

## Chapter 60

# Use of Images of Leaves and Fruits of Apple Trees for Automatic Identification of Symptoms of Diseases and Nutritional Disorders

**Lucas Garcia Nachtigall**

*Federal University of Pelotas, Brazil*

**Ricardo Matsumura Araujo**

*Federal University of Pelotas, Brazil*

**Gilmar Ribeiro Nachtigall**

*Embrapa Grape & Wine, Brazil*

### ABSTRACT

*Rapid diagnosis of symptoms caused by pest attack, diseases and nutritional or physiological disorders in apple orchards is essential to avoid greater losses. This paper aimed to evaluate the efficiency of Convolutional Neural Networks (CNN) to automatically detect and classify symptoms of diseases, nutritional deficiencies and damage caused by herbicides in apple trees from images of their leaves and fruits. A novel data set was developed containing labeled examples consisting of approximately 10,000 images of leaves and apple fruits divided into 12 classes, which were classified by algorithms of machine learning, with emphasis on models of deep learning. The results showed trained CNNs can overcome the performance of experts and other algorithms of machine learning in the classification of symptoms in apple trees from leaves images, with an accuracy of 97.3% and obtain 91.1% accuracy with fruit images. In this way, the use of Convolutional Neural Networks may enable the diagnosis of symptoms in apple trees in a fast, precise and usual way.*

DOI: 10.4018/978-1-7998-0414-7.ch060

## **1. INTRODUCTION**

Approximately 25% of apple production is lost by attack of pests, diseases and nutritional disorders of plants. A rapid and efficient diagnosis of these situations is essential to avoid greater losses. It is estimated that 80 to 90% of the damage caused by pests and diseases which attack the culture of the apple tree occurs in the leaves and fruits. Among these diseases, scab of apple tree and the spot of *Glomerella* are the most important ones (Valdebenito-Sanhueza et al., 2008). In the case of pests, where leaves and fruits serve as food source or hosts, the major issues are due to the attacks of the fruit fly, fruit moth and big caterpillars (Kovaleski, 2004). On the other hand, the disturbances caused by the excess or lack of nutrients are visible mainly in the leaves during the vegetative growth phase (Nachtigall et al., 2004).

A correct diagnosis is essential in order to define strategies of management and control, and consequently for the rational use of fertilizers and pesticides. One main obstacle towards a quick diagnosis is the need for trained experts, making it costly to cover large areas in a timely manner. Moreover, experts often specialize in different issues, increasing the rate of misdiagnosis.

Some approaches exist to try and reduce the dependency on experts. A widely used one is a simple printed guide containing photos and explanations on how to diagnose a wide range of issues (Valdebenito-Sanhueza et al., 2008). Expert Systems, often built on top of Case-Based Reasoning algorithms, are applied to some cultures - e.g. vine (Fialho et al., 2012). These systems still require considerable amounts of training and are often not very accurate, mainly due to the typically very large number of questions required to be answered by the user and the sensitivity to wrong answers.

The concept of using machine learning to detect symptoms in plants has been shown to be a promising alternative in recent years, where several studies using different approaches have been carried out to identify or classify symptoms in cultivated plants. Rumpf et al. (2010) aimed to discriminate diseased from non-diseased sugar beet leaves, to differentiate between the three types of diseases and to identify diseases even before specific symptoms became visible. The authors used Support Vector Machines with a radial basis function as kernel to perform the identification and classification of symptoms of healthy or unhealthy leaves. As input they used nine spectral vegetation indexes, related to physiological parameters as features for an automatic classification, resulting in classification accuracies up to 97% on sugar beet leaves and diseased leaves, up to 86% classification accuracy between the three diseases symptoms and accuracy between 65% and 90% for pre-symptomatic detection of plant diseases.

Al-Hiary et al. (2011) proposed a methodology to automatically detect and classify plant leaf diseases from images. The process consists of six main phases: image acquisition, image pre-processing, image segmentation, feature extraction, statistical analysis and classification by a MLP. The authors used 32 samples for each of the six classes of leaves. Features were manually defined as 10 texture features extracted from the image.

A Perceptron Multilayer for classifying grape leaf diseases was used by Sannakki et al. (2013). Clustering was used to segment the image into groups, followed by lesion and manually defined feature extraction. They used a very small dataset (33 examples) and were able to achieve perfect accuracy in an also-small (4 examples) test set.

Revathi and Hemalatha (2014) focus on cotton leaf spot diseases. The authors used a dataset with 270 images divided into 6 disease classes. Features were manually defined, consisting of leaf edge, color and texture features. A Cross Information Gain Deep Forward Neural Network was used to per-

13 more pages are available in the full version of this document, which may be purchased using the "Add to Cart" button on the publisher's webpage:  
[www.igi-global.com/chapter/use-of-images-of-leaves-and-fruits-of-apple-trees-for-automatic-identification-of-symptoms-of-diseases-and-nutritional-disorders/237922](http://www.igi-global.com/chapter/use-of-images-of-leaves-and-fruits-of-apple-trees-for-automatic-identification-of-symptoms-of-diseases-and-nutritional-disorders/237922)

## Related Content

---

### Artificial Polynomial and Trigonometric Higher Order Neural Network Group Models

Ming Zhang (2013). *Artificial Higher Order Neural Networks for Modeling and Simulation* (pp. 78-102).  
[www.irma-international.org/chapter/artificial-polynomial-trigonometric-higher-order/71796](http://www.irma-international.org/chapter/artificial-polynomial-trigonometric-higher-order/71796)

### Backpropagation Neural Network for Interval Prediction of Three-Phase Ampacity Level in Power Systems

Rafik Fainti, Miltiadis Alamaniotis and Lefteri H. Tsoukalas (2020). *Deep Learning and Neural Networks: Concepts, Methodologies, Tools, and Applications* (pp. 883-904).  
[www.irma-international.org/chapter/backpropagation-neural-network-for-interval-prediction-of-three-phase-ampacity-level-in-power-systems/237911](http://www.irma-international.org/chapter/backpropagation-neural-network-for-interval-prediction-of-three-phase-ampacity-level-in-power-systems/237911)

### Predicting Hypoglycemia in Diabetic Patients Using Time-Sensitive Artificial Neural Networks

Khouloud Safi Eljil, Ghassan Qadah and Michel Pasquier (2020). *Deep Learning and Neural Networks: Concepts, Methodologies, Tools, and Applications* (pp. 1244-1262).  
[www.irma-international.org/chapter/predicting-hypoglycemia-in-diabetic-patients-using-time-sensitive-artificial-neural-networks/237932](http://www.irma-international.org/chapter/predicting-hypoglycemia-in-diabetic-patients-using-time-sensitive-artificial-neural-networks/237932)

### Optimization of Cutting Parameters for AISI H13 Tool Steel by Taguchi Method and Artificial Neural Network

Hrshikesh Pathak, Sanghamitra Das, Rakesh Doley and Satadru Kashyap (2020). *Deep Learning and Neural Networks: Concepts, Methodologies, Tools, and Applications* (pp. 531-551).  
[www.irma-international.org/chapter/optimization-of-cutting-parameters-for-aisi-h13-tool-steel-by-taguchi-method-and-artificial-neural-network/237891](http://www.irma-international.org/chapter/optimization-of-cutting-parameters-for-aisi-h13-tool-steel-by-taguchi-method-and-artificial-neural-network/237891)

### Efficiently Processing Big Data in Real-Time Employing Deep Learning Algorithms

Murad Khan, Bhagya Nathali Silva and Kijun Han (2020). *Deep Learning and Neural Networks: Concepts, Methodologies, Tools, and Applications* (pp. 1344-1357).  
[www.irma-international.org/chapter/efficiently-processing-big-data-in-real-time-employing-deep-learning-algorithms/237938](http://www.irma-international.org/chapter/efficiently-processing-big-data-in-real-time-employing-deep-learning-algorithms/237938)