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Classification of Beans Leaf Diseases using Fine Tuned CNN Model

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Abstract

Automation in the agricultural field is a requirement of all the countries. Usually, plant diseases are observed in the form of visual symptoms and many deep learning-based models have achieved outstanding results in the classification of plant leaf diseases in recent years. Beans plant diseases like bean rust disease and angular leaf spot disease reduce the bean crop yield. To treat the problem at an early stage, an appropriate diagnosis for this crop disease is required. In this paper, three deep learning-based pre-trained models namely MobileNetV2, EfficientNetB6, and NasNet were used to perform transfer learning on the Beans Leaf image dataset containing 1295 images with three different classes. Furthermore, different optimization techniques were also used to highlight the variation in performance of different Convolutional Neural Network (CNN) models. The analysis of experimental results shows that EfficientNetB6 performs better with 91.74% accuracy than other models. This study would be helpful to understand the role of different optimizers on the CNN models. Furthermore, agricultural scientists could employ a real-time-based application of the best-suited model for the farmers to adopt prevention measures in disease-vulnerable areas. As a result, prompt action would aid in minimizing plant productivity loss. It will further revenue the economic growth and agricultural productivity.

Keywords: Plant Disease; CNN; Transfer Learning; Disease Classification; Beans Leaf

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1. Introduction

In the last decade, several researchers have used classic Machine Learning (ML) approaches as well as Deep Learning (DL) models to identify plant diseases in a variety of crops from different plant datasets [1]. The use of DL approaches in agriculture has exploded in recent years. Computer vision and artificial intelligence advancements may lead to novel solutions. These methods are more accurate than previous ones, leading to improved decision-making. DL approaches are currently being utilized to solve complicated problems in a reasonable amount of time, because of advancements in hardware technology [2]. DL is already a state-of-the-art technology, and it could be useful for a variety of other applications as well. In hyperspectral analysis, a variety of deep neural networks have produced impressive results. Crop classification [3], yield prediction [4], fruit counting [5], disease detection [6], and other vision task experiments have proven the effectiveness of convolutional neural networks (CNNs). It has been seen that AlexNet [7] CNN architecture became the standard for all visual-related tasks after winning ImageNet challenges (ILSVRC) 2012. Furthermore, GoogleNet [8], SqeezNet [9], MobileNetV2 [10], MobileNet [11], EfficientNet [12] are examples of some well-known convolutional neural networks employed for the image classification tasks. Fig 1 shows the evolutions of standard CNN architectures proposed to solve the problems identified in the previous research.

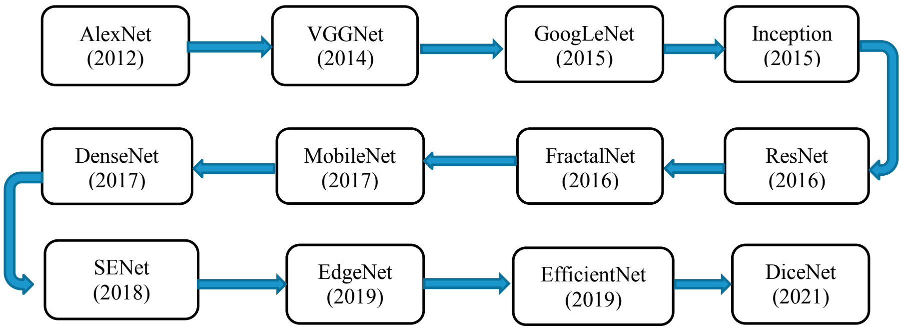

Fig. 1. Evolution of various CNN Architectures

In precision agriculture, an accurate disease classification model is required for the identification of plant diseases. Classification techniques could identify and discriminate different types of plant diseases based on the symptoms present in the leaf image at an early stage. It has been seen that various authors have developed, tested, and validated various classification algorithms for the accurate diagnosis of different plant diseases such as fruit classification [13], disease classification [14], species classification [15], etc. For example, Shrivastava et. al. [16] performed rice plant disease classification using a pre-trained CNN model and Support Vector Machine; Lu et. al. [17] implemented an automatic wheat dieses diagnosis system using VGG-FCN-VD16 and VGG-FCN-S architecture. In the current study, the authors have used the Beans leaf image dataset for disease classification.

Beans image data set is a multiclass dataset with three different categories: two disease categories and one healthy category. The disease groups include Angular Leaf Spot and Bean Rust. This dataset is a collection of 1295 images of leaves captured with cell phone cameras in the fields. In this study, the authors have performed bean leaf disease classification with MobileNetV2, EfficientNetB6, and NasNet convolutional neural network architecture with different combinations of optimizers and fixed values of batch size, learning rate, epochs, and activation functions, etc. The classification result of different architectures on the beans dataset was calculated and compared.

This paper is structured as follows: section 2 stated the related works from previous studies; section 3 discussed the materials and methods; section 4 covers the results with the help of a table, bar chart, and graph; section 5 outlines the conclusion and future direction.

2. Literature Review

In recent years researchers have shown more interest in the identification and categorization of plant diseases automatically. CNN has been used in many agricultural activities including disease detection in crops, crop monitoring, intelligent spraying, crop yield prediction, crop price prediction, crop and soil monitoring, disease diagnosis, farm monitoring, and so on. A summary of current published studies on plant leaf disease classification is presented here.

Gokulnath et. al. [18] suggested a loss-fused CNN model for disease identification on the PlantVillage dataset, with an accuracy of 98.93%. Chen et. al. [19] suggested an improvement on the final layer VGG trained on ImageNet and transferred the acquired feature information to the Inception Module and found 92% accuracy on a merged dataset of maize and rice. Shijie et. al. [20] presented VGG16 with MSVM for tomatoes with 10 different disease classes with 89% accuracy. In the paper, Picon et. al. [21] presented a model for mobile captured devices with an accuracy of 96%. Sahu et. al. [22] experimented on GoogleNet and VGG16 with beans dataset and found GoogleNet performed better with an accuracy of 95%. Tiwari et. al. [23] identified 27 diseases in six different crops with a novel deep convolutional neural network and enhanced the CNN on a complicated and difficult dataset, the network has a cross-validation accuracy of 99.58% on average.

It has been observed that most of the studies were conducted using the PlantVillage dataset. Therefore, the nature of the result of the classifications is quite similar. Moreover, a few of the researchers have used deep learning models for the beans crop disease classification. Hence, to avoid the repetition of results, the beans leaf disease image dataset has been used with three DL-based models by applying different optimization algorithms in this study. After finding the best suitable combination of the DL model and optimization algorithm, a multiclass disease classification was performed on the beans leaf image dataset.

Table 1. Literature review of the CNN model based on crops, CNN models, datasets, size of datasets, and size of images used for training.

[Reference] Author(Year)	Crops	DL Architecture	Data Set	Data Set Size	Image Size	Merits
[24] Yun et. al. (2022)	Corn Potato Tomato etc.	CBAM	PlantVillage	54,303	256× 256	The proposed model reduces the training parameters as well as shortens the training time.
[25] Verma et. al (2022)	Tomato	AlexNet SqueezeNet ResNet50 VGG16/19 InceptionV3	PlantVillage	54,303	32x32 64x64	The proposed methodology improves the performance substantially as compared to standard CNN models.
[26] Sahu et. al. (2020)	Bean	Transfer Learning	iBean	1296	256×256	A retrained model by tuning the hyper parameter is a better choice for the small dataset.
[27] Umit et. al (2020)	Tomato Potato Cherry etc.	EfficientNet	PlantVillage	55448	132×132	The proposed model was found to perform better than other existing CNN models.
[28]Sembiring et.al. (2020)	Tomato	VGG 16 ShuffleNet SqueezeNet	PlantVillage	13262	256x256	The suggested design is both shorter and more performant than the other present architecture.
[29]Ahmed et. al(2021)	Grape Apple Potato Corn etc.	CNN Model	PlantVillage	96206	200x200	A mobile-based CNN model was proposed to automate the plant disease identification procedure.

3. Material and Methods

Several phases are required to implement CNN architectures, starting with dataset collecting and ending with performance analysis and visualization mappings. Begin with dataset collection and splitting the dataset into 80:10:10 ratios for training, testing and validation respectively. The detailed procedures are shown below in Fig 2.

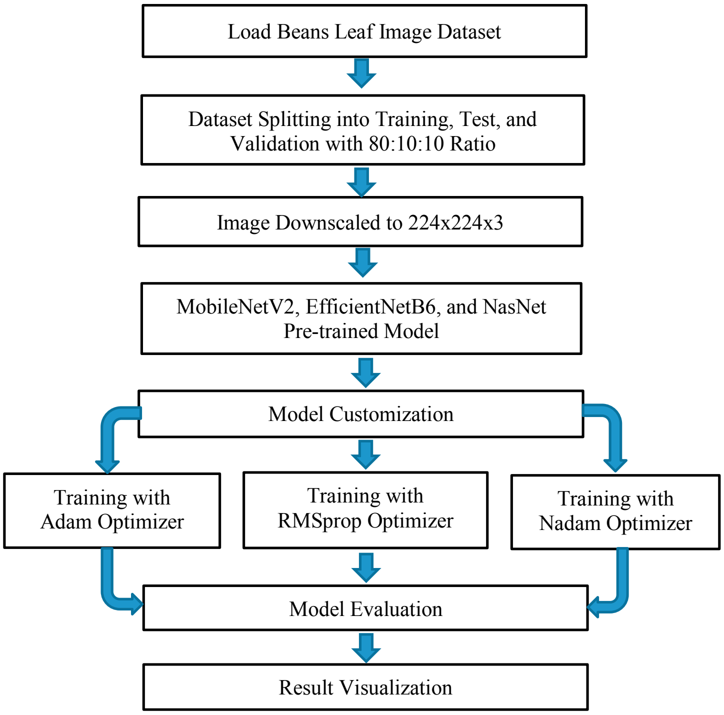

Fig. 2. Methodology for CNN based Beans Leaf Disease Classification with Transfer Learning

3.1. Datasets

Beans Leaf Dataset is a collection of 1295 images of beans captured with cell phone cameras in the fields as summarized in Table 2. It is separated into three categories: two disease categories and one healthy category. The disease groups include Angular Leaf Spot and Bean Rust. Experts from Uganda's National Crops Resources Research Institute (NaCRRI) interpreted the data, which was acquired by the Makerere AI research group.

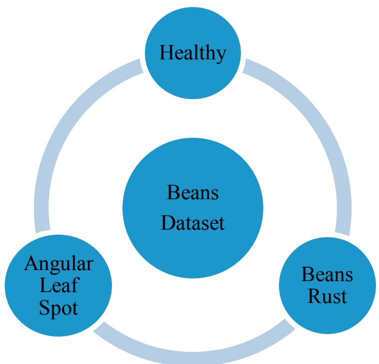

Fig. 3. Beans Leaf Image Dataset

Fig. 4. Image from beans leaf dataset (a) shows Bean Rust Disease, (b) shows Angular Leaf Spot Disease, and (c)shows Healthy images

Table 2. Detail Description of Beams Leaf Image Dataset

Class	Dataset	Description
Angular Leaf Spot Disease	432	This bacterial infection is caused by Pseudomonas syringae pv. Lochrymans. Water-soaked lesions bound by the veins of the leaf are the most common symptom.
Bean Rust Disease	436	The fungus uromyces appendiculatus causes rust, which can harm any part of the plant above ground.
Healthy	427	Leaves are healthy in a suitable environment.
Total	1295	Image count in the Beans Dataset

3.2. Transfer Learning

Different pre-trained CNN models were applied for transfer learning over Beans datasets.

- MobileNetV2, the inverted residual structure of this model is built on residual connections between bottleneck layers. In the intermediate expansion layer filters, light-weight depth-wise convolutions are utilized as a source of non-linearity. The architecture of MobileNetV2 incorporates a fully convolutional layer with 32 filters, followed by 19 residual bottleneck layers.
- EfficientNetB6, is a CNN that uses a compound coefficient to adjust the depth, breadth, and resolution of the network consistently for improved performance. Unlike the traditional method, which changes these parameters at random, the EfficientNet scaling strategy uses a set of preset scaling coefficients to increase network breadth, depth, and resolution.
- NasNet, Neural Search Architecture (NAS) deep networks have been used in several applications where the right design is essential for optimum performance. The first study in this area was NASNet, which represents the construction of CNN as a multi-step selection problem that can be solved through deep learning.

3.3. Hyperparameter Tuning

All the pre-trained models were trained over different optimizers with a fixed learning rate of 0.001, batch size 32, epochs 25, and dropout 0.3 as shown in Table 3.

Table 3. Different hyperparameters were used in the experiments.

Hyperparameters	Description
Learning rate	0.001
Batch Size	32
Epochs	25
Dropout	0.3
Optimizers	Adam, RMSprop, Nadam

4. Result and Discussion

In this study, the experiment has been performed on three different CNN models namely MobileNetV2, EfficientNetB6, and NasNet with open source libraries TensorFlow and Keras with the help of Google Colab deep learning server. The total of 1295 images in the Beans dataset was divided into three parts: train, test, and validation with 1034, 128, and 133 images respectively. In the beans dataset, there are three different classes: healthy class, angular leaf spot disease class, and bean rust disease class with 427,432, and 436 images respectively.

All the CNN models in this experiment were trained with fixed learning rates, epochs, and batch size with different optimization techniques (Adam, SGD, Nadam), and the results were compared. Training, validation accuracy, and loss results were summarized in Table 4. It was observed that EfficientNet with Adam optimizer achieved the highest validation accuracy of 91.74%. Moreover, MobileNetV2 with Nadam optimizer attained 91.73% validation accuracy and MobileNetV2 with RMSprop optimizer gave 91.72% validation accuracy.

Table 4. Training (Tr), Validation (Val) accuracy, and loss result for Different Optimizers.

Optimizer	CNN Model	Tr-Acc(%)	Val-Acc (%)	Tr-Loss	Val-loss
Adam	EfficientNetB6	96.62	91.74	0.0936	0.2849
	MobileNetV2	94.39	91.72	0.1489	0.2110
	NasNet	84.14	86.47	0.3749	0.3224
RMSProp	EfficientNetB6	94.87	88.72	0.1573	0.2492
	MobileNetV2	94.78	91.72	0.1343	0.1888
	NasNet	85.49	84.21	0.3579	0.3262
Nadam	EfficientNetB6	94.39	88.72	0.1864	0.2634
	MobileNetV2	94.78	91.73	0.1450	0.2055
	NasNet	85.59	86.45	0.3697	0.3349

Fig. 5 showcase the results in the form of a bar chart for training accuracy and loss along with validation accuracy and loss in the comparative charts for all variations. It can be observed that EfficientNetB6 with Adam optimizer achieved the highest validation accuracy of 91.74%. Moreover, MobileNetV2 with Nadam optimizer attained 91.73% validation accuracy and NasNet with Adam optimizer gave 86.47% validation accuracy.

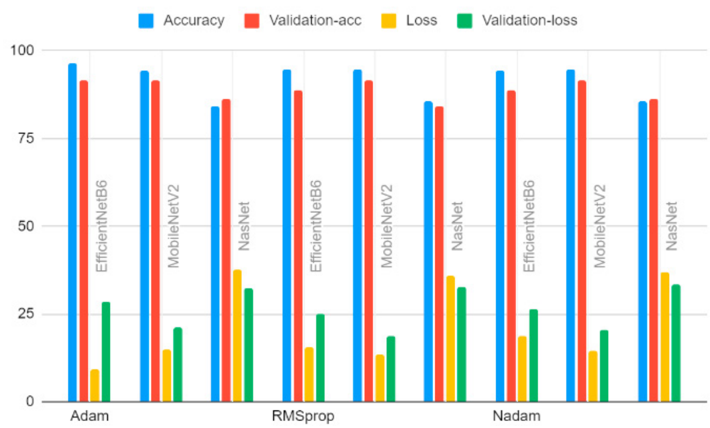

Fig. 5. Analysis of CNN models with different optimizers

Following are some major findings that have been made from the experimentations:

- As per Fig.6. (a-c), MobileNetV2 model attained 91.73% validation accuracy with Nadam optimizer and validation loss of 0.2055, Moreover, the same model with Adam and RMSprop optimizer attained 91.72% and 91.72% validation accuracy with 0.2055 and 0.1888 validation loss respectively.
- In Fig.7. (a-c), EfficientNet with Adam optimizer achieved the highest validation accuracy of 91.74% and loss of 0.2849 while employing RMSprop and Nadam optimizer the validation accuracy was comparatively low

for both the model i.e. 88.72%. The validation loss for RMSprop and Nadam optimizer was 0.2492 and 0.2634 respectively.

- Subsequently, in Fig.8. (a-c), NasNet model gave 86.47% highest validation accuracy with Adam optimizer and loss of 0.3224. Similarly, Nadam and RMSprop optimizer achieved 86.46% and 84.21% validation accuracy respectively. The evaluated validation loss for Nadam and RMSprop optimizer was 0.3349 and 0.3262 respectively.

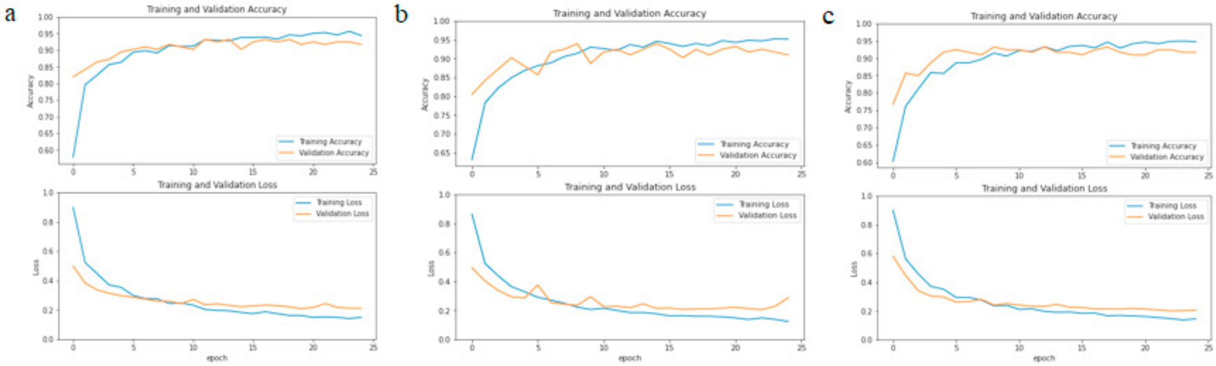

Fig. 6. Accuracy and loss graph of MobileNetV2 with (a) Adam; (b) RMSprop; (c) Nadam

Fig. 7. Accuracy and loss graph of EfficientNetB6 with (a) Adam; (b) RMSprop; (c) Nadam

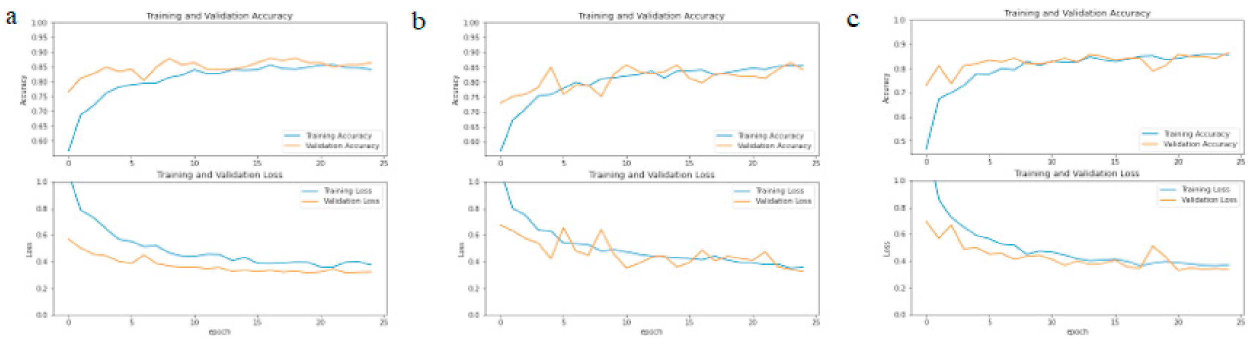

Fig. 8. Accuracy and loss graph of NASNet with (a) Adam; (b) RMSprop; (c) Nadam

The model implementation indicates that EfficientNetB6 with Adam optimizer achieved the highest validation accuracy of 91.74% and the validation loss of 0.2849.

5. Conclusion and Future Direction

Plant disease has been a serious concern in agriculture for years. Smart agriculture has enabled early disease identification and loss minimization by making the best decisions possible based on DL results. In this paper, the authors use a Beans leaf dataset of 1295 images captured by smartphone cameras from the field. Beans can be affected by several diseases, such as angular leaf spot disease and bean rust disease, which can harm bean leaves, causing serious damage to bean crops and reducing the beans crop yield. So to improve the quality and quantity of the product, identification of disease is necessary at an early stage. The authors of this research used a performance comparison of MobileNetV2, EfficientNetB6, and NasNet for disease classification on beans leaf image datasets with Adam, RMSprop, and Nadam optimizers with fixed learning rates, epochs, and batch size. The finding of the experiments was that EfficientNetB6 with Adam optimizer achieved the highest validation accuracy of 91.74%. Furthermore, MobileNetV2 with Nadam optimizer attained 91.73% validation accuracy and MobileNetV2 with RMSprop optimizer gave 91.72% validation accuracy. In the future, this study would be extended by using various pre-processing and resampling techniques to enhance the classification accuracy of the implemented model. Moreover, the authors are planning to collect a real-field image dataset to predict the diseases at an early stage. A hybridized model could also be proposed using various deep learning, machine learning, and optimization techniques such as particle swarm optimization, fuzzy logic, etc.

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