontal flip   rotate   zoom   shear

horseweed

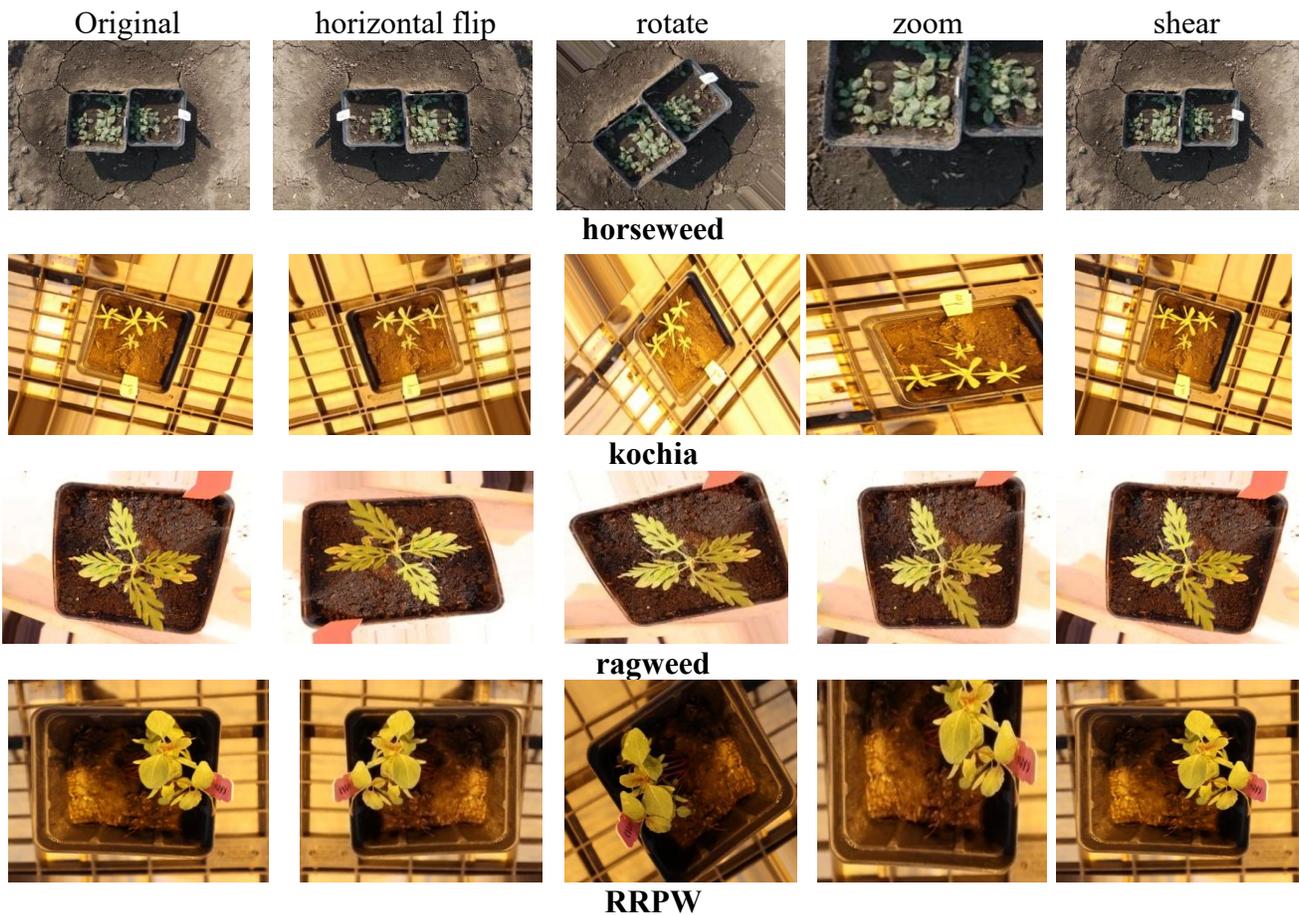**kochia**

ragweed

RRPW

Fig 2. Data augmentation method for weed sample

2.2. Transfer learning

CNN can capture both simple and complex features on the basis of the convolutional layers of the model. The retrieved features are transformed into a one-dimensional vector, which is then sent to a sequence of fully connected layers for classification. Although CNN has been very successful, one of its drawbacks is that it needs a large amount of training data samples to prevent overfitting. For some research challenges, it is not possible to collect a large amount of annotated data, and most of the data is not even accessible. Crop-weed datasets typically have very few images to train. Additionally, crop-weed datasets often suffer from class imbalance, where some species have much more data than others. This issue can be resolved by transferring learning. The goal of transfer learning is to convert the knowledge of architectures that were initially trained on a large-scale dataset, e.g., ImageNet, into new tasks (similar or different problems), such as identifying weed types in a weed dataset with less data. The pretrained models' layers are empirically fine-tuned to suit the new input images in the new task. Fine-tuning of pretrained architectures can be performed by unfreezing all or some layers in the convolutional base [25-26] Fig 3.
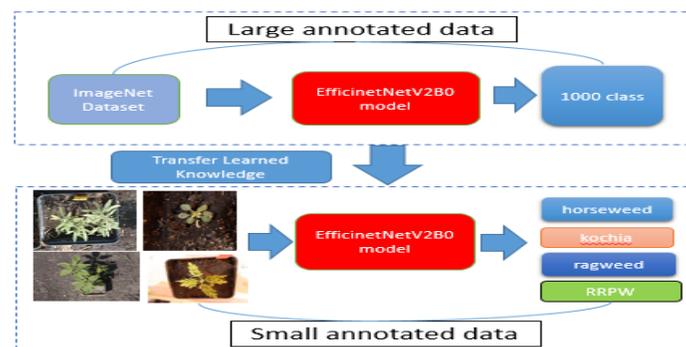

Fig 3. The general concept of transfer learning.

2.3 EfficinetNetV2B0 ARCHITECTURE

EfficientNetV2B0 is a deep CNN architecture designed to belong to the family of EfficientNetV2, which was developed by the Google Brain team [27]. This family achieves state-of-the-art accuracy in several classification tasks on the basis of a far smaller model and faster convergence speed. EffcientNetV2B0 is the smallest model in this family, and uses less computing power to achieve greater accuracy. Fig 4 shows the general structure of the modified EffcientNetV2 B0, which initially performs a 3×3 convolution on the input image size of 224×224×3. Next, it extracts the feature maps (7×7×1280) from the input image by combining 5 FusedMBConv (Fused Mobile Inverted Residual Bottleneck Convolution) [28] and 16 MBConv [29] modules. The model then uses a global average pooling layer and a fully connected layer with a Softmax activation function for multiclass classification. The stacked feature maps are assigned to the fully connected layer after being transformed into 1×1×1280 dimensions by the global average pooling2D layer. In the final step, the fully connected layer with a Softmax activation function predicts the probability of the label of the input weed image. Notably, this model's classification process differs from that of the original EffcientNetV2B0, which was built to categorize images into thousand categories.
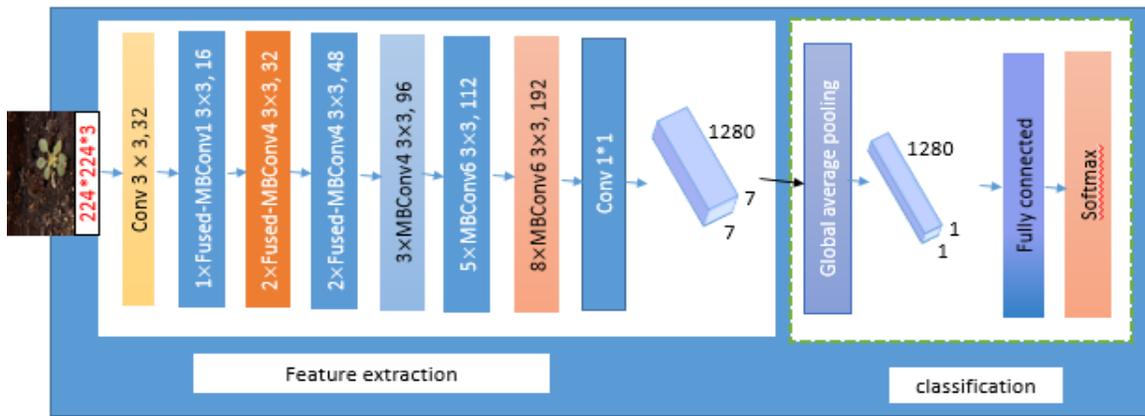
Fig 4. The proposed method of EffcientNetV2B0

As mentioned above, MBConv and Fused MBConv are the primary feature extraction blocks in EfficientNetV2B0 [27]. MBConv begins with a 1 × 1 convolution operation, which improves the channel depth and allows the network to produce richer feature representations. Next, 3 × 3 depthwise convolutions are used to simplify the calculation and minimize the number of variables. Then, a squeeze-and-excitation (SE) block enhances the representation power of the architecture. The final result of this block is produced by using another 1 × 1 convolution to lower the dimensionality of the output feature maps. In addition, a residual connection is implemented to further improve the performance. Even though deep convolutions have fewer parameters, they often cannot take full advantage of modern accelerators. On the other hand, the Fused-MBConv attempts to address this issue by substituting the depthwise and expansion conv1 × 1 in MBConv conv3 × 3 with a single regular conv3 × 3, making training faster (see Fig 5). Importantly, the training process is slowed and the parameters are increased when the design uses only Fused-MBConv. As a result, EffcientNetV2B0 employs a combination of MBConv and Fused-MBConv to increase training speed with minimal parameter overheads and improve the feature extraction process. [27]. The training procedure for the modified EffcientNetV2B0 model to categorize weed types as kochia, horseweed, ragweed, and RRPW will be covered in the subsection that follows.
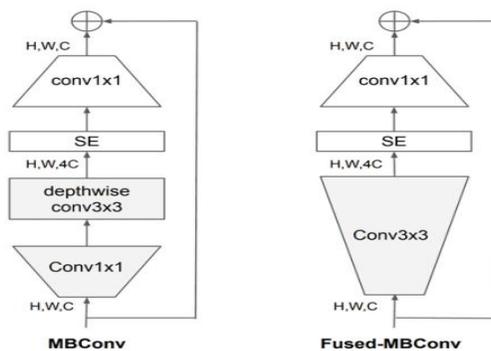

Fig 5. Structure of MBConv and Fused-MBConv [27].

3. Experimental setup
3.1 System and software requirements

The experiments are carried out on a Dell PC. The models are trained on an Intel(R) Core (TM) i7-4770 CPU @ 3.40 GHz with 8 GB of RAM. The code is implemented in the Python programming language, with TensorFlow as the backend and the Keras API as the frontend.

3.2 Hyper-parameters settings

All 3,424 weeds were labelled for the k-fold cross-validation with k = 5. Each model was pretrained with the corresponding weights on ImageNet. All the images are resized to 224×224 pixels. The batch size, loss function, learning rate, epoch and optimization are all empirically adjusted until the best sets of hyperparameters for training the model and the desired results are achieved. The classification of weed types such as kochia, horseweed, ragweed, and redroot pigweed, is a multidimensional classification problem. The loss function uses sparse categorical cross entropy, and stochastic gradient descent (SGD) is the optimizer used for all the models, with an initial learning rate of 0.00005 (5e-4). First, all the images in the training set are loaded with a mini-batch size of 32. The fine-tuned EfficientNetV2B0 is trained for 150 epochs. In order to fine-tune the pretrained EfficientNetV2B0 model on the weed images, the Softmax layer is replaced from the network with a 4-neuron fully connected layer. Table 1 presents an optimized value for each hyperparameter used in the studies.

Table 1 List of Hyper-parameters and their respective values

Hyper-parameters	Values
Input shape	(224, 224, 3)
Output layer activation function	Softmax
epoch	150
Batch size	32
Optimizer	SGD
Initial learning rate	$0.5 \times 10{-3}$
Loss function	sparse categorical cross-entropy

3.3 Performance evaluation metrics

The measurement of the proposed methodology is based on the following performance metrics: accuracy (A), confusion matrix, recall (R), precision (P), F1-score (F1), and macro-averaging.
3.3.1. Accuracy
The number of accurately predicted labels out of all labels. It provides the percentage of testing accuracy for the suggested model. Equation (1) provides the accuracy calculation formula.

$$Accuracy = \frac{TP}{TP + TN + FP + FN} \tag{1}$$

Where true positive (TP): is the number of positively predicted labels that are positive, false positive (FP) is the number of positively predicted labels but is negative, false negative (FN) is the number of negatively predicted labels but is positive, and true negative (TN) is the number of negatively predicted labels that are negative.

3.3.2 Precision

The percentage of true positive predictions. The formula below can be used to calculate precision.

$$precision = \frac{TP}{TP + FP} \tag{2}$$

3.3.3 Sensitivity/Recall

Recall of the model is very important in weed management problems such as weed classification. It is very important in the correct classification of weed images and is commonly referred to as the true positive rate (TPR). The true positive rate (TPR) of the test is the percentage of positive predicted labels. The formula below shows that the recall of the model is calculated:

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

3.3.4 F1-score

The F1- score is the average of the precision and recall that and reflect the overall model performance. The formula for calculating the F1- score can be found in Equation (4).

$$F1 - score = \frac{2*Precision*Recall}{Precision+Recall} \tag{4}$$

3.3.5 Confusion matrix

A confusion matrix is also called the error matrix, which is specially a type of tabular structure that provides information about the true labels and the predicted class. The confusion matrix provides not only the overall model performance, but also an in-depth evaluation of the model's generalizability for each class.

4. Results and discussion

This section discusses the evaluation performance of the proposed model for multi-classification of weed species into horseweed, kochia, ragweed, and redroot pigweed. Table 2 summarizes the comparison of the proposed EfficientNetV2B0 with EfficientNetB0, DenseNet121, InceptionResNetV2, NASNetMobile, and Xception in terms of precision, recall, F1-score, Marco average, and weighted average. We compared their classification accuracy, feature discrimination, and training efficiency to determine the best model for our SSWM application.

EfficientNetV2B0 achieved an overall Marco averages precision , reall, and F1-score of 100%. For horseweed and ragweed predictions, it had a precision of 0.99 and a recall of 1, while kochia and RRPW predictions had a precision of 1 but a recall of 0.99,1, respectively. The F1-scores were 1 for horseweed , ragweed, and RRPW 0.99 for kochia classifications, demonstrating a balanced precision-recall tradeoff, crucial for accurate weed classified. Similarly, the EfficientNetB0 model was achieving an overall Marco averages precision , reall, and F1-score of 0.99. For horseweed and RRPW cases, it had a precision of 1 and a recall of 0.99 and 0.97, while for kochia cases, it had a precision and a recall of 0.99. For ragweed , it had a precision of 0.98

and a recall of 1. The F1-scores were 1 for horseweed and 0.99 for RRPW, kochia, and ragweed classifications, indicating the model's high accuracy in categorizing weed images. The model with the least generalizability is NASNetMobile, with a Marco average precision, recall of 0.95, 0.96 with a Marco average F1-score of 0.96. The NASNetMobile model determines horseweed, kochia, ragweed and redroot pigweed with precisions of 0.98, 0.98, 0.92, and 0.93, recall 0.95,0.96,0.97, and 0.95, F1-score 0.96,0.97,0.95,0.94 respectively as showing Table 2.

Weed category	Precision						Recall						F1-score					
	EfficientNetB0	EfficientNetV2B0	Xception	DenseNet121	NASNetMobile	InceptionResNetV2	EfficientNetB0	EfficientNetV2B0	Xception	DenseNet121	NASNetMobile	InceptionResNetV2	EfficientNetB0	EfficientNetV2B0	Xception	DenseNet121	NASNetMobile	InceptionResNetV2
horseweed	1	0.99	0.98	0.99	0.98	0.99	0.99	1	0.99	0.98	0.95	0.99	1	1	0.98	0.99	0.96	0.99
kochia	0.99	1	0.98	0.99	0.98	0.97	0.99	0.99	0.98	0.98	0.96	0.97	0.99	0.99	0.98	0.98	0.97	0.98
ragweed	0.98	0.99	0.96	0.97	0.92	0.97	1	1	0.95	0.98	0.97	0.97	0.99	1	0.95	0.98	0.95	0.98
RRPW	1	1	0.99	0.99	0.93	1	0.97	1	0.97	0.97	0.95	1	0.99	1	0.98	0.98	0.94	0.96
Marco avg	0.99	1	0.97	0.98	0.95	0.98	0.99	1	0.97	0.98	0.96	0.98	0.99	1	0.97	0.98	0.96	0.98
Weighted avg	0.99	1	0.97	0.98	0.96	0.98	0.99	1	0.97	0.98	0.96	0.98	0.99	1	0.97	0.98	0.96	0.98

Table 2 Performance of classifcation models for horseweed, kochia, ragweed, and RRPW classes

Curves of the learning process for model training and validation (accuracy, loss) are shown in Fig 6. The accuracy of the different models improved, and the loss decreased with increasing number of epochs. Most of the models exhibit large changes in accuracy and loss at epoch 5, except for NASNetMobile. In training models EfficientNetB0, EfficientNetV2B0, DenseNet121, InceptionResNetV2, NASNetMobile and Xception reach loss 0.001, 0.005, 0.0003, 0.0002, 0.0003 and 0.002, respectively, However, in validation 0.037, 0.018, 0.035, 0.140 , 0.121 and 0.104, respectively.
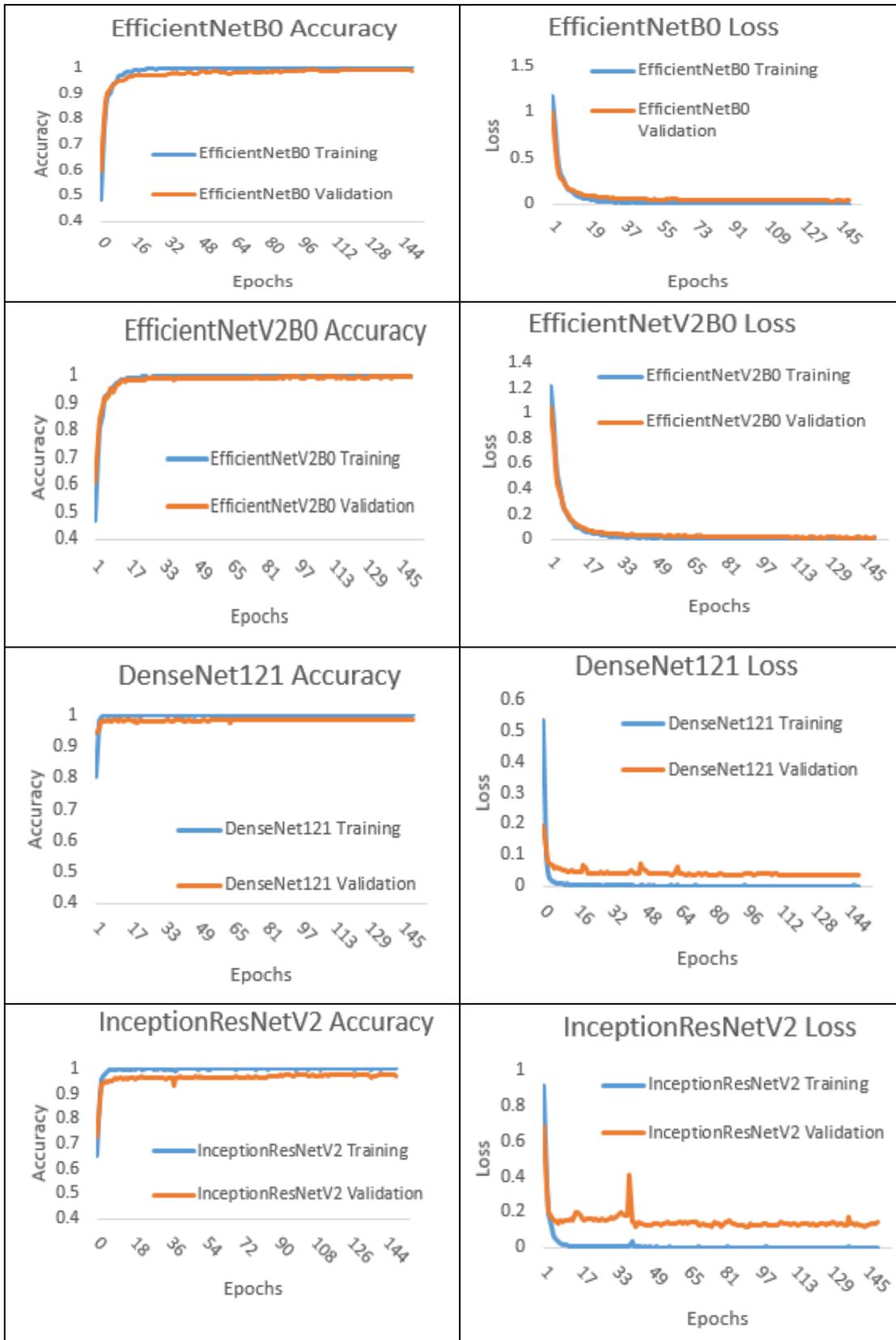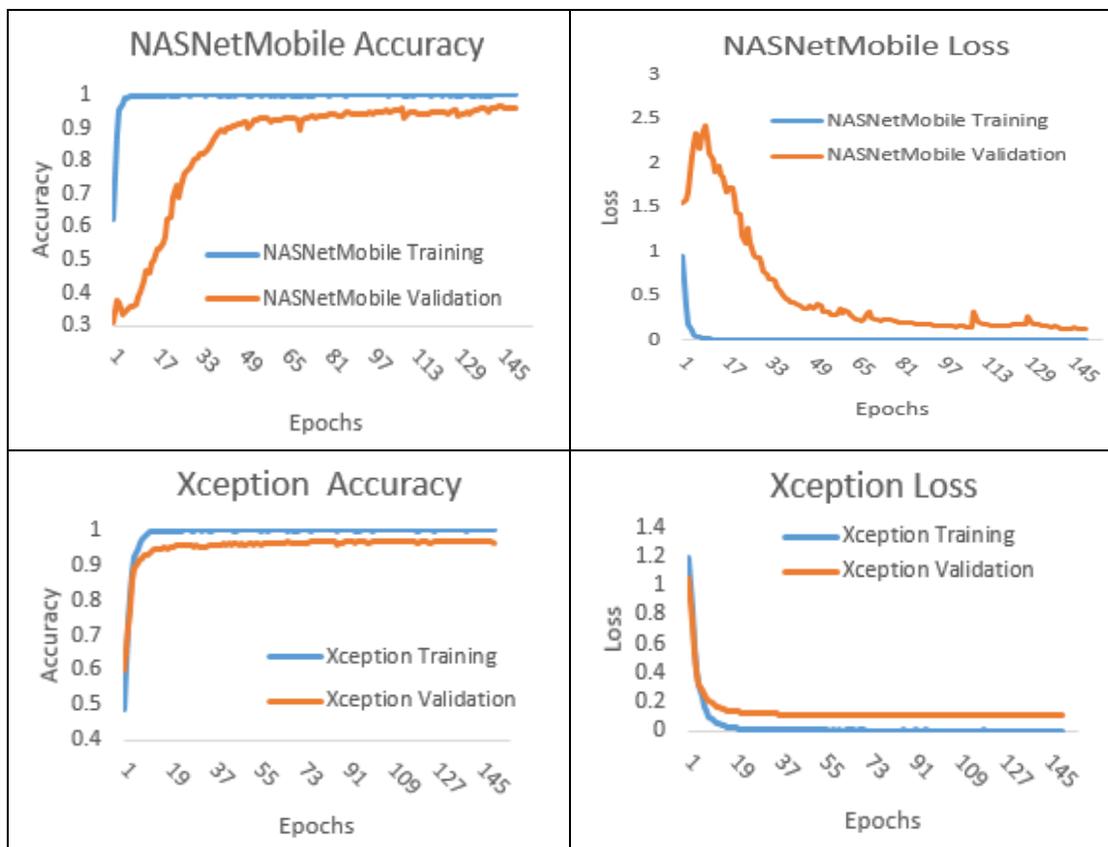
Fig. 6 Training and validation accuracy–loss curves of the proposed models

Fig. 7 shows the confusion matrices associated with the performance of all the networks. Confusion matrices are powerful for comparing models and understanding their performance across different classes and elements of the classification task. According to the confusion matrix, the EfficientNetV2B0 model was better at predicting than the other models.In the EfficientNetB0 model confusion matrix, the prediction accuracy reaches 100% only on ragweed. The EfficientNetv2B0 model had 100% prediction accuracy for all class except for kochia 99%. The InceptionResNetV2 model had a lower prediction accuracy for the class redroot pigweed (93%). The model with the lowest prediction accuracy is NASNet Mobile, which ranges from 95% to 97%.
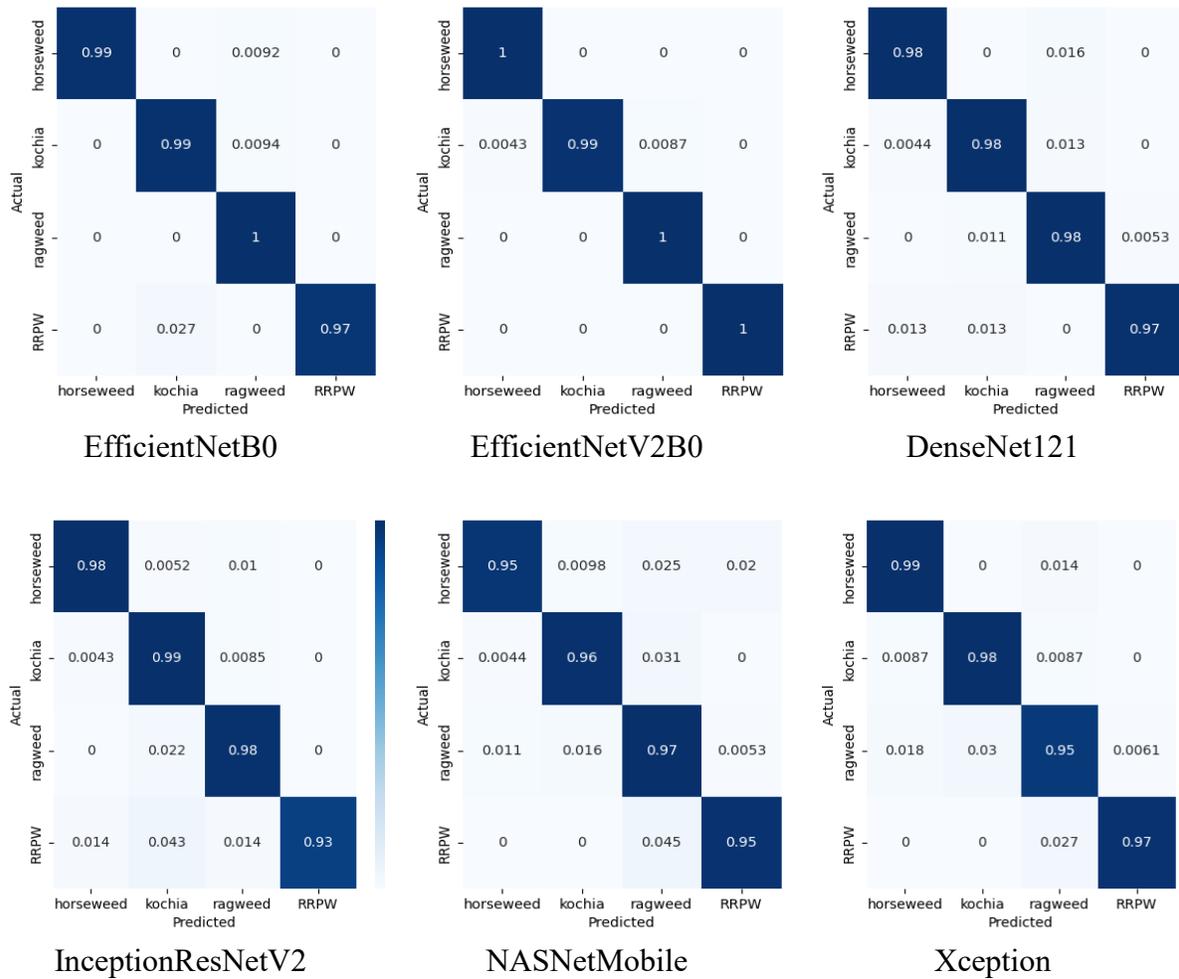
Fig 7. EfficientNetB0- EfficientNetV2B0 - EfficientNetV2S-Xception-DenseNet121, NASNetMobile and InceptionResNetV2 confusion matrices for weed species (horseweed, kochia, ragweedand redroot pigweed)

The computational complexity of the proposed model

This study also investigated the model's performance in terms of total parameters, model size, inference time and test accuracy. Table 3 summarizes the comparison of the proposed EfficientNetB0 and EfficientNetv2B0 methods on the basis of the previously indicated criteria. EfficientNetv2B0 is the fastest of them all, with approximately 7.2M parameters. EfficientNetv2B0 has the best accuracy of 99.5% with inference time 20 second. The EfficientNetB0 model is robust with few parameters and small sizes. However, in terms of robustness and accuracy, EfficientNetv2B0 is the best.

Table 3 Comparison of inference time, #parameters, and model sizes for different models

Model	Parameters (million)	Size (MB)	Inference time (Second)	Test accuracy
EfficientNetV2B0	7.2M	29	20	**99.5**
EfficientNetB0	5.3M	29	21	99.1
DenseNet121	8.1 M	33	56	98.5
InceptionResNetV2	55.9 M	215	54	97.8
NASNetMobile	5.3 M	23	17	95.9
Xception	22.9 M	88	55	97.3

5. Conclusion

This study uses transfer learning with EffcientNetv2B0 to classify a multi-class of weed species, such as horseweed, kochia, ragweed, and redroot pigweed.. A special dataset with 3,424 images of 4 different types of weeds was collected from three geographical locations in North Dakota throughout four growth seasons, at different phases of growth andunder natural light conditions. The proposed method, EffcientNetv2B0, outperforms several current methods for comparable classification problems by achieving overall test accuracy, marco average precision, recall and F1-score of 99.5%, 100%, 100% and 100%, respectively. In the future, rather than using deep CNN based techniques, a transformer based architecture can be suggested for weed type classification that can extract richer feature maps and reduce network complexity.

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