WEST UNIVERSITY OF TIMIŞOARA
FACULTY OF MATHEMATICS AND COMPUTER SCIENCE
MASTER STUDY PROGRAM: ARTIFICIAL INTELLIGENCE AND DISTRIBUTED COMPUTING

MASTER THESIS

SUPERVISOR:
Conf. Dr. Kaslik Eva

GRADUATE:
Ricardo Belinha

TIMIŞOARA
2022

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Neural Networks Based Recognition of the Species and Subspecies of Vegetable Leaves

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I would want to extend my gratitude to those who were as vital to my success but are not included above.

Abstract

The objective of this master's thesis is to illustrate how to create a neural network using MATLAB as an integrated development environment. MATLAB will be used to develop the neural network because it was not used within the Artificial Intelligence and Distributed Computing Master's program and I would like to get familiar with it. For this project, a graphical user interface was developed for easier interaction between the software and the user. The user will be able to configure the model and use different types of transfer functions, training algorithms, and different numbers of hidden layers.

A neural network is a simulation of the workings of the human brain that enables computer systems to spot patterns and address common problems. My interest in leaves served as the source of inspiration for this endeavor. Nowadays, using technology to study is a more mature activity, and as a result, adults have more difficulty managing their time than children do. Learning rapidly is great since it will supply the people with some of the same learnt information and emotional fulfillment that science manuals do. I decided to expand my understanding of leaves and created this neural network to help aspiring apprentices in this field classify leaves more swiftly and effortlessly.

In the past, businesses and individuals have been successful in creating neural networks that discriminate items and/or persons using visual categorization. Since neural networks described a significant advancement in image recognition, similar applications were incredibly beneficial in comprehending the value and significance of a neural network. Everything, from social network photo tagging (Chapter 3.1.1) to self-driving automobiles (Chapter 3.1.6), relied on such fundamental concepts. As can be shown, neural networks are constantly working hard in the background of numerous applications, from examining one's vacation photos (Chapter 3.1.3) to providing healthcare (Chapter 3.1.2). The related applications demonstrate how a neural network with picture recognition can significantly improve a person's life.

The unique feature of the thesis is that I created the neural network fully on my own, making it possible to use it enthusiastically and without an internet connection to determine the specie and sub specie of a leaf. One can contend that by focusing on gathering the necessary data to classify the leaves, the neural network aids users in self-development.

The script has been written so that it can collect input and adapt. For a better weight adjustment, the neural network will train multiple times. The model will then be prepared to categorize and recognize unknown inputs. The development of the script helps in the comprehension of the various steps necessary to construct two completely functional neural networks that are capable of training using a variety of configurations and ultimately classifying the specie and sub specie of a leaf. As can be observed in section 2.2.1.2. The first neural network was trained using binary images, whereas the second used the attributes of the images. Both neural networks have undergone 1082 different types of training in total, with 24 instances of 100% overall success.

Due to the range of tools at the developer's disposal, using MATLAB to construct this project proved advantageous throughout. The Deep Learning Toolbox assisted with the training portion, enabling the developer to monitor the effectiveness of the preparation through charts and apps. In order to provide a user-friendly

interface and reduce the need for the user to learn a programming language or input commands, the MATLAB GUI assisted in the creation of the visual user interface. And last but certainly not least, the MATLAB Application Compiler, which builds an installer for the application and installs all the requirements required to run the project as well as the project itself, allowing it to be shared royalty-free with other users.

There are four chapters in this master's thesis.

The goal of the first chapter, "Problem Description," is to define a neural network, describe the thesis topic, and characterize the input data that the neural networks use.

The second chapter, "Related Work," is devoted to displaying some effective programs that employ image categorization to identify objects and/or persons.

The third chapter analyzes all of the output produced by this thesis project and presents the conclusions. The ideal neural network configurations will be identified.

The fourth chapter covers the functionality of the application, including details on the user guide and development guide.

As a conclusion, the project focuses on the creation of a neural network in MATLAB that can identify the specie and sub specie of a leaf using only an example of the iris neural network as a starting point. Users will have the chance to learn more about the various kinds of leaves that can be found worldwide. In addition, through this project, I want to motivate other programmers to create neural networks that take a straightforward photo as input and provide the user just enough feedback to keep learning more and more about a certain subject.

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Chapter 1

Introduction

This chapter attempts to briefly describe the choice of the subject and related applications of the submitted topic, the desired and pursued targets, and how the thesis is structured.

1.1 Generalities

This master's thesis aspires to demonstrate the procedure of creating a neural network by utilizing MATLAB as the integrated development environment.

A neural network is a representation of the human brain's functions that enables computer systems to identify patterns and solve common issues. The inspiration for this project appeared as a result of my curiosity about leaves. The fact is that utilizing technology to study is a mature pastime today, and as a result, adults struggle with time management in comparison to their younger counterparts. Learning quickly is ideal since it will give the individuals some of the same emotional gratification and learned information that science manuals provide. I chose to further my knowledge of leaves and constructed this neural network to assist future apprentices in this domain in classifying leaves more easily and quickly.

Historically, companies and individuals have succeeded in developing neural networks that use visual categorization to distinguish objects and/or people. As examples, we may point to social networks, COVID masks verifier, Google photos' location, reverse image search from Google, Shutterstock: image composition artificial intelligence, and the autopilot from Tesla. All of these firms and individuals show the use of neural networks and how they may have a significant influence on one's life.

The novel aspect of the thesis is that I constructed the neural network entirely on my own, allowing it to be utilized without an online connection and with great excitement in order to identify the specie and sub specie of a leaf. As a result, one might argue that the neural network assists users in self-development by concentrating on acquiring the essential information to categorize the leaves.

The script will be designed to receive input and learn from it. The neural network will train various times in order to better adjust the weights. And afterwards, the model will be ready to identify and classify unknown inputs.

Within this thesis, I wish to develop a neural network in MATLAB, using only an example of the iris neural network as a starting point, that recognizes the specie and sub specie of a leaf. It will give users the opportunity to learn more about the different types of leaves that exist in the world. Moreover, I intend to inspire other developers to develop neural networks that use a simple photo as input and provide the user with enough feedback in order to learn more and more about a specific topic.

1.2 Thesis structure

This master's thesis contains four chapters.

The first chapter, titled "Problem Description", is intended to explain what a neural network is, the thesis topic, and the input data utilized in the neural networks.

The second chapter, named "Related Work", focuses on showcasing some successful applications that use image classification to distinguish items and/or people.

The third chapter, summarizes the findings by analyzing all of the output generated by this thesis project. We will be able to determine which configurations are optimal for the neural network.

Last but not least, the fourth chapter discusses the application's functionality, containing information on the user guide and developer guide.

Chapter 2

Problem Description

This chapter gives details regarding what a neural network is, the thesis project itself, and the input data used in the neural networks.

2.1 Neural network

A neural network is composed of neurons, where each of these neurons corresponds to a unit of information processing. The information that enters the network (attributes or characteristics of the problem) is called input; to the information resulting from the processing, the output name is given (what is intended to be achieved). In neural networks, information processing is distributed over a large number of interconnected units. Each neuron is stimulated by one or more connections from other neurons, called synapses, and this signal is propagated throughout the system, in turn stimulating other neurons. In artificial neural networks, neurons are called perceptrons (Figure 2.1).

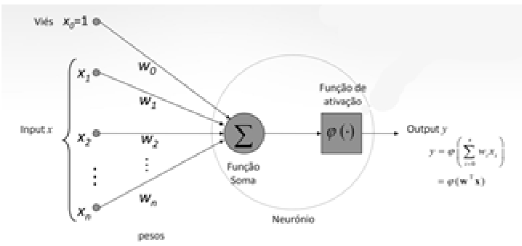

Figure 2.1: The Perceptron, or artificial neuron.

The output of the perceptron results from its training function or algorithm, the assigned weight, and the activation function. Training algorithms can be:

1. Perceptron Training Rule: random values are assigned to the coefficients w.
2. Gradient Descent: initializes the w coefficients randomly, applies them to all training examples in the unit, calculates the error generated for each w coefficient, and recalculates the error until it is low enough.
3. Stochastic Approximation to Gradient Descent: the correction value of each wi coefficient is calculated right after the presentation of a single example,

instead of adding up the errors of all the examples as in Gradient Descent.

The weight adjustment process is called an epoch; an epoch is when an entire dataset passes throughout the neural network back and forth once. The number of epochs rises according to the number of times w weights are adjusted and replaced.

As a result, the weights were adjusted more frequently when training with a neural network.

Briefly, in any of these training algorithms:

- Inputs that constitute training examples are applied to the perceptron or unit.

- Each one corresponds to a target value that is compared with a result: the output presented by the perceptron or linear unit.

- If this result generates a wrong classification, the synaptic coefficients or weights are readjusted.

- After training, in the presence of examples other than those used, the perceptron or unit must respond correctly.

The training functions can be:

- Hard-limit activation function (hardlim) - Figure 2.2.

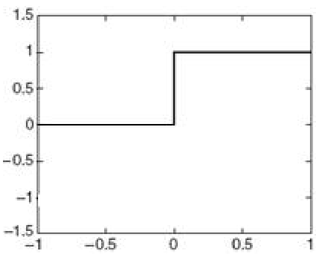

Figure 2.2: Plot: Hard-limit activation function (hardlim)

- Linear activation function (purelin) - Figure 2.3.

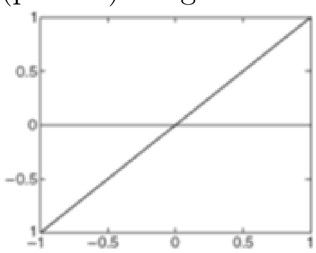

Figure 2.3: Plot: Linear activation function (purelin)

- Log-sigmoid activation function (logsig) - Figure 2.4.

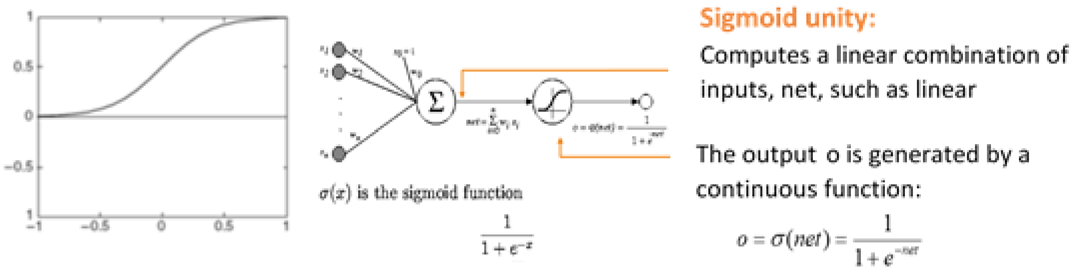

Figure 2.4: Plot: Log-sigmoid activation function (logsig)

- Hyperbolic tangent sigmoid activation function (tansig) - Figure 2.5.

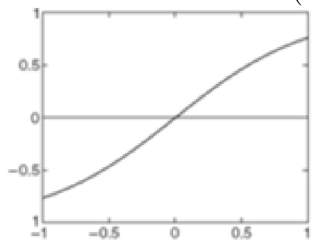

Figure 2.5: Plot: Hyperbolic tangent sigmoid activation function (tansig)

- Symmetric hard-limit activation function (hardlims) - Figure 2.6.

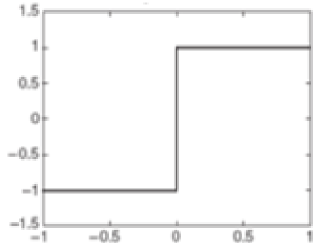

Figure 2.6: Plot: Symmetric hard-limit activation function (hardlims)

A set of perceptrons forms a neural network, the multilayer perceptron being a feed-forward network (Figure 2.7). The feed-forward network consists of an acyclic graph (usually completely connected), in which the inputs of each layer are the outputs of the previous layer.

Figure 2.7: Neural network

Perceptrons and linear units can only represent linear decision surfaces, giving results such as "positive" and "negative". Multilevel neural networks, trained by the BackPropagation Algorithm, adjust the weights of the networks from front to back, allowing you to train neural networks in multilayers so they can represent decision surfaces in very different ways.

The neural network is then composed of units organized into layers, usually 2 or 3, with the first units being the input units, which do not constitute a layer

(Figure 2.8). The inner units comprise the inner layer(s) or hidden layers, while the output units comprise the output layer.

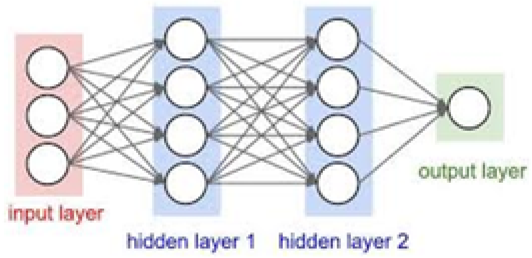

Figure 2.8: Neural network: input, hidden, and output layers.

The usefulness of neural networks is directly related to their ability to learn to classify, i.e., distinguish images, characters, sounds, etc., where each classification corresponds to an output or combination of different outputs. In order for this inherent utility to exist, three phases are needed, which are handled automatically by MATLAB[6] through the use of specific functions. By default, the program assigns them random values:

- Learning - generally there is a value of 70% when defined by the user.
- Validation - typically around 15%.
- Test - remaining 15%.

It is necessary to know these percentage metrics to know how good the system is, thus having a comparison term. When training, validation, and testing values are predefined, a hold-out validation process is generally used to have more data and to be able to prove that the samples created have statistical significance to represent the population.

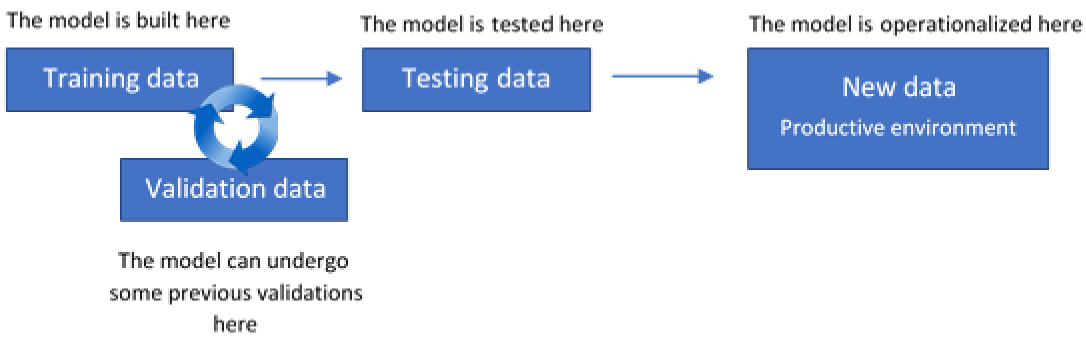

Figure 2.9: Training, validation, and testing.

If a model is tested with the same data that it was built with for training, its behavior cannot be generalized because it is unknown what its behavior is with previously unseen data and, for this, the data are used for testing (subchapter Leaves_3: test data). The same author, while training the network, the training data can be divided into several data sets: the validation data, used to perform the initial validations during network learning (subchapter Leaves_2: validation data); Throughout the entire process of training, validation, and testing, the homogeneity of data, applicable to the specific problem you have, must be maintained: if you work with leaf images at the beginning, you must work throughout the process with leaves.

Learning may be supervised, unsupervised, or by reinforcement learning (i.e., approximately "by reward"). It is done by changing the synaptic coefficients (weights, [w_n]) through an algorithm called backpropagation. Supervised training is done by applying previously classified examples (i.e., in which the intended inputs and outputs are already known) (Figure 2.10). Adjust the network parameters to find a function that performs the mapping between the provided input and output pairs.

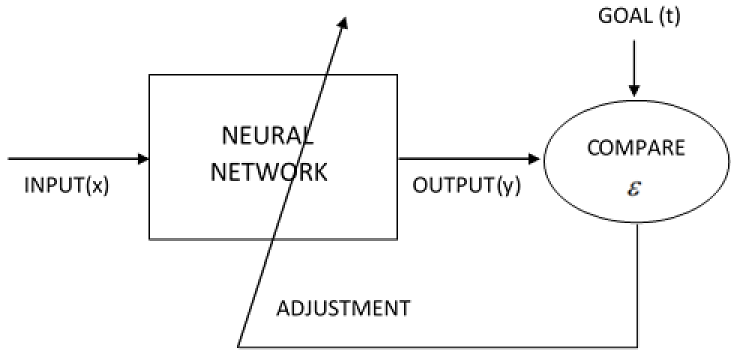

Figure 2.10: A scheme for the functioning of a neural network with supervised training.

There are two types of supervised training: offline and online. Once the network solution has been found, it must be maintained. If new data is added to the training set, a new training involving the previous data must be performed to avoid interference with the previous training. In unsupervised training (artificial neural networks), learning is done by discovering patterns in the input data. At the completion of a training session, the network is capable of resolving problems appropriately, whether successfully or not [3].

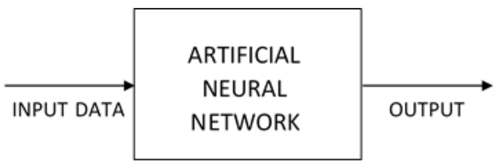

Figure 2.11: A neural network with unsupervised training (artificial neural network).

2.2 Introduction to the project

In this project, in order to train the neural network, three folders with black and white images of leaves were used as data for the training.

1. The folder "Leaves_1" contains 99 images;

2. The folder "Leaves_2" contains 1564 images;

3. The folder "Leaves_3" contains 20 images;

With the aim of creating a correspondence between the id of each image and its specie and sub specie, a table has been created. The input for the neural networks is the matrix containing such information.

Initially, the neural network was trained only with data from the folder Leaves_1 and, later with the data from the folder Leaves_2 was added to validate the training. At a later stage, the results are verified using the images contained in Leaves_3 and other images which were not previously provided.

A record of the results of every training performed on the neural networks has been kept, so all the training results were supervised, and the results can be compared in order to understand how different configurations can influence the final results.

2.2.1 Species

Figure 2.12 displays the species available in the folders "Leaves_1", "Leaves_2", and "Leaves_3", each specie being assigned a different color. Also, it can be observed the quantity of images (leaves) belonging to each specie.

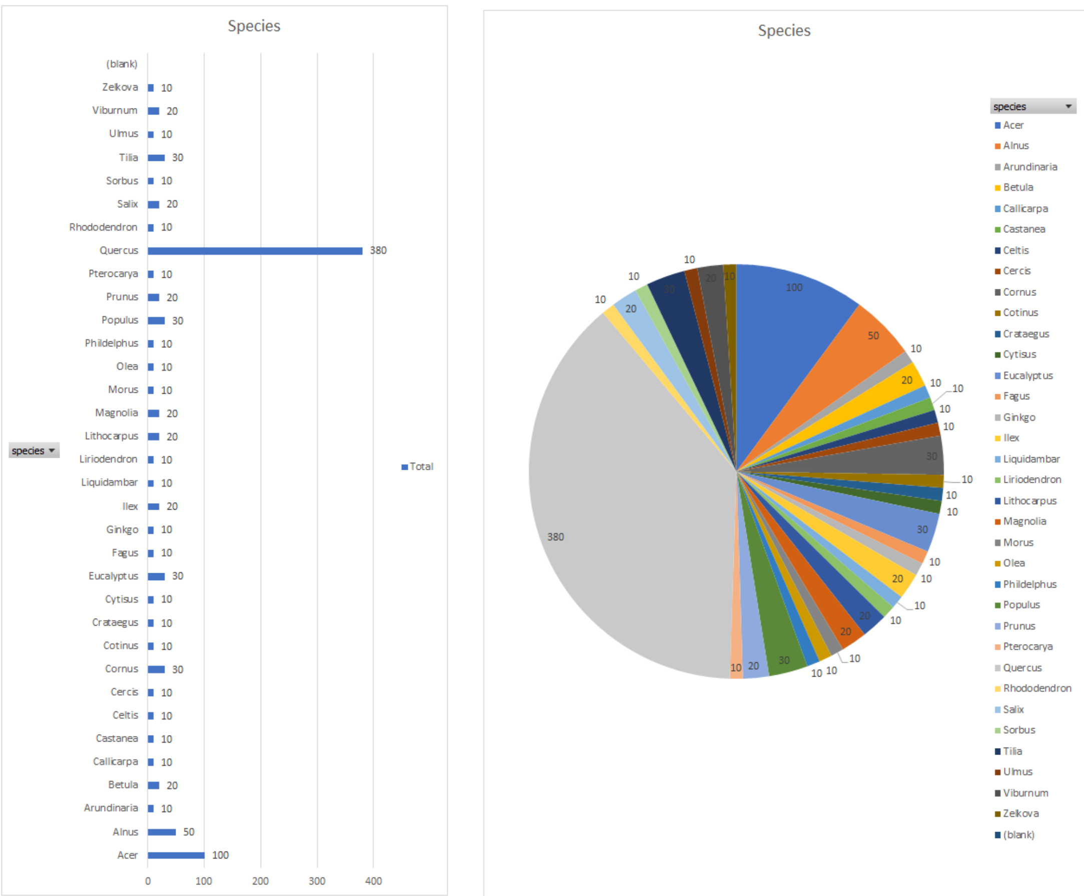

Figure 2.12: Species for the images in the folders: "Leaves_1", "Leaves_2", and "Leaves_3".

2.2.1.1 Procedure's description

In order to identify the species, it is necessary to process the input data. In view of this, a specific id has been assigned to each specie (Appendix A.1). Then, the images, which are in .JPG format (for example Figure 2.13), were converted to binary matrices, where the value 0 corresponds to black pixels and white pixels to the value 1. If the images were colored, they would be automatically transformed into black and white.

Figure 2.13: A sample image of a leaf.

As the size of the images for the leaves might be large, they will be reduced to 32 by 32 binary matrices, and the neural network output will be the classified specie (Figure 2.14).

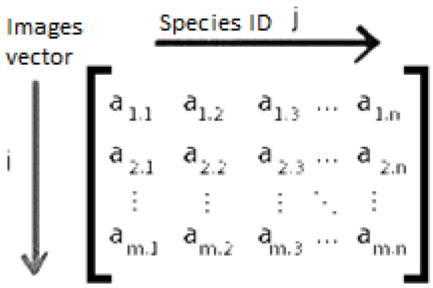

Figure 2.14: A matrix that contains image vectors in the rows and species IDs in the columns.

The matrix of vectorized images is then transposed, so that they can be entered as input data into the neural network (Figure 2.15).

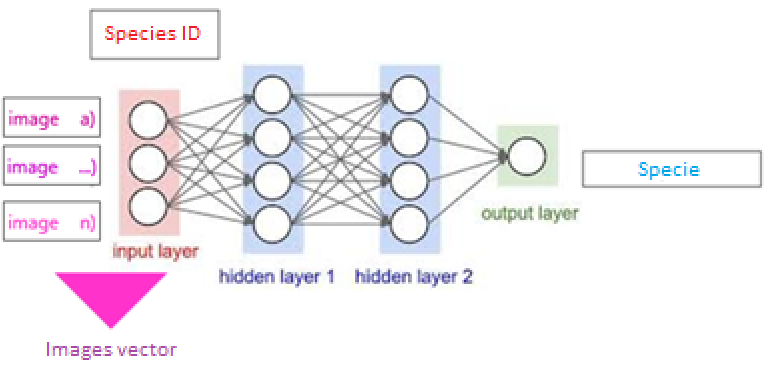

Figure 2.15: The neural network for species.

2.2.1.2 Characteristics

Extracting the characteristics from the leaf allows the neural network to quickly find the species and sub specie to which it belongs. The data from the leaf characteristics has been extracted using the function regionprops. The chosen characteristics to help train the neural network to identify the specie and sub specie of a leaf are the ones displayed in Table 2.1.

Table 2.1: The characteristics that were used to assess image region properties.

Characteristics	Description
ConvexArea	The number of pixels in "ConvexImage" is returned as a scalar.
Eccentricity	The eccentricity of the ellipse sharing the region's second moments returns as a scalar. The eccentricity of an ellipse is defined as the proportion of the distance between its foci to the length of its main axis. The value ranges from 0 to 1 (where 0 and 1 are degraded situations). An ellipse with an eccentricity of 0 is a circle, but one with an eccentricity of 1 is a line segment [5].
Extent	The ratio of pixels inside the area to those within the overall bounding box is returned as a scalar. Computed as the area of the bounding box divided by the size of the bounding box [5].
EquivDiameter	Returns the radius of a circle with the same area as the region as a scalar. Calculated as sqrt(4*area/pi) [5].
FilledArea	The number of pixels in the "FilledImage" is returned as a scalar [5].
MajorAxisLength	The main axis of the ellipse with the same standardized second central instants as the area is returned as a scalar with its length (in pixels) [5].
MinorAxisLength	The minor axis of the ellipse with the same standardized second central instants as the area is returned as a scalar with its length (in pixels) [5].
Orientation	The angle between the x-axis and the main axis of the ellipse is returned as a scalar with the same second instants as the area. The value is in degrees and ranges from -90 to 90 [5].
Perimeter	The distance around the area's border is returned as a scalar. The perimeter of an area is determined by calculating the distance between each pair of pixels (not broken) along the region's boundary. If the picture includes areas that are not contiguous, regionprops produce surprising results. This graphic depicts the pixels that were used to calculate the perimeter of this item [5].
Solidity	A scalar representing the ratio of pixels in the convex framework that are also in the area is returned. It is calculated as "Area" or "ConvexArea" [5].

2.2.2 Subspecies

In order to obtain the sub species, the same procedure as for the species was used, creating a new neural network. This time, a vector with the images, in binary, enters the network and targets the IDs of the images and the ID corresponding to their subspecies (Appendix A.2). The images are processed in the same way, thus obtaining the subspecies corresponding to the images. As we saw in Figure 2.12, the majority of leaves are from the Quercus species. Knowing this, it can be seen in Figure 2.16, the Quercus subspecies as an example.

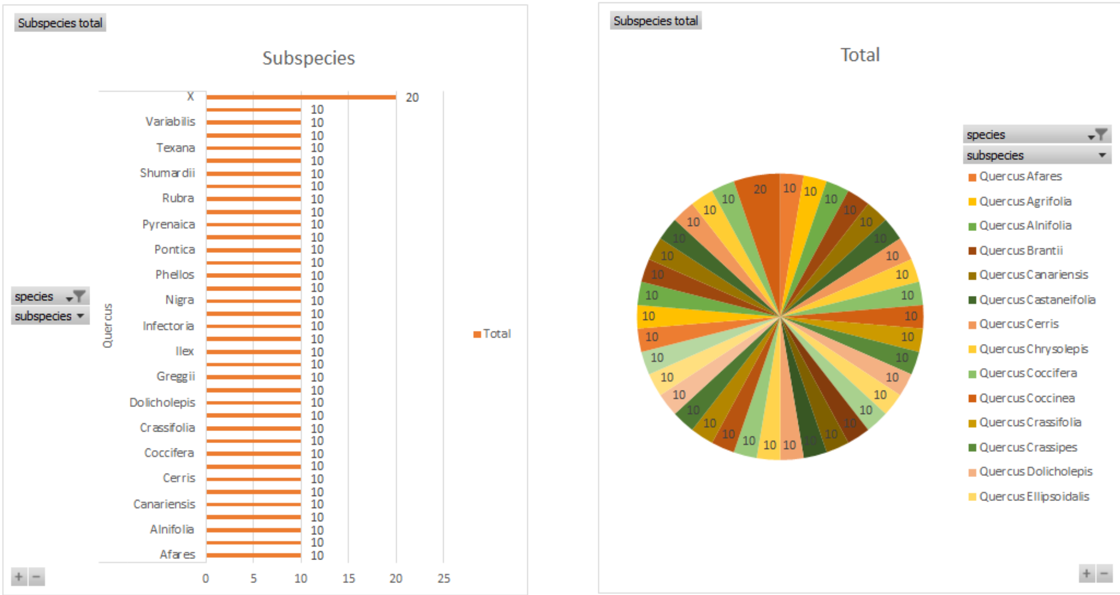

Figure 2.16: The subspecies for the specie "Quercus".

2.3 Goal of the project

The project is able to classify the specie and sub specie of an uploaded leaf based on all the training previously performed to prepare the neural networks. It will make use of the trained neural networks, the one trained by the images in binary or the one trained by the characteristics of the images, in order to classify the leaf. The results of the classification will be shown in the results section.

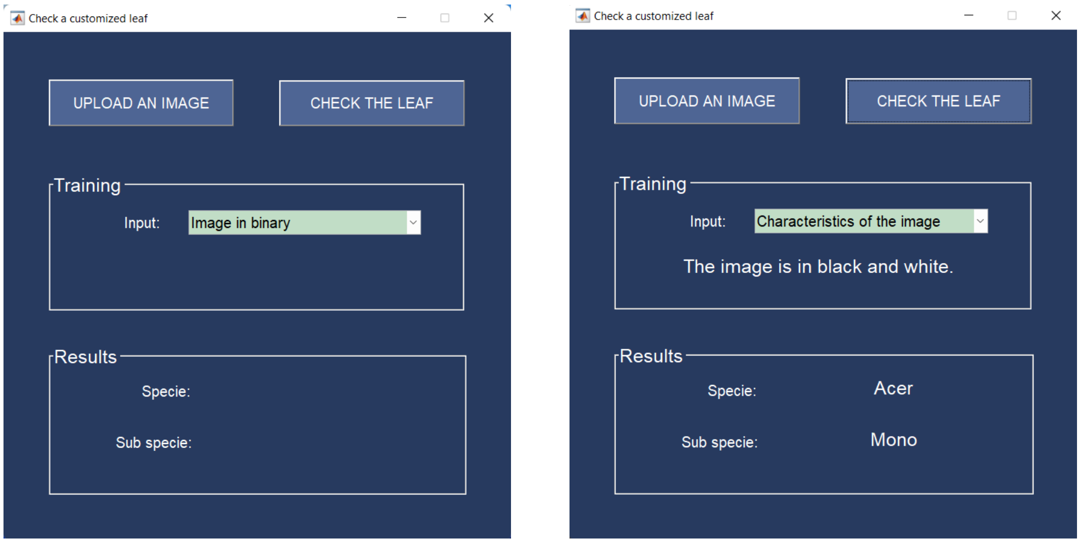

Figure 2.17: Neural Network - Check a customized leaf

Chapter 3

Related Work

This chapter intends to display some examples of other neural networks that have been developed and have become successful.

3.1 Similar products

Multiple individuals and companies have managed to develop neural networks that use image classification in order to recognize objects and/or people. As examples, we can mention social networks, COVID masks verifier, Google photos' location, reverse image search from Google, Shutterstock, image composition artificial intelligence, autopilot from Tesla, and a general analysis and comparison.

3.1.1 Social networks

In May 1997, the first true social media platform, named Six Degrees, was launched [8]. Since then, social media has grown enormously. Nowadays, social media has significantly influenced the world. The quick and broad use of these technologies is changing how individuals get news, communicate with each other, market their companies, and learn more about politics or any other subject.

Nowadays, the biggest social network platform in the world gathers 2.4 billion subscribers. Some different social networks have more than one billion subscribers as well. This implies that social networking platforms are used by one in every three people on the globe [10].

Even though these numbers are extremely high, if someone posts a picture where one appears and does not tag them, a notification will pop up immediately on one's device, alerting that someone posted a picture in which one might appear [1].

3.1.2 Covid masks verifier

On December 31, 2019, the World Health Organization received notification of cases of pneumonia of unidentified etiology in Wuhan City, China. Coronaviruses are a vast set of viruses that can generate a wide variety of diseases, ranging from the ordinary flu to deadly conditions [9].

The coronaviruses spread around the world and some mandatory rules have been imposed by every country in the world. One of these rules is the use of a healthcare mask. Since the usage of the mask became mandatory inside public spaces, some of the owners of those spaces have started using devices that recognize if one is using a mask or not. An example of the mentioned type of recognition is presented in Figure 3.1.

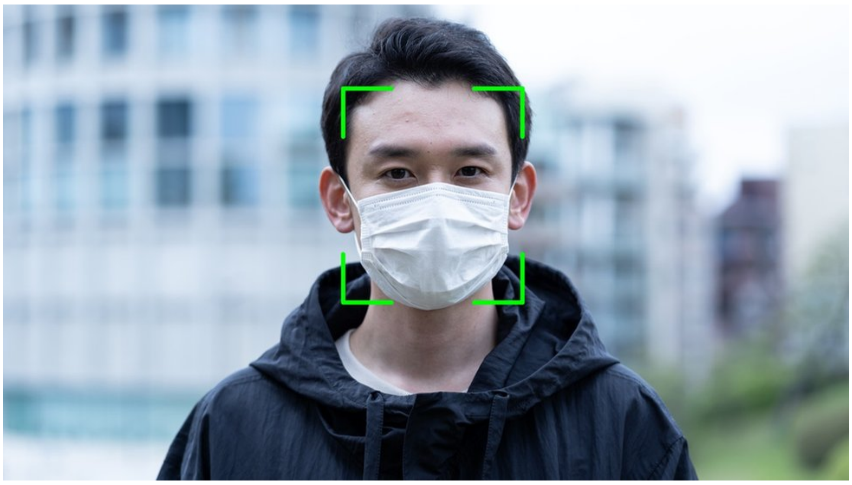

Figure 3.1: Covid masks verifier

3.1.3 Google: Photos' location

Google's neural network tells the user where photos were taken even when they do not have GPS turned on.

The system searches for visual indicators including architectural types, languages, and plant life and compares them to a database of 126 million geotagged photographs grouped into 26,000 grids. The lush foliage and Portuguese signage, for example, may indicate that you shot the photo in Brazil. It can even identify the locations of interior shots by starting with other, more identifiable images in the album [2].

Figure 3.2: Google Photos - Logo

3.1.4 Google: Reverse Image Search

In order to utilize Google's reverse image search, one just submits a photo and subsequently receives results of similar photos, similar articles, links, and information about the photo. An example of this search tool can be noticed in the figure 3.3.

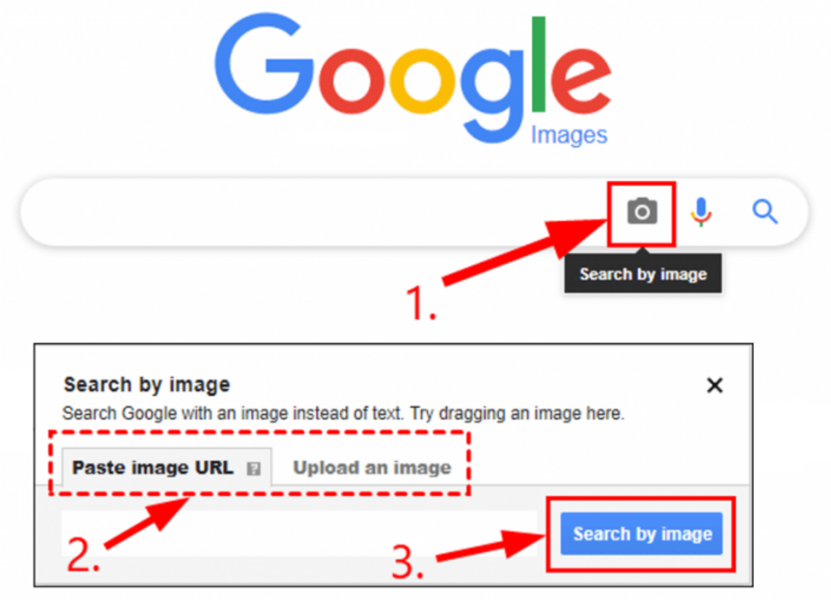

Figure 3.3: Google images - Search by image

3.1.5 Shutterstock: Image Composition AI

Shutterstock's AI enables the user to search for photos using words in a creative way. Instead of inputting words that describe a picture that the user wishes to locate, the user may position those words in relation to each other in the same manner that the objects would appear in the photo. An example can be seen in Figure 3.4.

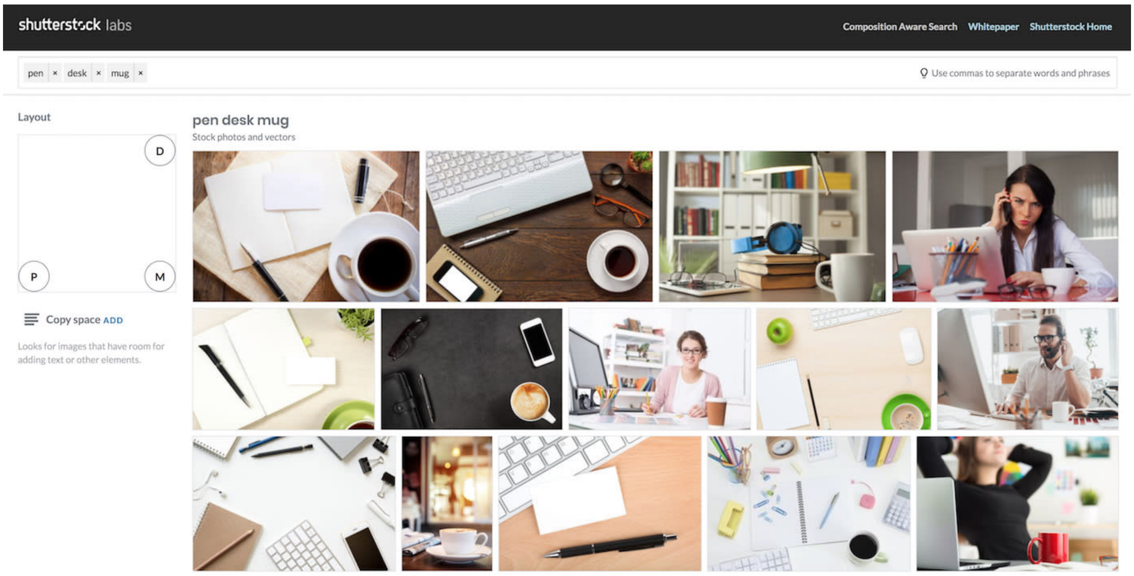

Figure 3.4: Shutterstock - Image search for photos using words

3.1.6 Tesla: Autopilot

Tesla refers to the usage of neural networks on their website. Their neural networks acquire knowledge from the most involved and diverse scenarios in the world, which are iteratively generated in real time by approximately 1 million cars.

Their full Autopilot neural network architecture consists of 48 neural networks that require 70,000 graphics processing units to train. Cooperatively, these neural networks output 1,000 different predictions at each timestep [7]. Figure 3.5 demonstrates a real scenario of the usage of the Autopilot by Tesla, where the way that the Autopilot sees and how the system works can be identified [7].

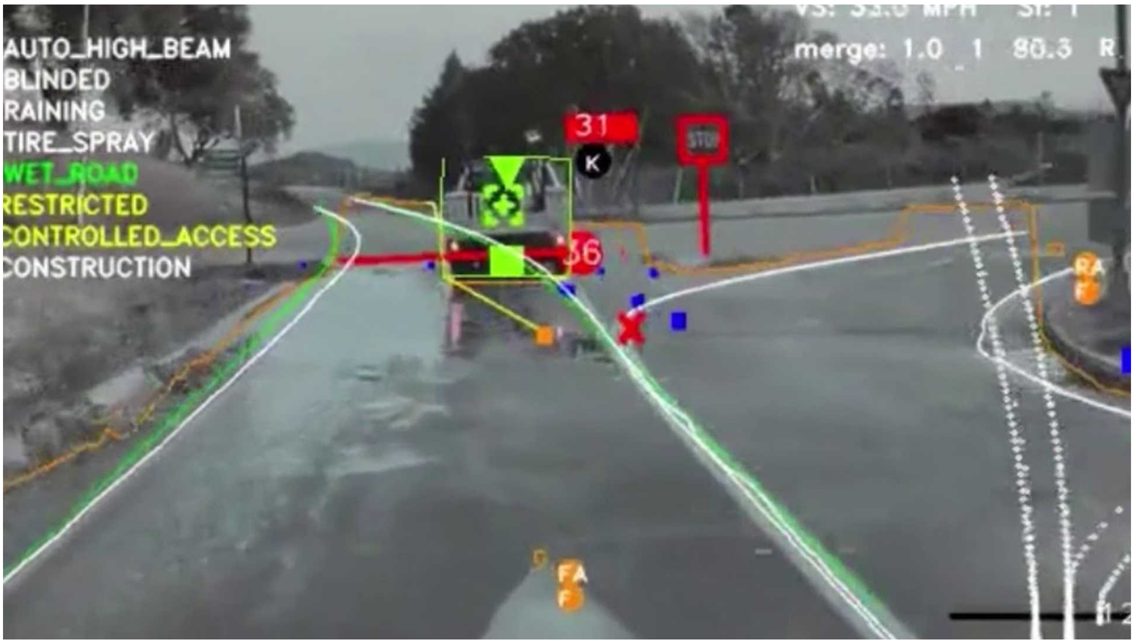

Figure 3.5: Tesla Autopilot - How it sees and how the system work

3.2 Analysis and comparison

All the neural networks mentioned above use image classification. Image classification designates the action of taking a picture as input (a photograph of a leaf) and outputting a class (like specie and sub specie of the leaf) or a possibility that the input is a certain class (there is a 90% possibility that that leaf is from specie X and sub specie Y).

The neural networks describe a vast breakthrough within image recognition. These neural networks are at the heart of everything, from photo tagging on social networks (Chapter 3.1.1) to self-driving cars (Chapter 3.1.6). These neural networks are always operating intensely in the background in a variety of applications, ranging from healthcare (Chapter 3.1.2) to viewing one's trip photographs (Chapter 3.1.3).

Chapter 4

Results

This chapter shows the most important results obtained from the neural networks.

4.1 Training

The neural network using as input the images in binary and the neural network using as input the characteristics of the images have trained 1082 times, in total, with different types of configuration.

All the training has been recorded in the Excel file "results.xlsx" which can be opened from the graphic user interface. The results of the training for the images in binary are in Appendix B, and the results of the training for the characteristics of the images are in Appendix C.

Both neural networks only achieved 100% of success rate when classifying the species for the leaves from the folder "Leaves_3".

The neural network using as input the images in binary has achieved 13 times 100% of success rate in total. 10 times of those 13, were using Perceptron Training Rule and Stochastic Approximation to Gradient Descent as training algorithms (5 times each of them). The transfer functions that most achieved 100% of success rate were the Linear and the Hyperbolic tangent sigmoid. Also, using 10 as hidden layer size achieved one more 100% success rate than using 2.

The neural network using as input the characteristics of the images has achieved 11 times 100% of success rate in total. 6 times of those 11, were using Stochastic Approximation to Gradient Descent as training algorithms. The transfer functions that most achieved 100% of success rate was the Hyperbolic tangent sigmoid which achieved 6 times. Also, using 10 as hidden layer size achieved 7 times 100% of success rate.

Since the input data was exactly the same to train both neural networks, it can be seen that Stochastic Approximation to Gradient Descent was the best training algorithm, Hyperbolic tangent sigmoid the best transfer function and 10 the best size for the hidden layers.

Chapter 5

Application Functionalities

This chapter is meant to describe the user guide and the developer guide.

5.1 User guide

The user will open the installer through its executable. There is no need to have MATLAB installed since the executable will install the prerequisites (if they are not already installed on one's computer) and the application itself.

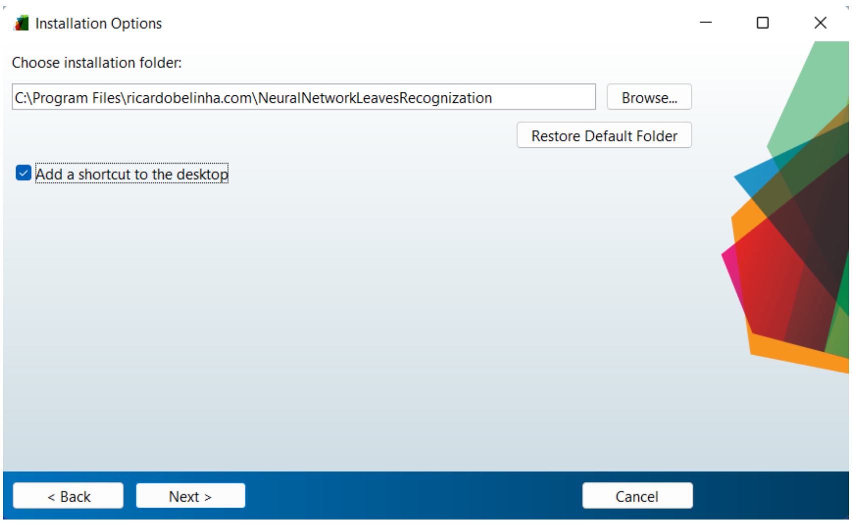

Figure 5.1: Installer

When the user opens the application, a main menu is shown, and it is possible to check the author's details, open the dissertation paper in ".PDF" format, or run the application, as it can be seen in figure 5.2.

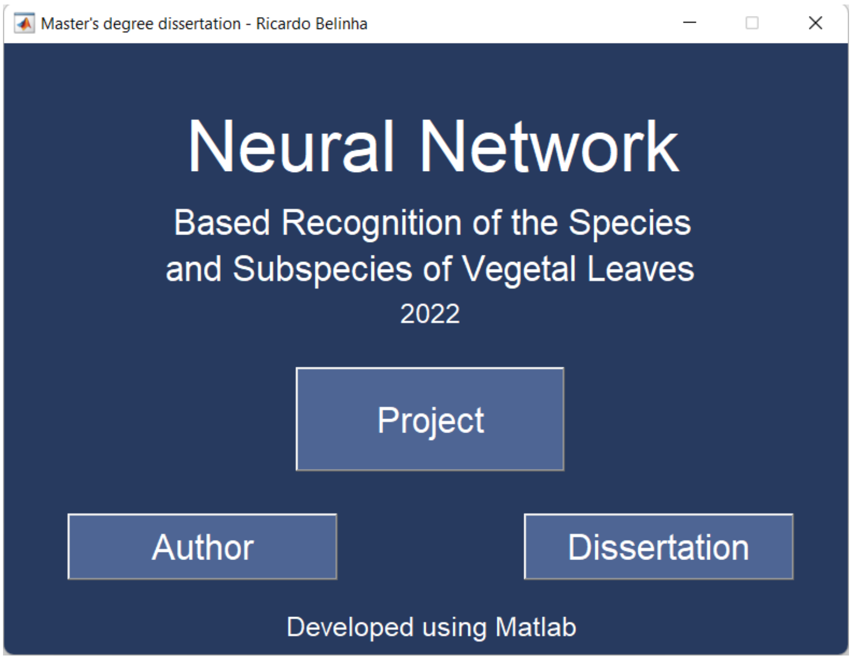

Figure 5.2: Main menu

If the user chooses to show the author's details, the information displayed in figure 5.3 is shown.

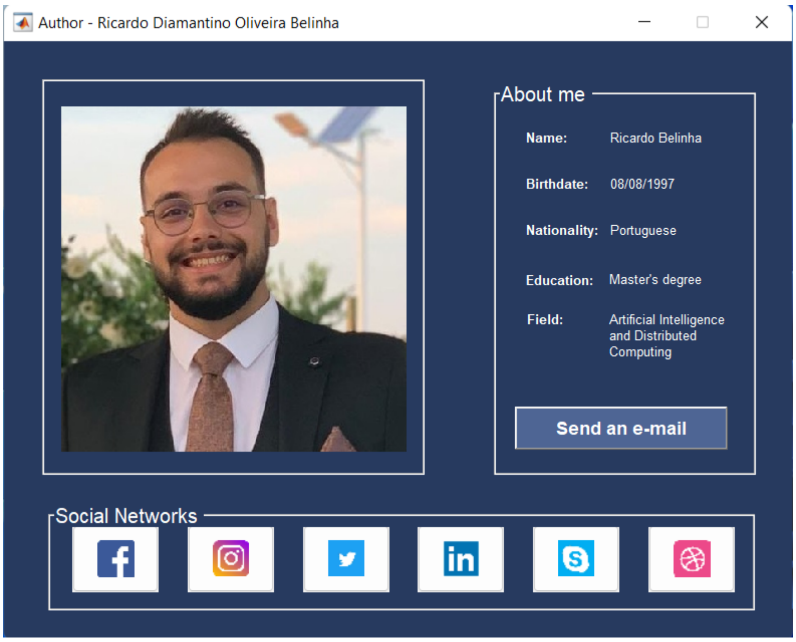

Figure 5.3: Author's details

When the user decides to run the application, one will be able to configure the entire neural network as one sees fit, as it can be seen in figure 5.4.

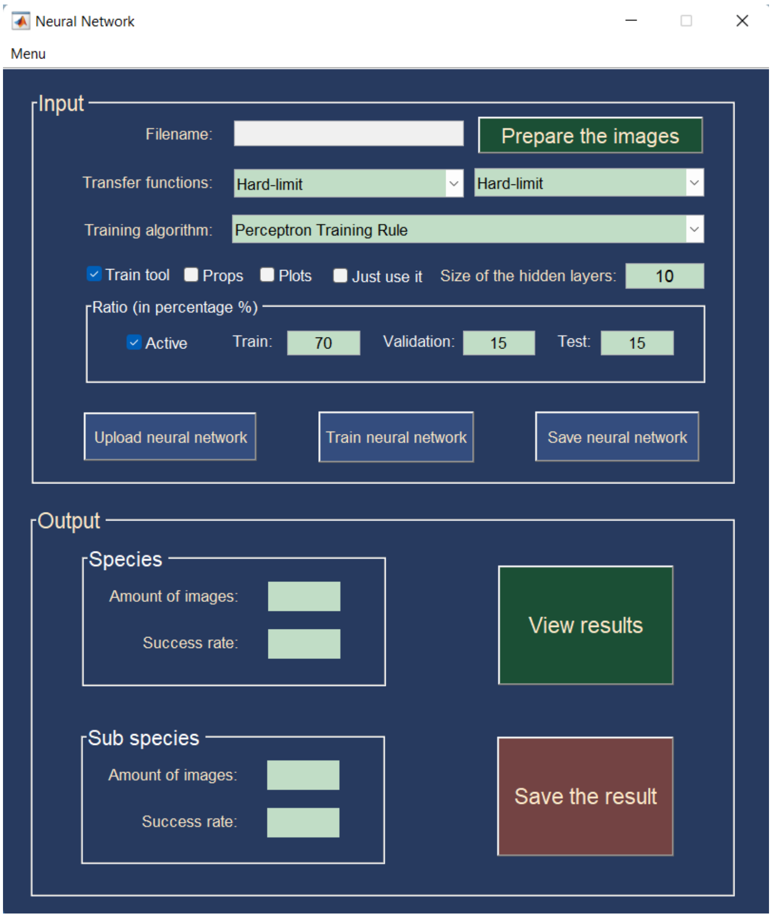

Figure 5.4: Neural Network

When clicking on the "Prepare the images" button, the graphic user interface will help the user to choose the folder that contains the images that will be uploaded to the software and used as training data for the neural neural network, as it can be seen in figure 5.5.

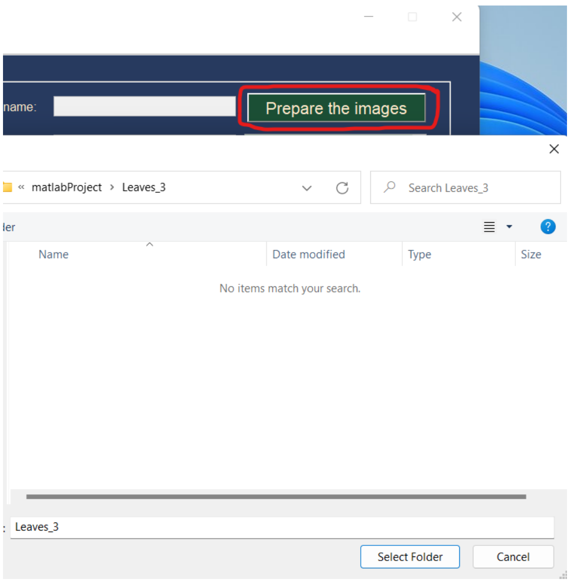

Figure 5.5: Neural Network - Preparing the images

When the user chooses the folder, the name of the folder will be displayed in the text box next to the filename, and the content of the folder will be taken as input. A notification will be displayed in order to inform the user that the images are ready to be entered as input data in the neural network, as it can be seen in figure 5.6.

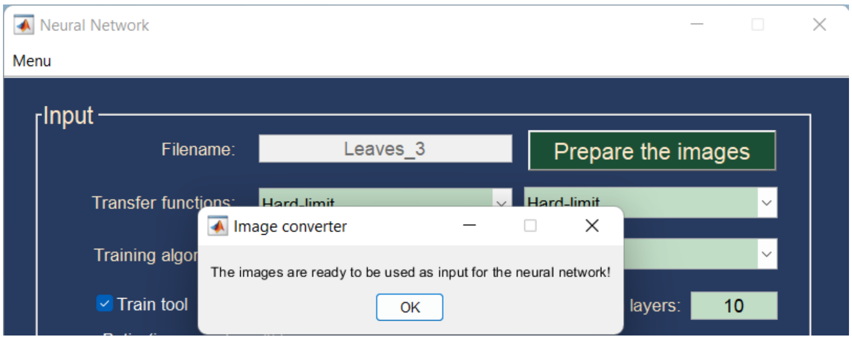

Figure 5.6: Neural Network - Feedback from preparing the images

The configuration of the neural network allows the user to try and test many different types of configurations in order to compare the results of such configurations. The neural network has as default, 2 layers defined with "net.numLayers = 2". The number of layers is not configurable. The figure 5.7 demonstrates which transfer functions are available for the first layer: hard-limit, linear, log-sigmoid, hyperbolic tangent sigmoid, and symmetric hard-limit.

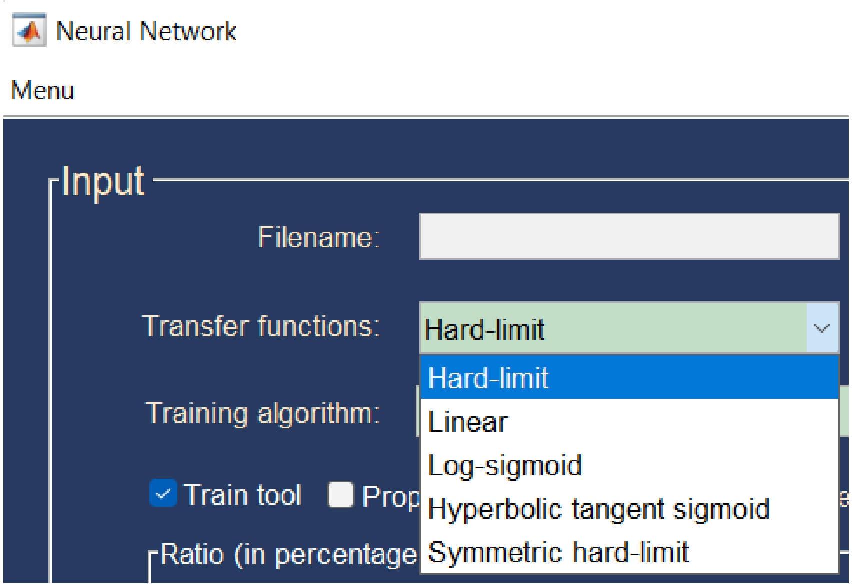

Figure 5.7: Neural Network - Configuration of the transfer function for the first layer

The figure 5.8 demonstrates which transfer functions are available for the second layer: hard-limit (hardlim), linear (purelin), log-sigmoid (logsig), hyperbolic tangent sigmoid (tansig), and symmetric hard-limit (hardlims). As it can be seen, it is possible to configure each layer with a different transfer function or the same.

While observing the results excel file, it can be seen that there was the "None" option for the transfer function for the second layer in this dropbox, but when selecting "None" as transfer function, it was using the default value from MATLAB for the transfer function, which is the hyperbolic tangent sigmoid (tansig). Since this transfer function can be directly selected by the user, the "None" option has been removed.

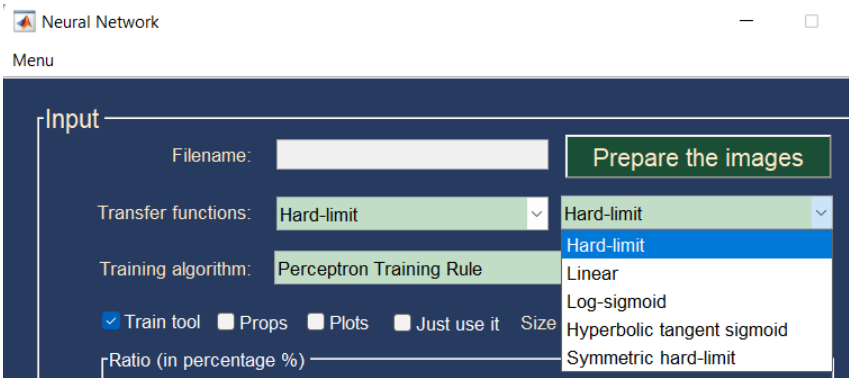

Figure 5.8: Neural Network - Configuration of the transfer function for the second layer

The figure 5.9 demonstrates which training algorithms are available: perceptron training rule (trainlm), gradient descent (traingd), and stochastic approximation to gradient descent (trainbfg).

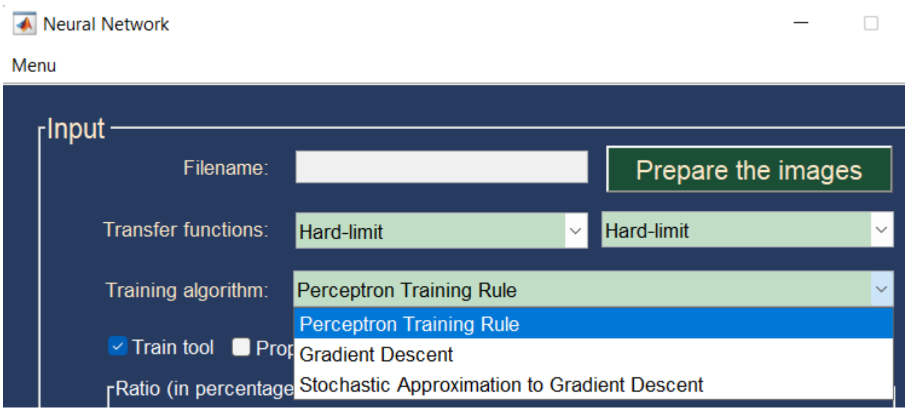

Figure 5.9: Neural Network - Configuration of the training algorithm

The size for the hidden layer in the neural network can also be configured as it can be seen in figure 5.10.

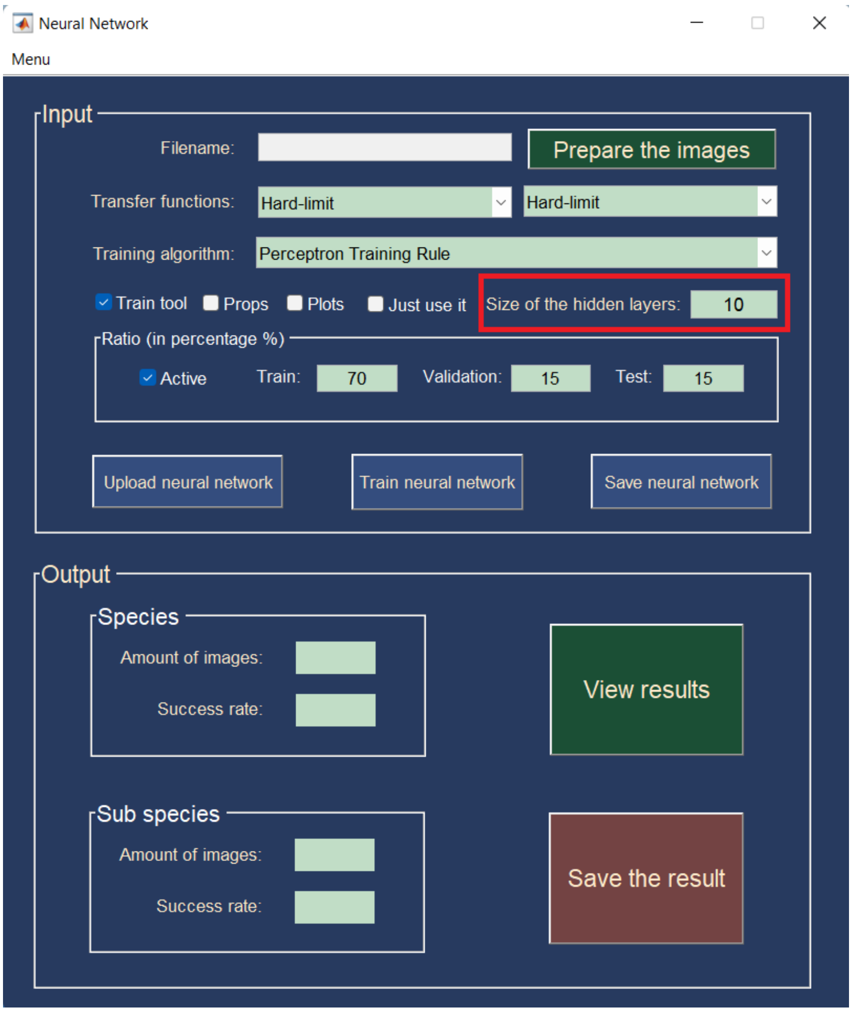

Figure 5.10: Neural Network - Configuration of the size for the hidden layer

All the steps above describe how the configuration of the neural network can be performed and how the training can be initiated. Figure 5.11 displays how to access the menu, where it is possible to close the application or upload an image to classify.

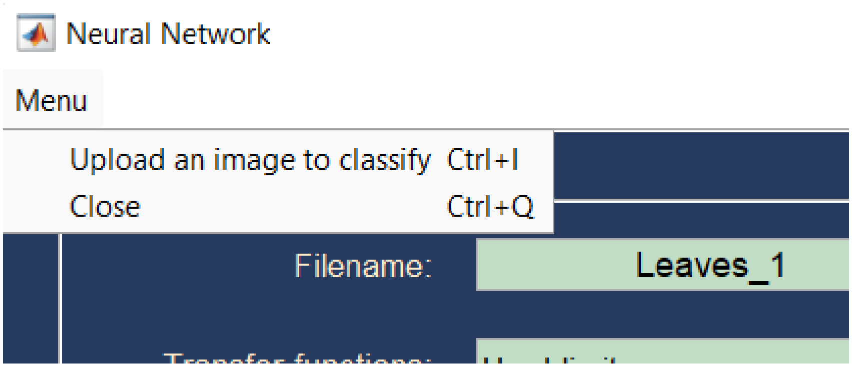

Figure 5.11: Neural Network - Menu

When the user chooses to upload an image to classify, a graphical user interface will open in order to select the image to use as input data. When the user decides to click on the "CHECK THE LEAF" button, the classification will be initiated and the output will be shown in the results group as soon as the validation finishes.

One can decide which neural network should be used: the neural network that has learned while training with the characteristics of the images or the other one that has trained with the images in binary. The results might differ since they are being classified in different ways.

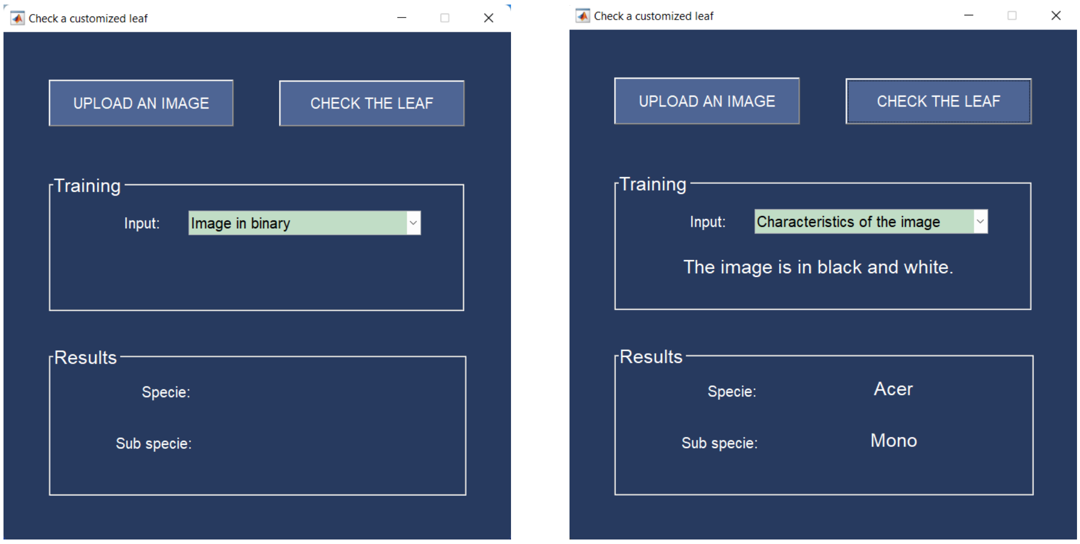

Figure 5.12: Neural Network - Check a customized leaf

5.2 Developer guide

This section will exhibit the technologies and tools that were used in this thesis, along with a brief description of their functionalities.

5.2.1 MATLAB

The MATLAB programming environment has various advantages over other methods or languages. The fundamental construction of a matrix utilizes a simple data element. A basic number is represented by a matrix with one row and one column. The MATLAB environment has a variety of mathematical algorithms that operate on data matrices and arrays. Notable instances include cross-products, dot-products, determinants, and inverted matrices. Rather than requiring a for or while loop, vectorized operations such as adding two arrays just require a single instruction. With communication in mind, the graphical output has been created. Using interactive graphical tools, users can quickly plot their own data and then change it by changing its size, color, and other things [6].

These are collections of methods that perform more specific tasks. They enhance the programming language as optimal for machine learning [6].

5.2.1.1 Deep Learn Toolbox

The Deep Learning Toolbox was crucial in deciding on MATLAB as the platform for coding my thesis project. This framework contains methods, training models, and applications for creating and executing deep neural networks. Convolutional neural networks and long-term memory (LSTM) networks may be used for classification and regression on image, time series, and text data. Users may examine activations, change network designs, and check preparation progress via charts and apps [4].

Users may outsource data processing beyond multicore central processing units and graphics processing units on the computer to clusters and clouds for additional training on large datasets [4].

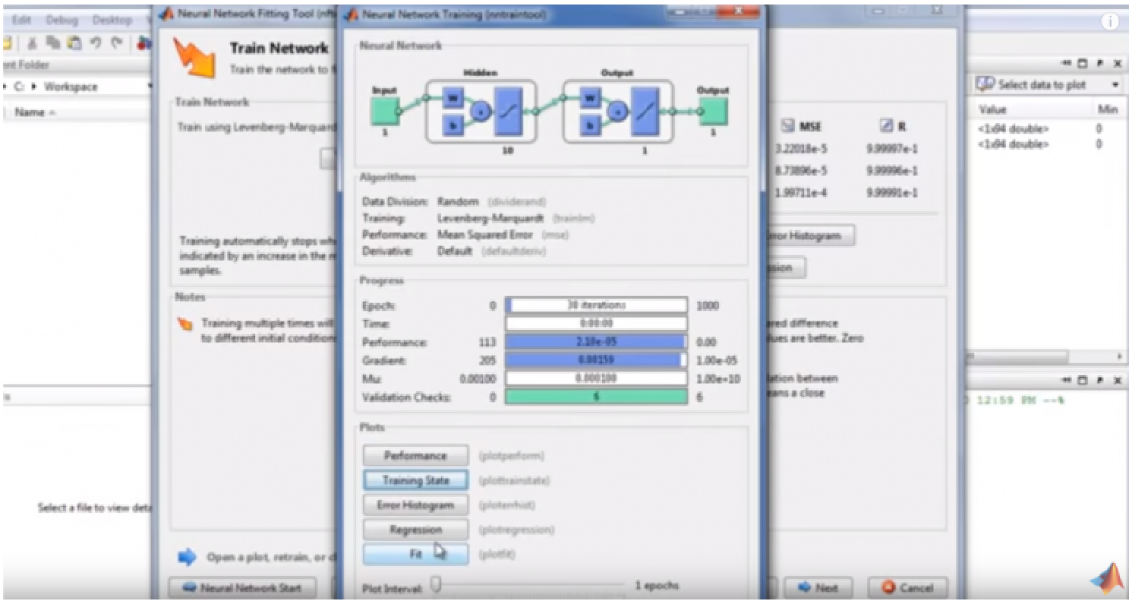

Figure 5.13: MATLAB - Deep Learn Toolbox

5.2.1.2 MATLAB GUI

Graphic User Interfaces (GUIs) let the user operate software programs using a friendly interface, reducing the need for others to learn a programming language or input commands. Applications that use a GUI can be shared for usage inside MATLAB, as well as as a separate desktop or online application.

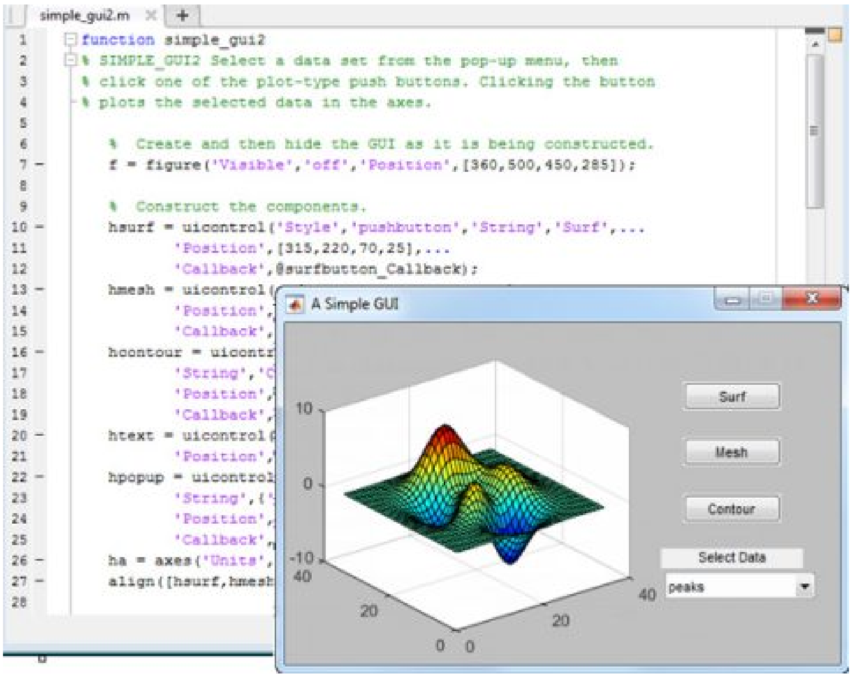

Figure 5.14: MATLAB - Example of a Graphic User Interface

5.2.1.3 MATLAB Application Compiler

MATLAB contains an application named ”Application Compiler” which helped to create the installer for the application, allowing it to be shared royalty-free with other users. The installer will download and install every needed prerequisite in order for the application to run without any problem. It is also easier for a non-developer user, since the graphic user interface will make everything easier. The user can choose to create a shortcut in their desktop and start using the application afterwards.

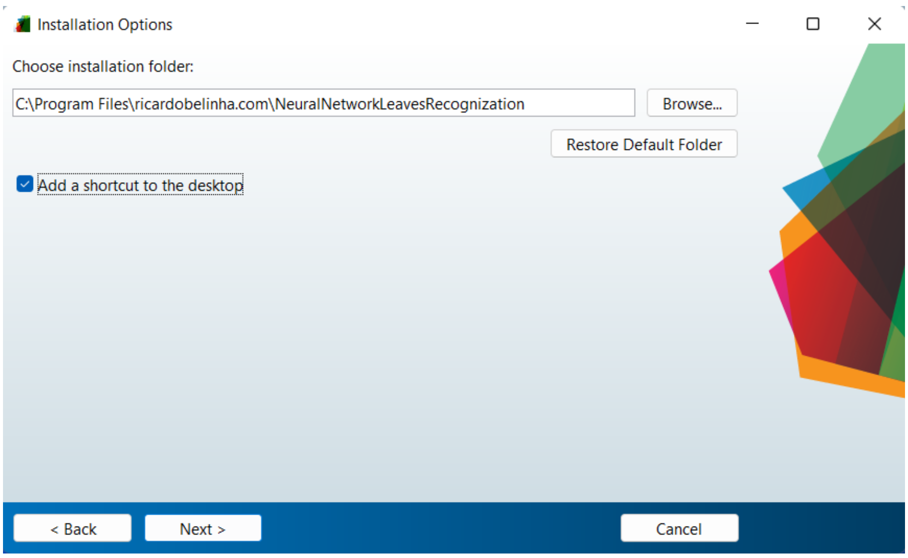

Figure 5.15: MATLAB - Application’s installer

5.2.2 Excel

Excel is also known as Microsoft's spreadsheet program, and it works by adjusting numbers and data using formulas and functions. Analysis performed by Excel is employed by organizations of all sizes around the globe to perform financial analysis. This tool is also very useful for entering and maintaining research study data. For this thesis project, Excel will be used to keep a record of the output data generated by the thesis script. Every time the script runs, the output data will be inserted into the same Excel file. It will be very helpful to compare the different results generated by different inputs.

Chapter 6

Conclusions and Future Work

This master's thesis used MATLAB to exhibit the process of developing a neural network that recognizes the specie and sub specie of a vegetable leaf.

The creation of the script aided in the understanding of the several processes required to produce two fully functional neural networks that are capable of training using numerous configurations and classifying the specie and sub specie of a leaf as a final result. The first neural network has been trained using the images in binary and the second one utilizes the characteristics of the images, as it can be seen in section 2.2.1.2. There have been performed, in total, 1082 different types of training for both neural networks, achieving an overall success rate of 100% 24 times.

The entire process of developing this project using MATLAB was beneficial due to the available applications that may support the developer. The Deep Learning Toolbox helped on the training part, which allows the developer to check the preparation progress via charts and apps. The MATLAB GUI helped to create the graphic user interface in order to provide a friendly interface, reducing the need for the user to learn a programming language or input commands to use the application. And, last but not least, the MATLAB Application Compiler, which creates an installer for the application, allowing it to be shared royalty-free with other users and installing all the prerequisites needed to run the project and the project itself.

The similar applications were truly helpful in terms of understanding the usefulness and importance of a neural network, since the neural networks described a vast breakthrough within image recognition. Those were the core of everything, from photo tagging on social networks (Chapter 3.1.1) to self-driving cars (Chapter 3.1.6). As it could be seen, neural networks are always running intensely in the background in many applications, ranging from healthcare (Chapter 3.1.2) to viewing one's trip photographs (Chapter 3.1.3). The similar applications show how positively a neural network with image recognition can impact one's life.

To summarize, everything was constructed from scratch, and the whole script is complete and ready for usage by anyone. The entire graphical user interface has been designed to make the script easier to use. As such, no prior knowledge of MATLAB coding is required.

In the future, I want to adapt this script to be able to run on all platforms and add augmented reality to it, which will attract more users and enable the script to be used to its full potential. Thus, users will be able to examine any leaf and determine its specie and sub specie. Moreover, for individuals who are passionate about leaves but have acrophobia, this software will also be great because it will be available to be used by drones, making it possible for these individuals to study many leaves from any type of tree. Furthermore, it would be an improvement in phytomorphology, combining technology and biology, contributing to the continuous development of science.

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Appendices

Appendix A

Mapping IDs with species and subspecies

A.1 Species and their IDs

id_specie	species
1	Acer
2	Alnus
3	Arundinaria
4	Betula
5	Callicarpa
6	Castanea
7	Celtis
8	Cercis
9	Cornus
10	Cotinus
11	Crataegus
12	Cytisus
13	Eucalyptus
14	Fagus
15	Ginkgo
16	Ilex
17	Liquidambar
18	Liriodendron
19	Lithocarpus
20	Magnolia
21	Morus
22	Olea
23	Phildelphus
24	Populus
25	Prunus
26	Pterocarya
27	Quercus
28	Rhododendron
29	Salix
30	Sorbus
31	Tilia
32	Ulmus
33	Viburnum
34	Zelkova

A.2 Subspecies and their IDs

id_subspecie	subspecies
1	Capillipes
2	Circinatum
3	Mono
4	Opalus
5	Palmatum
6	Pictum
7	Platanoids
8	Rubrum
9	Rufinerve
10	Saccharinum
11	Cordata
12	Maximowiczii
13	Rubra
14	Sieboldiana
15	Viridis
16	Simonii
17	Austrosinensis
18	Pendula
19	Bodinieri
20	Sativa
21	Koraiensis
22	Siliquastrum
23	Chinensis
24	Controversa
25	Macrophylla
26	Coggygria
27	Monogyna
28	Battandieri
29	Glaucescens
30	Neglecta
31	Urnigera
32	Sylvatica
33	Biloba

id_subspecie	subspecies
34	Aquifolium
35	Cornuta
36	Styraciflua
37	Tulipifera
38	Cleistocarpus
39	Edulis
40	Heptapeta
41	Salicifolia
42	Nigra
43	Europaea
44	Adenopoda
45	Grandidentata
46	Nigra
47	Avium
48	Shmittii
49	Stenoptera
50	Afares
51	Agrifolia
52	Alnifolia
53	Brantii
54	Canariensis
55	Castaneifolia
56	Cerris
57	Chrysolepis
58	Coccifera
59	Coccinea
60	Crassifolia
61	Crassipes
62	Dolicholepis
63	Ellipsoidalis
64	Greggii
65	Hartwissiana
66	Hispanica

id_subspecie	subspecies
67	Ilex
68	Imbricaria
69	Infectoria
70	Kewensis
71	Nigra
72	Palustris
73	Phellos
74	Phillyraeoides
75	Pontica
76	Pubescens
77	Pyrenaica
78	Rhysophylla
79	Rubra
80	Semecarpifolia
81	Shumardii
82	Suber
83	Texana
84	Trojana
85	Turneri
86	Variabilis
87	Vulcanica
88	Russellianum
89	Fragilis
90	Intergra
91	Aria
92	Oliveri
93	Platyphyllos
94	Tomentosa
95	Bergmanniana
96	Rhytidophylloides
97	Tinus
98	Serrata

Appendix B

Training results for the images in binary

Table B.1: Training - Image in binary with Leaves_1 - Part 1

		Transfer functions			Ratio (in percentage %)				Species			Species		
Folder	Hidden L.	1st	2nd	Training algorithm	Train	Validation	Test	Quant. images	Success %	Epoch	Duration	Success %	Epoch	Duration
Leaves_1	2	Hard-limit	Hard-limit	Perceptron Training Rule	80	10	10	99	0.00%	0	0	0.00%	0	0
Leaves_1	2	Hard-limit	Linear	Perceptron Training Rule	80	10	10	99	10.00%	0	0	0.00%	0	0
Leaves_1	2	Hard-limit	Log-sigmoid	Perceptron Training Rule	80	10	10	99	10.00%	0	0	0.00%	0	0
Leaves_1	2	Hard-limit	Hyperbolic tangent sigmoid	Perceptron Training Rule	80	10	10	99	0.00%	0	0	0.00%	0	0
Leaves_1	2	Hard-limit	Symmetric hard-limit	Perceptron Training Rule	80	10	10	99	10.00%	0	0	0.00%	0	0
Leaves_1	2	Hard-limit	None	Perceptron Training Rule	80	10	10	99	20.00%	0	0	0.00%	0	0
Leaves_1	2	Linear	Hard-limit	Perceptron Training Rule	80	10	10	99	20.00%	0	0	0.00%	0	0
Leaves_1	2	Linear	Linear	Perceptron Training Rule	80	10	10	99	10.00%	0	0	0.00%	0	0
Leaves_1	2	Linear	Log-sigmoid	Perceptron Training Rule	80	10	10	99	20.00%	0	0	0.00%	0	0
Leaves_1	2	Linear	Hyperbolic tangent sigmoid	Perceptron Training Rule	80	10	10	99	10.00%	0	0	0.00%	0	0
Leaves_1	2	Linear	Symmetric hard-limit	Perceptron Training Rule	80	10	10	99	20.00%	0	0	0.00%	0	0
Leaves_1	2	Linear	None	Perceptron Training Rule	80	10	10	99	0.00%	0	0	0.00%	0	0
Leaves_1	2	Log-sigmoid	Hard-limit	Perceptron Training Rule	80	10	10	99	10.00%	0	0	0.00%	0	0
Leaves_1	2	Log-sigmoid	Linear	Perceptron Training Rule	80	10	10	99	0.00%	0	0	10.00%	0	0
Leaves_1	2	Log-sigmoid	Log-sigmoid	Perceptron Training Rule	80	10	10	99	0.00%	0	0	0.00%	0	0
Leaves_1	2	Log-sigmoid	Hyperbolic tangent sigmoid	Perceptron Training Rule	80	10	10	99	0.00%	0	0	0.00%	0	0
Leaves_1	2	Log-sigmoid	Symmetric hard-limit	Perceptron Training Rule	80	10	10	99	10.00%	0	0	0.00%	0	0
Leaves_1	2	Log-sigmoid	None	Perceptron Training Rule	80	10	10	99	0.00%	0	0	10.00%	0	0
Leaves_1	2	Hyperbolic tangent sigmoid	Hard-limit	Perceptron Training Rule	80	10	10	99	10.00%	0	0	0.00%	0	0
Leaves_1	2	Hyperbolic tangent sigmoid	Linear	Perceptron Training Rule	80	10	10	99	20.00%	0	0	0.00%	0	0
Leaves_1	2	Hyperbolic tangent sigmoid	Log-sigmoid	Perceptron Training Rule	80	10	10	99	10.00%	0	0	0.00%	0	0
Leaves_1	2	Hyperbolic tangent sigmoid	Hyperbolic tangent sigmoid	Perceptron Training Rule	80	10	10	99	10.00%	0	0	0.00%	0	0
Leaves_1	2	Hyperbolic tangent sigmoid	Symmetric hard-limit	Perceptron Training Rule	80	10	10	99	0.00%	0	0	0.00%	0	0
Leaves_1	2	Hyperbolic tangent sigmoid	None	Perceptron Training Rule	80	10	10	99	0.00%	0	0	0.00%	0	0
Leaves_1	2	Symmetric hard-limit	Hard-limit	Perceptron Training Rule	80	10	10	99	0.00%	0	0	0.00%	0	0
Leaves_1	2	Symmetric hard-limit	Linear	Perceptron Training Rule	80	10	10	99	10.00%	0	0	0.00%	0	0
Leaves_1	2	Symmetric hard-limit	Log-sigmoid	Perceptron Training Rule	80	10	10	99	20.00%	0	0	0.00%	0	0
Leaves_1	2	Symmetric hard-limit	Hyperbolic tangent sigmoid	Perceptron Training Rule	80	10	10	99	0.00%	0	0	0.00%	0	0
Leaves_1	2	Symmetric hard-limit	Symmetric hard-limit	Perceptron Training Rule	80	10	10	99	10.00%	0	0	0.00%	0	0
Leaves_1	2	Symmetric hard-limit	None	Perceptron Training Rule	80	10	10	99	10.00%	0	0	0.00%	0	0
Leaves_1	2	Hard-limit	Hard-limit	Gradient Descent	80	10	10	99	0.00%	0	0	0.00%	0	0
Leaves_1	2	Hard-limit	Linear	Gradient Descent	80	10	10	99	10.00%	0	0	0.00%	0	0
Leaves_1	2	Hard-limit	Log-sigmoid	Gradient Descent	80	10	10	99	0.00%	0	0	0.00%	0	0
Leaves_1	2	Hard-limit	Hyperbolic tangent sigmoid	Gradient Descent	80	10	10	99	0.00%	0	0	0.00%	0	0
Leaves_1	2	Hard-limit	Symmetric hard-limit	Gradient Descent	80	10	10	99	10.00%	0	0	0.00%	0	0
Leaves_1	2	Hard-limit	None	Gradient Descent	80	10	10	99	20.00%	0	0	0.00%	0	0
Leaves_1	2	Linear	Hard-limit	Gradient Descent	80	10	10	99	10.00%	0	0	0.00%	0	0
Leaves_1	2	Linear	Linear	Gradient Descent	80	10	10	99	10.00%	0	0	0.00%	0	0
Leaves_1	2	Linear	Log-sigmoid	Gradient Descent	80	10	10	99	0.00%	0	0.04	0.00%	0	0
Leaves_1	2	Linear	Hyperbolic tangent sigmoid	Gradient Descent	80	10	10	99	20.00%	0	0	0.00%	0	0
Leaves_1	2	Linear	Symmetric hard-limit	Gradient Descent	80	10	10	99	20.00%	0	0	0.00%	0	0
Leaves_1	2	Linear	None	Gradient Descent	80	10	10	99	20.00%	0	0	0.00%	0	0
Leaves_1	2	Log-sigmoid	Hard-limit	Gradient Descent	80	10	10	99	10.00%	0	0	0.00%	0	0
Leaves_1	2	Log-sigmoid	Linear	Gradient Descent	80	10	10	99	10.00%	0	0	0.00%	0	0
Leaves_1	2	Log-sigmoid	Log-sigmoid	Gradient Descent	80	10	10	99	10.00%	0	0	0.00%	0	0

Table B.2: Training - Image in binary with Leaves_1 - Part 2

		Transfer functions			Ratio (in percentage %)				Species			Species		
Folder	Hidden L.	1st	2nd	Training algorithm	Train	Validation	Test	Quant. images	Success %	Epoch	Duration	Success %	Epoch	Duration
Leaves_1	2	Log-sigmoid	Hyperbolic tangent sigmoid	Gradient Descent	80	10	10	99	0.00%	0	0	0.00%	0	0
Leaves_1	2	Log-sigmoid	Symmetric hard-limit	Gradient Descent	80	10	10	99	20.00%	0	0	0.00%	0	0
Leaves_1	2	Log-sigmoid	None	Gradient Descent	80	10	10	99	30.00%	0	0	0.00%	0	0
Leaves_1	2	Hyperbolic tangent sigmoid	Hard-limit	Gradient Descent	80	10	10	99	10.00%	0	0	0.00%	0	0
Leaves_1	2	Hyperbolic tangent sigmoid	Linear	Gradient Descent	80	10	10	99	0.00%	0	0	0.00%	0	0
Leaves_1	2	Hyperbolic tangent sigmoid	Log-sigmoid	Gradient Descent	80	10	10	99	0.00%	0	0	10.00%	0	0
Leaves_1	2	Hyperbolic tangent sigmoid	Hyperbolic tangent sigmoid	Gradient Descent	80	10	10	99	10.00%	0	0	0.00%	0	0
Leaves_1	2	Hyperbolic tangent sigmoid	Symmetric hard-limit	Gradient Descent	80	10	10	99	10.00%	0	0	0.00%	0	0
Leaves_1	2	Hyperbolic tangent sigmoid	None	Gradient Descent	80	10	10	99	0.00%	0	0	0.00%	0	0
Leaves_1	2	Symmetric hard-limit	Hard-limit	Gradient Descent	80	10	10	99	0.00%	0	0	0.00%	0	0
Leaves_1	2	Symmetric hard-limit	Linear	Gradient Descent	80	10	10	99	30.00%	0	0	0.00%	0	0
Leaves_1	2	Symmetric hard-limit	Log-sigmoid	Gradient Descent	80	10	10	99	20.00%	0	0	0.00%	0	0
Leaves_1	2	Symmetric hard-limit	Hyperbolic tangent sigmoid	Gradient Descent	80	10	10	99	20.00%	0	0	0.00%	0	0
Leaves_1	2	Symmetric hard-limit	Symmetric hard-limit	Gradient Descent	80	10	10	99	0.00%	0	0	0.00%	0	0
Leaves_1	2	Symmetric hard-limit	None	Gradient Descent	80	10	10	99	10.00%	0	0	10.00%	0	0
Leaves_1	2	Hard-limit	Hard-limit	Stochastic Approximation to Gradient Descent	80	10	10	99	0.00%	0	0	0.00%	0	0
Leaves_1	2	Hard-limit	Linear	Stochastic Approximation to Gradient Descent	80	10	10	99	0.00%	0	0	10.00%	0	0
Leaves_1	2	Hard-limit	Log-sigmoid	Stochastic Approximation to Gradient Descent	80	10	10	99	10.00%	0	0	0.00%	0	0
Leaves_1	2	Hard-limit	Hyperbolic tangent sigmoid	Stochastic Approximation to Gradient Descent	80	10	10	99	0.00%	0	0	10.00%	0	0
Leaves_1	2	Hard-limit	Symmetric hard-limit	Stochastic Approximation to Gradient Descent	80	10	10	99	10.00%	0	0	0.00%	0	0
Leaves_1	2	Hard-limit	None	Stochastic Approximation to Gradient Descent	80	10	10	99	20.00%	0	0	0.00%	0	0
Leaves_1	2	Linear	Hard-limit	Stochastic Approximation to Gradient Descent	80	10	10	99	0.00%	0	0	0.00%	0	0
Leaves_1	2	Linear	Linear	Stochastic Approximation to Gradient Descent	80	10	10	99	30.00%	0	0	0.00%	0	0
Leaves_1	2	Linear	Log-sigmoid	Stochastic Approximation to Gradient Descent	80	10	10	99	0.00%	0	0	0.00%	0	0
Leaves_1	2	Linear	Hyperbolic tangent sigmoid	Stochastic Approximation to Gradient Descent	80	10	10	99	0.00%	0	0	0.00%	0	0
Leaves_1	2	Linear	Symmetric hard-limit	Stochastic Approximation to Gradient Descent	80	10	10	99	30.00%	0	0	0.00%	0	0
Leaves_1	2	Linear	None	Stochastic Approximation to Gradient Descent	80	10	10	99	10.00%	0	0	0.00%	0	0
Leaves_1	2	Log-sigmoid	Hard-limit	Stochastic Approximation to Gradient Descent	80	10	10	99	10.00%	0	0	0.00%	0	0
Leaves_1	2	Log-sigmoid	Linear	Stochastic Approximation to Gradient Descent	80	10	10	99	0.00%	0	0	0.00%	0	0
Leaves_1	2	Log-sigmoid	Log-sigmoid	Stochastic Approximation to Gradient Descent	80	10	10	99	20.00%	0	0	0.00%	0	0
Leaves_1	2	Log-sigmoid	Hyperbolic tangent sigmoid	Stochastic Approximation to Gradient Descent	80	10	10	99	20.00%	0	0	0.00%	0	0
Leaves_1	2	Log-sigmoid	Symmetric hard-limit	Stochastic Approximation to Gradient Descent	80	10	10	99	0.00%	0	0	0.00%	0	0
Leaves_1	2	Log-sigmoid	None	Stochastic Approximation to Gradient Descent	80	10	10	99	0.00%	0	0	0.00%	0	0
Leaves_1	2	Hyperbolic tangent sigmoid	Hard-limit	Stochastic Approximation to Gradient Descent	80	10	10	99	0.00%	0	0	10.00%	0	0
Leaves_1	2	Hyperbolic tangent sigmoid	Linear	Stochastic Approximation to Gradient Descent	80	10	10	99	30.00%	0	0	0.00%	0	0
Leaves_1	2	Hyperbolic tangent sigmoid	Log-sigmoid	Stochastic Approximation to Gradient Descent	80	10	10	99	10.00%	0	0	0.00%	0	0
Leaves_1	2	Hyperbolic tangent sigmoid	Hyperbolic tangent sigmoid	Stochastic Approximation to Gradient Descent	80	10	10	99	20.00%	0	0	0.00%	0	0
Leaves_1	2	Hyperbolic tangent sigmoid	Symmetric hard-limit	Stochastic Approximation to Gradient Descent	80	10	10	99	0.00%	0	0	0.00%	0	0
Leaves_1	2	Hyperbolic tangent sigmoid	None	Stochastic Approximation to Gradient Descent	80	10	10	99	20.00%	0	0	0.00%	0	0
Leaves_1	2	Symmetric hard-limit	Hard-limit	Stochastic Approximation to Gradient Descent	80	10	10	99	10.00%	0	0	0.00%	0	0
Leaves_1	2	Symmetric hard-limit	Linear	Stochastic Approximation to Gradient Descent	80	10	10	99	20.00%	0	0	0.00%	0	0

Table B.3: Training - Image in binary with Leaves_1 - Part 3

		Transfer functions			Ratio (in percentage %)				Species			Species		
Folder	Hidden L.	1st	2nd	Training algorithm	Train	Validation	Test	Quant. images	Success %	Epoch	Duration	Success %	Epoch	Duration
Leaves_1	2	Symmetric hard-limit	Log-sigmoid	Stochastic Approximation to Gradient Descent	80	10	10	99	0.00%	0	0	0.00%	0	0
Leaves_1	2	Symmetric hard-limit	Hyperbolic tangent sigmoid	Stochastic Approximation to Gradient Descent	80	10	10	99	0.00%	0	0	10.00%	0	0
Leaves_1	2	Symmetric hard-limit	Symmetric hard-limit	Stochastic Approximation to Gradient Descent	80	10	10	99	10.00%	0	0	0.00%	0	0
Leaves_1	2	Symmetric hard-limit	None	Stochastic Approximation to Gradient Descent	80	10	10	99	30.00%	0	0	0.00%	0	0
Leaves_1	10	Hard-limit	Hard-limit	Perceptron Training Rule	70	15	15	99	10.00%	0	0	0.00%	0	0
Leaves_1	10	Hard-limit	Linear	Perceptron Training Rule	70	15	15	99	10.00%	0	0	10.00%	0	0
Leaves_1	10	Hard-limit	Log-sigmoid	Perceptron Training Rule	70	15	15	99	10.00%	0	0	0.00%	0	0
Leaves_1	10	Hard-limit	Hyperbolic tangent sigmoid	Perceptron Training Rule	70	15	15	99	20.00%	0	0	0.00%	0	0
Leaves_1	10	Hard-limit	Symmetric hard-limit	Perceptron Training Rule	70	15	15	99	30.00%	0	0	0.00%	0	0
Leaves_1	10	Hard-limit	None	Perceptron Training Rule	70	15	15	99	10.00%	0	0	0.00%	0	0
Leaves_1	10	Linear	Hard-limit	Perceptron Training Rule	70	15	15	99	10.00%	0	0	0.00%	0	0
Leaves_1	10	Linear	Linear	Perceptron Training Rule	70	15	15	99	20.00%	0	0	0.00%	0	0
Leaves_1	10	Linear	Log-sigmoid	Perceptron Training Rule	70	15	15	99	20.00%	0	0	0.00%	0	0
Leaves_1	10	Linear	Hyperbolic tangent sigmoid	Perceptron Training Rule	70	15	15	99	10.00%	0	0	0.00%	0	0
Leaves_1	10	Linear	Symmetric hard-limit	Perceptron Training Rule	70	15	15	99	30.00%	0	0	0.00%	0	0
Leaves_1	10	Linear	None	Perceptron Training Rule	70	15	15	99	20.00%	0	0	0.00%	0	0
Leaves_1	10	Log-sigmoid	Hard-limit	Perceptron Training Rule	70	15	15	99	10.00%	0	0	0.00%	0	0
Leaves_1	10	Log-sigmoid	Linear	Perceptron Training Rule	70	15	15	99	20.00%	0	0	0.00%	0	0
Leaves_1	10	Log-sigmoid	Log-sigmoid	Perceptron Training Rule	70	15	15	99	20.00%	0	0	0.00%	0	0
Leaves_1	10	Log-sigmoid	Hyperbolic tangent sigmoid	Perceptron Training Rule	70	15	15	99	0.00%	0	0	0.00%	0	0
Leaves_1	10	Log-sigmoid	Symmetric hard-limit	Perceptron Training Rule	70	15	15	99	10.00%	0	0	0.00%	0	0
Leaves_1	10	Log-sigmoid	None	Perceptron Training Rule	70	15	15	99	10.00%	0	0	0.00%	0	0
Leaves_1	10	Hyperbolic tangent sigmoid	Hard-limit	Perceptron Training Rule	70	15	15	99	10.00%	0	0	0.00%	0	0
Leaves_1	10	Hyperbolic tangent sigmoid	Linear	Perceptron Training Rule	70	15	15	99	10.00%	0	0	0.00%	0	0
Leaves_1	10	Hyperbolic tangent sigmoid	Log-sigmoid	Perceptron Training Rule	70	15	15	99	0.00%	0	0	0.00%	0	0
Leaves_1	10	Hyperbolic tangent sigmoid	Hyperbolic tangent sigmoid	Perceptron Training Rule	70	15	15	99	10.00%	0	0	10.00%	0	0
Leaves_1	10	Hyperbolic tangent sigmoid	Symmetric hard-limit	Perceptron Training Rule	70	15	15	99	0.00%	0	0	0.00%	0	0
Leaves_1	10	Hyperbolic tangent sigmoid	None	Perceptron Training Rule	70	15	15	99	10.00%	0	0	0.00%	0	0
Leaves_1	10	Symmetric hard-limit	Hard-limit	Perceptron Training Rule	70	15	15	99	10.00%	0	0	0.00%	0	0
Leaves_1	10	Symmetric hard-limit	Linear	Perceptron Training Rule	70	15	15	99	10.00%	0	0	0.00%	0	0
Leaves_1	10	Symmetric hard-limit	Log-sigmoid	Perceptron Training Rule	70	15	15	99	20.00%	0	0	0.00%	0	0
Leaves_1	10	Symmetric hard-limit	Hyperbolic tangent sigmoid	Perceptron Training Rule	70	15	15	99	20.00%	0	0	0.00%	0	0
Leaves_1	10	Symmetric hard-limit	Symmetric hard-limit	Perceptron Training Rule	70	15	15	99	0.00%	0	0	0.00%	0	0
Leaves_1	10	Symmetric hard-limit	None	Perceptron Training Rule	70	15	15	99	10.00%	0	0	0.00%	0	0
Leaves_1	10	Hard-limit	Hard-limit	Gradient Descent	70	15	15	99	10.00%	0	0	0.00%	0	0
Leaves_1	10	Hard-limit	Linear	Gradient Descent	70	15	15	99	30.00%	0	0	0.00%	0	0
Leaves_1	10	Hard-limit	Hyperbolic tangent sigmoid	Gradient Descent	70	15	15	99	20.00%	0	0	0.00%	0	0
Leaves_1	10	Hard-limit	Log-sigmoid	Gradient Descent	70	15	15	99	10.00%	0	0	0.00%	0	0
Leaves_1	10	Hard-limit	Symmetric hard-limit	Gradient Descent	70	15	15	99	20.00%	0	0	0.00%	0	0
Leaves_1	10	Hard-limit	None	Gradient Descent	70	15	15	99	10.00%	0	0	0.00%	0	0
Leaves_1	10	Linear	Hard-limit	Gradient Descent	70	15	15	99	10.00%	0	0	0.00%	0	0
Leaves_1	10	Linear	Linear	Gradient Descent	70	15	15	99	20.00%	0	0	0.00%	0	0
Leaves_1	10	Linear	Log-sigmoid	Gradient Descent	70	15	15	99	10.00%	0	0	0.00%	0	0
Leaves_1	10	Linear	Hyperbolic tangent sigmoid	Gradient Descent	70	15	15	99	20.00%	0	0	0.00%	0	0

Table B.4: Training - Image in binary with Leaves_1 - Part 4

		Transfer functions			Ratio (in percentage %)				Species			Species		
Folder	Hidden L.	1st	2nd	Training algorithm	Train	Validation	Test	Quant. images	Success %	Epoch	Duration	Success %	Epoch	Duration
Leaves_1	10	Linear	Symmetric hard-limit	Gradient Descent	70	15	15	99	20.00%	0	0	0.00%	0	0
Leaves_1	10	Linear	None	Gradient Descent	70	15	15	99	10.00%	0	0	0.00%	0	0
Leaves_1	10	Log-sigmoid	Hard-limit	Gradient Descent	70	15	15	99	0.00%	0	0	0.00%	0	0
Leaves_1	10	Log-sigmoid	Linear	Gradient Descent	70	15	15	99	10.00%	0	0	0.00%	0	0
Leaves_1	10	Log-sigmoid	Log-sigmoid	Gradient Descent	70	15	15	99	20.00%	0	0	0.00%	0	0
Leaves_1	10	Log-sigmoid	Hyperbolic tangent sigmoid	Gradient Descent	70	15	15	99	10.00%	0	0	0.00%	0	0
Leaves_1	10	Log-sigmoid	Symmetric hard-limit	Gradient Descent	70	15	15	99	0.00%	0	0	0.00%	0	0
Leaves_1	10	Log-sigmoid	None	Gradient Descent	70	15	15	99	0.00%	0	0	0.00%	0	0
Leaves_1	10	Hyperbolic tangent sigmoid	Hard-limit	Gradient Descent	70	15	15	99	0.00%	0	0	0.00%	0	0
Leaves_1	10	Hyperbolic tangent sigmoid	Linear	Gradient Descent	70	15	15	99	10.00%	0	0	0.00%	0	0
Leaves_1	10	Hyperbolic tangent sigmoid	Log-sigmoid	Gradient Descent	70	15	15	99	10.00%	0	0	0.00%	0	0
Leaves_1	10	Hyperbolic tangent sigmoid	Hyperbolic tangent sigmoid	Gradient Descent	70	15	15	99	0.00%	0	0	0.00%	0	0
Leaves_1	10	Hyperbolic tangent sigmoid	Symmetric hard-limit	Gradient Descent	70	15	15	99	0.00%	0	0	0.00%	0	0
Leaves_1	10	Hyperbolic tangent sigmoid	None	Gradient Descent	70	15	15	99	10.00%	0	0	0.00%	0	0
Leaves_1	10	Symmetric hard-limit	Hard-limit	Gradient Descent	70	15	15	99	10.00%	0	0	0.00%	0	0
Leaves_1	10	Symmetric hard-limit	Linear	Gradient Descent	70	15	15	99	30.00%	0	0	0.00%	0	0
Leaves_1	10	Symmetric hard-limit	Log-sigmoid	Gradient Descent	70	15	15	99	20.00%	0	0	0.00%	0	0
Leaves_1	10	Symmetric hard-limit	Hyperbolic tangent sigmoid	Gradient Descent	70	15	15	99	10.00%	0	0	0.00%	0	0
Leaves_1	10	Symmetric hard-limit	Symmetric hard-limit	Gradient Descent	70	15	15	99	10.00%	0	0	0.00%	0	0
Leaves_1	10	Symmetric hard-limit	None	Gradient Descent	70	15	15	99	0.00%	0	0	0.00%	0	0
Leaves_1	10	Hard-limit	Hard-limit	Stochastic Approximation to Gradient Descent	70	15	15	99	0.00%	0	0	0.00%	0	0
Leaves_1	10	Hard-limit	Linear	Stochastic Approximation to Gradient Descent	70	15	15	99	20.00%	0	0	0.00%	0	0
Leaves_1	10	Hard-limit	Log-sigmoid	Stochastic Approximation to Gradient Descent	70	15	15	99	20.00%	0	0	0.00%	0	0
Leaves_1	10	Hard-limit	Hyperbolic tangent sigmoid	Stochastic Approximation to Gradient Descent	70	15	15	99	10.00%	0	0	0.00%	0	0
Leaves_1	10	Hard-limit	Symmetric hard-limit	Stochastic Approximation to Gradient Descent	70	15	15	99	0.00%	0	0	10.00%	0	0
Leaves_1	10	Hard-limit	None	Stochastic Approximation to Gradient Descent	70	15	15	99	10.00%	0	0	10.00%	0	0
Leaves_1	10	Linear	Hard-limit	Stochastic Approximation to Gradient Descent	70	15	15	99	10.00%	0	0	0.00%	0	0
Leaves_1	10	Linear	Linear	Stochastic Approximation to Gradient Descent	70	15	15	99	30.00%	0	0	10.00%	0	0
Leaves_1	10	Linear	Log-sigmoid	Stochastic Approximation to Gradient Descent	70	15	15	99	10.00%	0	0	0.00%	0	0
Leaves_1	10	Linear	Hyperbolic tangent sigmoid	Stochastic Approximation to Gradient Descent	70	15	15	99	10.00%	0	0	0.00%	0	0
Leaves_1	10	Linear	Symmetric hard-limit	Stochastic Approximation to Gradient Descent	70	15	15	99	20.00%	0	0	0.00%	0	0
Leaves_1	10	Linear	None	Stochastic Approximation to Gradient Descent	70	15	15	99	0.00%	0	0	0.00%	0	0
Leaves_1	10	Log-sigmoid	Hard-limit	Stochastic Approximation to Gradient Descent	70	15	15	99	10.00%	0	0	0.00%	0	0
Leaves_1	10	Log-sigmoid	Linear	Stochastic Approximation to Gradient Descent	70	15	15	99	0.00%	0	0	0.00%	0	0
Leaves_1	10	Log-sigmoid	Log-sigmoid	Stochastic Approximation to Gradient Descent	70	15	15	99	0.00%	0	0	0.00%	0	0
Leaves_1	10	Log-sigmoid	Hyperbolic tangent sigmoid	Stochastic Approximation to Gradient Descent	70	15	15	99	10.00%	0	0	0.00%	0	0
Leaves_1	10	Log-sigmoid	Symmetric hard-limit	Stochastic Approximation to Gradient Descent	70	15	15	99	10.00%	0	0	0.00%	0	0
Leaves_1	10	Log-sigmoid	None	Stochastic Approximation to Gradient Descent	70	15	15	99	10.00%	0	0	10.00%	0	0
Leaves_1	10	Hyperbolic tangent sigmoid	Hard-limit	Stochastic Approximation to Gradient Descent	70	15	15	99	10.00%	0	0	10.00%	0	0
Leaves_1	10	Hyperbolic tangent sigmoid	Linear	Stochastic Approximation to Gradient Descent	70	15	15	99	30.00%	0	0	10.00%	0	0
Leaves_1	10	Hyperbolic tangent sigmoid	Log-sigmoid	Stochastic Approximation to Gradient Descent	70	15	15	99	0.00%	0	0	0.00%	0	0
Leaves_1	10	Hyperbolic tangent sigmoid	Hyperbolic tangent sigmoid	Stochastic Approximation to Gradient Descent	70	15	15	99	10.00%	0	0	0.00%	0	0
Leaves_1	10	Hyperbolic tangent sigmoid	Symmetric hard-limit	Stochastic Approximation to Gradient Descent	70	15	15	99	0.00%	0	0	10.00%	0	0
Leaves_1	10	Hyperbolic tangent sigmoid	None	Stochastic Approximation to Gradient Descent	70	15	15	99	0.00%	0	0	0.00%	0	0
Leaves_1	10	Symmetric hard-limit	Hard-limit	Stochastic Approximation to Gradient Descent	70	15	15	99	10.00%	0	0	0.00%	0	0
Leaves_1	10	Symmetric hard-limit	Linear	Stochastic Approximation to Gradient Descent	70	15	15	99	0.00%	0	0	0.00%	0	0
Leaves_1	10	Symmetric hard-limit	Log-sigmoid	Stochastic Approximation to Gradient Descent	70	15	15	99	0.00%	0	0	0.00%	0	0
Leaves_1	10	Symmetric hard-limit	Hyperbolic tangent sigmoid	Stochastic Approximation to Gradient Descent	70	15	15	99	0.00%	0	0	0.00%	0	0
Leaves_1	10	Symmetric hard-limit	Symmetric hard-limit	Stochastic Approximation to Gradient Descent	70	15	15	99	10.00%	0	0	0.00%	0	0
Leaves_1	10	Symmetric hard-limit	None	Stochastic Approximation to Gradient Descent	70	15	15	99	0.00%	0	0	0.00%	0	0

Table B.5: Training - Image in binary with Leaves_2 - Part 1

		Transfer functions			Ratio (in percentage %)				Species			Species		
Folder	Hidden L.	1st	2nd	Training algorithm	Train	Validation	Test	Quant. images	Success %	Epoch	Duration	Success %	Epoch	Duration
Leaves_2	2	Hard-limit	Hard-limit	Perceptron Training Rule	80	10	10	1564	5.15%	0	0	2.08%	0	0
Leaves_2	2	Hard-limit	Linear	Perceptron Training Rule	80	10	10	1564	12.37%	0	0	3.13%	0	0
Leaves_2	2	Hard-limit	Log-sigmoid	Perceptron Training Rule	80	10	10	1564	12.37%	0	0	2.08%	0	0
Leaves_2	2	Hard-limit	Hyperbolic tangent sigmoid	Perceptron Training Rule	80	10	10	1564	11.34%	0	0	2.08%	0	0
Leaves_2	2	Hard-limit	Symmetric hard-limit	Perceptron Training Rule	80	10	10	1564	11.34%	0	0	1.04%	0	0
Leaves_2	2	Hard-limit	None	Perceptron Training Rule	80	10	10	1564	8.25%	0	0	2.08%	0	0
Leaves_2	2	Linear	Hard-limit	Perceptron Training Rule	80	10	10	1564	9.28%	0	0	2.08%	0	0
Leaves_2	2	Linear	Linear	Perceptron Training Rule	80	10	10	1564	6.19%	0	0	0.00%	0	0
Leaves_2	2	Linear	Log-sigmoid	Perceptron Training Rule	80	10	10	1564	6.19%	0	0	0.00%	0	0
Leaves_2	2	Linear	Hyperbolic tangent sigmoid	Perceptron Training Rule	80	10	10	1564	11.34%	0	0	4.17%	0	0
Leaves_2	2	Linear	Symmetric hard-limit	Perceptron Training Rule	80	10	10	1564	13.40%	0	0	1.04%	0	0
Leaves_2	2	Linear	None	Perceptron Training Rule	80	10	10	1564	9.28%	0	0	2.08%	0	0
Leaves_2	2	Log-sigmoid	Hard-limit	Perceptron Training Rule	80	10	10	1564	11.34%	0	0	0.00%	0	0
Leaves_2	2	Log-sigmoid	Linear	Perceptron Training Rule	80	10	10	1564	10.31%	0	0	1.04%	0	0
Leaves_2	2	Log-sigmoid	Log-sigmoid	Perceptron Training Rule	80	10	10	1564	9.28%	0	0	2.08%	0	0
Leaves_2	2	Log-sigmoid	Hyperbolic tangent sigmoid	Perceptron Training Rule	80	10	10	1564	9.28%	0	0	1.04%	0	0
Leaves_2	2	Log-sigmoid	Symmetric hard-limit	Perceptron Training Rule	80	10	10	1564	10.31%	0	0	2.08%	0	0
Leaves_2	2	Log-sigmoid	None	Perceptron Training Rule	80	10	10	1564	8.25%	0	0	1.04%	0	0
Leaves_2	2	Hyperbolic tangent sigmoid	Hard-limit	Perceptron Training Rule	80	10	10	1564	5.15%	0	0	5.21%	0	0
Leaves_2	2	Hyperbolic tangent sigmoid	Linear	Perceptron Training Rule	80	10	10	1564	8.25%	0	0	0.00%	0	0
Leaves_2	2	Hyperbolic tangent sigmoid	Log-sigmoid	Perceptron Training Rule	80	10	10	1564	4.12%	0	0	0.00%	0	0
Leaves_2	2	Hyperbolic tangent sigmoid	Hyperbolic tangent sigmoid	Perceptron Training Rule	80	10	10	1564	11.34%	0	0	0.00%	0	0
Leaves_2	2	Hyperbolic tangent sigmoid	Symmetric hard-limit	Perceptron Training Rule	80	10	10	1564	5.15%	0	0	2.08%	0	0
Leaves_2	2	Hyperbolic tangent sigmoid	None	Perceptron Training Rule	80	10	10	1564	8.25%	0	0	2.08%	0	0
Leaves_2	2	Symmetric hard-limit	Hard-limit	Perceptron Training Rule	80	10	10	1564	6.19%	0	0	1.04%	0	0
Leaves_2	2	Symmetric hard-limit	Linear	Perceptron Training Rule	80	10	10	1564	10.31%	0	0	0.00%	0	0
Leaves_2	2	Symmetric hard-limit	Log-sigmoid	Perceptron Training Rule	80	10	10	1564	9.28%	0	0	1.04%	0	0
Leaves_2	2	Symmetric hard-limit	Hyperbolic tangent sigmoid	Perceptron Training Rule	80	10	10	1564	5.15%	0	0	2.08%	0	0
Leaves_2	2	Symmetric hard-limit	Symmetric hard-limit	Perceptron Training Rule	80	10	10	1564	10.31%	0	0	2.08%	0	0
Leaves_2	2	Symmetric hard-limit	None	Perceptron Training Rule	80	10	10	1564	11.34%	0	0	1.04%	0	0
Leaves_2	2	Hard-limit	Hard-limit	Gradient Descent	80	10	10	1564	5.15%	0	0	0.00%	0	0
Leaves_2	2	Hard-limit	Linear	Gradient Descent	80	10	10	1564	7.22%	0	0	1.04%	0	0
Leaves_2	2	Hard-limit	Log-sigmoid	Gradient Descent	80	10	10	1564	9.28%	0	0	0.00%	0	0
Leaves_2	2	Hard-limit	Hyperbolic tangent sigmoid	Gradient Descent	80	10	10	1564	3.09%	0	0	3.13%	0	0
Leaves_2	2	Hard-limit	Symmetric hard-limit	Gradient Descent	80	10	10	1564	6.19%	0	0	1.04%	0	0
Leaves_2	2	Hard-limit	None	Gradient Descent	80	10	10	1564	7.22%	0	0	1.04%	0	0
Leaves_2	2	Linear	Hard-limit	Gradient Descent	80	10	10	1564	11.34%	0	0	1.04%	0	0
Leaves_2	2	Linear	Linear	Gradient Descent	80	10	10	1564	11.34%	0	0	1.04%	0	0
Leaves_2	2	Linear	Log-sigmoid	Gradient Descent	80	10	10	1564	15.46%	0	0	1.04%	0	0
Leaves_2	2	Linear	Hyperbolic tangent sigmoid	Gradient Descent	80	10	10	1564	8.25%	0	0	2.08%	0	0
Leaves_2	2	Linear	Symmetric hard-limit	Gradient Descent	80	10	10	1564	13.40%	0	0	2.08%	0	0
Leaves_2	2	Linear	None	Gradient Descent	80	10	10	1564	9.28%	0	0	1.04%	0	0
Leaves_2	2	Log-sigmoid	Hard-limit	Gradient Descent	80	10	10	1564	11.34%	0	0	3.13%	0	0
Leaves_2	2	Log-sigmoid	Linear	Gradient Descent	80	10	10	1564	10.31%	0	0	1.04%	0	0
Leaves_2	2	Log-sigmoid	Log-sigmoid	Gradient Descent	80	10	10	1564	12.37%	0	0	2.08%	0	0

Table B.6: Training - Image in binary with Leaves_2 - Part 2

		Transfer functions			Ratio (in percentage %)				Species			Species		
Folder	Hidden L.	1st	2nd	Training algorithm	Train	Validation	Test	Quant. images	Success %	Epoch	Duration	Success %	Epoch	Duration
Leaves_2	2	Log-sigmoid	Hyperbolic tangent sigmoid	Gradient Descent	80	10	10	1564	14.43%	0	0	0.00%	0	0
Leaves_2	2	Log-sigmoid	Symmetric hard-limit	Gradient Descent	80	10	10	1564	7.22%	0	0	1.04%	0	0
Leaves_2	2	Log-sigmoid	None	Gradient Descent	80	10	10	1564	17.53%	0	0	1.04%	0	0
Leaves_2	2	Hyperbolic tangent sigmoid	Hard-limit	Gradient Descent	80	10	10	1564	10.31%	0	0	2.08%	0	0
Leaves_2	2	Hyperbolic tangent sigmoid	Linear	Gradient Descent	80	10	10	1564	9.28%	0	0	1.04%	0	0
Leaves_2	2	Hyperbolic tangent sigmoid	Log-sigmoid	Gradient Descent	80	10	10	1564	10.31%	0	0	1.04%	0	0
Leaves_2	2	Hyperbolic tangent sigmoid	Hyperbolic tangent sigmoid	Gradient Descent	80	10	10	1564	9.28%	0	0	1.04%	0	0
Leaves_2	2	Hyperbolic tangent sigmoid	Symmetric hard-limit	Gradient Descent	80	10	10	1564	7.22%	0	0	0.00%	0	0
Leaves_2	2	Hyperbolic tangent sigmoid	None	Gradient Descent	80	10	10	1564	10.31%	0	0	1.04%	0	0
Leaves_2	2	Symmetric hard-limit	Hard-limit	Gradient Descent	80	10	10	1564	13.40%	0	0	0.00%	0	0
Leaves_2	2	Symmetric hard-limit	Linear	Gradient Descent	80	10	10	1564	6.19%	0	0	1.04%	0	0
Leaves_2	2	Symmetric hard-limit	Log-sigmoid	Gradient Descent	80	10	10	1564	10.31%	0	0	1.04%	0	0
Leaves_2	2	Symmetric hard-limit	Hyperbolic tangent sigmoid	Gradient Descent	80	10	10	1564	9.28%	0	0	0.00%	0	0
Leaves_2	2	Symmetric hard-limit	Symmetric hard-limit	Gradient Descent	80	10	10	1564	15.46%	0	0	1.04%	0	0
Leaves_2	2	Symmetric hard-limit	None	Gradient Descent	80	10	10	1564	11.34%	0	0	1.04%	0	0
Leaves_2	2	Hard-limit	Hard-limit	Stochastic Approximation to Gradient Descent	80	10	10	1564	7.22%	0	0	1.04%	0	0
Leaves_2	2	Hard-limit	Linear	Stochastic Approximation to Gradient Descent	80	10	10	1564	14.43%	0	0	3.13%	0	0
Leaves_2	2	Hard-limit	Log-sigmoid	Stochastic Approximation to Gradient Descent	80	10	10	1564	11.34%	0	0	1.04%	0	0
Leaves_2	2	Hard-limit	Hyperbolic tangent sigmoid	Stochastic Approximation to Gradient Descent	80	10	10	1564	11.34%	0	0	1.04%	0	0
Leaves_2	2	Hard-limit	Symmetric hard-limit	Stochastic Approximation to Gradient Descent	80	10	10	1564	10.31%	0	0	0.00%	0	0
Leaves_2	2	Hard-limit	None	Stochastic Approximation to Gradient Descent	80	10	10	1564	12.37%	0	0	2.08%	0	0
Leaves_2	2	Linear	Hard-limit	Stochastic Approximation to Gradient Descent	80	10	10	1564	8.25%	0	0	1.04%	0	0
Leaves_2	2	Linear	Linear	Stochastic Approximation to Gradient Descent	80	10	10	1564	7.22%	0	0	1.04%	0	0
Leaves_2	2	Linear	Log-sigmoid	Stochastic Approximation to Gradient Descent	80	10	10	1564	8.25%	0	0	1.04%	0	0
Leaves_2	2	Linear	Hyperbolic tangent sigmoid	Stochastic Approximation to Gradient Descent	80	10	10	1564	11.34%	0	0	1.04%	0	0
Leaves_2	2	Linear	Symmetric hard-limit	Stochastic Approximation to Gradient Descent	80	10	10	1564	10.31%	0	0	2.08%	0	0
Leaves_2	2	Linear	None	Stochastic Approximation to Gradient Descent	80	10	10	1564	4.12%	0	0	0.00%	0	0
Leaves_2	2	Log-sigmoid	Hard-limit	Stochastic Approximation to Gradient Descent	80	10	10	1564	14.43%	0	0	0.00%	0	0
Leaves_2	2	Log-sigmoid	Linear	Stochastic Approximation to Gradient Descent	80	10	10	1564	12.37%	0	0	0.00%	0	0
Leaves_2	2	Log-sigmoid	Log-sigmoid	Stochastic Approximation to Gradient Descent	80	10	10	1564	5.15%	0	0	1.04%	0	0
Leaves_2	2	Log-sigmoid	Hyperbolic tangent sigmoid	Stochastic Approximation to Gradient Descent	80	10	10	1564	4.12%	0	0	2.08%	0	0
Leaves_2	2	Log-sigmoid	Symmetric hard-limit	Stochastic Approximation to Gradient Descent	80	10	10	1564	7.22%	0	0	2.08%	0	0
Leaves_2	2	Log-sigmoid	None	Stochastic Approximation to Gradient Descent	80	10	10	1564	12.37%	0	0	2.08%	0	0
Leaves_2	2	Hyperbolic tangent sigmoid	Hard-limit	Stochastic Approximation to Gradient Descent	80	10	10	1564	16.49%	0	0	1.04%	0	0
Leaves_2	2	Hyperbolic tangent sigmoid	Linear	Stochastic Approximation to Gradient Descent	80	10	10	1564	15.46%	0	0	0.00%	0	0
Leaves_2	2	Hyperbolic tangent sigmoid	Log-sigmoid	Stochastic Approximation to Gradient Descent	80	10	10	1564	10.31%	0	0	1.04%	0	0
Leaves_2	2	Hyperbolic tangent sigmoid	Hyperbolic tangent sigmoid	Stochastic Approximation to Gradient Descent	80	10	10	1564	9.28%	0	0	3.13%	0	0
Leaves_2	2	Hyperbolic tangent sigmoid	Symmetric hard-limit	Stochastic Approximation to Gradient Descent	80	10	10	1564	13.40%	0	0	3.13%	0	0
Leaves_2	2	Hyperbolic tangent sigmoid	None	Stochastic Approximation to Gradient Descent	80	10	10	1564	16.49%	0	0	0.00%	0	0
Leaves_2	2	Symmetric hard-limit	Hard-limit	Stochastic Approximation to Gradient Descent	80	10	10	1564	10.31%	0	0	1.04%	0	0
Leaves_2	2	Symmetric hard-limit	Linear	Stochastic Approximation to Gradient Descent	80	10	10	1564	14.43%	0	0	1.04%	0	0
Leaves_2	2	Symmetric hard-limit	Log-sigmoid	Stochastic Approximation to Gradient Descent	80	10	10	1564	6.19%	0	0	1.04%	0	0
Leaves_2	2	Symmetric hard-limit	Hyperbolic tangent sigmoid	Stochastic Approximation to Gradient Descent	80	10	10	1564	11.34%	0	0	0.00%	0	0
Leaves_2	2	Symmetric hard-limit	Symmetric hard-limit	Stochastic Approximation to Gradient Descent	80	10	10	1564	6.19%	0	0	1.04%	0	0
Leaves_2	2	Symmetric hard-limit	None	Stochastic Approximation to Gradient Descent	80	10	10	1564	10.31%	0	0	1.04%	0	0

Table B.7: Training - Image in binary with Leaves_2 - Part 3

		Transfer functions			Ratio (in percentage %)				Species			Species		
Folder	Hidden L.	1st	2nd	Training algorithm	Train	Validation	Test	Quant. images	Success %	Epoch	Duration	Success %	Epoch	Duration
Leaves_2	10	Hard-limit	Hard-limit	Perceptron Training Rule	70	15	15	1564	12.37%	0	0.01	0.00%	0	0
Leaves_2	10	Hard-limit	Linear	Perceptron Training Rule	70	15	15	1564	12.37%	0	0	2.08%	0	0
Leaves_2	10	Hard-limit	Log-sigmoid	Perceptron Training Rule	70	15	15	1564	5.15%	0	0	2.08%	0	0
Leaves_2	10	Hard-limit	Hyperbolic tangent sigmoid	Perceptron Training Rule	70	15	15	1564	11.34%	0	0	2.08%	0	0
Leaves_2	10	Hard-limit	Symmetric hard-limit	Perceptron Training Rule	70	15	15	1564	12.37%	0	0	2.08%	0	0
Leaves_2	10	Hard-limit	None	Perceptron Training Rule	70	15	15	1564	15.46%	0	0	2.08%	0	0
Leaves_2	10	Linear	Hard-limit	Perceptron Training Rule	70	15	15	1564	13.40%	0	0	2.08%	0	0
Leaves_2	10	Linear	Linear	Perceptron Training Rule	70	15	15	1564	12.37%	0	0.01	0.00%	0	0
Leaves_2	10	Linear	Log-sigmoid	Perceptron Training Rule	70	15	15	1564	12.37%	0	0	2.08%	0	0
Leaves_2	10	Linear	Hyperbolic tangent sigmoid	Perceptron Training Rule	70	15	15	1564	5.15%	0	0	2.08%	0	0
Leaves_2	10	Linear	Symmetric hard-limit	Perceptron Training Rule	70	15	15	1564	11.34%	0	0	2.08%	0	0
Leaves_2	10	Linear	None	Perceptron Training Rule	70	15	15	1564	12.37%	0	0	2.08%	0	0
Leaves_2	10	Log-sigmoid	Hard-limit	Perceptron Training Rule	70	15	15	1564	15.46%	0	0	2.08%	0	0
Leaves_2	10	Log-sigmoid	Linear	Perceptron Training Rule	70	15	15	1564	13.40%	0	0	2.08%	0	0
Leaves_2	10	Log-sigmoid	Log-sigmoid	Perceptron Training Rule	70	15	15	1564	12.37%	0	0	4.17%	0	0
Leaves_2	10	Log-sigmoid	Hyperbolic tangent sigmoid	Perceptron Training Rule	70	15	15	1564	8.25%	0	0	1.04%	0	0
Leaves_2	10	Log-sigmoid	Symmetric hard-limit	Perceptron Training Rule	70	15	15	1564	10.31%	0	0	0.00%	0	0
Leaves_2	10	Log-sigmoid	None	Perceptron Training Rule	70	15	15	1564	10.31%	0	0	2.08%	0	0
Leaves_2	10	Hyperbolic tangent sigmoid	Hard-limit	Perceptron Training Rule	70	15	15	1564	4.12%	0	0	0.00%	0	0
Leaves_2	10	Hyperbolic tangent sigmoid	Linear	Perceptron Training Rule	70	15	15	1564	10.31%	0	0	1.04%	0	0
Leaves_2	10	Hyperbolic tangent sigmoid	Log-sigmoid	Perceptron Training Rule	70	15	15	1564	13.40%	0	0	2.08%	0	0
Leaves_2	10	Hyperbolic tangent sigmoid	Hyperbolic tangent sigmoid	Perceptron Training Rule	70	15	15	1564	11.34%	0	0	1.04%	0	0
Leaves_2	10	Hyperbolic tangent sigmoid	Symmetric hard-limit	Perceptron Training Rule	70	15	15	1564	8.25%	0	0	2.08%	0	0
Leaves_2	10	Hyperbolic tangent sigmoid	None	Perceptron Training Rule	70	15	15	1564	6.19%	0	0	0.00%	0	0
Leaves_2	10	Symmetric hard-limit	Hard-limit	Perceptron Training Rule	70	15	15	1564	8.25%	0	0	0.00%	0	0
Leaves_2	10	Symmetric hard-limit	Linear	Perceptron Training Rule	70	15	15	1564	7.22%	0	0	2.08%	0	0
Leaves_2	10	Symmetric hard-limit	Log-sigmoid	Perceptron Training Rule	70	15	15	1564	12.37%	0	0	3.13%	0	0
Leaves_2	10	Symmetric hard-limit	Hyperbolic tangent sigmoid	Perceptron Training Rule	70	15	15	1564	8.25%	0	0	1.04%	0	0
Leaves_2	10	Symmetric hard-limit	Symmetric hard-limit	Perceptron Training Rule	70	15	15	1564	6.19%	0	0	0.00%	0	0
Leaves_2	10	Symmetric hard-limit	None	Perceptron Training Rule	70	15	15	1564	16.49%	0	0	1.04%	0	0
Leaves_2	10	Hard-limit	Hard-limit	Gradient Descent	70	15	15	1564	8.25%	0	0	0.00%	0	0
Leaves_2	10	Hard-limit	Linear	Gradient Descent	70	15	15	1564	13.40%	0	0	2.08%	0	0
Leaves_2	10	Hard-limit	Log-sigmoid	Gradient Descent	70	15	15	1564	6.19%	0	0	3.13%	0	0
Leaves_2	10	Hard-limit	Hyperbolic tangent sigmoid	Gradient Descent	70	15	15	1564	7.22%	0	0	2.08%	0	0
Leaves_2	10	Hard-limit	Symmetric hard-limit	Gradient Descent	70	15	15	1564	4.12%	0	0	1.04%	0	0
Leaves_2	10	Hard-limit	None	Gradient Descent	70	15	15	1564	10.31%	0	0	3.13%	0	0
Leaves_2	10	Linear	Hard-limit	Gradient Descent	70	15	15	1564	8.25%	0	0	0.00%	0	0
Leaves_2	10	Linear	Linear	Gradient Descent	70	15	15	1564	10.31%	0	0	2.08%	0	0
Leaves_2	10	Linear	Log-sigmoid	Gradient Descent	70	15	15	1564	9.28%	0	0	0.00%	0	0
Leaves_2	10	Linear	Hyperbolic tangent sigmoid	Gradient Descent	70	15	15	1564	7.22%	0	0	2.08%	0	0
Leaves_2	10	Linear	Symmetric hard-limit	Gradient Descent	70	15	15	1564	6.19%	0	0	1.04%	0	0
Leaves_2	10	Linear	None	Gradient Descent	70	15	15	1564	8.25%	0	0	2.08%	0	0
Leaves_2	10	Log-sigmoid	Hard-limit	Gradient Descent	70	15	15	1564	4.12%	0	0	1.04%	0	0
Leaves_2	10	Log-sigmoid	Linear	Gradient Descent	70	15	15	1564	12.37%	0	0	1.04%	0	0
Leaves_2	10	Log-sigmoid	Log-sigmoid	Gradient Descent	70	15	15	1564	9.28%	0	0	1.04%	0	0

Table B.8: Training - Image in binary with Leaves_2 - Part 4

		Transfer functions			Ratio (in percentage %)				Species			Species		
Folder	Hidden L.	1st	2nd	Training algorithm	Train	Validation	Test	Quant. images	Success %	Epoch	Duration	Success %	Epoch	Duration
Leaves_2	10	Log-sigmoid	Hyperbolic tangent sigmoid	Gradient Descent	70	15	15	1564	12.37%	0	0	1.04%	0	0
Leaves_2	10	Log-sigmoid	Symmetric hard-limit	Gradient Descent	70	15	15	1564	12.37%	0	0	2.08%	0	0
Leaves_2	10	Log-sigmoid	None	Gradient Descent	70	15	15	1564	9.28%	0	0	2.08%	0	0
Leaves_2	10	Hyperbolic tangent sigmoid	Hard-limit	Gradient Descent	70	15	15	1564	7.22%	0	0	0.00%	0	0
Leaves_2	10	Hyperbolic tangent sigmoid	Linear	Gradient Descent	70	15	15	1564	8.25%	0	0	0.00%	0	0
Leaves_2	10	Hyperbolic tangent sigmoid	Log-sigmoid	Gradient Descent	70	15	15	1564	7.22%	0	0	2.08%	0	0
Leaves_2	10	Hyperbolic tangent sigmoid	Hyperbolic tangent sigmoid	Gradient Descent	70	15	15	1564	11.34%	0	0	1.04%	0	0
Leaves_2	10	Hyperbolic tangent sigmoid	Symmetric hard-limit	Gradient Descent	70	15	15	1564	7.22%	0	0	0.00%	0	0
Leaves_2	10	Hyperbolic tangent sigmoid	None	Gradient Descent	70	15	15	1564	10.31%	0	0	1.04%	0	0
Leaves_2	10	Symmetric hard-limit	Hard-limit	Gradient Descent	70	15	15	1564	10.31%	0	0	0.00%	0	0
Leaves_2	10	Symmetric hard-limit	Linear	Gradient Descent	70	15	15	1564	4.12%	0	0	1.04%	0	0
Leaves_2	10	Symmetric hard-limit	Log-sigmoid	Gradient Descent	70	15	15	1564	12.37%	0	0	1.04%	0	0
Leaves_2	10	Symmetric hard-limit	Hyperbolic tangent sigmoid	Gradient Descent	70	15	15	1564	9.28%	0	0	2.08%	0	0
Leaves_2	10	Symmetric hard-limit	Symmetric hard-limit	Gradient Descent	70	15	15	1564	13.40%	0	0	1.04%	0	0
Leaves_2	10	Symmetric hard-limit	None	Gradient Descent	70	15	15	1564	12.37%	0	0	0.00%	0	0
Leaves_2	10	Hard-limit	Hard-limit	Stochastic Approximation to Gradient Descent	70	15	15	1564	9.28%	0	0	0.00%	0	0
Leaves_2	10	Hard-limit	Linear	Stochastic Approximation to Gradient Descent	70	15	15	1564	15.46%	0	0	0.00%	0	0
Leaves_2	10	Hard-limit	Log-sigmoid	Stochastic Approximation to Gradient Descent	70	15	15	1564	7.22%	0	0	2.08%	0	0
Leaves_2	10	Hard-limit	Hyperbolic tangent sigmoid	Stochastic Approximation to Gradient Descent	70	15	15	1564	9.28%	0	0	1.04%	0	0
Leaves_2	10	Hard-limit	Symmetric hard-limit	Stochastic Approximation to Gradient Descent	70	15	15	1564	9.28%	0	0	3.13%	0	0
Leaves_2	10	Hard-limit	None	Stochastic Approximation to Gradient Descent	70	15	15	1564	6.19%	0	0	3.13%	0	0
Leaves_2	10	Linear	Hard-limit	Stochastic Approximation to Gradient Descent	70	15	15	1564	8.25%	0	0	0.00%	0	0
Leaves_2	10	Linear	Linear	Stochastic Approximation to Gradient Descent	70	15	15	1564	4.12%	0	0	1.04%	0	0
Leaves_2	10	Linear	Log-sigmoid	Stochastic Approximation to Gradient Descent	70	15	15	1564	9.28%	0	0	1.04%	0	0
Leaves_2	10	Linear	Hyperbolic tangent sigmoid	Stochastic Approximation to Gradient Descent	70	15	15	1564	5.15%	0	0	0.00%	0	0
Leaves_2	10	Linear	Symmetric hard-limit	Stochastic Approximation to Gradient Descent	70	15	15	1564	9.28%	0	0	0.00%	0	0
Leaves_2	10	Linear	None	Stochastic Approximation to Gradient Descent	70	15	15	1564	9.28%	0	0	3.13%	0	0
Leaves_2	10	Log-sigmoid	Hard-limit	Stochastic Approximation to Gradient Descent	70	15	15	1564	10.31%	0	0	0.00%	0	0
Leaves_2	10	Log-sigmoid	Linear	Stochastic Approximation to Gradient Descent	70	15	15	1564	13.40%	0	0	1.04%	0	0
Leaves_2	10	Log-sigmoid	Log-sigmoid	Stochastic Approximation to Gradient Descent	70	15	15	1564	11.34%	0	0	3.13%	0	0
Leaves_2	10	Log-sigmoid	Hyperbolic tangent sigmoid	Stochastic Approximation to Gradient Descent	70	15	15	1564	15.46%	0	0	2.08%	0	0
Leaves_2	10	Log-sigmoid	Symmetric hard-limit	Stochastic Approximation to Gradient Descent	70	15	15	1564	9.28%	0	0	3.13%	0	0
Leaves_2	10	Log-sigmoid	None	Stochastic Approximation to Gradient Descent	70	15	15	1564	7.22%	0	0	1.04%	0	0
Leaves_2	10	Hyperbolic tangent sigmoid	Hard-limit	Stochastic Approximation to Gradient Descent	70	15	15	1564	9.28%	0	0	1.04%	0	0
Leaves_2	10	Hyperbolic tangent sigmoid	Linear	Stochastic Approximation to Gradient Descent	70	15	15	1564	13.40%	0	0	0.00%	0	0
Leaves_2	10	Hyperbolic tangent sigmoid	Log-sigmoid	Stochastic Approximation to Gradient Descent	70	15	15	1564	8.25%	0	0	2.08%	0	0
Leaves_2	10	Hyperbolic tangent sigmoid	Hyperbolic tangent sigmoid	Stochastic Approximation to Gradient Descent	70	15	15	1564	9.28%	0	0	0.00%	0	0
Leaves_2	10	Hyperbolic tangent sigmoid	Symmetric hard-limit	Stochastic Approximation to Gradient Descent	70	15	15	1564	7.22%	0	0	2.08%	0	0
Leaves_2	10	Hyperbolic tangent sigmoid	None	Stochastic Approximation to Gradient Descent	70	15	15	1564	8.25%	0	0	1.04%	0	0
Leaves_2	10	Symmetric hard-limit	Hard-limit	Stochastic Approximation to Gradient Descent	70	15	15	1564	12.37%	0	0	1.04%	0	0
Leaves_2	10	Symmetric hard-limit	Linear	Stochastic Approximation to Gradient Descent	70	15	15	1564	10.31%	0	0	0.00%	0	0
Leaves_2	10	Symmetric hard-limit	Log-sigmoid	Stochastic Approximation to Gradient Descent	70	15	15	1564	7.22%	0	0	1.04%	0	0
Leaves_2	10	Symmetric hard-limit	Hyperbolic tangent sigmoid	Stochastic Approximation to Gradient Descent	70	15	15	1564	14.43%	0	0	1.04%	0	0
Leaves_2	10	Symmetric hard-limit	Symmetric hard-limit	Stochastic Approximation to Gradient Descent	70	15	15	1564	11.34%	0	0	1.04%	0	0
Leaves_2	10	Symmetric hard-limit	None	Stochastic Approximation to Gradient Descent	70	15	15	1564	7.22%	0	0	1.04%	0	0

Table B.9: Training - Image in binary with Leaves_3 - Part 1

		Transfer functions			Ratio (in percentage %)				Species			Species		
Folder	Hidden L.	1st	2nd	Training algorithm	Train	Validation	Test	Quant. images	Success %	Epoch	Duration	Success %	Epoch	Duration
Leaves_3	2	Hard-limit	Hard-limit	Perceptron Training Rule	80	10	10	20	100.00%	0	0	0.00%	0	0
Leaves_3	2	Hard-limit	Linear	Perceptron Training Rule	80	10	10	20	0.00%	0	0	0.00%	0	0
Leaves_3	2	Hard-limit	Log-sigmoid	Perceptron Training Rule	80	10	10	20	50.00%	0	0	0.00%	0	0
Leaves_3	2	Hard-limit	Hyperbolic tangent sigmoid	Perceptron Training Rule	80	10	10	20	0.00%	0	0	0.00%	0	0
Leaves_3	2	Hard-limit	Symmetric hard-limit	Perceptron Training Rule	80	10	10	20	0.00%	0	0	0.00%	0	0
Leaves_3	2	Hard-limit	None	Perceptron Training Rule	80	10	10	20	0.00%	0	0	0.00%	0	0
Leaves_3	2	Linear	Hard-limit	Perceptron Training Rule	80	10	10	20	0.00%	0	0	0.00%	0	0
Leaves_3	2	Linear	Linear	Perceptron Training Rule	80	10	10	20	0.00%	0	0	0.00%	0	0
Leaves_3	2	Linear	Log-sigmoid	Perceptron Training Rule	80	10	10	20	0.00%	0	0	0.00%	0	0
Leaves_3	2	Linear	Hyperbolic tangent sigmoid	Perceptron Training Rule	80	10	10	20	50.00%	0	0	0.00%	0	0
Leaves_3	2	Linear	Symmetric hard-limit	Perceptron Training Rule	80	10	10	20	100.00%	0	0	0.00%	0	0
Leaves_3	2	Linear	None	Perceptron Training Rule	80	10	10	20	50.00%	0	0	0.00%	0	0
Leaves_3	2	Log-sigmoid	Hard-limit	Perceptron Training Rule	80	10	10	20	0.00%	0	0	0.00%	0	0
Leaves_3	2	Log-sigmoid	Linear	Perceptron Training Rule	80	10	10	20	0.00%	0	0	0.00%	0	0
Leaves_3	2	Log-sigmoid	Log-sigmoid	Perceptron Training Rule	80	10	10	20	0.00%	0	0	0.00%	0	0
Leaves_3	2	Log-sigmoid	Hyperbolic tangent sigmoid	Perceptron Training Rule	80	10	10	20	50.00%	0	0	0.00%	0	0
Leaves_3	2	Log-sigmoid	Symmetric hard-limit	Perceptron Training Rule	80	10	10	20	0.00%	0	0	0.00%	0	0
Leaves_3	2	Log-sigmoid	None	Perceptron Training Rule	80	10	10	20	0.00%	0	0	0.00%	0	0
Leaves_3	2	Hyperbolic tangent sigmoid	Hard-limit	Perceptron Training Rule	80	10	10	20	0.00%	0	0	0.00%	0	0
Leaves_3	2	Hyperbolic tangent sigmoid	Linear	Perceptron Training Rule	80	10	10	20	50.00%	0	0	0.00%	0	0
Leaves_3	2	Hyperbolic tangent sigmoid	Log-sigmoid	Perceptron Training Rule	80	10	10	20	100.00%	0	0	0.00%	0	0
Leaves_3	2	Hyperbolic tangent sigmoid	Hyperbolic tangent sigmoid	Perceptron Training Rule	80	10	10	20	0.00%	0	0	0.00%	0	0
Leaves_3	2	Hyperbolic tangent sigmoid	Symmetric hard-limit	Perceptron Training Rule	80	10	10	20	0.00%	0	0	0.00%	0	0
Leaves_3	2	Hyperbolic tangent sigmoid	None	Perceptron Training Rule	80	10	10	20	50.00%	0	0	0.00%	0	0
Leaves_3	2	Symmetric hard-limit	Hard-limit	Perceptron Training Rule	80	10	10	20	0.00%	0	0	0.00%	0	0
Leaves_3	2	Symmetric hard-limit	Linear	Perceptron Training Rule	80	10	10	20	50.00%	0	0	0.00%	0	0
Leaves_3	2	Symmetric hard-limit	Log-sigmoid	Perceptron Training Rule	80	10	10	20	50.00%	0	0	0.00%	0	0
Leaves_3	2	Symmetric hard-limit	Hyperbolic tangent sigmoid	Perceptron Training Rule	80	10	10	20	50.00%	0	0	0.00%	0	0
Leaves_3	2	Symmetric hard-limit	Symmetric hard-limit	Perceptron Training Rule	80	10	10	20	50.00%	0	0	0.00%	0	0
Leaves_3	2	Symmetric hard-limit	None	Perceptron Training Rule	80	10	10	20	0.00%	0	0	0.00%	0	0
Leaves_3	2	Hard-limit	Hard-limit	Gradient Descent	80	10	10	20	0.00%	0	0	0.00%	0	0
Leaves_3	2	Hard-limit	Linear	Gradient Descent	80	10	10	20	0.00%	0	0	0.00%	0	0
Leaves_3	2	Hard-limit	Log-sigmoid	Gradient Descent	80	10	10	20	0.00%	0	0	0.00%	0	0
Leaves_3	2	Hard-limit	Hyperbolic tangent sigmoid	Gradient Descent	80	10	10	20	50.00%	0	0	0.00%	0	0
Leaves_3	2	Hard-limit	Symmetric hard-limit	Gradient Descent	80	10	10	20	100.00%	0	0	0.00%	0	0
Leaves_3	2	Hard-limit	None	Gradient Descent	80	10	10	20	50.00%	0	0	0.00%	0	0
Leaves_3	2	Linear	Hard-limit	Gradient Descent	80	10	10	20	0.00%	0	0	0.00%	0	0
Leaves_3	2	Linear	Linear	Gradient Descent	80	10	10	20	0.00%	0	0	0.00%	0	0
Leaves_3	2	Linear	Log-sigmoid	Gradient Descent	80	10	10	20	50.00%	0	0	0.00%	0	0
Leaves_3	2	Linear	Hyperbolic tangent sigmoid	Gradient Descent	80	10	10	20	50.00%	0	0	0.00%	0	0
Leaves_3	2	Linear	Symmetric hard-limit	Gradient Descent	80	10	10	20	0.00%	0	0	0.00%	0	0
Leaves_3	2	Linear	None	Gradient Descent	80	10	10	20	50.00%	0	0	0.00%	0	0
Leaves_3	2	Log-sigmoid	Hard-limit	Gradient Descent	80	10	10	20	0.00%	0	0	0.00%	0	0
Leaves_3	2	Log-sigmoid	Linear	Gradient Descent	80	10	10	20	0.00%	0	0	0.00%	0	0
Leaves_3	2	Log-sigmoid	Log-sigmoid	Gradient Descent	80	10	10	20	50.00%	0	0	0.00%	0	0

Table B.10: Training - Image in binary with Leaves_3 - Part 2

		Transfer functions			Ratio (in percentage %)				Species			Species		
Folder	Hidden L.	1st	2nd	Training algorithm	Train	Validation	Test	Quant. images	Success %	Epoch	Duration	Success %	Epoch	Duration
Leaves_3	2	Log-sigmoid	Hyperbolic tangent sigmoid	Gradient Descent	80	10	10	20	0.00%	0	0	0.00%	0	0
Leaves_3	2	Log-sigmoid	Symmetric hard-limit	Gradient Descent	80	10	10	20	50.00%	0	0	0.00%	0	0
Leaves_3	2	Log-sigmoid	None	Gradient Descent	80	10	10	20	0.00%	0	0	0.00%	0	0
Leaves_3	2	Hyperbolic tangent sigmoid	Hard-limit	Gradient Descent	80	10	10	20	50.00%	0	0	0.00%	0	0
Leaves_3	2	Hyperbolic tangent sigmoid	Linear	Gradient Descent	80	10	10	20	0.00%	0	0	0.00%	0	0
Leaves_3	2	Hyperbolic tangent sigmoid	Log-sigmoid	Gradient Descent	80	10	10	20	0.00%	0	0	0.00%	0	0
Leaves_3	2	Hyperbolic tangent sigmoid	Hyperbolic tangent sigmoid	Gradient Descent	80	10	10	20	0.00%	0	0	0.00%	0	0
Leaves_3	2	Hyperbolic tangent sigmoid	Symmetric hard-limit	Gradient Descent	80	10	10	20	0.00%	0	0	0.00%	0	0
Leaves_3	2	Hyperbolic tangent sigmoid	None	Gradient Descent	80	10	10	20	50.00%	0	0	0.00%	0	0
Leaves_3	2	Symmetric hard-limit	Hard-limit	Gradient Descent	80	10	10	20	0.00%	0	0	0.00%	0	0
Leaves_3	2	Symmetric hard-limit	Linear	Gradient Descent	80	10	10	20	0.00%	0	0	0.00%	0	0
Leaves_3	2	Symmetric hard-limit	Log-sigmoid	Gradient Descent	80	10	10	20	0.00%	0	0	0.00%	0	0
Leaves_3	2	Symmetric hard-limit	Hyperbolic tangent sigmoid	Gradient Descent	80	10	10	20	50.00%	0	0	0.00%	0	0
Leaves_3	2	Symmetric hard-limit	Symmetric hard-limit	Gradient Descent	80	10	10	20	50.00%	0	0	0.00%	0	0
Leaves_3	2	Symmetric hard-limit	None	Gradient Descent	80	10	10	20	0.00%	0	0	0.00%	0	0
Leaves_3	2	Hard-limit	Hard-limit	Stochastic Approximation to Gradient Descent	80	10	10	20	0.00%	0	0	0.00%	0	0
Leaves_3	2	Hard-limit	Linear	Stochastic Approximation to Gradient Descent	80	10	10	20	0.00%	0	0	0.00%	0	0
Leaves_3	2	Hard-limit	Log-sigmoid	Stochastic Approximation to Gradient Descent	80	10	10	20	0.00%	0	0	0.00%	0	0
Leaves_3	2	Hard-limit	Hyperbolic tangent sigmoid	Stochastic Approximation to Gradient Descent	80	10	10	20	0.00%	0	0	0.00%	0	0
Leaves_3	2	Hard-limit	Symmetric hard-limit	Stochastic Approximation to Gradient Descent	80	10	10	20	0.00%	0	0	0.00%	0	0
Leaves_3	2	Hard-limit	None	Stochastic Approximation to Gradient Descent	80	10	10	20	0.00%	0	0	0.00%	0	0
Leaves_3	2	Linear	Hard-limit	Stochastic Approximation to Gradient Descent	80	10	10	20	100.00%	0	0	0.00%	0	0
Leaves_3	2	Linear	Linear	Stochastic Approximation to Gradient Descent	80	10	10	20	50.00%	0	0	0.00%	0	0
Leaves_3	2	Linear	Log-sigmoid	Stochastic Approximation to Gradient Descent	80	10	10	20	100.00%	0	0	0.00%	0	0
Leaves_3	2	Linear	Hyperbolic tangent sigmoid	Stochastic Approximation to Gradient Descent	80	10	10	20	0.00%	0	0	0.00%	0	0
Leaves_3	2	Linear	Symmetric hard-limit	Stochastic Approximation to Gradient Descent	80	10	10	20	50.00%	0	0	0.00%	0	0
Leaves_3	2	Linear	None	Stochastic Approximation to Gradient Descent	80	10	10	20	0.00%	0	0	0.00%	0	0
Leaves_3	2	Log-sigmoid	Hard-limit	Stochastic Approximation to Gradient Descent	80	10	10	20	0.00%	0	0	0.00%	0	0
Leaves_3	2	Log-sigmoid	Linear	Stochastic Approximation to Gradient Descent	80	10	10	20	0.00%	0	0	0.00%	0	0
Leaves_3	2	Log-sigmoid	Log-sigmoid	Stochastic Approximation to Gradient Descent	80	10	10	20	0.00%	0	0	0.00%	0	0
Leaves_3	2	Log-sigmoid	Hyperbolic tangent sigmoid	Stochastic Approximation to Gradient Descent	80	10	10	20	0.00%	0	0	0.00%	0	0
Leaves_3	2	Log-sigmoid	Symmetric hard-limit	Stochastic Approximation to Gradient Descent	80	10	10	20	0.00%	0	0	0.00%	0	0
Leaves_3	2	Log-sigmoid	None	Stochastic Approximation to Gradient Descent	80	10	10	20	50.00%	0	0	0.00%	0	0
Leaves_3	2	Hyperbolic tangent sigmoid	Hard-limit	Stochastic Approximation to Gradient Descent	80	10	10	20	0.00%	0	0	0.00%	0	0
Leaves_3	2	Hyperbolic tangent sigmoid	Linear	Stochastic Approximation to Gradient Descent	80	10	10	20	50.00%	0	0	0.00%	0	0
Leaves_3	2	Hyperbolic tangent sigmoid	Log-sigmoid	Stochastic Approximation to Gradient Descent	80	10	10	20	0.00%	0	0	0.00%	0	0
Leaves_3	2	Hyperbolic tangent sigmoid	Hyperbolic tangent sigmoid	Stochastic Approximation to Gradient Descent	80	10	10	20	0.00%	0	0	0.00%	0	0
Leaves_3	2	Hyperbolic tangent sigmoid	Symmetric hard-limit	Stochastic Approximation to Gradient Descent	80	10	10	20	50.00%	0	0	0.00%	0	0
Leaves_3	2	Hyperbolic tangent sigmoid	None	Stochastic Approximation to Gradient Descent	80	10	10	20	50.00%	0	0	0.00%	0	0
Leaves_3	2	Symmetric hard-limit	Hard-limit	Stochastic Approximation to Gradient Descent	80	10	10	20	0.00%	0	0	0.00%	0	0
Leaves_3	2	Symmetric hard-limit	Linear	Stochastic Approximation to Gradient Descent	80	10	10	20	0.00%	0	0	0.00%	0	0
Leaves_3	2	Symmetric hard-limit	Log-sigmoid	Stochastic Approximation to Gradient Descent	80	10	10	20	0.00%	0	0	0.00%	0	0
Leaves_3	2	Symmetric hard-limit	Hyperbolic tangent sigmoid	Stochastic Approximation to Gradient Descent	80	10	10	20	50.00%	0	0	0.00%	0	0
Leaves_3	2	Symmetric hard-limit	Symmetric hard-limit	Stochastic Approximation to Gradient Descent	80	10	10	20	0.00%	0	0	0.00%	0	0
Leaves_3	2	Symmetric hard-limit	None	Stochastic Approximation to Gradient Descent	80	10	10	20	50.00%	0	0	0.00%	0	0

Table B.11: Training - Image in binary with Leaves_3 - Part 3

		Transfer functions			Ratio (in percentage %)				Species			Species		
Folder	Hidden L.	1st	2nd	Training algorithm	Train	Validation	Test	Quant. images	Success %	Epoch	Duration	Success %	Epoch	Duration
Leaves_3	10	Hard-limit	Hard-limit	Perceptron Training Rule	70	15	15	20	0.00%	0	0	0.00%	0	0
Leaves_3	10	Hard-limit	Linear	Perceptron Training Rule	70	15	15	20	50.00%	0	0	0.00%	0	0
Leaves_3	10	Hard-limit	Log-sigmoid	Perceptron Training Rule	70	15	15	20	0.00%	0	0	0.00%	0	0
Leaves_3	10	Hard-limit	Hyperbolic tangent sigmoid	Perceptron Training Rule	70	15	15	20	0.00%	0	0	0.00%	0	0
Leaves_3	10	Hard-limit	Symmetric hard-limit	Perceptron Training Rule	70	15	15	20	50.00%	0	0	0.00%	0	0
Leaves_3	10	Hard-limit	None	Perceptron Training Rule	70	15	15	20	0.00%	0	0	0.00%	0	0
Leaves_3	10	Linear	Hard-limit	Perceptron Training Rule	70	15	15	20	0.00%	0	0	0.00%	0	0
Leaves_3	10	Linear	Linear	Perceptron Training Rule	70	15	15	20	0.00%	0	0	0.00%	0	0
Leaves_3	10	Linear	Log-sigmoid	Perceptron Training Rule	70	15	15	20	100.00%	0	0	0.00%	0	0
Leaves_3	10	Linear	Hyperbolic tangent sigmoid	Perceptron Training Rule	70	15	15	20	50.00%	0	0	0.00%	0	0
Leaves_3	10	Linear	Symmetric hard-limit	Perceptron Training Rule	70	15	15	20	50.00%	0	0	0.00%	0	0
Leaves_3	10	Linear	None	Perceptron Training Rule	70	15	15	20	0.00%	0	0	0.00%	0	0
Leaves_3	10	Log-sigmoid	Hard-limit	Perceptron Training Rule	70	15	15	20	0.00%	0	0	0.00%	0	0
Leaves_3	10	Log-sigmoid	Linear	Perceptron Training Rule	70	15	15	20	50.00%	0	0	0.00%	0	0
Leaves_3	10	Log-sigmoid	Log-sigmoid	Perceptron Training Rule	70	15	15	20	100.00%	0	0	0.00%	0	0
Leaves_3	10	Log-sigmoid	Hyperbolic tangent sigmoid	Perceptron Training Rule	70	15	15	20	0.00%	0	0	0.00%	0	0
Leaves_3	10	Log-sigmoid	Symmetric hard-limit	Perceptron Training Rule	70	15	15	20	0.00%	0	0	0.00%	0	0
Leaves_3	10	Log-sigmoid	None	Perceptron Training Rule	70	15	15	20	0.00%	0	0	0.00%	0	0
Leaves_3	10	Hyperbolic tangent sigmoid	Hard-limit	Perceptron Training Rule	70	15	15	20	0.00%	0	0	0.00%	0	0
Leaves_3	10	Hyperbolic tangent sigmoid	Linear	Perceptron Training Rule	70	15	15	20	0.00%	0	0	0.00%	0	0
Leaves_3	10	Hyperbolic tangent sigmoid	Log-sigmoid	Perceptron Training Rule	70	15	15	20	0.00%	0	0	0.00%	0	0
Leaves_3	10	Hyperbolic tangent sigmoid	Hyperbolic tangent sigmoid	Perceptron Training Rule	70	15	15	20	0.00%	0	0	0.00%	0	0
Leaves_3	10	Hyperbolic tangent sigmoid	Symmetric hard-limit	Perceptron Training Rule	70	15	15	20	0.00%	0	0	0.00%	0	0
Leaves_3	10	Hyperbolic tangent sigmoid	None	Perceptron Training Rule	70	15	15	20	0.00%	0	0	0.00%	0	0
Leaves_3	10	Symmetric hard-limit	Hard-limit	Perceptron Training Rule	70	15	15	20	50.00%	0	0	0.00%	0	0
Leaves_3	10	Symmetric hard-limit	Linear	Perceptron Training Rule	70	15	15	20	0.00%	0	0	0.00%	0	0
Leaves_3	10	Symmetric hard-limit	Log-sigmoid	Perceptron Training Rule	70	15	15	20	0.00%	0	0	0.00%	0	0
Leaves_3	10	Symmetric hard-limit	Hyperbolic tangent sigmoid	Perceptron Training Rule	70	15	15	20	0.00%	0	0	0.00%	0	0
Leaves_3	10	Symmetric hard-limit	Symmetric hard-limit	Perceptron Training Rule	70	15	15	20	0.00%	0	0	0.00%	0	0
Leaves_3	10	Symmetric hard-limit	None	Perceptron Training Rule	70	15	15	20	0.00%	0	0	0.00%	0	0
Leaves_3	10	Hard-limit	Hard-limit	Gradient Descent	70	15	15	20	50.00%	0	0	0.00%	0	0
Leaves_3	10	Hard-limit	Linear	Gradient Descent	70	15	15	20	0.00%	0	0	0.00%	0	0
Leaves_3	10	Hard-limit	Log-sigmoid	Gradient Descent	70	15	15	20	50.00%	0	0	0.00%	0	0
Leaves_3	10	Hard-limit	Hyperbolic tangent sigmoid	Gradient Descent	70	15	15	20	0.00%	0	0	0.00%	0	0
Leaves_3	10	Hard-limit	Symmetric hard-limit	Gradient Descent	70	15	15	20	50.00%	0	0	0.00%	0	0
Leaves_3	10	Hard-limit	None	Gradient Descent	70	15	15	20	50.00%	0	0	0.00%	0	0
Leaves_3	10	Linear	Hard-limit	Gradient Descent	70	15	15	20	0.00%	0	0	0.00%	0	0
Leaves_3	10	Linear	Linear	Gradient Descent	70	15	15	20	0.00%	0	0	0.00%	0	0
Leaves_3	10	Linear	Log-sigmoid	Gradient Descent	70	15	15	20	50.00%	0	0	0.00%	0	0
Leaves_3	10	Linear	Hyperbolic tangent sigmoid	Gradient Descent	70	15	15	20	0.00%	0	0	0.00%	0	0
Leaves_3	10	Linear	Symmetric hard-limit	Gradient Descent	70	15	15	20	0.00%	0	0	0.00%	0	0
Leaves_3	10	Linear	None	Gradient Descent	70	15	15	20	0.00%	0	0	0.00%	0	0
Leaves_3	10	Log-sigmoid	Hard-limit	Gradient Descent	70	15	15	20	0.00%	0	0	0.00%	0	0
Leaves_3	10	Log-sigmoid	Linear	Gradient Descent	70	15	15	20	0.00%	0	0	0.00%	0	0
Leaves_3	10	Log-sigmoid	Log-sigmoid	Gradient Descent	70	15	15	20	0.00%	0	0	0.00%	0	0

Table B.12: Training - Image in binary with Leaves_3 - Part 4

		Transfer functions			Ratio (in percentage %)				Species			Species		
Folder	Hidden L.	1st	2nd	Training algorithm	Train	Validation	Test	Quant. images	Success %	Epoch	Duration	Success %	Epoch	Duration
Leaves_3	10	Log-sigmoid	Hyperbolic tangent sigmoid	Gradient Descent	70	15	15	20	0.00%	0	0	0.00%	0	0
Leaves_3	10	Log-sigmoid	Symmetric hard-limit	Gradient Descent	70	15	15	20	0.00%	0	0	0.00%	0	0
Leaves_3	10	Log-sigmoid	None	Gradient Descent	70	15	15	20	0.00%	0	0	0.00%	0	0
Leaves_3	10	Hyperbolic tangent sigmoid	Hard-limit	Gradient Descent	70	15	15	20	50.00%	0	0	0.00%	0	0
Leaves_3	10	Hyperbolic tangent sigmoid	Linear	Gradient Descent	70	15	15	20	50.00%	0	0	0.00%	0	0
Leaves_3	10	Hyperbolic tangent sigmoid	Log-sigmoid	Gradient Descent	70	15	15	20	0.00%	0	0	0.00%	0	0
Leaves_3	10	Hyperbolic tangent sigmoid	Hyperbolic tangent sigmoid	Gradient Descent	70	15	15	20	0.00%	0	0	0.00%	0	0
Leaves_3	10	Hyperbolic tangent sigmoid	Symmetric hard-limit	Gradient Descent	70	15	15	20	50.00%	0	0	0.00%	0	0
Leaves_3	10	Hyperbolic tangent sigmoid	None	Gradient Descent	70	15	15	20	100.00%	0	0	0.00%	0	0
Leaves_3	10	Symmetric hard-limit	Hard-limit	Gradient Descent	70	15	15	20	0.00%	0	0	0.00%	0	0
Leaves_3	10	Symmetric hard-limit	Linear	Gradient Descent	70	15	15	20	100.00%	0	0	0.00%	0	0
Leaves_3	10	Symmetric hard-limit	Log-sigmoid	Gradient Descent	70	15	15	20	0.00%	0	0	0.00%	0	0
Leaves_3	10	Symmetric hard-limit	Hyperbolic tangent sigmoid	Gradient Descent	70	15	15	20	0.00%	0	0	0.00%	0	0
Leaves_3	10	Symmetric hard-limit	Symmetric hard-limit	Gradient Descent	70	15	15	20	0.00%	0	0	0.00%	0	0
Leaves_3	10	Symmetric hard-limit	None	Gradient Descent	70	15	15	20	50.00%	0	0	0.00%	0	0
Leaves_3	10	Hard-limit	Hard-limit	Stochastic Approximation to Gradient Descent	70	15	15	20	50.00%	0	0	0.00%	0	0
Leaves_3	10	Hard-limit	Linear	Stochastic Approximation to Gradient Descent	70	15	15	20	0.00%	0	0	0.00%	0	0
Leaves_3	10	Hard-limit	Log-sigmoid	Stochastic Approximation to Gradient Descent	70	15	15	20	0.00%	0	0	0.00%	0	0.01
Leaves_3	10	Hard-limit	Hyperbolic tangent sigmoid	Stochastic Approximation to Gradient Descent	70	15	15	20	0.00%	0	0	0.00%	0	0
Leaves_3	10	Hard-limit	Symmetric hard-limit	Stochastic Approximation to Gradient Descent	70	15	15	20	0.00%	0	0	0.00%	0	0
Leaves_3	10	Hard-limit	None	Stochastic Approximation to Gradient Descent	70	15	15	20	50.00%	0	0	0.00%	0	0
Leaves_3	10	Linear	Hard-limit	Stochastic Approximation to Gradient Descent	70	15	15	20	0.00%	0	0	0.00%	0	0
Leaves_3	10	Linear	Linear	Stochastic Approximation to Gradient Descent	70	15	15	20	0.00%	0	0	0.00%	0	0
Leaves_3	10	Linear	Log-sigmoid	Stochastic Approximation to Gradient Descent	70	15	15	20	50.00%	0	0	0.00%	0	0
Leaves_3	10	Linear	Hyperbolic tangent sigmoid	Stochastic Approximation to Gradient Descent	70	15	15	20	0.00%	0	0	0.00%	0	0
Leaves_3	10	Linear	Symmetric hard-limit	Stochastic Approximation to Gradient Descent	70	15	15	20	50.00%	0	0	0.00%	0	0
Leaves_3	10	Linear	None	Stochastic Approximation to Gradient Descent	70	15	15	20	100.00%	0	0	0.00%	0	0
Leaves_3	10	Log-sigmoid	Hard-limit	Stochastic Approximation to Gradient Descent	70	15	15	20	0.00%	0	0	0.00%	0	0
Leaves_3	10	Log-sigmoid	Linear	Stochastic Approximation to Gradient Descent	70	15	15	20	50.00%	0	0	0.00%	0	0
Leaves_3	10	Log-sigmoid	Log-sigmoid	Stochastic Approximation to Gradient Descent	70	15	15	20	50.00%	0	0	0.00%	0	0
Leaves_3	10	Log-sigmoid	Hyperbolic tangent sigmoid	Stochastic Approximation to Gradient Descent	70	15	15	20	0.00%	0	0	0.00%	0	0
Leaves_3	10	Log-sigmoid	Symmetric hard-limit	Stochastic Approximation to Gradient Descent	70	15	15	20	50.00%	0	0	0.00%	0	0
Leaves_3	10	Log-sigmoid	None	Stochastic Approximation to Gradient Descent	70	15	15	20	0.00%	0	0	0.00%	0	0
Leaves_3	10	Hyperbolic tangent sigmoid	Hard-limit	Stochastic Approximation to Gradient Descent	70	15	15	20	100.00%	0	0	0.00%	0	0
Leaves_3	10	Hyperbolic tangent sigmoid	Linear	Stochastic Approximation to Gradient Descent	70	15	15	20	0.00%	0	0	0.00%	0	0
Leaves_3	10	Hyperbolic tangent sigmoid	Log-sigmoid	Stochastic Approximation to Gradient Descent	70	15	15	20	0.00%	0	0	0.00%	0	0
Leaves_3	10	Hyperbolic tangent sigmoid	Hyperbolic tangent sigmoid	Stochastic Approximation to Gradient Descent	70	15	15	20	100.00%	0	0	0.00%	0	0
Leaves_3	10	Hyperbolic tangent sigmoid	Symmetric hard-limit	Stochastic Approximation to Gradient Descent	70	15	15	20	50.00%	0	0	0.00%	0	0
Leaves_3	10	Hyperbolic tangent sigmoid	None	Stochastic Approximation to Gradient Descent	70	15	15	20	50.00%	0	0	0.00%	0	0
Leaves_3	10	Symmetric hard-limit	Hard-limit	Stochastic Approximation to Gradient Descent	70	15	15	20	0.00%	0	0	0.00%	0	0
Leaves_3	10	Symmetric hard-limit	Linear	Stochastic Approximation to Gradient Descent	70	15	15	20	0.00%	0	0	0.00%	0	0
Leaves_3	10	Symmetric hard-limit	Log-sigmoid	Stochastic Approximation to Gradient Descent	70	15	15	20	0.00%	0	0	0.00%	0	0
Leaves_3	10	Symmetric hard-limit	Hyperbolic tangent sigmoid	Stochastic Approximation to Gradient Descent	70	15	15	20	50.00%	0	0	0.00%	0	0
Leaves_3	10	Symmetric hard-limit	Symmetric hard-limit	Stochastic Approximation to Gradient Descent	70	15	15	20	0.00%	0	0	0.00%	0	0
Leaves_3	10	Symmetric hard-limit	None	Stochastic Approximation to Gradient Descent	70	15	15	20	50.00%	0	0	0.00%	0	0

Appendix C

Training results for the characteristics of the image

Table C.1: Training - Characteristics of the image with Leaves_1 - Part 1

		Transfer functions			Ratio (in percentage %)				Species			Species		
Folder	Hidden L.	1st	2nd	Training algorithm	Train	Validation	Test	Quant. images	Success %	Epoch	Duration	Success %	Epoch	Duration
Leaves_1	2	Hard-limit	Hard-limit	Perceptron Training Rule	80	10	10	99	0.00%	0	0	0.00%	0	0
Leaves_1	2	Hard-limit	Linear	Perceptron Training Rule	80	10	10	99	0.00%	0	0	0.00%	0	0
Leaves_1	2	Hard-limit	Log-sigmoid	Perceptron Training Rule	80	10	10	99	10.00%	0	0	0.00%	0	0
Leaves_1	2	Hard-limit	Hyperbolic tangent sigmoid	Perceptron Training Rule	80	10	10	99	10.00%	0	0	0.00%	0	0
Leaves_1	2	Hard-limit	Symmetric hard-limit	Perceptron Training Rule	80	10	10	99	0.00%	0	0	0.00%	0	0
Leaves_1	2	Hard-limit	None	Perceptron Training Rule	80	10	10	99	20.00%	0	0	0.00%	0	0
Leaves_1	2	Linear	Hard-limit	Perceptron Training Rule	80	10	10	99	0.00%	0	0	0.00%	0	0
Leaves_1	2	Linear	Linear	Perceptron Training Rule	80	10	10	99	20.00%	0	0	0.00%	0	0
Leaves_1	2	Linear	Log-sigmoid	Perceptron Training Rule	80	10	10	99	10.00%	0	0	0.00%	0	0
Leaves_1	2	Linear	Hyperbolic tangent sigmoid	Perceptron Training Rule	80	10	10	99	10.00%	0	0	0.00%	0	0
Leaves_1	2	Linear	Symmetric hard-limit	Perceptron Training Rule	80	10	10	99	10.00%	0	0	0.00%	0	0
Leaves_1	2	Linear	None	Perceptron Training Rule	80	10	10	99	20.00%	0	0	0.00%	0	0
Leaves_1	2	Log-sigmoid	Hard-limit	Perceptron Training Rule	80	10	10	99	0.00%	0	0	0.00%	0	0
Leaves_1	2	Log-sigmoid	Linear	Perceptron Training Rule	80	10	10	99	20.00%	0	0	0.00%	0	0
Leaves_1	2	Log-sigmoid	Log-sigmoid	Perceptron Training Rule	80	10	10	99	10.00%	0	0	0.00%	0	0
Leaves_1	2	Log-sigmoid	Hyperbolic tangent sigmoid	Perceptron Training Rule	80	10	10	99	10.00%	0	0	10.00%	0	0
Leaves_1	2	Log-sigmoid	Symmetric hard-limit	Perceptron Training Rule	80	10	10	99	10.00%	0	0	0.00%	0	0
Leaves_1	2	Log-sigmoid	None	Perceptron Training Rule	80	10	10	99	20.00%	0	0	0.00%	0	0
Leaves_1	2	Hyperbolic tangent sigmoid	Hard-limit	Perceptron Training Rule	80	10	10	99	10.00%	0	0	10.00%	0	0
Leaves_1	2	Hyperbolic tangent sigmoid	Linear	Perceptron Training Rule	80	10	10	99	0.00%	0	0	0.00%	0	0
Leaves_1	2	Hyperbolic tangent sigmoid	Log-sigmoid	Perceptron Training Rule	80	10	10	99	20.00%	0	0	0.00%	0	0
Leaves_1	2	Hyperbolic tangent sigmoid	Hyperbolic tangent sigmoid	Perceptron Training Rule	80	10	10	99	10.00%	0	0	0.00%	0	0
Leaves_1	2	Hyperbolic tangent sigmoid	Symmetric hard-limit	Perceptron Training Rule	80	10	10	99	10.00%	0	0	0.00%	0	0
Leaves_1	2	Hyperbolic tangent sigmoid	None	Perceptron Training Rule	80	10	10	99	0.00%	0	0	10.00%	0	0
Leaves_1	2	Symmetric hard-limit	Hard-limit	Perceptron Training Rule	80	10	10	99	0.00%	0	0	0.00%	0	0
Leaves_1	2	Symmetric hard-limit	Linear	Perceptron Training Rule	80	10	10	99	20.00%	0	0	0.00%	0	0
Leaves_1	2	Symmetric hard-limit	Log-sigmoid	Perceptron Training Rule	80	10	10	99	10.00%	0	0	0.00%	0	0
Leaves_1	2	Symmetric hard-limit	Hyperbolic tangent sigmoid	Perceptron Training Rule	80	10	10	99	0.00%	0	0	0.00%	0	0
Leaves_1	2	Symmetric hard-limit	Symmetric hard-limit	Perceptron Training Rule	80	10	10	99	0.00%	0	0	0.00%	0	0
Leaves_1	2	Symmetric hard-limit	None	Perceptron Training Rule	80	10	10	99	0.00%	0	0	10.00%	0	0
Leaves_1	2	Hard-limit	Hard-limit	Gradient Descent	80	10	10	99	10.00%	0	0	0.00%	0	0
Leaves_1	2	Hard-limit	Linear	Gradient Descent	80	10	10	99	10.00%	0	0	0.00%	0	0
Leaves_1	2	Hard-limit	Log-sigmoid	Gradient Descent	80	10	10	99	0.00%	0	0	0.00%	0	0
Leaves_1	2	Hard-limit	Hyperbolic tangent sigmoid	Gradient Descent	80	10	10	99	10.00%	0	0	0.00%	0	0
Leaves_1	2	Hard-limit	Symmetric hard-limit	Gradient Descent	80	10	10	99	30.00%	0	0	0.00%	0	0
Leaves_1	2	Hard-limit	None	Gradient Descent	80	10	10	99	0.00%	0	0	0.00%	0	0
Leaves_1	2	Linear	Hard-limit	Gradient Descent	80	10	10	99	0.00%	0	0	0.00%	0	0
Leaves_1	2	Linear	Linear	Gradient Descent	80	10	10	99	20.00%	0	0	0.00%	0	0
Leaves_1	2	Linear	Log-sigmoid	Gradient Descent	80	10	10	99	0.00%	0	0	0.00%	0	0
Leaves_1	2	Linear	Hyperbolic tangent sigmoid	Gradient Descent	80	10	10	99	10.00%	0	0	0.00%	0	0
Leaves_1	2	Linear	Symmetric hard-limit	Gradient Descent	80	10	10	99	0.00%	0	0	0.00%	0	0
Leaves_1	2	Linear	None	Gradient Descent	80	10	10	99	10.00%	0	0	0.00%	0	0

Table C.2: Training - Characteristics of the image with Leaves_1 - Part 2

		Transfer functions			Ratio (in percentage %)				Species			Species		
Folder	Hidden L.	1st	2nd	Training algorithm	Train	Validation	Test	Quant. images	Success %	Epoch	Duration	Success %	Epoch	Duration
Leaves_1	2	Log-sigmoid	Hard-limit	Gradient Descent	80	10	10	99	20.00%	0	0	0.00%	0	0
Leaves_1	2	Log-sigmoid	Linear	Gradient Descent	80	10	10	99	0.00%	0	0	0.00%	0	0
Leaves_1	2	Log-sigmoid	Log-sigmoid	Gradient Descent	80	10	10	99	10.00%	0	0	0.00%	0	0
Leaves_1	2	Log-sigmoid	Hyperbolic tangent sigmoid	Gradient Descent	80	10	10	99	10.00%	0	0	0.00%	0	0
Leaves_1	2	Log-sigmoid	Symmetric hard-limit	Gradient Descent	80	10	10	99	0.00%	0	0	0.00%	0	0
Leaves_1	2	Log-sigmoid	None	Gradient Descent	80	10	10	99	10.00%	0	0	0.00%	0	0
Leaves_1	2	Hyperbolic tangent sigmoid	Hard-limit	Gradient Descent	80	10	10	99	10.00%	0	0	0.00%	0	0
Leaves_1	2	Hyperbolic tangent sigmoid	Linear	Gradient Descent	80	10	10	99	10.00%	0	0	0.00%	0	0
Leaves_1	2	Hyperbolic tangent sigmoid	Log-sigmoid	Gradient Descent	80	10	10	99	10.00%	0	0	0.00%	0	0
Leaves_1	2	Hyperbolic tangent sigmoid	Hyperbolic tangent sigmoid	Gradient Descent	80	10	10	99	0.00%	0	0	0.00%	0	0
Leaves_1	2	Hyperbolic tangent sigmoid	Symmetric hard-limit	Gradient Descent	80	10	10	99	0.00%	0	0	0.00%	0	0
Leaves_1	2	Hyperbolic tangent sigmoid	None	Gradient Descent	80	10	10	99	30.00%	0	0	0.00%	0	0
Leaves_1	2	Symmetric hard-limit	Hard-limit	Gradient Descent	80	10	10	99	10.00%	0	0	0.00%	0	0
Leaves_1	2	Symmetric hard-limit	Linear	Gradient Descent	80	10	10	99	0.00%	0	0	0.00%	0	0
Leaves_1	2	Symmetric hard-limit	Log-sigmoid	Gradient Descent	80	10	10	99	0.00%	0	0	0.00%	0	0
Leaves_1	2	Symmetric hard-limit	Hyperbolic tangent sigmoid	Gradient Descent	80	10	10	99	10.00%	0	0	10.00%	0	0
Leaves_1	2	Symmetric hard-limit	Symmetric hard-limit	Gradient Descent	80	10	10	99	30.00%	0	0	0.00%	0	0
Leaves_1	2	Symmetric hard-limit	None	Gradient Descent	80	10	10	99	20.00%	0	0	0.00%	0	0
Leaves_1	2	Hard-limit	Hard-limit	Stochastic Approximation to Gradient Descent	80	10	10	99	0.00%	0	0	0.00%	0	0
Leaves_1	2	Hard-limit	Linear	Stochastic Approximation to Gradient Descent	80	10	10	99	10.00%	0	0	0.00%	0	0
Leaves_1	2	Hard-limit	Log-sigmoid	Stochastic Approximation to Gradient Descent	80	10	10	99	0.00%	0	0	0.00%	0	0
Leaves_1	2	Hard-limit	Hyperbolic tangent sigmoid	Stochastic Approximation to Gradient Descent	80	10	10	99	10.00%	0	0	0.00%	0	0
Leaves_1	2	Hard-limit	Symmetric hard-limit	Stochastic Approximation to Gradient Descent	80	10	10	99	10.00%	0	0	0.00%	0	0
Leaves_1	2	Hard-limit	None	Stochastic Approximation to Gradient Descent	80	10	10	99	20.00%	0	0	0.00%	0	0
Leaves_1	2	Linear	Hard-limit	Stochastic Approximation to Gradient Descent	80	10	10	99	0.00%	0	0.02	0.00%	0	0
Leaves_1	2	Linear	Linear	Stochastic Approximation to Gradient Descent	80	10	10	99	0.00%	0	0	0.00%	0	0
Leaves_1	2	Linear	Log-sigmoid	Stochastic Approximation to Gradient Descent	80	10	10	99	20.00%	0	0	0.00%	0	0
Leaves_1	2	Linear	Hyperbolic tangent sigmoid	Stochastic Approximation to Gradient Descent	80	10	10	99	20.00%	0	0	0.00%	0	0
Leaves_1	2	Linear	Symmetric hard-limit	Stochastic Approximation to Gradient Descent	80	10	10	99	0.00%	0	0	0.00%	0	0
Leaves_1	2	Linear	None	Stochastic Approximation to Gradient Descent	80	10	10	99	0.00%	0	0	0.00%	0	0
Leaves_1	2	Log-sigmoid	Hard-limit	Stochastic Approximation to Gradient Descent	80	10	10	99	0.00%	0	0	0.00%	0	0
Leaves_1	2	Log-sigmoid	Linear	Stochastic Approximation to Gradient Descent	80	10	10	99	10.00%	0	0	0.00%	0	0
Leaves_1	2	Log-sigmoid	Log-sigmoid	Stochastic Approximation to Gradient Descent	80	10	10	99	10.00%	0	0	0.00%	0	0
Leaves_1	2	Log-sigmoid	Hyperbolic tangent sigmoid	Stochastic Approximation to Gradient Descent	80	10	10	99	0.00%	0	0	0.00%	0	0
Leaves_1	2	Log-sigmoid	Symmetric hard-limit	Stochastic Approximation to Gradient Descent	80	10	10	99	30.00%	0	0	0.00%	0	0
Leaves_1	2	Log-sigmoid	None	Stochastic Approximation to Gradient Descent	80	10	10	99	10.00%	0	0	0.00%	0	0
Leaves_1	2	Hyperbolic tangent sigmoid	Hard-limit	Stochastic Approximation to Gradient Descent	80	10	10	99	0.00%	0	0	0.00%	0	0
Leaves_1	2	Hyperbolic tangent sigmoid	Linear	Stochastic Approximation to Gradient Descent	80	10	10	99	20.00%	0	0	0.00%	0	0
Leaves_1	2	Hyperbolic tangent sigmoid	Log-sigmoid	Stochastic Approximation to Gradient Descent	80	10	10	99	20.00%	0	0	0.00%	0	0
Leaves_1	2	Hyperbolic tangent sigmoid	Hyperbolic tangent sigmoid	Stochastic Approximation to Gradient Descent	80	10	10	99	0.00%	0	0	0.00%	0	0
Leaves_1	2	Hyperbolic tangent sigmoid	Symmetric hard-limit	Stochastic Approximation to Gradient Descent	80	10	10	99	10.00%	0	0	0.00%	0	0
Leaves_1	2	Hyperbolic tangent sigmoid	None	Stochastic Approximation to Gradient Descent	80	10	10	99	0.00%	0	0	0.00%	0	0
Leaves_1	2	Symmetric hard-limit	Hard-limit	Stochastic Approximation to Gradient Descent	80	10	10	99	20.00%	0	0	0.00%	0	0
Leaves_1	2	Symmetric hard-limit	Linear	Stochastic Approximation to Gradient Descent	80	10	10	99	20.00%	0	0	0.00%	0	0
Leaves_1	2	Symmetric hard-limit	Log-sigmoid	Stochastic Approximation to Gradient Descent	80	10	10	99	20.00%	0	0	0.00%	0	0
Leaves_1	2	Symmetric hard-limit	Hyperbolic tangent sigmoid	Stochastic Approximation to Gradient Descent	80	10	10	99	0.00%	0	0	10.00%	0	0
Leaves_1	2	Symmetric hard-limit	Symmetric hard-limit	Stochastic Approximation to Gradient Descent	80	10	10	99	10.00%	0	0	0.00%	0	0
Leaves_1	2	Symmetric hard-limit	None	Stochastic Approximation to Gradient Descent	80	10	10	99	20.00%	0	0	10.00%	0	0

Table C.3: Training - Characteristics of the image with Leaves_1 - Part 3

		Transfer functions			Ratio (in percentage %)				Species			Species		
Folder	Hidden L.	1st	2nd	Training algorithm	Train	Validation	Test	Quant. images	Success %	Epoch	Duration	Success %	Epoch	Duration
Leaves_1	10	Hard-limit	Hard-limit	Perceptron Training Rule	70	15	15	99	0.00%	0	0.01	0.00%	0	0
Leaves_1	10	Hard-limit	Linear	Perceptron Training Rule	70	15	15	99	0.00%	0	0	0.00%	0	0
Leaves_1	10	Hard-limit	Log-sigmoid	Perceptron Training Rule	70	15	15	99	20.00%	0	0	0.00%	0	0
Leaves_1	10	Hard-limit	Hyperbolic tangent sigmoid	Perceptron Training Rule	70	15	15	99	20.00%	0	0	0.00%	0	0
Leaves_1	10	Hard-limit	Symmetric hard-limit	Perceptron Training Rule	70	15	15	99	0.00%	0	0	0.00%	0	0
Leaves_1	10	Hard-limit	None	Perceptron Training Rule	70	15	15	99	0.00%	0	0	0.00%	0	0
Leaves_1	10	Linear	Hard-limit	Perceptron Training Rule	70	15	15	99	0.00%	0	0	0.00%	0	0
Leaves_1	10	Linear	Linear	Perceptron Training Rule	70	15	15	99	10.00%	0	0	0.00%	0	0
Leaves_1	10	Linear	Log-sigmoid	Perceptron Training Rule	70	15	15	99	10.00%	0	0	0.00%	0	0
Leaves_1	10	Linear	Hyperbolic tangent sigmoid	Perceptron Training Rule	70	15	15	99	0.00%	0	0	0.00%	0	0
Leaves_1	10	Linear	Symmetric hard-limit	Perceptron Training Rule	70	15	15	99	30.00%	0	0	0.00%	0	0
Leaves_1	10	Linear	None	Perceptron Training Rule	70	15	15	99	10.00%	0	0	0.00%	0	0
Leaves_1	10	Log-sigmoid	Hard-limit	Perceptron Training Rule	70	15	15	99	0.00%	0	0	0.00%	0	0
Leaves_1	10	Log-sigmoid	Linear	Perceptron Training Rule	70	15	15	99	20.00%	0	0	0.00%	0	0
Leaves_1	10	Log-sigmoid	Log-sigmoid	Perceptron Training Rule	70	15	15	99	20.00%	0	0	0.00%	0	0
Leaves_1	10	Log-sigmoid	Hyperbolic tangent sigmoid	Perceptron Training Rule	70	15	15	99	0.00%	0	0	0.00%	0	0
Leaves_1	10	Log-sigmoid	Symmetric hard-limit	Perceptron Training Rule	70	15	15	99	10.00%	0	0	0.00%	0	0
Leaves_1	10	Log-sigmoid	None	Perceptron Training Rule	70	15	15	99	0.00%	0	0	0.00%	0	0
Leaves_1	10	Hyperbolic tangent sigmoid	Hard-limit	Perceptron Training Rule	70	15	15	99	20.00%	0	0	0.00%	0	0
Leaves_1	10	Hyperbolic tangent sigmoid	Linear	Perceptron Training Rule	70	15	15	99	20.00%	0	0	0.00%	0	0
Leaves_1	10	Hyperbolic tangent sigmoid	Log-sigmoid	Perceptron Training Rule	70	15	15	99	20.00%	0	0	0.00%	0	0
Leaves_1	10	Hyperbolic tangent sigmoid	Hyperbolic tangent sigmoid	Perceptron Training Rule	70	15	15	99	0.00%	0	0	10.00%	0	0
Leaves_1	10	Hyperbolic tangent sigmoid	Symmetric hard-limit	Perceptron Training Rule	70	15	15	99	10.00%	0	0	0.00%	0	0
Leaves_1	10	Hyperbolic tangent sigmoid	None	Perceptron Training Rule	70	15	15	99	20.00%	0	0	10.00%	0	0
Leaves_1	10	Symmetric hard-limit	Hard-limit	Perceptron Training Rule	70	15	15	99	10.00%	0	0	0.00%	0	0
Leaves_1	10	Symmetric hard-limit	Linear	Perceptron Training Rule	70	15	15	99	10.00%	0	0	10.00%	0	0
Leaves_1	10	Symmetric hard-limit	Log-sigmoid	Perceptron Training Rule	70	15	15	99	10.00%	0	0	10.00%	0	0
Leaves_1	10	Symmetric hard-limit	Hyperbolic tangent sigmoid	Perceptron Training Rule	70	15	15	99	20.00%	0	0	0.00%	0	0
Leaves_1	10	Symmetric hard-limit	Symmetric hard-limit	Perceptron Training Rule	70	15	15	99	20.00%	0	0	0.00%	0	0
Leaves_1	10	Symmetric hard-limit	None	Perceptron Training Rule	70	15	15	99	20.00%	0	0	0.00%	0	0
Leaves_1	10	Hard-limit	Hard-limit	Gradient Descent	70	15	15	99	20.00%	0	0	0.00%	0	0
Leaves_1	10	Hard-limit	Linear	Gradient Descent	70	15	15	99	10.00%	0	0	0.00%	0	0
Leaves_1	10	Hard-limit	Log-sigmoid	Gradient Descent	70	15	15	99	0.00%	0	0	0.00%	0	0
Leaves_1	10	Hard-limit	Hyperbolic tangent sigmoid	Gradient Descent	70	15	15	99	0.00%	0	0	0.00%	0	0
Leaves_1	10	Hard-limit	Symmetric hard-limit	Gradient Descent	70	15	15	99	10.00%	0	0	0.00%	0	0
Leaves_1	10	Hard-limit	None	Gradient Descent	70	15	15	99	10.00%	0	0	0.00%	0	0
Leaves_1	10	Linear	Hard-limit	Gradient Descent	70	15	15	99	20.00%	0	0	0.00%	0	0
Leaves_1	10	Linear	Linear	Gradient Descent	70	15	15	99	10.00%	0	0	10.00%	0	0
Leaves_1	10	Linear	Log-sigmoid	Gradient Descent	70	15	15	99	10.00%	0	0	10.00%	0	0
Leaves_1	10	Linear	Hyperbolic tangent sigmoid	Gradient Descent	70	15	15	99	0.00%	0	0	0.00%	0	0
Leaves_1	10	Linear	Symmetric hard-limit	Gradient Descent	70	15	15	99	10.00%	0	0	0.00%	0	0
Leaves_1	10	Linear	None	Gradient Descent	70	15	15	99	10.00%	0	0	0.00%	0	0
Leaves_1	10	Log-sigmoid	Hard-limit	Gradient Descent	70	15	15	99	10.00%	0	0	0.00%	0	0

Table C.4: Training - Characteristics of the image with Leaves_1 - Part 4

		Transfer functions			Ratio (in percentage %)				Species			Species		
Folder	Hidden L.	1st	2nd	Training algorithm	Train	Validation	Test	Quant. images	Success %	Epoch	Duration	Success %	Epoch	Duration
Leaves_1	10	Log-sigmoid	Linear	Gradient Descent	70	15	15	99	0.00%	0	0	0.00%	0	0
Leaves_1	10	Log-sigmoid	Log-sigmoid	Gradient Descent	70	15	15	99	10.00%	0	0	0.00%	0	0
Leaves_1	10	Log-sigmoid	Hyperbolic tangent sigmoid	Gradient Descent	70	15	15	99	0.00%	0	0	0.00%	0	0
Leaves_1	10	Log-sigmoid	Symmetric hard-limit	Gradient Descent	70	15	15	99	10.00%	0	0	0.00%	0	0
Leaves_1	10	Log-sigmoid	None	Gradient Descent	70	15	15	99	10.00%	0	0	10.00%	0	0
Leaves_1	10	Hyperbolic tangent sigmoid	Hard-limit	Gradient Descent	70	15	15	99	30.00%	0	0	0.00%	0	0
Leaves_1	10	Hyperbolic tangent sigmoid	Linear	Gradient Descent	70	15	15	99	20.00%	0	0	0.00%	0	0
Leaves_1	10	Hyperbolic tangent sigmoid	Log-sigmoid	Gradient Descent	70	15	15	99	10.00%	0	0	0.00%	0	0
Leaves_1	10	Hyperbolic tangent sigmoid	Hyperbolic tangent sigmoid	Gradient Descent	70	15	15	99	10.00%	0	0	0.00%	0	0
Leaves_1	10	Hyperbolic tangent sigmoid	Symmetric hard-limit	Gradient Descent	70	15	15	99	20.00%	0	0	0.00%	0	0
Leaves_1	10	Hyperbolic tangent sigmoid	None	Gradient Descent	70	15	15	99	0.00%	0	0	0.00%	0	0
Leaves_1	10	Symmetric hard-limit	Hard-limit	Gradient Descent	70	15	15	99	20.00%	0	0	0.00%	0	0
Leaves_1	10	Symmetric hard-limit	Linear	Gradient Descent	70	15	15	99	10.00%	0	0	0.00%	0	0
Leaves_1	10	Symmetric hard-limit	Log-sigmoid	Gradient Descent	70	15	15	99	10.00%	0	0	0.00%	0	0
Leaves_1	10	Symmetric hard-limit	Hyperbolic tangent sigmoid	Gradient Descent	70	15	15	99	10.00%	0	0	0.00%	0	0
Leaves_1	10	Symmetric hard-limit	Symmetric hard-limit	Gradient Descent	70	15	15	99	10.00%	0	0	0.00%	0	0
Leaves_1	10	Symmetric hard-limit	None	Gradient Descent	70	15	15	99	20.00%	0	0	0.00%	0	0
Leaves_1	10	Hard-limit	Hard-limit	Stochastic Approximation to Gradient Descent	70	15	15	99	10.00%	0	0	0.00%	0	0
Leaves_1	10	Hard-limit	Linear	Stochastic Approximation to Gradient Descent	70	15	15	99	20.00%	0	0	0.00%	0	0
Leaves_1	10	Hard-limit	Log-sigmoid	Stochastic Approximation to Gradient Descent	70	15	15	99	10.00%	0	0	0.00%	0	0
Leaves_1	10	Hard-limit	Hyperbolic tangent sigmoid	Stochastic Approximation to Gradient Descent	70	15	15	99	0.00%	0	0	0.00%	0	0
Leaves_1	10	Hard-limit	Symmetric hard-limit	Stochastic Approximation to Gradient Descent	70	15	15	99	0.00%	0	0	0.00%	0	0
Leaves_1	10	Hard-limit	None	Stochastic Approximation to Gradient Descent	70	15	15	99	0.00%	0	0	0.00%	0	0
Leaves_1	10	Linear	Hard-limit	Stochastic Approximation to Gradient Descent	70	15	15	99	30.00%	0	0	0.00%	0	0
Leaves_1	10	Linear	Linear	Stochastic Approximation to Gradient Descent	70	15	15	99	0.00%	0	0	0.00%	0	0
Leaves_1	10	Linear	Log-sigmoid	Stochastic Approximation to Gradient Descent	70	15	15	99	10.00%	0	0	0.00%	0	0
Leaves_1	10	Linear	Hyperbolic tangent sigmoid	Stochastic Approximation to Gradient Descent	70	15	15	99	0.00%	0	0	0.00%	0	0
Leaves_1	10	Linear	Symmetric hard-limit	Stochastic Approximation to Gradient Descent	70	15	15	99	0.00%	0	0	0.00%	0	0
Leaves_1	10	Linear	None	Stochastic Approximation to Gradient Descent	70	15	15	99	0.00%	0	0	0.00%	0	0
Leaves_1	10	Log-sigmoid	Hard-limit	Stochastic Approximation to Gradient Descent	70	15	15	99	20.00%	0	0	0.00%	0	0
Leaves_1	10	Log-sigmoid	Linear	Stochastic Approximation to Gradient Descent	70	15	15	99	0.00%	0	0	0.00%	0	0
Leaves_1	10	Log-sigmoid	Log-sigmoid	Stochastic Approximation to Gradient Descent	70	15	15	99	20.00%	0	0	0.00%	0	0
Leaves_1	10	Log-sigmoid	Hyperbolic tangent sigmoid	Stochastic Approximation to Gradient Descent	70	15	15	99	10.00%	0	0	0.00%	0	0
Leaves_1	10	Log-sigmoid	Symmetric hard-limit	Stochastic Approximation to Gradient Descent	70	15	15	99	10.00%	0	0	0.00%	0	0
Leaves_1	10	Log-sigmoid	None	Stochastic Approximation to Gradient Descent	70	15	15	99	0.00%	0	0	0.00%	0	0
Leaves_1	10	Hyperbolic tangent sigmoid	Hard-limit	Stochastic Approximation to Gradient Descent	70	15	15	99	0.00%	0	0	0.00%	0	0
Leaves_1	10	Hyperbolic tangent sigmoid	Linear	Stochastic Approximation to Gradient Descent	70	15	15	99	20.00%	0	0	0.00%	0	0
Leaves_1	10	Hyperbolic tangent sigmoid	Log-sigmoid	Stochastic Approximation to Gradient Descent	70	15	15	99	20.00%	0	0	0.00%	0	0
Leaves_1	10	Hyperbolic tangent sigmoid	Hyperbolic tangent sigmoid	Stochastic Approximation to Gradient Descent	70	15	15	99	0.00%	0	0	0.00%	0	0
Leaves_1	10	Hyperbolic tangent sigmoid	Symmetric hard-limit	Stochastic Approximation to Gradient Descent	70	15	15	99	10.00%	0	0	0.00%	0	0
Leaves_1	10	Hyperbolic tangent sigmoid	None	Stochastic Approximation to Gradient Descent	70	15	15	99	0.00%	0	0	10.00%	0	0
Leaves_1	10	Symmetric hard-limit	Hard-limit	Stochastic Approximation to Gradient Descent	70	15	15	99	10.00%	0	0	0.00%	0	0
Leaves_1	10	Symmetric hard-limit	Linear	Stochastic Approximation to Gradient Descent	70	15	15	99	0.00%	0	0	0.00%	0	0
Leaves_1	10	Symmetric hard-limit	Log-sigmoid	Stochastic Approximation to Gradient Descent	70	15	15	99	10.00%	0	0	0.00%	0	0
Leaves_1	10	Symmetric hard-limit	Hyperbolic tangent sigmoid	Stochastic Approximation to Gradient Descent	70	15	15	99	0.00%	0	0	0.00%	0	0
Leaves_1	10	Symmetric hard-limit	Symmetric hard-limit	Stochastic Approximation to Gradient Descent	70	15	15	99	10.00%	0	0	0.00%	0	0
Leaves_1	10	Symmetric hard-limit	None	Stochastic Approximation to Gradient Descent	70	15	15	99	10.00%	0	0	0.00%	0	0

Table C.5: Training - Characteristics of the image with Leaves_2 - Part 1

		Transfer functions			Ratio (in percentage %)				Species			Species		
Folder	Hidden L.	1st	2nd	Training algorithm	Train	Validation	Test	Quant. images	Success %	Epoch	Duration	Success %	Epoch	Duration
Leaves_2	2	Hard-limit	Hard-limit	Perceptron Training Rule	80	10	10	1564	6.19%	0	0	0.00%	0	0
Leaves_2	2	Hard-limit	Linear	Perceptron Training Rule	80	10	10	1564	6.19%	0	0	1.04%	0	0
Leaves_2	2	Hard-limit	Log-sigmoid	Perceptron Training Rule	80	10	10	1564	4.12%	0	0.01	4.17%	0	0
Leaves_2	2	Hard-limit	Hyperbolic tangent sigmoid	Perceptron Training Rule	80	10	10	1564	13.40%	0	0	1.04%	0	0
Leaves_2	2	Hard-limit	Symmetric hard-limit	Perceptron Training Rule	80	10	10	1564	7.22%	0	0	0.00%	0	0
Leaves_2	2	Hard-limit	None	Perceptron Training Rule	80	10	10	1564	6.19%	0	0	1.04%	0	0
Leaves_2	2	Linear	Hard-limit	Perceptron Training Rule	80	10	10	1564	9.28%	0	0	1.04%	0	0
Leaves_2	2	Linear	Linear	Perceptron Training Rule	80	10	10	1564	11.34%	0	0	3.13%	0	0
Leaves_2	2	Linear	Log-sigmoid	Perceptron Training Rule	80	10	10	1564	10.31%	0	0	1.04%	0	0
Leaves_2	2	Linear	Hyperbolic tangent sigmoid	Perceptron Training Rule	80	10	10	1564	8.25%	0	0	1.04%	0	0
Leaves_2	2	Linear	Symmetric hard-limit	Perceptron Training Rule	80	10	10	1564	7.22%	0	0	0.00%	0	0
Leaves_2	2	Linear	None	Perceptron Training Rule	80	10	10	1564	10.31%	0	0	3.13%	0	0
Leaves_2	2	Log-sigmoid	Hard-limit	Perceptron Training Rule	80	10	10	1564	8.25%	0	0	0.00%	0	0
Leaves_2	2	Log-sigmoid	Linear	Perceptron Training Rule	80	10	10	1564	4.12%	0	0	0.00%	0	0
Leaves_2	2	Log-sigmoid	Log-sigmoid	Perceptron Training Rule	80	10	10	1564	8.25%	0	0	1.04%	0	0
Leaves_2	2	Log-sigmoid	Hyperbolic tangent sigmoid	Perceptron Training Rule	80	10	10	1564	8.25%	0	0	2.08%	0	0
Leaves_2	2	Log-sigmoid	Symmetric hard-limit	Perceptron Training Rule	80	10	10	1564	7.22%	0	0	2.08%	0	0
Leaves_2	2	Log-sigmoid	None	Perceptron Training Rule	80	10	10	1564	8.25%	0	0	0.00%	0	0
Leaves_2	2	Hyperbolic tangent sigmoid	Hard-limit	Perceptron Training Rule	80	10	10	1564	12.37%	0	0	1.04%	0	0
Leaves_2	2	Hyperbolic tangent sigmoid	Linear	Perceptron Training Rule	80	10	10	1564	10.31%	0	0	1.04%	0	0
Leaves_2	2	Hyperbolic tangent sigmoid	Log-sigmoid	Perceptron Training Rule	80	10	10	1564	8.25%	0	0	1.04%	0	0
Leaves_2	2	Hyperbolic tangent sigmoid	Hyperbolic tangent sigmoid	Perceptron Training Rule	80	10	10	1564	6.19%	0	0	1.04%	0	0
Leaves_2	2	Hyperbolic tangent sigmoid	Symmetric hard-limit	Perceptron Training Rule	80	10	10	1564	6.19%	0	0	0.00%	0	0
Leaves_2	2	Hyperbolic tangent sigmoid	None	Perceptron Training Rule	80	10	10	1564	2.06%	0	0	2.08%	0	0
Leaves_2	2	Symmetric hard-limit	Hard-limit	Perceptron Training Rule	80	10	10	1564	12.37%	0	0	1.04%	0	0
Leaves_2	2	Symmetric hard-limit	Linear	Perceptron Training Rule	80	10	10	1564	6.19%	0	0	0.00%	0	0
Leaves_2	2	Symmetric hard-limit	Log-sigmoid	Perceptron Training Rule	80	10	10	1564	7.22%	0	0	0.00%	0	0
Leaves_2	2	Symmetric hard-limit	Hyperbolic tangent sigmoid	Perceptron Training Rule	80	10	10	1564	12.37%	0	0	0.00%	0	0
Leaves_2	2	Symmetric hard-limit	Symmetric hard-limit	Perceptron Training Rule	80	10	10	1564	4.12%	0	0	0.00%	0	0
Leaves_2	2	Symmetric hard-limit	None	Perceptron Training Rule	80	10	10	1564	10.31%	0	0	1.04%	0	0
Leaves_2	2	Hard-limit	Hard-limit	Gradient Descent	80	10	10	1564	13.40%	0	0	1.04%	0	0
Leaves_2	2	Hard-limit	Linear	Gradient Descent	80	10	10	1564	8.25%	0	0	0.00%	0	0
Leaves_2	2	Hard-limit	Log-sigmoid	Gradient Descent	80	10	10	1564	7.22%	0	0	1.04%	0	0
Leaves_2	2	Hard-limit	Hyperbolic tangent sigmoid	Gradient Descent	80	10	10	1564	5.15%	0	0	2.08%	0	0
Leaves_2	2	Hard-limit	Symmetric hard-limit	Gradient Descent	80	10	10	1564	2.06%	0	0	0.00%	0	0
Leaves_2	2	Hard-limit	None	Gradient Descent	80	10	10	1564	11.34%	0	0	0.00%	0	0
Leaves_2	2	Linear	Hard-limit	Gradient Descent	80	10	10	1564	7.22%	0	0	2.08%	0	0
Leaves_2	2	Linear	Linear	Gradient Descent	80	10	10	1564	12.37%	0	0	2.08%	0	0
Leaves_2	2	Linear	Log-sigmoid	Gradient Descent	80	10	10	1564	7.22%	0	0	0.00%	0	0
Leaves_2	2	Linear	Hyperbolic tangent sigmoid	Gradient Descent	80	10	10	1564	14.43%	0	0	1.04%	0	0
Leaves_2	2	Linear	Symmetric hard-limit	Gradient Descent	80	10	10	1564	6.19%	0	0	3.13%	0	0
Leaves_2	2	Linear	None	Gradient Descent	80	10	10	1564	7.22%	0	0	0.00%	0	0
Leaves_2	2	Log-sigmoid	Hard-limit	Gradient Descent	80	10	10	1564	5.15%	0	0	0.00%	0	0
Leaves_2	2	Log-sigmoid	Linear	Gradient Descent	80	10	10	1564	8.25%	0	0	2.08%	0	0
Leaves_2	2	Log-sigmoid	Log-sigmoid	Gradient Descent	80	10	10	1564	10.31%	0	0	1.04%	0	0

Table C.6: Training - Characteristics of the image with Leaves_2 - Part 2

		Transfer functions			Ratio (in percentage %)				Species			Species		
Folder	Hidden L.	1st	2nd	Training algorithm	Train	Validation	Test	Quant. images	Success %	Epoch	Duration	Success %	Epoch	Duration
Leaves_2	2	Log-sigmoid	Hyperbolic tangent sigmoid	Gradient Descent	80	10	10	1564	11.34%	0	0	1.04%	0	0
Leaves_2	2	Log-sigmoid	Symmetric hard-limit	Gradient Descent	80	10	10	1564	10.31%	0	0	0.00%	0	0
Leaves_2	2	Log-sigmoid	None	Gradient Descent	80	10	10	1564	10.31%	0	0	3.13%	0	0
Leaves_2	2	Hyperbolic tangent sigmoid	Hard-limit	Gradient Descent	80	10	10	1564	8.25%	0	0	0.00%	0	0
Leaves_2	2	Hyperbolic tangent sigmoid	Linear	Gradient Descent	80	10	10	1564	9.28%	0	0	0.00%	0	0
Leaves_2	2	Hyperbolic tangent sigmoid	Log-sigmoid	Gradient Descent	80	10	10	1564	14.43%	0	0	0.00%	0	0
Leaves_2	2	Hyperbolic tangent sigmoid	Hyperbolic tangent sigmoid	Gradient Descent	80	10	10	1564	8.25%	0	0	1.04%	0	0
Leaves_2	2	Hyperbolic tangent sigmoid	Symmetric hard-limit	Gradient Descent	80	10	10	1564	8.25%	0	0	0.00%	0	0
Leaves_2	2	Hyperbolic tangent sigmoid	None	Gradient Descent	80	10	10	1564	8.25%	0	0	2.08%	0	0
Leaves_2	2	Symmetric hard-limit	Hard-limit	Gradient Descent	80	10	10	1564	8.25%	0	0	2.08%	0	0
Leaves_2	2	Symmetric hard-limit	Linear	Gradient Descent	80	10	10	1564	10.31%	0	0	2.08%	0	0
Leaves_2	2	Symmetric hard-limit	Log-sigmoid	Gradient Descent	80	10	10	1564	7.22%	0	0	0.00%	0	0
Leaves_2	2	Symmetric hard-limit	Hyperbolic tangent sigmoid	Gradient Descent	80	10	10	1564	4.12%	0	0	1.04%	0	0
Leaves_2	2	Symmetric hard-limit	Symmetric hard-limit	Gradient Descent	80	10	10	1564	8.25%	0	0	1.04%	0	0
Leaves_2	2	Symmetric hard-limit	None	Gradient Descent	80	10	10	1564	6.19%	0	0	1.04%	0	0
Leaves_2	2	Hard-limit	Hard-limit	Stochastic Approximation to Gradient Descent	80	10	10	1564	8.25%	0	0	2.08%	0	0
Leaves_2	2	Hard-limit	Linear	Stochastic Approximation to Gradient Descent	80	10	10	1564	7.22%	0	0	0.00%	0	0
Leaves_2	2	Hard-limit	Log-sigmoid	Stochastic Approximation to Gradient Descent	80	10	10	1564	11.34%	0	0	2.08%	0	0
Leaves_2	2	Hard-limit	Hyperbolic tangent sigmoid	Stochastic Approximation to Gradient Descent	80	10	10	1564	11.34%	0	0	0.00%	0	0
Leaves_2	2	Hard-limit	Symmetric hard-limit	Stochastic Approximation to Gradient Descent	80	10	10	1564	7.22%	0	0	1.04%	0	0
Leaves_2	2	Hard-limit	None	Stochastic Approximation to Gradient Descent	80	10	10	1564	8.25%	0	0	1.04%	0	0
Leaves_2	2	Linear	Hard-limit	Stochastic Approximation to Gradient Descent	80	10	10	1564	14.43%	0	0	0.00%	0	0
Leaves_2	2	Linear	Linear	Stochastic Approximation to Gradient Descent	80	10	10	1564	7.22%	0	0	2.08%	0	0
Leaves_2	2	Linear	Log-sigmoid	Stochastic Approximation to Gradient Descent	80	10	10	1564	16.49%	0	0	0.00%	0	0
Leaves_2	2	Linear	Hyperbolic tangent sigmoid	Stochastic Approximation to Gradient Descent	80	10	10	1564	10.31%	0	0	1.04%	0	0
Leaves_2	2	Linear	Symmetric hard-limit	Stochastic Approximation to Gradient Descent	80	10	10	1564	7.22%	0	0	0.00%	0	0
Leaves_2	2	Linear	None	Stochastic Approximation to Gradient Descent	80	10	10	1564	9.28%	0	0	1.04%	0	0
Leaves_2	2	Log-sigmoid	Hard-limit	Stochastic Approximation to Gradient Descent	80	10	10	1564	8.25%	0	0	1.04%	0	0
Leaves_2	2	Log-sigmoid	Linear	Stochastic Approximation to Gradient Descent	80	10	10	1564	10.31%	0	0	0.00%	0	0
Leaves_2	2	Log-sigmoid	Log-sigmoid	Stochastic Approximation to Gradient Descent	80	10	10	1564	8.25%	0	0	1.04%	0	0
Leaves_2	2	Log-sigmoid	Hyperbolic tangent sigmoid	Stochastic Approximation to Gradient Descent	80	10	10	1564	13.40%	0	0	1.04%	0	0
Leaves_2	2	Log-sigmoid	Symmetric hard-limit	Stochastic Approximation to Gradient Descent	80	10	10	1564	7.22%	0	0	0.00%	0	0
Leaves_2	2	Log-sigmoid	None	Stochastic Approximation to Gradient Descent	80	10	10	1564	9.28%	0	0	1.04%	0	0
Leaves_2	2	Hyperbolic tangent sigmoid	Hard-limit	Stochastic Approximation to Gradient Descent	80	10	10	1564	12.37%	0	0	0.00%	0	0
Leaves_2	2	Hyperbolic tangent sigmoid	Linear	Stochastic Approximation to Gradient Descent	80	10	10	1564	8.25%	0	0	0.00%	0	0
Leaves_2	2	Hyperbolic tangent sigmoid	Log-sigmoid	Stochastic Approximation to Gradient Descent	80	10	10	1564	6.19%	0	0	2.08%	0	0
Leaves_2	2	Hyperbolic tangent sigmoid	Hyperbolic tangent sigmoid	Stochastic Approximation to Gradient Descent	80	10	10	1564	11.34%	0	0	0.00%	0	0
Leaves_2	2	Hyperbolic tangent sigmoid	Symmetric hard-limit	Stochastic Approximation to Gradient Descent	80	10	10	1564	12.37%	0	0.02	1.04%	0	0
Leaves_2	2	Hyperbolic tangent sigmoid	None	Stochastic Approximation to Gradient Descent	80	10	10	1564	12.37%	0	0	0.00%	0	0
Leaves_2	2	Symmetric hard-limit	Hard-limit	Stochastic Approximation to Gradient Descent	80	10	10	1564	5.15%	0	0	2.08%	0	0
Leaves_2	2	Symmetric hard-limit	Linear	Stochastic Approximation to Gradient Descent	80	10	10	1564	10.31%	0	0	1.04%	0	0
Leaves_2	2	Symmetric hard-limit	Log-sigmoid	Stochastic Approximation to Gradient Descent	80	10	10	1564	10.31%	0	0	0.00%	0	0
Leaves_2	2	Symmetric hard-limit	Hyperbolic tangent sigmoid	Stochastic Approximation to Gradient Descent	80	10	10	1564	14.43%	0	0	1.04%	0	0
Leaves_2	2	Symmetric hard-limit	Symmetric hard-limit	Stochastic Approximation to Gradient Descent	80	10	10	1564	10.31%	0	0	1.04%	0	0
Leaves_2	2	Symmetric hard-limit	None	Stochastic Approximation to Gradient Descent	80	10	10	1564	9.28%	0	0	4.17%	0	0

Table C.7: Training - Characteristics of the image with Leaves_2 - Part 3

		Transfer functions			Ratio (in percentage %)				Species			Species		
Folder	Hidden L.	1st	2nd	Training algorithm	Train	Validation	Test	Quant. images	Success %	Epoch	Duration	Success %	Epoch	Duration
Leaves_2	10	Hard-limit	Hard-limit	Perceptron Training Rule	70	15	15	1564	9.28%	0	0	4.17%	0	0
Leaves_2	10	Hard-limit	Linear	Perceptron Training Rule	70	15	15	1564	8.25%	0	0	1.04%	0	0
Leaves_2	10	Hard-limit	Log-sigmoid	Perceptron Training Rule	70	15	15	1564	9.28%	0	0	0.00%	0	0
Leaves_2	10	Hard-limit	Hyperbolic tangent sigmoid	Perceptron Training Rule	70	15	15	1564	4.12%	0	0	2.08%	0	0
Leaves_2	10	Hard-limit	Symmetric hard-limit	Perceptron Training Rule	70	15	15	1564	9.28%	0	0	2.08%	0	0
Leaves_2	10	Hard-limit	None	Perceptron Training Rule	70	15	15	1564	12.37%	0	0	0.00%	0	0
Leaves_2	10	Linear	Hard-limit	Perceptron Training Rule	70	15	15	1564	10.31%	0	0	0.00%	0	0
Leaves_2	10	Linear	Linear	Perceptron Training Rule	70	15	15	1564	8.25%	0	0	1.04%	0	0
Leaves_2	10	Linear	Log-sigmoid	Perceptron Training Rule	70	15	15	1564	5.15%	0	0	0.00%	0	0
Leaves_2	10	Linear	Hyperbolic tangent sigmoid	Perceptron Training Rule	70	15	15	1564	7.22%	0	0	1.04%	0	0
Leaves_2	10	Linear	Symmetric hard-limit	Perceptron Training Rule	70	15	15	1564	6.19%	0	0	1.04%	0	0
Leaves_2	10	Linear	None	Perceptron Training Rule	70	15	15	1564	13.40%	0	0	0.00%	0	0
Leaves_2	10	Log-sigmoid	Hard-limit	Perceptron Training Rule	70	15	15	1564	6.19%	0	0	2.08%	0	0
Leaves_2	10	Log-sigmoid	Linear	Perceptron Training Rule	70	15	15	1564	6.19%	0	0	0.00%	0	0
Leaves_2	10	Log-sigmoid	Log-sigmoid	Perceptron Training Rule	70	15	15	1564	15.46%	0	0	0.00%	0	0
Leaves_2	10	Log-sigmoid	Hyperbolic tangent sigmoid	Perceptron Training Rule	70	15	15	1564	8.25%	0	0	0.00%	0	0
Leaves_2	10	Log-sigmoid	Symmetric hard-limit	Perceptron Training Rule	70	15	15	1564	12.37%	0	0	1.04%	0	0
Leaves_2	10	Log-sigmoid	None	Perceptron Training Rule	70	15	15	1564	5.15%	0	0	0.00%	0	0
Leaves_2	10	Hyperbolic tangent sigmoid	Hard-limit	Perceptron Training Rule	70	15	15	1564	6.19%	0	0	0.00%	0	0
Leaves_2	10	Hyperbolic tangent sigmoid	Linear	Perceptron Training Rule	70	15	15	1564	4.12%	0	0	1.04%	0	0
Leaves_2	10	Hyperbolic tangent sigmoid	Log-sigmoid	Perceptron Training Rule	70	15	15	1564	9.28%	0	0	0.00%	0	0
Leaves_2	10	Hyperbolic tangent sigmoid	Hyperbolic tangent sigmoid	Perceptron Training Rule	70	15	15	1564	8.25%	0	0	1.04%	0	0
Leaves_2	10	Hyperbolic tangent sigmoid	Symmetric hard-limit	Perceptron Training Rule	70	15	15	1564	9.28%	0	0	2.08%	0	0
Leaves_2	10	Hyperbolic tangent sigmoid	None	Perceptron Training Rule	70	15	15	1564	8.25%	0	0	0.00%	0	0
Leaves_2	10	Symmetric hard-limit	Hard-limit	Perceptron Training Rule	70	15	15	1564	5.15%	0	0	2.08%	0	0
Leaves_2	10	Symmetric hard-limit	Linear	Perceptron Training Rule	70	15	15	1564	6.19%	0	0	0.00%	0	0
Leaves_2	10	Symmetric hard-limit	Log-sigmoid	Perceptron Training Rule	70	15	15	1564	6.19%	0	0	1.04%	0	0
Leaves_2	10	Symmetric hard-limit	Hyperbolic tangent sigmoid	Perceptron Training Rule	70	15	15	1564	3.09%	0	0	1.04%	0	0
Leaves_2	10	Symmetric hard-limit	Symmetric hard-limit	Perceptron Training Rule	70	15	15	1564	11.34%	0	0	0.00%	0	0
Leaves_2	10	Symmetric hard-limit	None	Perceptron Training Rule	70	15	15	1564	8.25%	0	0	1.04%	0	0
Leaves_2	10	Hard-limit	Hard-limit	Gradient Descent	70	15	15	1564	12.37%	0	0.01	1.04%	0	0
Leaves_2	10	Hard-limit	Linear	Gradient Descent	70	15	15	1564	12.37%	0	0	0.00%	0	0
Leaves_2	10	Hard-limit	Log-sigmoid	Gradient Descent	70	15	15	1564	5.15%	0	0	2.08%	0	0
Leaves_2	10	Hard-limit	Hyperbolic tangent sigmoid	Gradient Descent	70	15	15	1564	10.31%	0	0	1.04%	0	0
Leaves_2	10	Hard-limit	Symmetric hard-limit	Gradient Descent	70	15	15	1564	10.31%	0	0	0.00%	0	0
Leaves_2	10	Hard-limit	None	Gradient Descent	70	15	15	1564	14.43%	0	0	1.04%	0	0
Leaves_2	10	Linear	Hard-limit	Gradient Descent	70	15	15	1564	10.31%	0	0	1.04%	0	0
Leaves_2	10	Linear	Linear	Gradient Descent	70	15	15	1564	9.28%	0	0	4.17%	0	0
Leaves_2	10	Linear	Log-sigmoid	Gradient Descent	70	15	15	1564	8.25%	0	0	1.04%	0	0
Leaves_2	10	Linear	Hyperbolic tangent sigmoid	Gradient Descent	70	15	15	1564	9.28%	0	0	4.17%	0	0
Leaves_2	10	Linear	Symmetric hard-limit	Gradient Descent	70	15	15	1564	9.28%	0	0	0.00%	0	0
Leaves_2	10	Linear	None	Gradient Descent	70	15	15	1564	4.12%	0	0	2.08%	0	0
Leaves_2	10	Log-sigmoid	Hard-limit	Gradient Descent	70	15	15	1564	9.28%	0	0	2.08%	0	0
Leaves_2	10	Log-sigmoid	Linear	Gradient Descent	70	15	15	1564	12.37%	0	0	0.00%	0	0
Leaves_2	10	Log-sigmoid	Log-sigmoid	Gradient Descent	70	15	15	1564	10.31%	0	0	0.00%	0	0

Table C.8: Training - Characteristics of the image with Leaves_2 - Part 4

		Transfer functions			Ratio (in percentage %)				Species			Species		
Folder	Hidden L.	1st	2nd	Training algorithm	Train	Validation	Test	Quant. images	Success %	Epoch	Duration	Success %	Epoch	Duration
Leaves_2	10	Log-sigmoid	Hyperbolic tangent sigmoid	Gradient Descent	70	15	15	1564	8.25%	0	0	1.04%	0	0
Leaves_2	10	Log-sigmoid	Symmetric hard-limit	Gradient Descent	70	15	15	1564	5.15%	0	0	0.00%	0	0
Leaves_2	10	Log-sigmoid	None	Gradient Descent	70	15	15	1564	7.22%	0	0	1.04%	0	0
Leaves_2	10	Hyperbolic tangent sigmoid	Hard-limit	Gradient Descent	70	15	15	1564	6.19%	0	0	1.04%	0	0
Leaves_2	10	Hyperbolic tangent sigmoid	Linear	Gradient Descent	70	15	15	1564	13.40%	0	0	0.00%	0	0
Leaves_2	10	Hyperbolic tangent sigmoid	Log-sigmoid	Gradient Descent	70	15	15	1564	6.19%	0	0	2.08%	0	0
Leaves_2	10	Hyperbolic tangent sigmoid	Hyperbolic tangent sigmoid	Gradient Descent	70	15	15	1564	6.19%	0	0	0.00%	0	0
Leaves_2	10	Hyperbolic tangent sigmoid	Symmetric hard-limit	Gradient Descent	70	15	15	1564	15.46%	0	0	0.00%	0	0
Leaves_2	10	Hyperbolic tangent sigmoid	None	Gradient Descent	70	15	15	1564	8.25%	0	0	0.00%	0	0
Leaves_2	10	Symmetric hard-limit	Hard-limit	Gradient Descent	70	15	15	1564	12.37%	0	0	1.04%	0	0
Leaves_2	10	Symmetric hard-limit	Linear	Gradient Descent	70	15	15	1564	5.15%	0	0	0.00%	0	0
Leaves_2	10	Symmetric hard-limit	Log-sigmoid	Gradient Descent	70	15	15	1564	6.19%	0	0	0.00%	0	0
Leaves_2	10	Symmetric hard-limit	Hyperbolic tangent sigmoid	Gradient Descent	70	15	15	1564	4.12%	0	0	1.04%	0	0
Leaves_2	10	Symmetric hard-limit	Symmetric hard-limit	Gradient Descent	70	15	15	1564	9.28%	0	0	0.00%	0	0
Leaves_2	10	Symmetric hard-limit	None	Gradient Descent	70	15	15	1564	8.25%	0	0	1.04%	0	0
Leaves_2	10	Hard-limit	Hard-limit	Stochastic Approximation to Gradient Descent	70	15	15	1564	9.28%	0	0	2.08%	0	0
Leaves_2	10	Hard-limit	Linear	Stochastic Approximation to Gradient Descent	70	15	15	1564	8.25%	0	0	0.00%	0	0
Leaves_2	10	Hard-limit	Log-sigmoid	Stochastic Approximation to Gradient Descent	70	15	15	1564	5.15%	0	0	2.08%	0	0
Leaves_2	10	Hard-limit	Hyperbolic tangent sigmoid	Stochastic Approximation to Gradient Descent	70	15	15	1564	6.19%	0	0	0.00%	0	0
Leaves_2	10	Hard-limit	Symmetric hard-limit	Stochastic Approximation to Gradient Descent	70	15	15	1564	6.19%	0	0	1.04%	0	0
Leaves_2	10	Hard-limit	None	Stochastic Approximation to Gradient Descent	70	15	15	1564	3.09%	0	0	1.04%	0	0
Leaves_2	10	Linear	Hard-limit	Stochastic Approximation to Gradient Descent	70	15	15	1564	11.34%	0	0	0.00%	0	0
Leaves_2	10	Linear	Linear	Stochastic Approximation to Gradient Descent	70	15	15	1564	8.25%	0	0	1.04%	0	0
Leaves_2	10	Linear	Log-sigmoid	Stochastic Approximation to Gradient Descent	70	15	15	1564	12.37%	0	0	2.08%	0	0
Leaves_2	10	Linear	Hyperbolic tangent sigmoid	Stochastic Approximation to Gradient Descent	70	15	15	1564	12.37%	0	0	1.04%	0	0
Leaves_2	10	Linear	Symmetric hard-limit	Stochastic Approximation to Gradient Descent	70	15	15	1564	10.31%	0	0	0.00%	0	0
Leaves_2	10	Linear	None	Stochastic Approximation to Gradient Descent	70	15	15	1564	6.19%	0	0	1.04%	0	0
Leaves_2	10	Log-sigmoid	Hard-limit	Stochastic Approximation to Gradient Descent	70	15	15	1564	7.22%	0	0	0.00%	0	0
Leaves_2	10	Log-sigmoid	Linear	Stochastic Approximation to Gradient Descent	70	15	15	1564	7.22%	0	0	1.04%	0	0
Leaves_2	10	Log-sigmoid	Log-sigmoid	Stochastic Approximation to Gradient Descent	70	15	15	1564	11.34%	0	0	1.04%	0	0
Leaves_2	10	Log-sigmoid	Hyperbolic tangent sigmoid	Stochastic Approximation to Gradient Descent	70	15	15	1564	8.25%	0	0	1.04%	0	0
Leaves_2	10	Log-sigmoid	Symmetric hard-limit	Stochastic Approximation to Gradient Descent	70	15	15	1564	10.31%	0	0	0.00%	0	0
Leaves_2	10	Log-sigmoid	None	Stochastic Approximation to Gradient Descent	70	15	15	1564	8.25%	0	0	0.00%	0	0
Leaves_2	10	Hyperbolic tangent sigmoid	Hard-limit	Stochastic Approximation to Gradient Descent	70	15	15	1564	3.09%	0	0	0.00%	0	0
Leaves_2	10	Hyperbolic tangent sigmoid	Linear	Stochastic Approximation to Gradient Descent	70	15	15	1564	12.37%	0	0	0.00%	0	0
Leaves_2	10	Hyperbolic tangent sigmoid	Log-sigmoid	Stochastic Approximation to Gradient Descent	70	15	15	1564	9.28%	0	0	0.00%	0	0
Leaves_2	10	Hyperbolic tangent sigmoid	Hyperbolic tangent sigmoid	Stochastic Approximation to Gradient Descent	70	15	15	1564	12.37%	0	0	1.04%	0	0
Leaves_2	10	Hyperbolic tangent sigmoid	Symmetric hard-limit	Stochastic Approximation to Gradient Descent	70	15	15	1564	11.34%	0	0	0.00%	0	0
Leaves_2	10	Hyperbolic tangent sigmoid	None	Stochastic Approximation to Gradient Descent	70	15	15	1564	7.22%	0	0	0.00%	0	0
Leaves_2	10	Symmetric hard-limit	Hard-limit	Stochastic Approximation to Gradient Descent	70	15	15	1564	14.43%	0	0	1.04%	0	0
Leaves_2	10	Symmetric hard-limit	Linear	Stochastic Approximation to Gradient Descent	70	15	15	1564	7.22%	0	0	2.08%	0	0
Leaves_2	10	Symmetric hard-limit	Log-sigmoid	Stochastic Approximation to Gradient Descent	70	15	15	1564	8.25%	0	0	1.04%	0	0
Leaves_2	10	Symmetric hard-limit	Hyperbolic tangent sigmoid	Stochastic Approximation to Gradient Descent	70	15	15	1564	8.25%	0	0	1.04%	0	0
Leaves_2	10	Symmetric hard-limit	Symmetric hard-limit	Stochastic Approximation to Gradient Descent	70	15	15	1564	6.19%	0	0	1.04%	0	0
Leaves_2	10	Symmetric hard-limit	None	Stochastic Approximation to Gradient Descent	70	15	15	1564	6.19%	0	0	0.00%	0	0

Table C.9: Training - Characteristics of the image with Leaves_3 - Part 1

		Transfer functions			Ratio (in percentage %)				Species			Species		
Folder	Hidden L.	1st	2nd	Training algorithm	Train	Validation	Test	Quant. images	Success %	Epoch	Duration	Success %	Epoch	Duration
Leaves_3	2	Hard-limit	Hard-limit	Perceptron Training Rule	80	10	10	20	50.00%	0	0	0.00%	0	0
Leaves_3	2	Hard-limit	Linear	Perceptron Training Rule	80	10	10	20	0.00%	0	0	0.00%	0	0
Leaves_3	2	Hard-limit	Log-sigmoid	Perceptron Training Rule	80	10	10	20	50.00%	0	0	0.00%	0	0
Leaves_3	2	Hard-limit	Hyperbolic tangent sigmoid	Perceptron Training Rule	80	10	10	20	0.00%	0	0	0.00%	0	0
Leaves_3	2	Hard-limit	Symmetric hard-limit	Perceptron Training Rule	80	10	10	20	50.00%	0	0	0.00%	0	0
Leaves_3	2	Hard-limit	None	Perceptron Training Rule	80	10	10	20	0.00%	0	0	0.00%	0	0
Leaves_3	2	Linear	Hard-limit	Perceptron Training Rule	80	10	10	20	0.00%	0	0	0.00%	0	0
Leaves_3	2	Linear	Linear	Perceptron Training Rule	80	10	10	20	50.00%	0	0	0.00%	0	0
Leaves_3	2	Linear	Log-sigmoid	Perceptron Training Rule	80	10	10	20	50.00%	0	0	0.00%	0	0
Leaves_3	2	Linear	Hyperbolic tangent sigmoid	Perceptron Training Rule	80	10	10	20	0.00%	0	0	0.00%	0	0
Leaves_3	2	Linear	Symmetric hard-limit	Perceptron Training Rule	80	10	10	20	0.00%	0	0	0.00%	0	0
Leaves_3	2	Linear	None	Perceptron Training Rule	80	10	10	20	0.00%	0	0	0.00%	0	0
Leaves_3	2	Log-sigmoid	Hard-limit	Perceptron Training Rule	80	10	10	20	50.00%	0	0	0.00%	0	0
Leaves_3	2	Log-sigmoid	Linear	Perceptron Training Rule	80	10	10	20	50.00%	0	0	0.00%	0	0
Leaves_3	2	Log-sigmoid	Log-sigmoid	Perceptron Training Rule	80	10	10	20	0.00%	0	0	0.00%	0	0
Leaves_3	2	Log-sigmoid	Hyperbolic tangent sigmoid	Perceptron Training Rule	80	10	10	20	0.00%	0	0	0.00%	0	0
Leaves_3	2	Log-sigmoid	Symmetric hard-limit	Perceptron Training Rule	80	10	10	20	50.00%	0	0	0.00%	0	0
Leaves_3	2	Log-sigmoid	None	Perceptron Training Rule	80	10	10	20	50.00%	0	0	0.00%	0	0
Leaves_3	2	Hyperbolic tangent sigmoid	Hard-limit	Perceptron Training Rule	80	10	10	20	100.00%	0	0	0.00%	0	0
Leaves_3	2	Hyperbolic tangent sigmoid	Linear	Perceptron Training Rule	80	10	10	20	50.00%	0	0	0.00%	0	0
Leaves_3	2	Hyperbolic tangent sigmoid	Log-sigmoid	Perceptron Training Rule	80	10	10	20	0.00%	0	0	0.00%	0	0
Leaves_3	2	Hyperbolic tangent sigmoid	Hyperbolic tangent sigmoid	Perceptron Training Rule	80	10	10	20	50.00%	0	0	0.00%	0	0
Leaves_3	2	Hyperbolic tangent sigmoid	Symmetric hard-limit	Perceptron Training Rule	80	10	10	20	0.00%	0	0	0.00%	0	0
Leaves_3	2	Hyperbolic tangent sigmoid	None	Perceptron Training Rule	80	10	10	20	0.00%	0	0	0.00%	0	0
Leaves_3	2	Symmetric hard-limit	Hard-limit	Perceptron Training Rule	80	10	10	20	0.00%	0	0	0.00%	0	0
Leaves_3	2	Symmetric hard-limit	Linear	Perceptron Training Rule	80	10	10	20	50.00%	0	0	0.00%	0	0
Leaves_3	2	Symmetric hard-limit	Log-sigmoid	Perceptron Training Rule	80	10	10	20	50.00%	0	0	0.00%	0	0
Leaves_3	2	Symmetric hard-limit	Hyperbolic tangent sigmoid	Perceptron Training Rule	80	10	10	20	50.00%	0	0	0.00%	0	0
Leaves_3	2	Symmetric hard-limit	Symmetric hard-limit	Perceptron Training Rule	80	10	10	20	0.00%	0	0	0.00%	0	0
Leaves_3	2	Symmetric hard-limit	None	Perceptron Training Rule	80	10	10	20	0.00%	0	0	0.00%	0	0
Leaves_3	2	Hard-limit	Hard-limit	Gradient Descent	80	10	10	20	0.00%	0	0	0.00%	0	0
Leaves_3	2	Hard-limit	Linear	Gradient Descent	80	10	10	20	0.00%	0	0	0.00%	0	0
Leaves_3	2	Hard-limit	Log-sigmoid	Gradient Descent	80	10	10	20	0.00%	0	0	0.00%	0	0
Leaves_3	2	Hard-limit	Hyperbolic tangent sigmoid	Gradient Descent	80	10	10	20	50.00%	0	0	0.00%	0	0
Leaves_3	2	Hard-limit	Symmetric hard-limit	Gradient Descent	80	10	10	20	50.00%	0	0	0.00%	0	0
Leaves_3	2	Hard-limit	None	Gradient Descent	80	10	10	20	50.00%	0	0	0.00%	0	0
Leaves_3	2	Linear	Hard-limit	Gradient Descent	80	10	10	20	0.00%	0	0	0.00%	0	0
Leaves_3	2	Linear	Linear	Gradient Descent	80	10	10	20	0.00%	0	0	0.00%	0	0
Leaves_3	2	Linear	Log-sigmoid	Gradient Descent	80	10	10	20	0.00%	0	0	0.00%	0	0
Leaves_3	2	Linear	Hyperbolic tangent sigmoid	Gradient Descent	80	10	10	20	50.00%	0	0	0.00%	0	0
Leaves_3	2	Linear	Symmetric hard-limit	Gradient Descent	80	10	10	20	0.00%	0	0	0.00%	0	0
Leaves_3	2	Linear	None	Gradient Descent	80	10	10	20	50.00%	0	0	0.00%	0	0
Leaves_3	2	Log-sigmoid	Hard-limit	Gradient Descent	80	10	10	20	0.00%	0	0	0.00%	0	0
Leaves_3	2	Log-sigmoid	Linear	Gradient Descent	80	10	10	20	0.00%	0	0	0.00%	0	0
Leaves_3	2	Log-sigmoid	Log-sigmoid	Gradient Descent	80	10	10	20	0.00%	0	0	0.00%	0	0

Table C.10: Training - Characteristics of the image with Leaves_3 - Part 2

		Transfer functions			Ratio (in percentage %)				Species			Species		
Folder	Hidden L.	1st	2nd	Training algorithm	Train	Validation	Test	Quant. images	Success %	Epoch	Duration	Success %	Epoch	Duration
Leaves_3	2	Log-sigmoid	Hyperbolic tangent sigmoid	Gradient Descent	80	10	10	20	0.00%	0	0	0.00%	0	0
Leaves_3	2	Log-sigmoid	Symmetric hard-limit	Gradient Descent	80	10	10	20	50.00%	0	0	0.00%	0	0
Leaves_3	2	Log-sigmoid	None	Gradient Descent	80	10	10	20	50.00%	0	0	0.00%	0	0
Leaves_3	2	Hyperbolic tangent sigmoid	Hard-limit	Gradient Descent	80	10	10	20	0.00%	0	0	0.00%	0	0
Leaves_3	2	Hyperbolic tangent sigmoid	Linear	Gradient Descent	80	10	10	20	0.00%	0	0	0.00%	0	0
Leaves_3	2	Hyperbolic tangent sigmoid	Log-sigmoid	Gradient Descent	80	10	10	20	50.00%	0	0	0.00%	0	0
Leaves_3	2	Hyperbolic tangent sigmoid	Hyperbolic tangent sigmoid	Gradient Descent	80	10	10	20	0.00%	0	0	0.00%	0	0
Leaves_3	2	Hyperbolic tangent sigmoid	Symmetric hard-limit	Gradient Descent	80	10	10	20	50.00%	0	0	0.00%	0	0
Leaves_3	2	Hyperbolic tangent sigmoid	None	Gradient Descent	80	10	10	20	100.00%	0	0	0.00%	0	0
Leaves_3	2	Symmetric hard-limit	Hard-limit	Gradient Descent	80	10	10	20	0.00%	0	0	0.00%	0	0
Leaves_3	2	Symmetric hard-limit	Linear	Gradient Descent	80	10	10	20	0.00%	0	0	0.00%	0	0
Leaves_3	2	Symmetric hard-limit	Log-sigmoid	Gradient Descent	80	10	10	20	50.00%	0	0	0.00%	0	0
Leaves_3	2	Symmetric hard-limit	Hyperbolic tangent sigmoid	Gradient Descent	80	10	10	20	0.00%	0	0	0.00%	0	0
Leaves_3	2	Symmetric hard-limit	Symmetric hard-limit	Gradient Descent	80	10	10	20	50.00%	0	0	0.00%	0	0
Leaves_3	2	Symmetric hard-limit	None	Gradient Descent	80	10	10	20	0.00%	0	0	0.00%	0	0
Leaves_3	2	Hard-limit	Hard-limit	Stochastic Approximation to Gradient Descent	80	10	10	20	50.00%	0	0	0.00%	0	0
Leaves_3	2	Hard-limit	Linear	Stochastic Approximation to Gradient Descent	80	10	10	20	0.00%	0	0	0.00%	0	0
Leaves_3	2	Hard-limit	Log-sigmoid	Stochastic Approximation to Gradient Descent	80	10	10	20	0.00%	0	0	0.00%	0	0
Leaves_3	2	Hard-limit	Hyperbolic tangent sigmoid	Stochastic Approximation to Gradient Descent	80	10	10	20	50.00%	0	0	0.00%	0	0
Leaves_3	2	Hard-limit	Symmetric hard-limit	Stochastic Approximation to Gradient Descent	80	10	10	20	0.00%	0	0	0.00%	0	0
Leaves_3	2	Hard-limit	None	Stochastic Approximation to Gradient Descent	80	10	10	20	0.00%	0	0	0.00%	0	0
Leaves_3	2	Linear	Hard-limit	Stochastic Approximation to Gradient Descent	80	10	10	20	100.00%	0	0	0.00%	0	0
Leaves_3	2	Linear	Linear	Stochastic Approximation to Gradient Descent	80	10	10	20	0.00%	0	0	0.00%	0	0
Leaves_3	2	Linear	Log-sigmoid	Stochastic Approximation to Gradient Descent	80	10	10	20	0.00%	0	0	0.00%	0	0
Leaves_3	2	Linear	Hyperbolic tangent sigmoid	Stochastic Approximation to Gradient Descent	80	10	10	20	50.00%	0	0	0.00%	0	0
Leaves_3	2	Linear	Symmetric hard-limit	Stochastic Approximation to Gradient Descent	80	10	10	20	50.00%	0	0	0.00%	0	0
Leaves_3	2	Linear	None	Stochastic Approximation to Gradient Descent	80	10	10	20	0.00%	0	0	0.00%	0	0
Leaves_3	2	Log-sigmoid	Hard-limit	Stochastic Approximation to Gradient Descent	80	10	10	20	50.00%	0	0	0.00%	0	0
Leaves_3	2	Log-sigmoid	Linear	Stochastic Approximation to Gradient Descent	80	10	10	20	0.00%	0	0	0.00%	0	0
Leaves_3	2	Log-sigmoid	Log-sigmoid	Stochastic Approximation to Gradient Descent	80	10	10	20	50.00%	0	0	0.00%	0	0
Leaves_3	2	Log-sigmoid	Hyperbolic tangent sigmoid	Stochastic Approximation to Gradient Descent	80	10	10	20	0.00%	0	0	0.00%	0	0
Leaves_3	2	Log-sigmoid	Symmetric hard-limit	Stochastic Approximation to Gradient Descent	80	10	10	20	0.00%	0	0	0.00%	0	0
Leaves_3	2	Log-sigmoid	None	Stochastic Approximation to Gradient Descent	80	10	10	20	0.00%	0	0	0.00%	0	0
Leaves_3	2	Hyperbolic tangent sigmoid	Hard-limit	Stochastic Approximation to Gradient Descent	80	10	10	20	0.00%	0	0	0.00%	0	0
Leaves_3	2	Hyperbolic tangent sigmoid	Linear	Stochastic Approximation to Gradient Descent	80	10	10	20	50.00%	0	0	0.00%	0	0
Leaves_3	2	Hyperbolic tangent sigmoid	Log-sigmoid	Stochastic Approximation to Gradient Descent	80	10	10	20	50.00%	0	0	0.00%	0	0
Leaves_3	2	Hyperbolic tangent sigmoid	Hyperbolic tangent sigmoid	Stochastic Approximation to Gradient Descent	80	10	10	20	50.00%	0	0	0.00%	0	0
Leaves_3	2	Hyperbolic tangent sigmoid	Symmetric hard-limit	Stochastic Approximation to Gradient Descent	80	10	10	20	0.00%	0	0	0.00%	0	0
Leaves_3	2	Hyperbolic tangent sigmoid	None	Stochastic Approximation to Gradient Descent	80	10	10	20	0.00%	0	0	0.00%	0	0
Leaves_3	2	Symmetric hard-limit	Hard-limit	Stochastic Approximation to Gradient Descent	80	10	10	20	50.00%	0	0	0.00%	0	0
Leaves_3	2	Symmetric hard-limit	Linear	Stochastic Approximation to Gradient Descent	80	10	10	20	0.00%	0	0	0.00%	0	0
Leaves_3	2	Symmetric hard-limit	Log-sigmoid	Stochastic Approximation to Gradient Descent	80	10	10	20	50.00%	0	0	0.00%	0	0
Leaves_3	2	Symmetric hard-limit	Hyperbolic tangent sigmoid	Stochastic Approximation to Gradient Descent	80	10	10	20	100.00%	0	0	0.00%	0	0
Leaves_3	2	Symmetric hard-limit	Symmetric hard-limit	Stochastic Approximation to Gradient Descent	80	10	10	20	50.00%	0	0	0.00%	0	0
Leaves_3	2	Symmetric hard-limit	None	Stochastic Approximation to Gradient Descent	80	10	10	20	50.00%	0	0	0.00%	0	0

Table C.11: Training - Characteristics of the image with Leaves_3 - Part 3

		Transfer functions			Ratio (in percentage %)				Species			Species		
Folder	Hidden L.	1st	2nd	Training algorithm	Train	Validation	Test	Quant. images	Success %	Epoch	Duration	Success %	Epoch	Duration
Leaves_3	10	Hard-limit	Hard-limit	Perceptron Training Rule	70	15	15	20	0.00%	0	0	0.00%	0	0
Leaves_3	10	Hard-limit	Linear	Perceptron Training Rule	70	15	15	20	0.00%	0	0	0.00%	0	0
Leaves_3	10	Hard-limit	Log-sigmoid	Perceptron Training Rule	70	15	15	20	0.00%	0	0	0.00%	0	0
Leaves_3	10	Hard-limit	Hyperbolic tangent sigmoid	Perceptron Training Rule	70	15	15	20	0.00%	0	0	0.00%	0	0
Leaves_3	10	Hard-limit	Symmetric hard-limit	Perceptron Training Rule	70	15	15	20	0.00%	0	0	0.00%	0	0
Leaves_3	10	Hard-limit	None	Perceptron Training Rule	70	15	15	20	50.00%	0	0	0.00%	0	0
Leaves_3	10	Linear	Hard-limit	Perceptron Training Rule	70	15	15	20	50.00%	0	0	0.00%	0	0
Leaves_3	10	Linear	Linear	Perceptron Training Rule	70	15	15	20	50.00%	0	0	0.00%	0	0
Leaves_3	10	Linear	Log-sigmoid	Perceptron Training Rule	70	15	15	20	50.00%	0	0	0.00%	0	0
Leaves_3	10	Linear	Hyperbolic tangent sigmoid	Perceptron Training Rule	70	15	15	20	0.00%	0	0	0.00%	0	0
Leaves_3	10	Linear	Symmetric hard-limit	Perceptron Training Rule	70	15	15	20	50.00%	0	0	0.00%	0	0
Leaves_3	10	Linear	None	Perceptron Training Rule	70	15	15	20	50.00%	0	0	0.00%	0	0
Leaves_3	10	Log-sigmoid	Hard-limit	Perceptron Training Rule	70	15	15	20	0.00%	0	0	0.00%	0	0
Leaves_3	10	Log-sigmoid	Linear	Perceptron Training Rule	70	15	15	20	50.00%	0	0	0.00%	0	0
Leaves_3	10	Log-sigmoid	Log-sigmoid	Perceptron Training Rule	70	15	15	20	0.00%	0	0	0.00%	0	0
Leaves_3	10	Log-sigmoid	Hyperbolic tangent sigmoid	Perceptron Training Rule	70	15	15	20	50.00%	0	0	0.00%	0	0
Leaves_3	10	Log-sigmoid	Symmetric hard-limit	Perceptron Training Rule	70	15	15	20	0.00%	0	0	0.00%	0	0
Leaves_3	10	Log-sigmoid	None	Perceptron Training Rule	70	15	15	20	50.00%	0	0	0.00%	0	0
Leaves_3	10	Hyperbolic tangent sigmoid	Hard-limit	Perceptron Training Rule	70	15	15	20	0.00%	0	0	0.00%	0	0
Leaves_3	10	Hyperbolic tangent sigmoid	Linear	Perceptron Training Rule	70	15	15	20	50.00%	0	0	0.00%	0	0
Leaves_3	10	Hyperbolic tangent sigmoid	Log-sigmoid	Perceptron Training Rule	70	15	15	20	50.00%	0	0	0.00%	0	0
Leaves_3	10	Hyperbolic tangent sigmoid	Hyperbolic tangent sigmoid	Perceptron Training Rule	70	15	15	20	0.00%	0	0	0.00%	0	0
Leaves_3	10	Hyperbolic tangent sigmoid	Symmetric hard-limit	Perceptron Training Rule	70	15	15	20	0.00%	0	0	0.00%	0	0
Leaves_3	10	Hyperbolic tangent sigmoid	None	Perceptron Training Rule	70	15	15	20	50.00%	0	0	0.00%	0	0
Leaves_3	10	Symmetric hard-limit	Hard-limit	Perceptron Training Rule	70	15	15	20	0.00%	0	0	0.00%	0	0
Leaves_3	10	Symmetric hard-limit	Linear	Perceptron Training Rule	70	15	15	20	0.00%	0	0	0.00%	0	0
Leaves_3	10	Symmetric hard-limit	Log-sigmoid	Perceptron Training Rule	70	15	15	20	50.00%	0	0	0.00%	0	0
Leaves_3	10	Symmetric hard-limit	Hyperbolic tangent sigmoid	Perceptron Training Rule	70	15	15	20	0.00%	0	0	0.00%	0	0
Leaves_3	10	Symmetric hard-limit	Symmetric hard-limit	Perceptron Training Rule	70	15	15	20	0.00%	0	0	0.00%	0	0
Leaves_3	10	Symmetric hard-limit	None	Perceptron Training Rule	70	15	15	20	50.00%	0	0	0.00%	0	0
Leaves_3	10	Hard-limit	Hard-limit	Gradient Descent	70	15	15	20	50.00%	0	0	0.00%	0	0
Leaves_3	10	Hard-limit	Linear	Gradient Descent	70	15	15	20	100.00%	0	0	0.00%	0	0
Leaves_3	10	Hard-limit	Log-sigmoid	Gradient Descent	70	15	15	20	0.00%	0	0	0.00%	0	0
Leaves_3	10	Hard-limit	Hyperbolic tangent sigmoid	Gradient Descent	70	15	15	20	50.00%	0	0	0.00%	0	0
Leaves_3	10	Hard-limit	Symmetric hard-limit	Gradient Descent	70	15	15	20	0.00%	0	0	0.00%	0	0
Leaves_3	10	Hard-limit	None	Gradient Descent	70	15	15	20	50.00%	0	0	0.00%	0	0
Leaves_3	10	Linear	Hard-limit	Gradient Descent	70	15	15	20	0.00%	0	0	0.00%	0	0
Leaves_3	10	Linear	Linear	Gradient Descent	70	15	15	20	0.00%	0	0	0.00%	0	0
Leaves_3	10	Linear	Log-sigmoid	Gradient Descent	70	15	15	20	0.00%	0	0	0.00%	0	0
Leaves_3	10	Linear	Hyperbolic tangent sigmoid	Gradient Descent	70	15	15	20	0.00%	0	0	0.00%	0	0
Leaves_3	10	Linear	Symmetric hard-limit	Gradient Descent	70	15	15	20	100.00%	0	0	0.00%	0	0
Leaves_3	10	Linear	None	Gradient Descent	70	15	15	20	50.00%	0	0	0.00%	0	0
Leaves_3	10	Log-sigmoid	Hard-limit	Gradient Descent	70	15	15	20	50.00%	0	0	0.00%	0	0
Leaves_3	10	Log-sigmoid	Linear	Gradient Descent	70	15	15	20	0.00%	0	0	0.00%	0	0
Leaves_3	10	Log-sigmoid	Log-sigmoid	Gradient Descent	70	15	15	20	50.00%	0	0	0.00%	0	0

Table C.12: Training - Characteristics of the image with Leaves_3 - Part 4

		Transfer functions			Ratio (in percentage %)				Species			Species		
Folder	Hidden L.	1st	2nd	Training algorithm	Train	Validation	Test	Quant. images	Success %	Epoch	Duration	Success %	Epoch	Duration
Leaves_3	10	Log-sigmoid	Hyperbolic tangent sigmoid	Gradient Descent	70	15	15	20	50.00%	0	0	0.00%	0	0
Leaves_3	10	Log-sigmoid	Symmetric hard-limit	Gradient Descent	70	15	15	20	50.00%	0	0	0.00%	0	0
Leaves_3	10	Log-sigmoid	None	Gradient Descent	70	15	15	20	50.00%	0	0	0.00%	0	0
Leaves_3	10	Hyperbolic tangent sigmoid	Hard-limit	Gradient Descent	70	15	15	20	50.00%	0	0	0.00%	0	0
Leaves_3	10	Hyperbolic tangent sigmoid	Linear	Gradient Descent	70	15	15	20	50.00%	0	0	0.00%	0	0
Leaves_3	10	Hyperbolic tangent sigmoid	Log-sigmoid	Gradient Descent	70	15	15	20	0.00%	0	0	0.00%	0	0
Leaves_3	10	Hyperbolic tangent sigmoid	Hyperbolic tangent sigmoid	Gradient Descent	70	15	15	20	0.00%	0	0	0.00%	0	0
Leaves_3	10	Hyperbolic tangent sigmoid	Symmetric hard-limit	Gradient Descent	70	15	15	20	100.00%	0	0	0.00%	0	0
Leaves_3	10	Hyperbolic tangent sigmoid	None	Gradient Descent	70	15	15	20	0.00%	0	0	0.00%	0	0
Leaves_3	10	Symmetric hard-limit	Hard-limit	Gradient Descent	70	15	15	20	50.00%	0	0	0.00%	0	0
Leaves_3	10	Symmetric hard-limit	Linear	Gradient Descent	70	15	15	20	50.00%	0	0	0.00%	0	0
Leaves_3	10	Symmetric hard-limit	Log-sigmoid	Gradient Descent	70	15	15	20	0.00%	0	0	0.00%	0	0
Leaves_3	10	Symmetric hard-limit	Hyperbolic tangent sigmoid	Gradient Descent	70	15	15	20	0.00%	0	0	0.00%	0	0
Leaves_3	10	Symmetric hard-limit	Symmetric hard-limit	Gradient Descent	70	15	15	20	0.00%	0	0	0.00%	0	0
Leaves_3	10	Symmetric hard-limit	None	Gradient Descent	70	15	15	20	50.00%	0	0	0.00%	0	0
Leaves_3	10	Hard-limit	Hard-limit	Stochastic Approximation to Gradient Descent	70	15	15	20	50.00%	0	0	0.00%	0	0
Leaves_3	10	Hard-limit	Linear	Stochastic Approximation to Gradient Descent	70	15	15	20	0.00%	0	0	0.00%	0	0
Leaves_3	10	Hard-limit	Log-sigmoid	Stochastic Approximation to Gradient Descent	70	15	15	20	100.00%	0	0	0.00%	0	0
Leaves_3	10	Hard-limit	Hyperbolic tangent sigmoid	Stochastic Approximation to Gradient Descent	70	15	15	20	50.00%	0	0	0.00%	0	0
Leaves_3	10	Hard-limit	Symmetric hard-limit	Stochastic Approximation to Gradient Descent	70	15	15	20	0.00%	0	0	0.00%	0	0
Leaves_3	10	Hard-limit	None	Stochastic Approximation to Gradient Descent	70	15	15	20	50.00%	0	0	0.00%	0	0
Leaves_3	10	Linear	Hard-limit	Stochastic Approximation to Gradient Descent	70	15	15	20	0.00%	0	0	0.00%	0	0
Leaves_3	10	Linear	Linear	Stochastic Approximation to Gradient Descent	70	15	15	20	50.00%	0	0	0.00%	0	0
Leaves_3	10	Linear	Log-sigmoid	Stochastic Approximation to Gradient Descent	70	15	15	20	0.00%	0	0	0.00%	0	0
Leaves_3	10	Linear	Hyperbolic tangent sigmoid	Stochastic Approximation to Gradient Descent	70	15	15	20	50.00%	0	0	0.00%	0	0
Leaves_3	10	Linear	Symmetric hard-limit	Stochastic Approximation to Gradient Descent	70	15	15	20	0.00%	0	0	0.00%	0	0
Leaves_3	10	Linear	None	Stochastic Approximation to Gradient Descent	70	15	15	20	50.00%	0	0	0.00%	0	0
Leaves_3	10	Log-sigmoid	Hard-limit	Stochastic Approximation to Gradient Descent	70	15	15	20	50.00%	0	0	0.00%	0	0
Leaves_3	10	Log-sigmoid	Linear	Stochastic Approximation to Gradient Descent	70	15	15	20	50.00%	0	0	0.00%	0	0
Leaves_3	10	Log-sigmoid	Log-sigmoid	Stochastic Approximation to Gradient Descent	70	15	15	20	0.00%	0	0	0.00%	0	0
Leaves_3	10	Log-sigmoid	Hyperbolic tangent sigmoid	Stochastic Approximation to Gradient Descent	70	15	15	20	100.00%	0	0	0.00%	0	0
Leaves_3	10	Log-sigmoid	Symmetric hard-limit	Stochastic Approximation to Gradient Descent	70	15	15	20	50.00%	0	0	0.00%	0	0
Leaves_3	10	Log-sigmoid	None	Stochastic Approximation to Gradient Descent	70	15	15	20	50.00%	0	0	0.00%	0	0
Leaves_3	10	Hyperbolic tangent sigmoid	Hard-limit	Stochastic Approximation to Gradient Descent	70	15	15	20	0.00%	0	0	0.00%	0	0
Leaves_3	10	Hyperbolic tangent sigmoid	Linear	Stochastic Approximation to Gradient Descent	70	15	15	20	0.00%	0	0	0.00%	0	0
Leaves_3	10	Hyperbolic tangent sigmoid	Log-sigmoid	Stochastic Approximation to Gradient Descent	70	15	15	20	100.00%	0	0	0.00%	0	0
Leaves_3	10	Hyperbolic tangent sigmoid	Hyperbolic tangent sigmoid	Stochastic Approximation to Gradient Descent	70	15	15	20	50.00%	0	0	0.00%	0	0
Leaves_3	10	Hyperbolic tangent sigmoid	Symmetric hard-limit	Stochastic Approximation to Gradient Descent	70	15	15	20	0.00%	0	0	0.00%	0	0
Leaves_3	10	Hyperbolic tangent sigmoid	None	Stochastic Approximation to Gradient Descent	70	15	15	20	0.00%	0	0	0.00%	0	0
Leaves_3	10	Symmetric hard-limit	Hard-limit	Stochastic Approximation to Gradient Descent	70	15	15	20	50.00%	0	0	0.00%	0	0
Leaves_3	10	Symmetric hard-limit	Linear	Stochastic Approximation to Gradient Descent	70	15	15	20	100.00%	0	0	0.00%	0	0
Leaves_3	10	Symmetric hard-limit	Log-sigmoid	Stochastic Approximation to Gradient Descent	70	15	15	20	50.00%	0	0	0.00%	0	0
Leaves_3	10	Symmetric hard-limit	Hyperbolic tangent sigmoid	Stochastic Approximation to Gradient Descent	70	15	15	20	50.00%	0	0	0.00%	0	0
Leaves_3	10	Symmetric hard-limit	Symmetric hard-limit	Stochastic Approximation to Gradient Descent	70	15	15	20	50.00%	0	0	0.00%	0	0
Leaves_3	10	Symmetric hard-limit	None	Stochastic Approximation to Gradient Descent	70	15	15	20	50.00%	0	0	0.00%	0	0