Depthwise separable convolution architectures for plant disease classification

Introduction:

Agriculture productiveness is something on which the economy highly hangs upon. Climate and other environmental conditions cannot be administered by farmers. Disease reduction is a key factor to consider in the context of agriculture. Crops affected by pests or diseases should be considered immediately. If proper leaf care is done at the outset, it can prevent the spread of disease to plants. On the alert, with hard eyes, it is difficult to detect the disease with a leaf. This can lead to improper use of pesticides and ultimately lead to crop failure. Due to several environmental factors, several diseases affect plants. This leads to reduced crop quality and production. An automated disease-detection system is mandatory as this system will be useful for monitoring plants which is why immediate steps can be taken. It is found that imaging techniques will provide effective results in diagnosing diseases. Here a machine-based program helps farmers identify plant diseases by inserting a leaf image into the system. The program contains a set of algorithms for pre-screening, feature extraction, and based machine programming that can identify the type of disease.

Diseases can be caused by bacteria or any virus also it may be a fungal one that is inflicting diseases that cause the loss of money every year thus affecting the country and its people. Most of the time, the diseases can be identified through the leaves or by the trunk of the tree sometimes also by its root, but leaves are easy to identify among others. Because of the difficulty in checking each plant root the disease and its causes are mostly ignored by the farmers. Hence Diseases are detected on the leaves of the plant. Therefore, Technology is needed that help the farmers to identify the disease and take preventive measures such that it helps recover the crop that is to get infected in the future. Farmers can avoid going to the labs as this technology helps them identify the disease on their own. This type of Detection might prove gain in looking at huge fields of crops and leaf disease detection analysis helps in identifying the diseases.

Short Summary:

This journal has used 2 models, they are ModefiedMobleNet and ReducedMobleNet, the convolution architecture that they have used in this paper is depthwise one and their results which were obtained by passing the image into the model were checked with MoblieNet, AlexNet, and some other architectures. To enhance the results and improve it some optimizers like Adam and nadam have been used. Nadam performed comparatively better when verified with other optimizers, and with a faster convergence rate than the ones that also have been implemented before other optimizers. In this paper, the data set they have had a total of, nearly 82,000 images of different plant leaves, and 55 different and unique classes of diseased plants were used from the freely available Plant Village dataset for the training and testing of the model.

Contributions:

- Proposed depthwise separable convolution models, such as customized MobileNet variants, specifically designed for detecting plant diseases
- Compiled a new dataset of 6,580 plant leaf images for rigorous testing and evaluation of the models.
- Showcased significant improvements in computational efficiency, memory usage, and classification accuracy.
- Achieved high disease detection accuracy (up to 99.55%) using the developed models.
- Conducted thorough comparisons with traditional CNN architectures like VGG16, and AlexNet, demonstrating the new models' advantages.

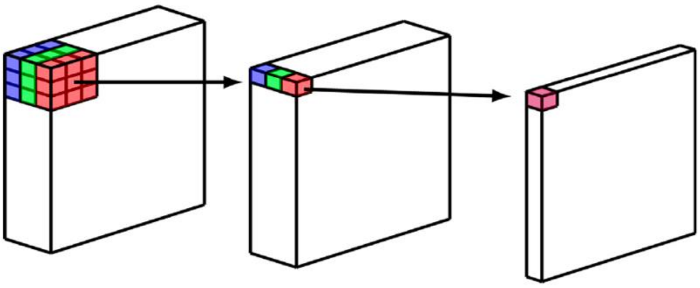
Methodology:

Data collection:

A dataset comprising 6,580 images was created, highlighting various plant species and associated diseases. This extensive collection aimed to provide a wide range of examples to support effective model training. By incorporating multiple types of plants, the dataset enhances the models' ability to generalize, ensuring accurate disease classification across diverse conditions. Serving as the study's foundation, this rich dataset allows for performance evaluation in practical scenarios, ensuring reliability in real-world applications.

Feature Extraction:

The research utilized a modified adaptive centroid-based segmentation method to focus on specific areas within the images. This technique boosts disease detection accuracy by highlighting relevant leaf regions while reducing background interference. By enhancing image clarity for training, this segmentation strategy enables the depthwise separable convolution models to learn effectively, leading to improved classification outcomes. Additionally, this approach streamlines data analysis by minimizing the volume of information to process.



Model design:

The study involved creating several depthwise separable convolution models, including tailored versions of MobileNet. These models capitalize on a simplified architecture to deliver high performance with reduced computational demands. By integrating depthwise separable convolutions, the models achieve accuracy while significantly cutting down on parameters and processing time. This innovative strategy ensures that the models are appropriate for deployment on resource-limited devices, such as mobile phones and IoT applications, without sacrificing their disease detection capabilities.

Modified MobileNet architecture.

Layer Size/Stride	Output Shape	Parameters
3,3 Conv,32/S2	74,74,32	896
3,3 Maxpooling/S2	36,36,32	0
2∗(3,3 SeparableConv, 128/S1	32,32,128	21920
3,3 Maxpooling/S2)	15,15,128	0
2∗(3,3 SeparableConv, 256/S1	11,11,256	101760
3,3 Maxpooling/S2)	5,5,256	0
2∗(3,3 SeparableConv, 512/S1	1,1,512	400128
Global Average Pooling	1,1,512	0
Dense	1,1,16	32
Softmax	1,1,16	0

Reduced MobileNet architecture.

Layer Size/Stride	Output Shape	Parameters
3,3 Conv,32/S2	74,74,32	992
3,3 DepthwiseConv, 32/S1	75,75,64	2720
1,1 PointwiseConv, 64/S1		
3,3 DepthwiseConv, 64/S2	38,38,128	9536
1,1 PointwiseConv, 128/S1		
3,3 DepthwiseConv, 128/S1	38,38,128	18560
1,1 PointwiseConv, 128/S1		
3,3 DepthwiseConv, 128/S2	19,19,256	35456
1,1 PointwiseConv, 256/S1		
3,3 DepthwiseConv, 256/S1	19,19,256	69888
1,1 PointwiseConv, 256/S1		
3,3 DepthwiseConv, 256/S2	10,10,512	136448
1,1 PointwiseConv, 512/S1		
3,3 DepthwiseConv, 512/S1	10,10,512	270848
1,1 PointwiseConv, 512/S1		
Global Average Pooling	1,1,512	0
Dense	1,1,16	8208
Softmax	1,1,16	0

Critical Analysis:

The use of depthwise separable convolutions reduces processing requirements, enabling compatibility with mobile and IoT devices. An accuracy of 99.55% highlights the effectiveness of the model in practical settings. It effectively addresses a range of plant diseases across different species, showcasing its adaptability. The complexity of deep learning models may impact their decision-making processes, making it harder for agricultural professionals to interpret results. The existing dataset of 6,580 images could benefit from increased size and diversity for better representativeness. Further evaluation in diverse environmental contexts may be necessary to validate the model's robustness.

Comparing accuracies (%) of PlantVillage Dataset.

Model	Test Accuracy	Number of parameters (in millions)
AlexNet (Ferentinos, 2018)	99.44	3.3
VGG (Ferentinos, 2018)	99.53	14.7
Modified MobileNet	97.65	0.5
Reduced MobileNet	98.34	0.54
MobileNet	98.65	3.2

Test Accuracies (%) on PlantLeaf3 dataset for different width multiplier.

Width Multiplier(α)	Reduced MobileNet	MobileNet
1	99.37	99.62
0.75	98.52	98.76
0.5	98.02	98.82
0.25	97.35	96.17

Test Accuracies (%) on PlantLeaf1 dataset for various optimizers.

Models	SGD	Adam	Nadam
MobileNet	97.07	97.26	97.64
Reduced MobileNet	96.43	98.04	98.2

Conclusion:

The models' effectiveness was rigorously analyzed using various metrics, such as accuracy, F1-score, computational efficiency, and memory utilization. Their results were compared against established CNN architectures like VGG16, and AlexNet to assess the new models' effectiveness. This evaluation not only underscored the depthwise separable convolution models' high accuracy but also showcased their resource efficiency. The comparison aimed to demonstrate their practicality for real-world agricultural applications.

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