<u>*Araştırma Makalesi*</u>

<u>*Research Article*</u>

Convolutional Neural Networks for Image-Based Digital Plant Phenotyping

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Abstract

Plants are one of the most important components of the environment. Millions of people are undernourished because of global warming whose adverse effects such as drought has made it difficult for sustainable crop breeding programs. This paper is aimed to propose and test computer vision and machine learning image-based methods precisely convolutional neural networks; for a benchmark suggested by the International Plant Phenotyping Network to help researchers, plant breeders choose desirable crop traits, and link them to specific genes that helped in the production of viable plants that could withstand harsher environmental conditions. Also as a first of its kind in Turkey and its environ, this paper is aimed to provide a ground base for future research in this area of agriculture. The benchmark chosen is the classification of mutants' benchmark (plant disease detection). In this paper, the dataset chosen was two of the main cash crops that can be found in Turkey were used: Maize and Grapes. Three different plant diseases affecting Grape and Maize were used respectively and a class of healthy grape and maize annotated images were added amounting to a total of 8 different classes and 1600 annotated images for both training and testing for the custom convolutional neural network to be proposed. The results show that the custom model achieved 97.03 % accuracy on the test dataset after training. The research thus concluded that, the custom model performed better than most currently used convolutional neural network models and can be used as a basis for further research in the field of image detection.

Keywords: Digital Plant Phenotyping, Convolutional Neural Network (CNN), Computer Vision, Plant Disease Detection.

Görüntü Tabanlı Dijital Bitki Fenotiplemesi için Konvolüsyonel Sinir Ağları

Öz

Bitkiler çevrenin en önemli bileşenlerinden biridir. Küresel ısınmanın, sürdürülebilir ürün yetiştirme programlarını zorlaştıran, kuraklık gibi etkileri sebebiyle, milyonlarca insan yetersiz beslenmektedir. Bu çalışmanın amacı bilgisayar görüsü, resim tabanlı makine öğrenmesi teknikleri ve evrişimli sinir ağları kullanarak, Uluslararası Bitki Fenotipleme Ağı tarafından araştırmacılara yardımcı olmak amacıyla, bitki yetiştiricilerinin arzu edeceği mahsul özelliklerine sahip ve daha zorlu çevre koşullarına dayanabilecek, canlı bitkilerin üretimine yardımcı olacak genleri belirlemek için, bir model sunmak ve test etmektir. Ayrıca, Türkiye'de ve çevresinde türünün ilk örneği olan bu çalışma, tarımın bu alanında gelecekteki akademik araştırmalar için bir zemin sağlamayı amaçlamaktadır. Seçilen ölçüt mutantların sınıflandırılma kriteridir (bitki hastalık tespiti). Bu araştırmada seçilen veri kümesi, Türkiye'de bulunabilecek başlıca bitki ürünlerinden mısır ve üzümdür. Üzüm ve mısırı etkileyen üç farklı bitki hastalığı sırasıyla kullanılmıştır ve özel evrişimli sinir ağı için toplam 8 farklı sınıfta, eğitim ve test olmak üzere 1600 açıklamalı görüntüye karşılık gelen sağlıklı üzüm ve mısır veri kümesi görüntüsü eklenmiştir. Sonuçlar, geliştirilen modelin eğitimden sonra test veri kümesinde % 97.03 doğruluk elde ettiğini göstermektedir. Böylece çalışmada, geliştirilen modelin şu anda kullanılan evrişimli sinir

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ağı modellerinden daha iyi performans gösterdiği ve görüntü algılama alanında daha fazla araştırma için bir temel olarak kullanılabileceği sonucuna varılmıştır.

Anahtar Kelimeler: Dijital Bitki Fenotipleme, Konvolüsyon Sinir Ağları (CNN), Bilgisayar Görüsü, Bitki Hastalığı Tespiti.

1. Introduction

Millions of people are undernourished because of the global warming whose adverse effects such as drought have made it difficult for sustainable crop breeding programs. Plant phenotyping, which is the classification and identification of plant effects on the phenotype (for instance the plants physical characteristics such as the height, leaf shape, biomass and others) as a consequence of the differences in genotype (uniqueness of DNA) and the environment, emerged as a science to help plant breeders choose desirable crop traits, and link them to specific genes that helped in the production of viable plants that could withstand harsher environmental conditions. Lots of measurements are required for having progress on genetics. The complex nature of plants and the lack of techniques thereof, made the process much difficult. It was usually destructive, very cost-intensive, time consuming and prone to human errors. This led to the innovation of semi-automated and fully automated methods such as the non-invasive, image-based methods. The image-based methods provide automated tools and algorithms to extract phenotypic traits from various imaging modalities including ground based imagery, aerial drone imagery, satellite imagery and video, and neutron imaging tomography of plant root systems to help plant breeders, produce plants with beneficial phenotypes which helps in increased crop yield and increased resistance to abiotic and biotic stresses (*Großkinsky, D. K. et al. 2015, Klukas, C. et al. 2014, Jordan Ubbens et al. 2017, Kawasaki Y. et al. 2015*).

In this paper, accurate general classification recognition algorithms will be the basis for the classification of mutants (plant disease detection) benchmark. Extensively annotated ground-based static imaging data will be the main datasets for the project. Training, Testing and validation datasets will then be derived from the main dataset. The approach will be tested on quality datasets from github called "Plant Village-Datasets" by spMohanty (*Brahimi et al. 2017, D. F. Specht 1988, D. Gavrila et al. 1999, D. Lowe 1999, Glorot, X. et al. 2010*).

2. Theoretical Background

Image-based plant phenotyping is the classification and identification of plant effects on the phenotype as a result of the differences in genotype and the environment like the physical characteristics of plants such as height, leaf shape, biomass and others. This has emerged as a science to help plant growers choose the desired crop characteristics and using computer algorithms as an emerging technology to help identify specific genes that help them in the production of live plants to withstand harsh environmental conditions. Various imaging methods such as ground-based images, aerial drone images, satellite images and video and neutron imaging tomography have been adopted in the processes of image based plant phenotyping. And thus we have an idea of what the output can be: an automated technique that can help the plant biologist identify certain characteristics of plant systems. We can easily compile most of these imaginary data with specific criteria, and what we want is to learn what constitutes the genotypes and phenotypes necessary for these images. In other words, the computer would like to automatically extract the algorithm for this task. Although we do not know the details of the underlying process of data generation in nature (for instance plant disease), we know that this is not entirely random. There are certain models in the data and with specific types of simulations can be extracted. The process may not be fully defined, but a good and useful approach can be established (*Hartmann, A. et al. 2011, Kingma, D. P. et al. 2015, Kokorian, J. et al. 2010, M. T. Hagan et al. 2002, Önder K. et al. 2016, Sladojevic S. et al., 2016, Tang, X. et al., 2009, Van der Heijden et al. 2012, White, J.W., et al.. 2012*).

In addition, machine learning is useful to solve many problems in computer vision, speech recognition and robotics. By utilizing sample data or past experiences, machine learning programs computers to improve a performance criterion. A model with specific parameters introduces the learning process that enables the execution of a computer program to advance the parameters of the model applying training data or past experience. It can also be descriptive to obtain information from data or both. The goal of machine learning is to infer from a sample. Therefore it utilizes statistical theories to construct mathematical models.

Image-based digital plant phenotyping is a field that biologists have identified as the key sector to increase plant productivity and plant resistance needed to keep pace with increasing food demand and global food demand. In today's world, where data types and numbers are increasing, computer vision and artificial learning have become indispensable to overcome the difficulty in phenotyping. In the context of plant phenotyping, a criterion dataset collection is presented by International Plant Phenotyping Network (IPPN). They provide explanatory imaging data and propose appropriate evaluation criteria for plant/leaf segmentation, detection, monitoring and classification and regression problems. One of the main aims of this study is to help the improvement and evaluation of a classification of mutants (plant disease detection) computer vision and machine learning algorithm using a custom CNN.

2.1. Classification of Mutants (Plant Disease Detection) Custom Model

A convolutional neural network (CNN) is being used in wide research area included computer vision. In our paper, we use RGB images and it has three dimensions. Our CNN structure has three layers. These are convolutional layer, pooling layer and fully connected layer. First layer is convolutional layer and there is filtering system on this stage. After a series of convolution and pooling layers, there is typically one or more fully bonded layers. After each convolution and fully connect layer, a nonlinear function is

applied to calculate final activations for the layer. In the case of classification and regression, the number of units on the output layer corresponds to the number of classes. CNNs use iterative training strategies for deep architectures. In each layer, the gradient of the error signal calculated according to each parameter. Therefore, these parameters can be modified by applying a factor proportional to the gradient.

3. Experimental Results

Heavy lifting for machine learning is done almost exclusively by Keras. Keras is one of the popular frameworks for deep learning studies. It makes it easy to identify neural networks in a very legible way. The image data sets of the two main plants were used; grapes and corn. Sample images can be seen from Fig. 1. Three different plant diseases affecting grape and maize were used respectively and a class of healthy grape and maize annotated images was added. This gave us 8 main classes that could be used in the overall classification process.

Corn (Maize)	Healthy Maize (Gray Leaf Spor)	Maize (Common Rust)
Maize (Northern-Leaf Blight)	Grape (Healthy)	Grape (Black Rot)
Grape (Black Measles)	Grape (Leaf Blight)	

Figure 1. Sample images from the 'Plant Village' data set

A convolutional network model (Table I.) was constructed from scratch and trained to perform the necessary plant disease detection of the specified classes. We show the structure of our model, which has better classification performance then others. For the task of mutant classification (plant disease detection), a CNN with two 5×5 convolutional layers, two 3×3 convolutional layers and an output layer were formed. Each convolution layer was accompanied by a maximum pooling layer of 3×3 spatial size and in a 2 pixel step. The CONV layer has 32 filters with 3 x 3 cores and RELU activation (rectified linear unit). 'Batch normalization', 'max pooling', and 25% 'dropout' were applied. DropOut is a regularization technique that prevents complex peer adaptations in educational data to reduce excessive adaptation to neural networks. It is a very effective way to obtain average means with artificial neural networks. Then, only one set of FC (fully connected) layer RELU layers was created with an output class of 8 classes representing 8 different facilities to be trained. Keras 'Adam' optimizer was used to train the model. Deep learning with small data sets can be particularly difficult because small training sets can facilitate memorization of a deep network, which can lead to problematic over-equipping. This usually results in a low training error and a high test error. This inconsistency is called a generalization error. With the possible application of pre-processing techniques such as random rotations, shifts, flips, crops, and sheers on our training image dataset, the size of the training set increases artificially but effectively.

4. Conclusion and Discussion

For mutant classification (plant disease detection) , after a series of training and tests of the proposed model, the generated model architecture achieved 97.03 % test accuracy and a large part of the plant village dataset used is images of leaves and a simple background in a controlled environment. Illustrated results can be seen from Fig. 2. Using images with different attributes and complex backgrounds in the training and validation dataset can advance accuracy and produce a more useful classifier for practical

use. The Plant Village dataset is unstable beacuse some classes provide more images than others. This can be very deceptive and can lead to overclocking if not carefully trained. In these situations amplification techniques can be more helpful and efficent.
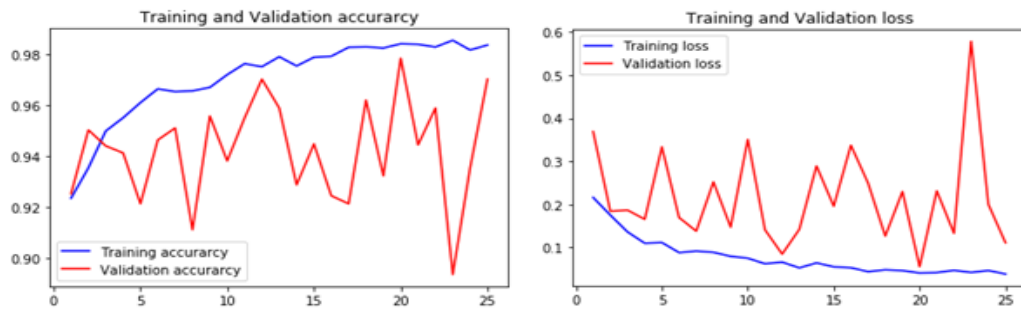

Figure 2. Accuracy and loss graphs of custom model after average testing, respectively

Compared to other popular studies in this field, which can be seen in Table I, it can be found that the model works extremely well, taking into account factors such as the number of images and class numbers.

Table I. Comparison of CNN models used infor plant village data set

Paper	Year	Number of Classes	Size of the Dataset	CNN Model	Accuracy (%)
Our CNN model	2020	8	1600	Custom	97.03
Kawasaki et al.	2015	3	800	Custom	94.90
Sladojevic et al.	2016	15	4483	CaffeNet	96.30
Brahimi et al.	2017	9	14828	AlexNet GoogleNet	99.18
Lu et al.	2017	10	500	AlexNet	95.48

There are many ways to build a neural network, and choice is guided by the purpose of the network. Designing a new type of network is certainly in the field of research, and even re-applying a type of network specified in an article is difficult. The practical thing to do is to find an example that does something in the direction you want and change it step by step or fine-tune it until you really do what you want.

4. Conclusions and Recommendations

In conclusion, the custom model proposed CNN model performs quite significantly with 97.03 % accuracy and also taking into account factors such as the number of images and class numbers. Care must be taken during pre-processing as there is a possibility of generalization occurring. The CNN model usage is much easier and can be adapted easily as we only use RGB images and rely on the network to learn the strong representation of differences in growth rates between mutants. Since this is one of the pioneers of the study in Turkey and its environs it can be concluded that this research can be used as basis for further research or fine tuning of the custom model created, this model not only helps the plant biologist in this article, but can also be applied in agriculture through simple practices and technological implementations that help farmers identify plant disease and recommend appropriate treatment. Because it is flexible and has a high level of accuracy, it can be used in other sectors where detection object is vital, such as camera detection.

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