An Effective Image Augmentation Approach for Maize Crop Disease Recognition and Classification

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Abstract. Deep learning techniques have been applied to computer vision applications like image recognition and classification successfully. Especially, convolutional neural networks preserve the characteristics of an object in an image using kernels and performs recognition very efficiently. However, the performance of these networks depends on larger datasets which is a big challenge to the researchers in the agriculture field. Image augmentation can be a better solution that supports the neural network model to perform the classification task efficiently with more input images. In this paper, several image augmentation techniques were applied to generate varieties of new images from the original image. The paper proposes a new CNN-based model for the classification of six diseased and one healthy maize crop images. The proposed model will be trained for twice independently with 4652 original dataset images and 10640 augmented images dataset. Finally, the outcomes will be analyzed separately with respect to precise and loss functions. Before the implementation of augmentation approach, the proposed model has achieved 99.61% training and 77.44% classification accuracies and does not control overfitting. Moreover, after applying augmentation techniques, the model has obtained 95.96% of training accuracy and 93.61% of classification accuracy and controlled overfitting. Therefore, it has been proved that the image augmentation approach and the proposed convolutional neural network model contribute a better solution while classifying maize crop diseases with a higher level of accuracy.

Keywords: Computer vision · Convolutional neural networks · Deep learning · Image augmentations · Image classification · Image preprocessing techniques

1 Introduction

A practical approach to deal with less images in computer vision is typical. Augment the training images artificially can extract new images and may reduce overfitting [8].

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Imbalanced datasets can also be solved by applying augmentation techniques to transfer the original shape of the plant generating additional images [9]. Image augmentations gives a resultant dataset that is six times greater than the quantity of original set. The proposed model LeafGAN boosted the accuracy by 7.4% [2]. Model generalization can be improved by performing image preprocessing and augmentation. The experiments were conducted to evaluate the efficiency of the proposed model to classify DiaMOS plant dataset [3].

An advanced machine learning (ML) model is proposed to classify the major diseases in banana crop using ariel images. The results obtained by the trained models proposed that image augmentation have given positive outcomes on disease classification. The model has a control on training rate without any overfitting [4]. An image augmentation strategy has been followed to amplify the original images and tested the performance classification of apple. The results have shown that the proposed model achieved 6.3% higher recognition accuracy [3]. An enhanced classification model is proposed to increase the classification accuracy and address the overfitting problem. The model has achieved 24.4% higher overall classification accuracy using conventional image augmentations [1]. Synthetic image is the most usual method of data augmentation. The proposed model achieved 7% higher improved accuracy over the existing models [5]. A transfer learning concept has implemented by modifying VGG-16 to classify the images obtained from different mango farms. Image augmentation process is adopted and achieved 73% accuracy on the training dataset and 73% on the testing set. Data augmentation leads to 13.43% improvement on the testing data [7]. A conditional deep neural network is proposed for vigor rating of plants and investigated that after data augmentations the model has improved the classification accuracy and succeeded to obtain 23% increase in F1score. The proposed approach has resolved the problem of insufficient data size in plant diseases task [11–14, 12].

In this article, we have identified the need to expand all the seven datasets with data augmentation techniques. Image augmentation generates the new images that allows to balance all the disease classes with equal number of images. Firstly, an image of a diseased leaf with RGB representation is augmented into different variations for each transformation type. Seven types of image transformations like random rotation, horizontal shift, vertical shift, horizontal flip, vertical flip, random zooming, and random brightness are applied to an image of a diseased leaf. The outcome of these techniques generates a set of newly generated set of images that are used further to train a convolutional neural network (CNN). The novelty of the proposed work is to generate the new images dataset, design a CNN model, perform disease classification with original and augmented datasets.

The other sections are organized as: Sect. 2 discusses the approach followed to apply the image augmentation techniques. Section 3 describes the experimental results achieved from the image augmentation approach followed by the conclusion in Sect. 4.

2 Image Augmentation Approach

Image Augmentation or simple IA is an essential approach that replicates the given image with few transformations. The augmentation technique increases the diversity of images by changing each image in different ways like rotating, shifting, zooming, and flipping.

In this paper, a supervised learning named RGB Image Augmentation Approach (IAA) is followed to generate new images. The approach directs to improve the traditional techniques like augmentation by considering the requirement for new augmentation techniques. Figure 1 shows some original images and the images generated after applying the augmentations. The study employs the IAA as a preprocessing procedure to identify the converted images automatically. The newly generated images serve as the preprocessing procedure to feed the convolutional neural networks with the input images for training.

(a) Original Images

(b) Augmented Images

Fig. 1. Sample Images (a) original (b) augmented.

3 Experimental Results and Observations

A CNN model is developed to implement the IA approach and perform the image classification in this section.

3.1 RGB Image Augmentation

A new CNN model is developed with four convolution and max-pooling layers one and all continued with 1 flatten and 2 dense layers. Figure 2 shows the summary of the proposed model and the related hyperparameters are shown in Fig. 3.

3.2 CNN Evaluation

The classification performance of the proposed CNN model is evaluating by conducting the experiments with 4652 leaf images collected from Kaggle repository (Kaggle Dataset n.d.). These images belong to seven different classes of maize crop. The image dataset is split into two subsets as training set and testing set. IAA will be applied on the training images to generate new images with different variants. After applying IAA, the quantity of the training dataset is increased to 10640 images. The testing dataset is prepared with

Layer (type)	Output Shape	Param #
conv2d_12 (Conv2D)	(None, 110, 110, 16)	448
max_pooling2d_12 (MaxPooling	(None, 55, 55, 16)	0
conv2d_13 (Conv2D)	(None, 53, 53, 32)	4640
max_pooling2d_13 (MaxPooling	(None, 26, 26, 32)	0
conv2d_14 (Conv2D)	(None, 24, 24, 64)	18496
max_pooling2d_14 (MaxPooling	(None, 12, 12, 64)	0
conv2d_15 (Conv2D)	(None, 10, 10, 128)	73856
max_pooling2d_15 (MaxPooling	(None, 5, 5, 128)	0
flatten_2 (Flatten)	(None, 3200)	0
dense_6 (Dense)	(None, 128)	409728
dense_7 (Dense)	(None, 7)	903

Total params: 508,071
Trainable params: 508,071
Non-trainable params: 0

Fig. 2. Proposed model summary

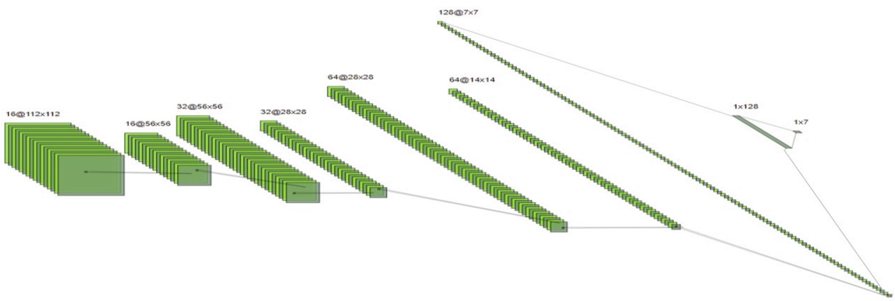


Fig. 3. The proposed 11-layer CNN model

2660 images that are randomly selected from the first dataset of 4652 images. The list of diseases and the number of images considered for each disease is depicted in Table 1. The model is evaluated with original and augmented datasets by training and testing individually. Later, the results obtained are used to validate and compare the actual predictions with respect to accuracy, loss and confusion matrix.

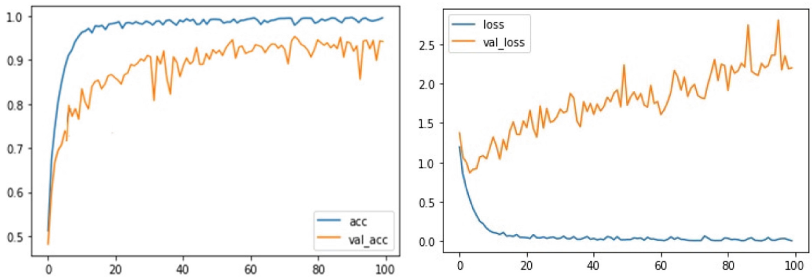
3.2.1 CNN Model Implementation

The present sequential model is designed with four convolution layers (Conv2D_1, 2, 3 and 4 layers) with kernel size 3×3 followed by four max-pooling layers with pool size 2 and 2 strides. The model has one fully connected layer, and two dense layers with 128 units for first and 7 units for the last layers. First, the proposed model is feed with original dataset (without augmentation) and performed the classification. Figure 4 shows the performance with training, testing accuracy and loss curves before implementing IAA. The accuracy and loss curves are plotted individually for better understanding and comparison of results.

Table 1. Details of training and testing datasets

Disease class	1	2	3	4	Total images
Anthracnose Leaf Blight - ALB	435	380	1520	380	2280
Anthracnose Stalk Rot – ASR	512	380	1520	380	2280
Eye Spot – ES	352	380	1520	380	2280
Gabriella Stalk Rot – GSR	452	380	1520	380	2280
Health – H	1320	380	1520	380	2280
Northern Corn Leaf Spot – NCLS	1170	380	1520	380	2280
Southern Rust - SR	411	380	1520	380	2280
Total	**4652**	**2660**	10640	**2660**	**13300**

1-Number of training images before IAA, 2-Number of testing image before IAA, 3-Number of training images after IAA, 4-Number of testing images after IAA.



(a) (b)

Fig. 4. Performance evaluation before applying the IAA technique

The plots in Fig. 4(a) shows the variation in learning of the proposed model using training and testing accuracies. The plots in Fig. 4(a) shows the variation in learning of the proposed model using training and testing losses. ‘Acc’ and ‘val_acc’ indicates the training and testing accuracy curves whereas ‘loss’ and ‘val_loss’ indicate the training and testing loss curves. The large gap between the accuracies and losses curves, a higher difference of 22.17% among the training and testing accuracies describe that the model is overfit to the training dataset and not performed the classification well on the testing set. Before applying IAA and after running the model using 100 epochs, the training accuracy of 99.61%, and the testing accuracy of 77.44% are obtained.

In addition to confusion metrics, the other performance metrics like precision, recall, and F1-score have also computed and the values are presented in Table 2. The confusion matrix of the proposed model shown in Fig. 5(a) and 5(b) revealed that the classification exhibited more than 95% accuracy in only two classes ES (95.7%) and H (97.8%). The precision metric values for ES and H disease classes are found as 93% and 91% respectively. The recall metric values for ES and H disease classes are found as 96% and 98% respectively. The F1-score metric value is reported as 96% for H disease class.

Table 2. Classification performance before and after applying IAA

Class #	1	2	1	2	1	2	Support
	Precision		Recall		F1-score		
0	0.61	0.89	0.71	0.95	0.65	0.92	380
1	0.87	0.97	0.89	0.90	0.88	0.93	380
2	0.78	0.94	0.96	0.94	0.86	0.94	380
3	0.93	0.88	0.98	1.00	0.96	0.93	380
4	0.91	0.95	0.71	0.94	0.80	0.95	380
5	0.59	0.95	0.58	0.87	0.59	0.91	380
6	0.77	0.98	0.59	0.95	0.67	0.97	380
		Accuracy			0.77	0.94	2660
Macro Avg	0.78	0.94	0.77	0.94	0.77	0.94	2660
Weighted Avg	0.78	0.94	0.59	0.94	0.67	0.94	2660

1-Before IAA and 1-After IAA.

The metric values revealed that the proposed model has performed the classification more efficiently only for two disease classes ES and H. It is observed that the model is not so efficient during the classification of other five diseases ALB, ASR, GSR, NCLS and SR. Second, the proposed model is feed with augmented dataset and performed the classification. Figure 6 shows the performance with training and testing accuracy and loss curves after applying IAA. The accuracy and loss curves are plotted separately or better understanding and comparison of results.

The plots in Fig. 6(a) shows the variation in learning of the proposed model using training and testing accuracies. The plots in Fig. 6(a) shows the variation in learning of the proposed model using training and testing losses. ‘Acc’ and ‘val_acc’ indicates the training and testing accuracy curves whereas ‘loss’ and ‘val_loss’ indicate the training and testing loss curves. The proposed model after training and testing with the images generated after applying IAA has obtained 95.96% training and 93.61% testing accuracies. A 2.35% difference among the accuracies between training and testing datasets shows that the model has performed well when compared the results obtained before applying IAA. The accuracy and loss curves describe that the present model is not overfit to the training images dataset and performed the classification well even on the testing dataset. The results shown in Fig. 6 explains that the proposed model is so efficient when it is trained with a greater number of input images. In this regard, image augmentation techniques have contributed a lot to increase the number of training images and achieve better classification performance.

In addition to confusion matrix, the performance metrics like precision, recall, and F1-score have also computed and the values are illustrated in Table 2. The confusion matrix of the proposed model depicted in Fig. 7(a) and 7(b) revealed that the classification exhibited 100% accuracy for H. The results exhibited more than 95% accuracy in only two classes ALB (95.2%) and SR (95%). It is observed that the classification exhibited

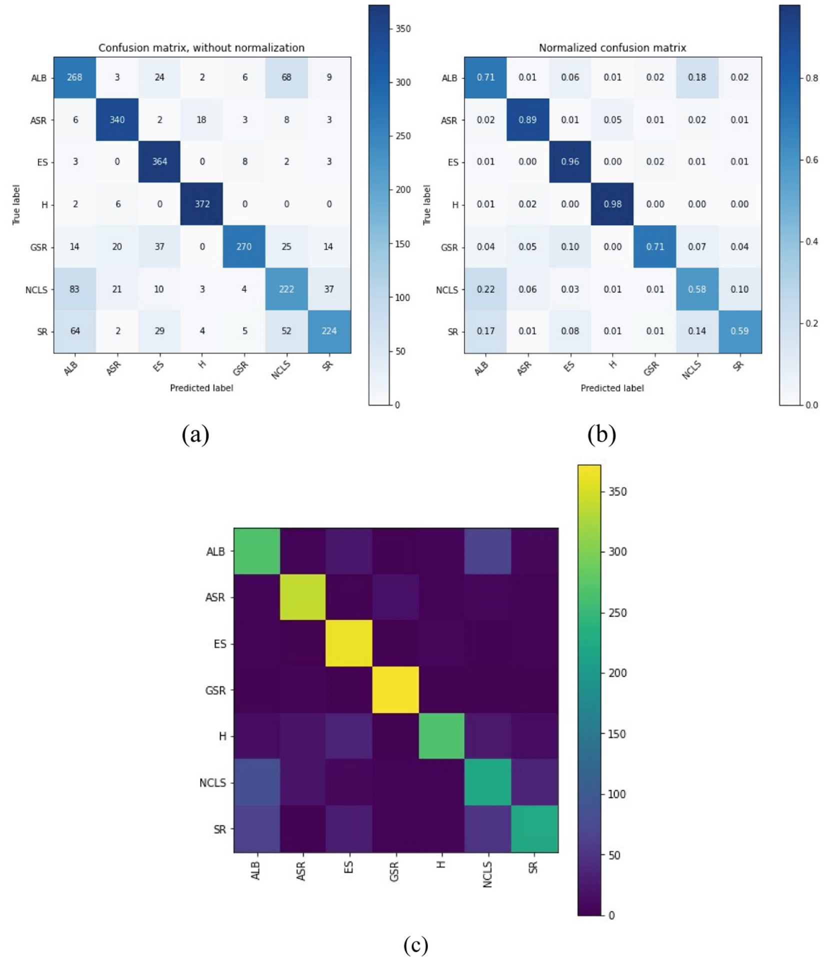


Fig. 5. Confusion Matrix before Implementing IAA Technique (a) without normalization (b) with normalization (c) color scale reflections

equal or more than 90% in two disease classes ES (93.6%), and GSR (94.2%). The classification exhibited equal or more than 95% accuracy in three classes ALB (95.2%), H (100%), and SR (95%). Precision metric values of ASR, ES, GSR, NCLS, and SR disease classes are found as 97%, 94%, 95%, 95% and 98% respectively. Recall metric values of ALB, ASR, ES, H, GSR, and SR disease classes are found as 95%, 90%, 94%, 100%, 94% and 95% respectively. The F1-score is reported 100% for H disease class. The results revealed that the proposed model has performed the classification of six disease classes ALB, ASR, ES, H, GSR, and SR more efficiently. It is observed that the model is not so efficient for classification of only one disease class NCLS. Figure 8 depicts the classification performance of the proposed model before and after applying IAA.

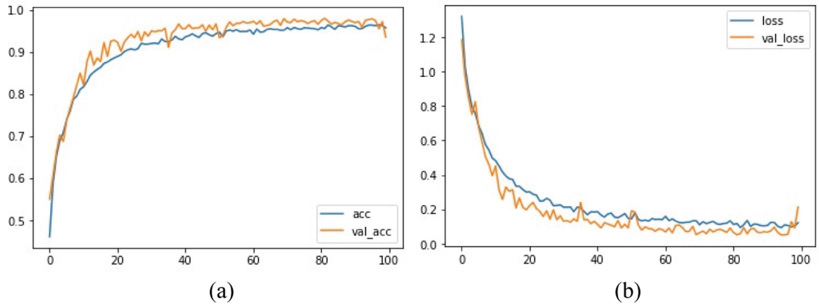


Fig. 6. Performance evaluation after applying the IAA technique

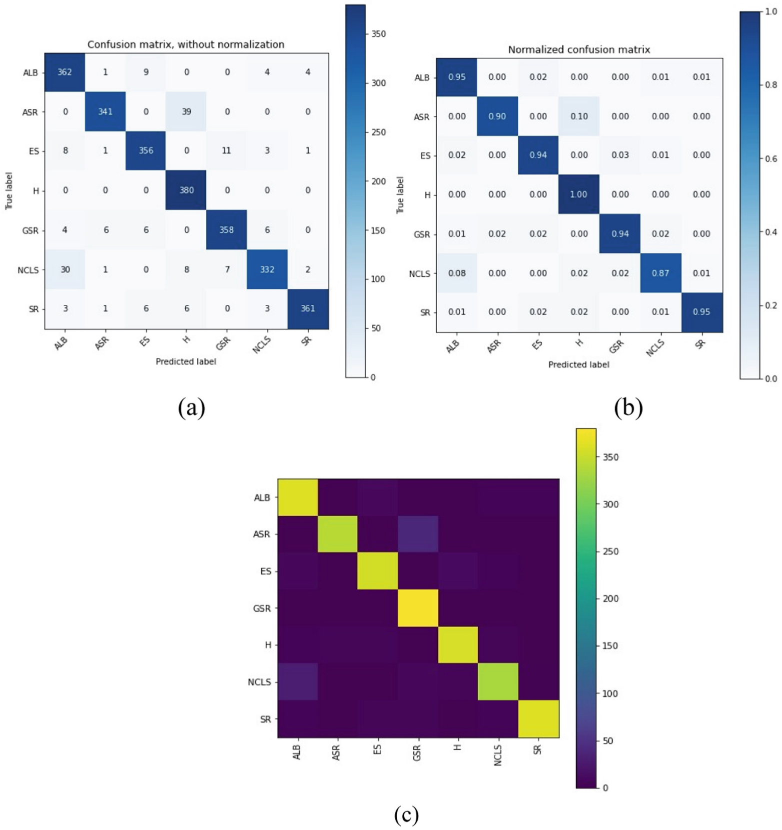


Fig. 7. Confusion Matrix after implementing IAA technique (a) without normalization (b) with normalization (c) color scale reflections

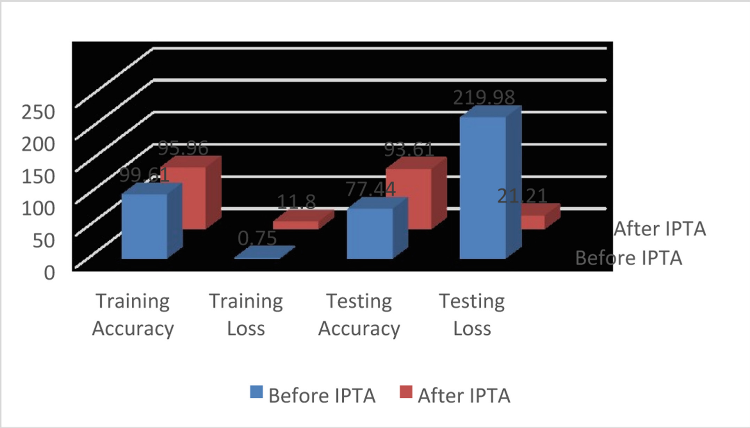


Fig. 8. Performance measure before/after IAA technique

4 Conclusion

An adoptive supervised learning approach IAA to perform image augmentations to generate the multiple images automatically in this paper. The enhanced dataset can be adaptive to train any CNN model. The present paper has proposed a new CNN-based model with 11 layers to perform the image classification of seven maize crop disease classes. Later, the model has trained and tested with different datasets. First, the model has trained with only 4652 images collected from Kaggle repository. Next, the same model has trained with 10640 augmented images. Finally, the accuracy and loss values have collected separately for two experiments and compared to identify the difference in classification performances. The first experimental results show that before applying augmentations, the proposed CNN model has obtained 99.61% training accuracy and testing accuracy of only 77.44%. The second experimental results show that after applying augmentation approach has obtained a training accuracy of 95.96% and testing accuracy of 93.61%. The observations have described that the proposed CNN model is so efficient while classifying the maize crop diseased and healthy images. CNN model is extremely effective when it comes to classifying the diseased images of maize crop. The findings drew attention to more advanced transformations for increasing the number of images in training set and assisting in the prevention of model overfitting.

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