Computing and Artificial Intelligence 2024, 2(2), 545.
https://doi.org/10.59400/cai.v2i2.545

Article

Plant leaf disease classification using FractalNet

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CITATION

Alaeddine H, Jihene M. Plant leaf disease classification using FractalNet. Computing and Artificial Intelligence. 2024; 2(2): 545. https://doi.org/10.59400/cai.v2i2.545

ARTICLE INFO

Received: 17 February 2024
Accepted: 12 June 2024
Available online: 17 July 2024

Abstract: In this work, an effort is made to apply the FractalNet model in the field of plant disease classification. The proposed model was trained and tested using a "PlantVillage" plant disease image dataset using a central processing unit (CPU) environment for 300 epochs. It produced an average classification accuracy of 99.9632% on the test dataset. The experimental results demonstrate the efficiency of the proposed model and show that the model achieved the highest values compared to other deep learning models in the PlantVillage datasets.

Keywords: FractalNet; convolution neural network; plant village; plant leaf disease

1. Introduction

Diseases, insects and nutrient deficiencies are the most common threats to crop growth, negatively affecting total crop production and the farmer's net profit. Diagnosis and treatment of diseases and application of fertilizers play an important role in reducing yield loss.

Therefore, accurate and early disease detection is necessary as it is among the best possible solutions for early disease control and improved crop performance as well as avoiding unnecessary waste of financial resources.

Conventional disease detection is not feasible for all cultivated fields and all farmers. This requires finding suitable human experts to diagnose and treat diseases, which takes time and money.

Hence the need for an intelligent system capable of automatically classifying and diagnosing plant diseases to overcome the difficulties of the traditional approach.

Today, with the activation and application of artificial intelligence in the field of agriculture and food security, many deep learning (DL) models have been used, and many models of deep learning methods have been proposed to detect and classify plant diseases.

In the research that follows, we present our approach to the challenge with two objectives. The first objective is to study and determine the relevance of the FractalNet for the task of classifying plant diseases. The second goal is to get the lowest possible error on a set of PlantVillage test images. It should be noted that no study has attempted to address this aspect before, as this is the first work that addresses the field of plant leaf disease classification using FractalNets.

The main contributions of this research are:

- We applied for the first time the FractalNet model on the PlantVillage database for the classification of plant diseases.
- We present a detailed experimental study of the FractalNet for the plant disease classification task on a set of PlantVillage test images.

- Finally, we show that the application of FractalNet allows to obtain state-of-the-art results on the PlantVillage dataset considerably improving the accuracy.

The rest of this work is organized as follows: In section 2, an overview of related works is given. Section 3 describes the database. In section 4, the data preparation, proposed model and implementation details were presented. Experimental evaluations and comparative analysis are presented and discussed in section 5. Advantage and future work are reported in section 6. The work is concluded in the last section.

2. Related works

Recent developments in artificial intelligence techniques enable the effective identification of many diseases and pest attacks in precision agriculture. This investigation deals with modern artificial intelligence approaches for the detection of plant diseases.

For the detection of rice plant diseases, Lu er al. [1] proposed a new method for identifying rice diseases. The model is able to identify ten rice diseases. Chen et al. [2] trained a model called DENSINCEP based on deep transfer learning.

Sun et al. [3] have developed an improved CNN that offers a test accuracy equivalent to 99.35%. Mohanty et al. [4] classified plant diseases using CNN models such as AlexNet and GoogLeNet. Too et al. [5] exploited CNN models such as ResNet50, VGG16, ResNet101, Resnet152, Inception V4 and DenseNets 121. Atila et al. [6] proposed an EfficientNet deep learning architecture for plant disease classification. Performance is compared to other CNN models such as AlexNet, VGG16 and ResNet50.

An effort is made by Alaeddine and Jihene [7] to apply the Wide Residual Networks model in the field of plant disease classification. Moreover, they have proposed DbneAlexnet in the study of Alaeddine and Jihene [8].

The literature review shows that most of the work in the literature exploits the PlantVillage dataset and performs disease classification of a particular plant or multiple plants [9–14]. Moreover, the literature review recognized that residual and dense convolutional neural networks performed better than other transfer learning techniques in plant disease detection [15]. Transfer learning techniques can lead to negative transfer and overfitting issues when using the architecture and weights of pretrained models for new applications. In addition, the study of the literature shows the importance of data augmentation for classification algorithms.

From these literatures, we consider all these previous approaches and the experiments already performed to determine the best deep learning model a new approach in order to obtain better accuracy on the PlantVillage dataset. In this context, we adapted the FractalNet model on the PlantVillage database for the classification of plant diseases.

3. PlantVillage database

The PlantVillage database is introduced by Hughes et al. [16] to enable the development of mobile diagnostics of diseases It consists of 61,486 images of healthy and unhealthy leaves classified into 38 groups by type and disease. The PlantVillage dataset was created with six different augmentation techniques to create more diverse datasets with different background conditions. The augmentations used in this process were scaling, rotation, noise injection, gamma correction, image flip, and PCA color augmentation.

The images in the database are colored and have different sizes that are why the images have been resized to 227 × 227, which is the default size accepted by the model. Examples of some plant diseases are shown in **Figure 1**.

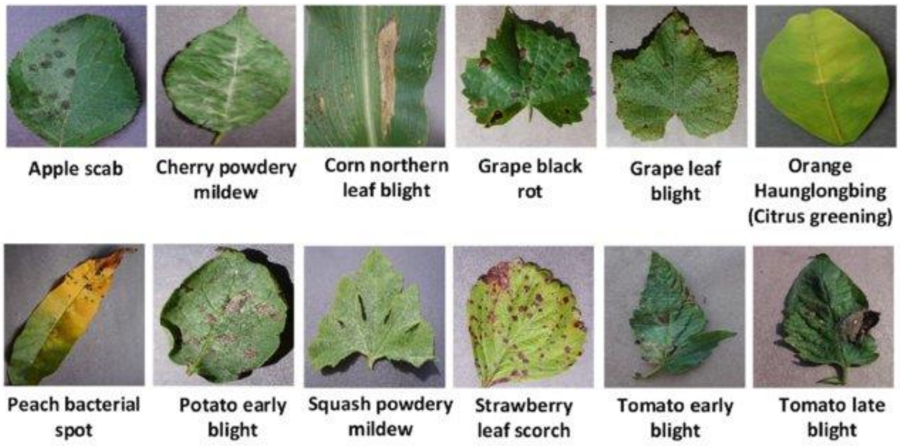

Figure 1. Some of the plant diseases in the PlantVillage dataset.

4. Materials and methods

The implementation steps of the proposed plant disease detection model are categorized into two phases. The implementation of the proposed model started with data preparation. The data preparation phase focuses on augmenting the data. The model training phase includes the design and training processes.

4.1. Data reparation

Implementing a deep learning algorithm starts with the data preparation phase. It includes data collection, data augmentation, and pre-processing steps. Some classes in the original dataset have fewer samples. On the other hand, some classes have more images. The difference sometimes reaches two thousand images. The number of samples must be equal in each class in order to increase the performance of the classification algorithms. Data augmentation techniques were used to increase the number of samples without the need to collect new data. Cropping, scaling, flipping, rotating, filling, affine transforming and tinting techniques were used to produce augmented images on the dataset. After data augmentation, the database was split for the training, validation and testing process.

4.2. FractalNet

FractalNet is introduced by Larsson et al. [17]. It is described as a type of convolutional neural network that avoids residual connections in favor of a "fractal" design. They involve the repeated application of a simple expansion rule to generate deep networks whose structural arrangements are precisely truncated fractals. These networks contain interactive subpaths of varying lengths, but do not include any direct or residual connections; each internal signal is transformed by a filter and a nonlinearity before being seen by the following layers.

4.2.1. FractalNet architecture

For the base case, $f_1(z)$ is the convolutional layer:

$$f_1(z) = \mathrm{conv}(z)$$

After that, the recursive fractals are:

$$f_{C+1}(z) = [(f_c \circ f_c)(z)] \oplus [\mathrm{conv}(z)]$$

where C denotes the number of columns as shown in **Figure 2b**. The number of convolutional layers at the deepest path of a single block is equivalent to $2^{(C-1)}$. For a number of columns C = 4, the number of convolutional layers is equivalent to $2^{(4-1)} = 2^3 = 8$ layers.

For the joining layer in green color, the elemental mean is calculated. It is not concatenation or addition.

For 5 blocks (B = 5) cascaded like FractalNet as shown in **Figure 2c**, the number of deepest-path convolutional layers in the entire network is $B \times 2^{(C-1)}$, i.e., $5 \times 2^{(4-1)} = 5 \times 2^3 = 5 \times 8 = 40$ layers.

A layer of 2 × 2 maximum pooling is performed between every two blocks to reduce the size of feature maps. Batch Normalization layers and ReLU activation functions are used after each convolution.

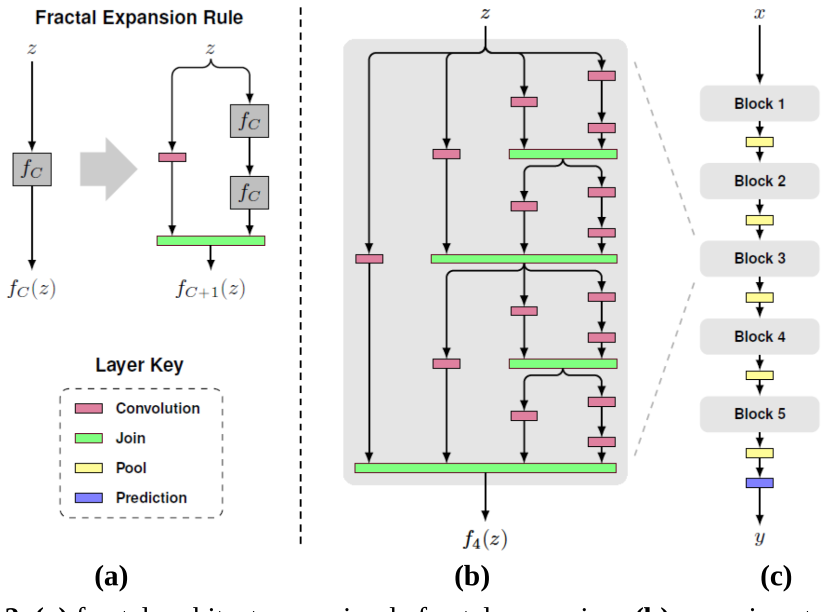

Figure 2. (a) fractal architecture: a simple fractal expansion; **(b)** recursive stacking of the fractal expansion in one block; **(c)** 5 cascading blocks like FractalNet [17].

4.2.2. Architecture of training models

For FractalNet-34, we use the same first and last layer as ResNet-34 [18], the middle of the network consists of 4 blocks (B = 4) and 4 columns (C = 4). We define the number of filter channels in blocks 1 to 4 as 128, 256, 512, 1024.

4.3. Implementation details

We formed our configurations using a ‘‘Root Mean Square Propagation Algorithm’’ with a batch size equivalent to 32 and a weight decrease of 0.0001.

The learning rate was initialized to 0.01 and divided by 10 twice before the end. We formed the network for about 300 cycles at most in a central processing unit (CPU). There was no significant change in performance after reaching 300 epochs. The python algorithm based on the deep learning library "Keras" to classify and recognize images provides the implementation of the CPU.

5. Results and discussion

5.1. The performances of FractalNet-34

Classification accuracy, precision, recall, and $F1$ score are the standard measures to assess the overall performance of classification techniques. FractalNet-34 performance is shown in **Table 1**:

Table 1. Performance of FractalNet-34.

Model	Accuracy	Precision	Sensitivity	$F1$-score	Specificity
FractalNet-34	99.9632	98.92	98.98	98.95	98.11

5.2. Discussions

The main objective of this work is to examine and evaluate the success of the FractalNet-34 model in the classification of plant diseases and to compare the performances obtained with models from the literature. This section deals with the performance of the proposed FractalNet-34 model in the classification of plant diseases. Furthermore, it compares the proposed model with other state-of-the-art deep learning models and techniques. A comparison with the results of different studies and works is presented in **Table 2**.

Table 2. PlantVillage test accuracy.

Ref.	Method	Precision (%)
[4]	GoogleNet	99.35
[5]	DenseNets-121	99.75
[6]	EfficientNet B5	98.42
	WRN-22-2	99.9394
[7]	WRN-28-10 (dropout)	99.9611
	WRN-40-2	99.9533
[19]	Hybrid principal component analysis	59.1
[20]	Dilated TL and ensemble learning	99.10
Our	**FractalNet**	**99.9632**

The experimental results demonstrate the effectiveness of the proposed contribution. Moreover, they show that the proposed model offers better results in terms of classification accuracy than the various other models.

6. Advantages and future work

The proposed model offers an interesting test precision compared to the various works reported in the literature. The importance of the exploited model also lies in its repetitive and homogeneous structure which makes it very suitable and compatible for integration into embedded system applications. In future work, it is planned to extend and augment the PlantVillage dataset artificially by increasing the number of classes. This will contribute to the development of models and architectures capable of achieving more precise and interesting accuracies.

7. Conclusion

The automatic detection and classification of plant diseases is a crucial process in agriculture. This work applied a new deep convolutional neural network for the classification of common diseases in different plants. In this work, some recent image augmentation techniques were used to prepare the proposed dataset for model training. The training process was performed on a CPU for up to 300 training epochs. The classification accuracy of the proposed model was 99.9632%.

Author contributions: Conceptualization, HA and MJ; methodology, HA; software, HA; validation, HA; formal analysis, HA; investigation, HA; resources, HA; data curation, HA; writing—original draft preparation, HA; writing—review and editing, HA; visualization, HA; supervision, HA and MJ; project administration, HA; funding acquisition, HA. All authors have read and agreed to the published version of the manuscript.

Conflict of interest: The authors declare no conflict of interest.

References

1. Lu Y, Yi S, Zeng N, et al. Identification of rice diseases using deep convolutional neural networks. Neurocomputing. 2017; 267: 378-384. doi: 10.1016/j.neucom.2017.06.023
2. Chen J, Zhang D, Nanehkaran YA, et al. Detection of rice plant diseases based on deep transfer learning. Journal of the Science of Food and Agriculture. 2020; 100(7): 3246-3256. doi: 10.1002/jsfa.10365
3. Sun J, Tan WJ, Mao HP, et al. Identification of Leaf Diseases of Various Plants Based on Improved Convolutional Neural Network. Agric. Eng. Newsp. 2017; 19: 209-215.
4. Mohanty SP, Hughes DP, Salathé M. Using Deep Learning for Image-Based Plant Disease Detection. Frontiers in Plant Science. 2016; 7. doi: 10.3389/fpls.2016.01419
5. Too EC, Yujian L, Njuki S, et al. A comparative study of fine-tuning deep learning models for plant disease identification. Computers and Electronics in Agriculture. 2019; 161: 272-279. doi: 10.1016/j.compag.2018.03.032
6. Atila Ü, Uçar M, Akyol K, et al. Plant leaf disease classification using EfficientNet deep learning model. Ecological Informatics. 2021; 61: 101182. doi: 10.1016/j.ecoinf.2020.101182
7. Alaeddine H, Jihene M. Plant leaf disease classification using Wide Residual Networks. Multimedia Tools and Applications. 2023; 82(26): 40953-40965. doi: 10.1007/s11042-023-15226-y
8. Alaeddine H, Jihene M. Deep Batch-normalized eLU AlexNet for Plant Diseases Classification. In: 2021 18th International Multi-Conference on Systems, Signals & Devices (SSD); 22 March 2021. doi: 10.1109/ssd52085.2021.9429404
9. Cruz AC, Luvisi A, De Bellis L, et al. Vision-based plant disease detection system using transfer and deep learning. In: Proceedings of the 2017 Asabe Annual International Meeting; 16-19 July 2024; Washington.
10. Yamamoto K, Togami T, Yamaguchi N. Super-Resolution of Plant Disease Images for the Acceleration of Image-based Phenotyping and Vigor Diagnosis in Agriculture. Sensors. 2017; 17(11): 2557. doi: 10.3390/s17112557
11. Wallelign S, Polceanu M, Buche C. Soybean Plant Disease Identification Using Convolutional Neural Network. In: Proceedings of the Thirty-First International Florida Artificial Intelligence Research Society Conference (FLAIRS-31). pp. 146-151.

12. Sibiya M, Sumbwanyambe M. A Computational Procedure for the Recognition and Classification of Maize Leaf Diseases Out of Healthy Leaves Using Convolutional Neural Networks. AgriEngineering. 2019; 1(1): 119-131. doi: 10.3390/agriengineering1010009
13. Rangarajan AK, Purushothaman R, Ramesh A. Tomato crop disease classification using pre-trained deep learning algorithm. Procedia Computer Science. 2018; 133: 1040-1047. doi: 10.1016/j.procs.2018.07.070
14. Zhang K, Wu Q, Liu A, et al. Can Deep Learning Identify Tomato Leaf Disease? Advances in Multimedia. 2018; 2018: 1-10. doi: 10.1155/2018/6710865
15. Hu G, Wu H, Zhang Y, Wan M. A low shot learning method for tea leaf's disease identification. Computers and Electronics in Agriculture. 2019; 163. doi: 10.1016/j.compag.2019.104852.104852
16. Hughes DP, Salathe M. An open access repository of images on plant health to enable the development of mobile disease diagnostics. arXiv. 2015; arXiv:1511.08060.
17. Larsson G, Maire M, Shakhnarovich G. Fractalnet: Ultra-deep neural networks without residuals. arXiv. 2016; arXiv:1605.07648.
18. He K, Zhang X, Ren S, Sun J. Deep residual learning for image recognition. arXiv. 2015; arXiv:1512.03385.
19. Gadekallu TR, Rajput DS, Reddy MPK, et al. A novel PCA–whale optimization-based deep neural network model for classification of tomato plant diseases using GPU. Journal of Real-Time Image Processing. 2020; 18(4): 1383-1396. doi: 10.1007/s11554-020-00987-8
20. Saberi Anari M. A Hybrid Model for Leaf Diseases Classification Based on the Modified Deep Transfer Learning and Ensemble Approach for Agricultural AIoT-Based Monitoring. In: Kumar A (editor). Computational Intelligence and Neuroscience. 2022; 1-15. doi: 10.1155/2022/6504616