

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

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

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

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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).

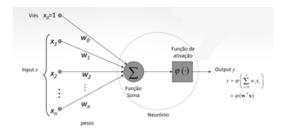


Figure 2.1: The Perceptron, or artificial neuron.

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.

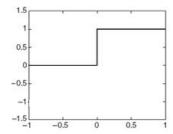


Figure 2.2: Plot: Hard-limit activation function (hardlim)

• Linear activation function (purelin) - Figure 2.3.

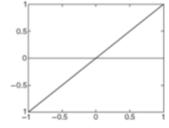


Figure 2.3: Plot: Linear activation function (purelin)

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

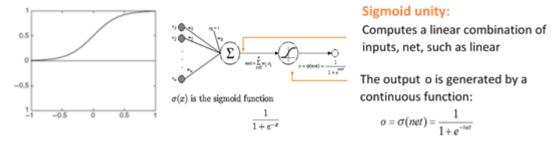


Figure 2.4: Plot: Log-sigmoid activation function (logsig)

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

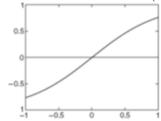


Figure 2.5: Plot: Hyperbolic tangent sigmoid activation function (tansig)

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

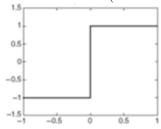


Figure 2.6: Plot: Symmetric hard-limit activation function (hardlims)

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.

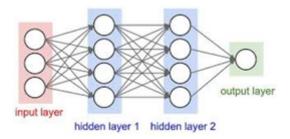


Figure 2.8: Neural network: input, hidden, and output layers.

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.

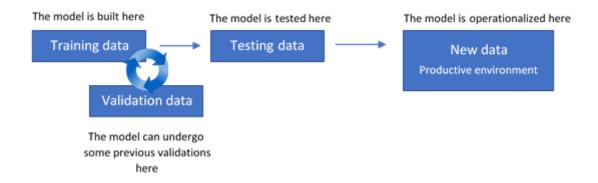


Figure 2.9: Training, validation, and testing.

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.

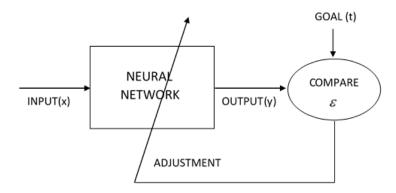


Figure 2.10: A scheme for the functioning of a neural network with supervised training.

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].

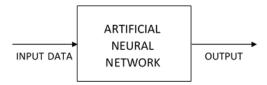


Figure 2.11: A neural network with unsupervised training (artificial neural network).

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.

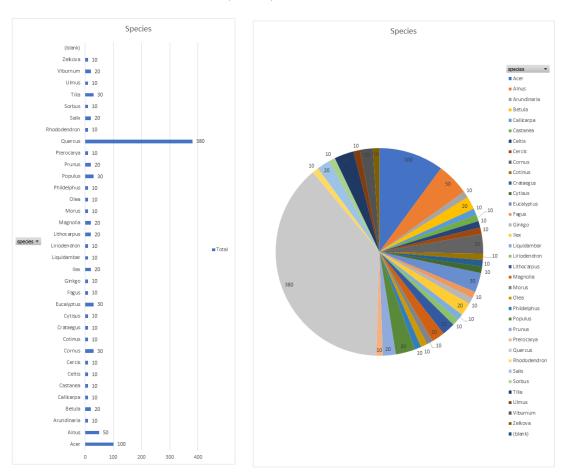


Figure 2.12: Species for the images in the folders: "Leaves_1", "Leaves_2", and "Leaves_3".

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).

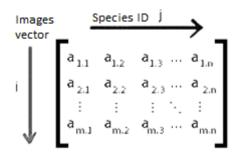


Figure 2.14: A matrix that contains image vectors in the rows and species IDs in the columns.

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

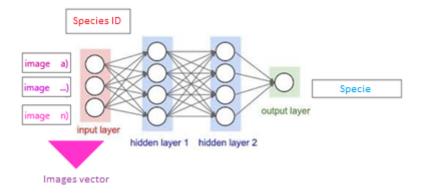


Figure 2.15: The neural network for species.

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.

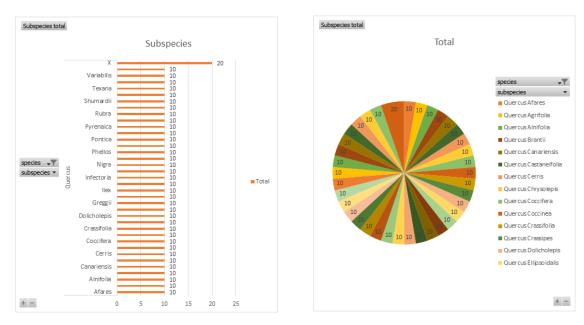


Figure 2.16: The subspecies for the specie "Quercus".

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.

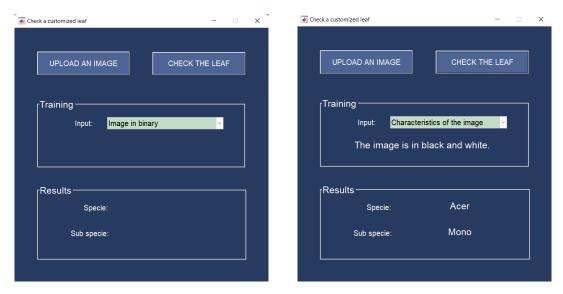


Figure 2.17: Neural Network - Check a customized leaf

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.

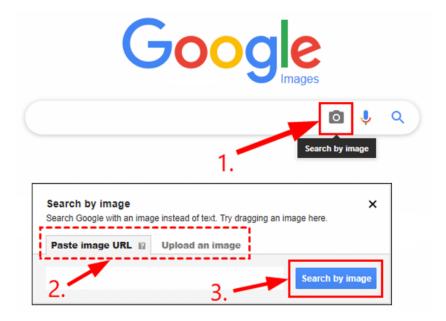


Figure 3.3: Google images - Search by image

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.

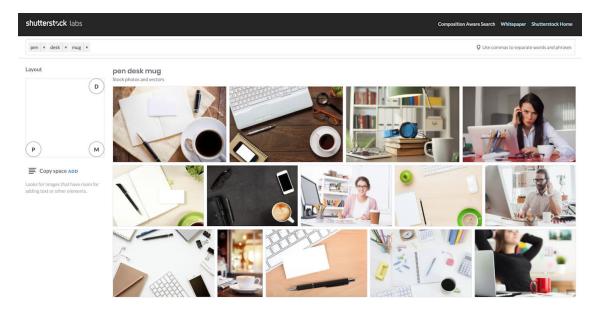


Figure 3.4: Shutterstock - Image search for photos using words

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 tiems. 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.

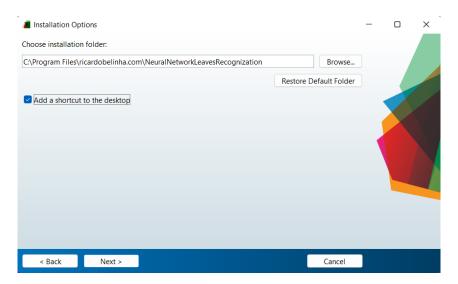


Figure 5.1: Installer

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.

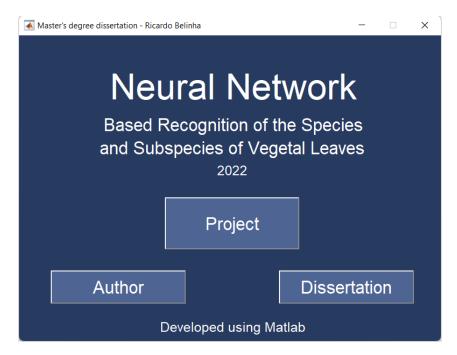


Figure 5.2: Main menu

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

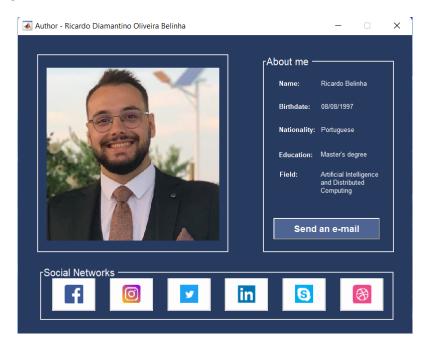


Figure 5.3: Author's details

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.

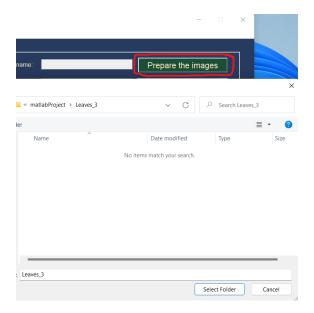


Figure 5.5: Neural Network - Preparing the images

When the user chooses the folder, the name of the folder will be dis-

played 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.

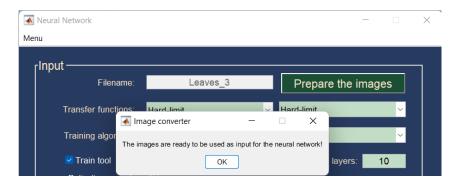


Figure 5.6: Neural Network - Feedback from preparing the images

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.

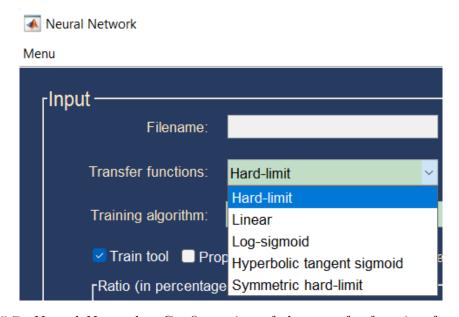


Figure 5.7: Neural Network - Configuration of the transfer function for the first layer

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

5.1. USER GUIDE 35

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).

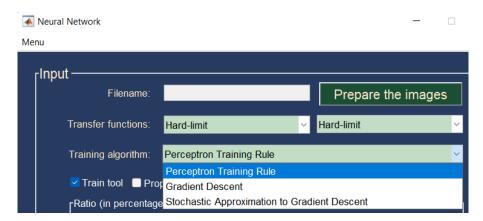


Figure 5.9: Neural Network - Configuration of the training algorithm

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

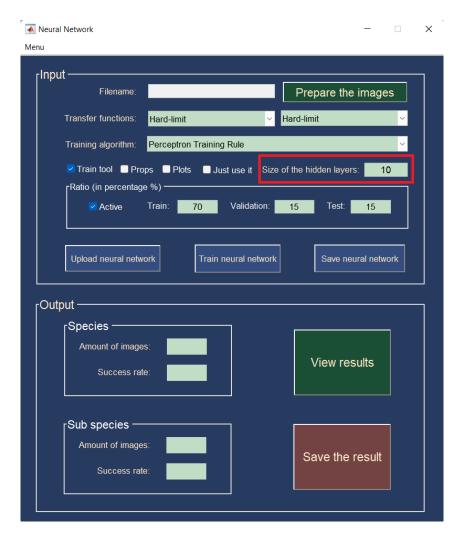


Figure 5.10: Neural Network - Configuration of the size for the hidden layer

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.

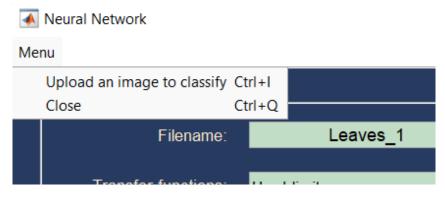


Figure 5.11: Neural Network - Menu

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.

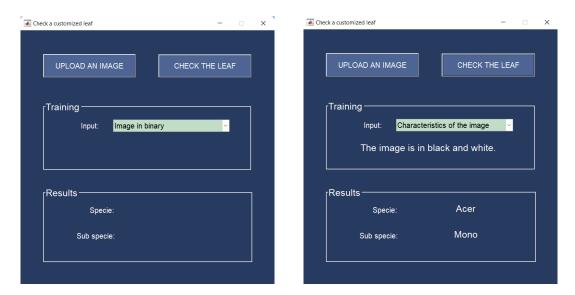


Figure 5.12: Neural Network - Check a customized leaf

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].

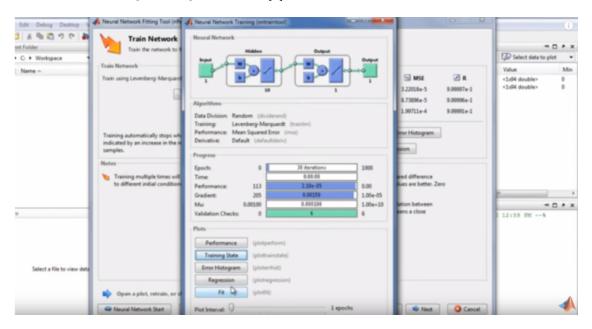


Figure 5.13: MATLAB - Deep Learn Toolbox

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.

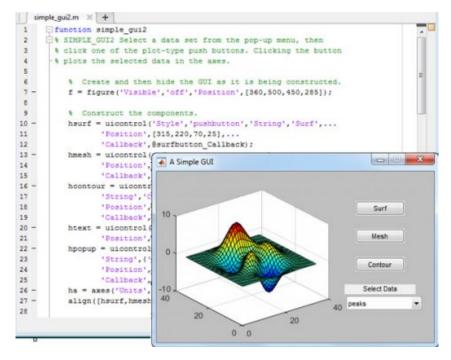


Figure 5.14: MATLAB - Example of a Graphic User Interface

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.

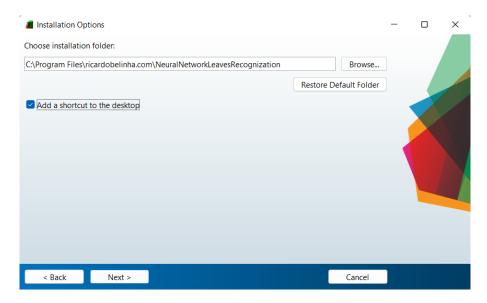


Figure 5.15: MATLAB - Application's installer

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 passion-

ate 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 | id_subspecie | subspecies | id_subspecie | subspecies |
|--------------|----------------|--------------|---------------|--------------|-------------------|
| 1 | Capillipes | 34 | Aquifolium | 67 | Ilex |
| 2 | Circinatum | 35 | Cornuta | 68 | Imbricaria |
| 3 | Mono | 36 | Styraciflua | | |
| 4 | Opalus | 37 | Tulipifera | 69 | Infectoria |
| 5 | Palmatum | 38 | Cleistocarpus | 70 | Kewensis |
| 6 | Pictum | 39 | Edulis | 71 | Nigra |
| 7 | Platanoids | 40 | Heptapeta | 72 | Palustris |
| 8 | Rubrum | 41 | Salicifolia | 73 | Phellos |
| 9 | Rufinerve | 42 | Nigra | 74 | Phillyraeoides |
| 10 | Saccharinum | 43 | Europaea | 75 | Pontica |
| 11 | Cordata | 44 | Adenopoda | 76 | Pubescens |
| 12 | Maximowiczii | 45 | Grandidentata | 77 | Pyrenaica |
| 13 | Rubra | 46 | Nigra | 78 | Rhysophylla |
| 14 | Sieboldiana | 47 | Avium | 79 | Rubra |
| 15 | Viridis | 48 | Shmittii | 80 | Semecarpifolia |
| 16 | Simonii | 49 | Stenoptera | 81 | Shumardii |
| 17 | Austrosinensis | 50 | Afares | 82 | Suber |
| 18 | Pendula | 51 | Agrifolia | 83 | Texana |
| 19 | Bodinieri | 52 | Alnifolia | 84 | Trojana |
| 20 | Sativa | 53 | Brantii | 85 | Turneri |
| 21 | Koraiensis | 54 | Canariensis | 86 | Variabilis |
| 22 | Siliquastrum | 55 | Castaneifolia | 87 | Vulcanica |
| 23 | Chinensis | 56 | Cerris | 88 | Russellianum |
| 24 | Controversa | 57 | Chrysolepis | 89 | Fragilis |
| 25 | Macrophylla | 58 | Coccifera | 90 | Intergra |
| 26 | Coggygria | 59 | Coccinea | 91 | Aria |
| 27 | Monogyna | 60 | Crassifolia | 92 | Oliveri |
| 28 | Battandieri | 61 | Crassipes | 93 | Platyphyllos |
| 29 | Glaucescens | 62 | Dolicholepis | 94 | Tomentosa |
| 30 | Neglecta | 63 | Ellipsoidalis | 95 | Bergmanniana |
| 31 | Urnigera | 64 | Greggii | 96 | Rhytidophylloides |
| 32 | Sylvatica | 65 | Hartwissiana | 97 | Tinus |
| 33 | Biloba | 66 | Hispanica | 98 | Serrata |
| 55 | Diioba | 30 | 1115panica | L | |

Appendix B

Training results for the images in binary

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

| | Transfer | Transfer functions | Ratio (in | (in percentage % | (% = | | | Species | | Species | |
|---------------|----------------------------|----------------------------|------------------------------------|------------------|------|---------------|-----------|------------------|-------------|---------|----------|
| Folder Hidden | n L. 1st | 2nd | Training algorithm Train Va | Validation | Test | Quant. images | Success % | Epoch Duration | % Saccess % | Epoch | Duration |
| Leaves_1 2 | Hard-limit | Hard-limit | Perceptron Training Rule 80 10 | | | 66 | 0.00% | 0 0 | 0.00% | 0 | 0 |
| Leaves_1 2 | Hard-limit | Linear | Perceptron Training Rule 80 10 | | 10 | 66 | 10.00% | 0 0 | 0.00% | 0 | 0 |
| Leaves_1 2 | Hard-limit | Log-sigmoid | Perceptron Training Rule 80 10 | | 10 | 66 | 10.00% | 0 0 | 0.00% | 0 | 0 |
| Leaves_1 2 | Hard-limit | Hyperbolic tangent sigmoid | Perceptron Training Rule 80 10 | | 10 | 66 | 0.00% | 0 0 | 0.00% | 0 | 0 |
| Leaves_1 2 | Hard-limit | Symmetric hard-limit | Perceptron Training Rule 80 10 | | 10 | 66 | 10.00% | 0 0 | 0.00% | 0 | 0 |
| Leaves_1 2 | Hard-limit | None | Perceptron Training Rule 80 10 | | | 66 | 20.00% | 0 0 | 0.00% | 0 | 0 |
| Leaves_1 2 | Linear | Hard-limit | Perceptron Training Rule 80 10 | | 10 | 66 | 20.00% | 0 0 | 0.00% | 0 | 0 |
| Leaves_1 2 | Linear | Linear | Perceptron Training Rule 80 10 | | | 66 | 10.00% | 0 0 | 0.00% | 0 | 0 |
| Leaves_1 2 | Linear | Log-sigmoid | Perceptron Training Rule 80 10 | | 10 | 66 | 20.00% | 0 0 | 0.00% | 0 | 0 |
| Leaves_1 2 | Linear | Hyperbolic tangent sigmoid | Perceptron Training Rule 80 10 | | 10 | 66 | 10.00% | 0 0 | 0.00% | 0 | 0 |
| Leaves_1 2 | Linear | Symmetric hard-limit | Perceptron Training Rule 80 10 | | | 66 | 20.00% | 0 0 | 0.00% | 0 | 0 |
| Leaves_1 2 | Linear | None | Perceptron Training Rule 80 10 | | 10 | 66 | %00.0 | 0 0 | 0.00% | 0 | 0 |
| Leaves_1 2 | Log-sigmoid | Hard-limit | Perceptron Training Rule 80 10 | | 10 | 66 | 10.00% | 0 0 | 0.00% | 0 | 0 |
| Leaves_1 2 | Log-sigmoid | Linear | Perceptron Training Rule 80 10 | | 10 | 66 | %00.0 | 0 0 | 10.00% | 0 | 0 |
| Leaves_1 2 | Log-sigmoid | Log-sigmoid | Perceptron Training Rule 80 10 | | 10 | 66 | 0.00% | | 0.00% | 0 | 0 |
| Leaves_1 2 | Log-sigmoid | Hyperbolic tangent sigmoid | Perceptron Training Rule 80 10 | | 10 | 66 | 0.00% | 0 0 | 0.00% | 0 | 0 |
| Leaves_1 2 | Log-sigmoid | Symmetric hard-limit | Perceptron Training Rule 80 10 | | 10 | 66 | 10.00% | 0 0 | 0.00% | 0 | 0 |
| Leaves_1 2 | Log-sigmoid | None | Perceptron Training Rule 80 10 | | 10 | 66 | 0.00% | 0 0 | 10.00% | 0 | 0 |
| Leaves_1 2 | Hyperbolic tangent sigmoid | Hard-limit | Perceptron Training Rule 80 10 | | 10 | 66 | 10.00% | 0 0 | 0.00% | 0 | 0 |
| Leaves_1 2 | Hyperbolic tangent sigmoid | Linear | Perceptron Training Rule 80 10 | | 10 | 66 | 20.00% | 0 0 | 0.00% | 0 | 0 |
| Leaves_1 2 | Hyperbolic tangent sigmoid | Log-sigmoid | Perceptron Training Rule 80 10 | | | 66 | 10.00% | 0 0 | 0.00% | 0 | 0 |
| Leaves_1 2 | Hyperbolic tangent sigmoid | Hyperbolic tangent sigmoid | Perceptron Training Rule 80 10 | | 10 | 66 | 10.00% | 0 0 | 0.00% | 0 | 0 |
| Leaves_1 2 | Hyperbolic tangent sigmoid | | Perceptron Training Rule 80 10 | | 10 | 66 | 0.00% | 0 0 | 0.00% | 0 | 0 |
| Leaves_1 2 | Hyperbolic tangent sigmoid | | Perceptron Training Rule 80 10 | | 10 | 66 | 0.00% | 0 0 | 0.00% | 0 | 0 |
| Leaves_1 2 | Symmetric hard-limit | Hard-limit | Perceptron Training Rule 80 10 | | 10 | 66 | 0.00% | 0 0 | 0.00% | 0 | 0 |
| Leaves_1 2 | Symmetric hard-limit | Linear | Perceptron Training Rule 80 10 | (| | 66 | 10.00% | 0 0 | 0.00% | 0 | 0 |
| Leaves_1 2 | Symmetric hard-limit | Log-sigmoid | Perceptron Training Rule 80 10 | | 10 | 66 | 20.00% | 0 0 | 0.00% | 0 | 0 |
| Leaves_1 2 | Symmetric hard-limit | Hyperbolic tangent sigmoid | Perceptron Training Rule 80 10 | | | 66 | 0.00% | 0 0 | 0.00% | 0 | 0 |
| Leaves_1 2 | Symmetric hard-limit | Symmetric hard-limit | Training Rule 80 | (| | 66 | 10.00% | | 0.00% | 0 | 0 |
| Leaves_1 2 | Symmetric hard-limit | None | ng Rule 80 | | | 66 | 10.00% | 0 0 | 0.00% | 0 | 0 |
| Leaves_1 2 | Hard-limit | Hard-limit | 08 | (| | 66 | 0.00% | | %00.0 | 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 | (| | 66 | 0.00% | 0 0 | 0.00% | 0 | 0 |
| Leaves_1 2 | Hard-limit | Hyperbolic tangent sigmoid | 08 | (| | 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 | (| | 66 | 20.00% | 0 0 | %00.0 | 0 | 0 |
| Leaves_1 2 | Linear | Hard-limit | | | 10 | 66 | 10.00% | 0 0 | 0.00% | 0 | 0 |
| Leaves_1 2 | Linear | Linear | 80 | | | 66 | 10.00% | | 0.00% | 0 | 0 |
| Leaves_1 2 | Linear | Log-sigmoid | Gradient Descent 80 10 | | 10 | 66 | %00.0 | 0 0.04 | 0.00% | 0 | 0 |
| Leaves_1 2 | Linear | Hyperbolic tangent sigmoid | 08 | (| | 66 | 20.00% | | 0.00% | 0 | 0 |
| Leaves_1 2 | Linear | Symmetric hard-limit | Gradient Descent 80 10 | (| | 99 | 20.00% | 0 0 | 0.00% | 0 | 0 |
| Leaves_1 2 | Linear | None | 80 |) | | 99 | 20.00% | 0 0 | 0.00% | 0 | 0 |
| Leaves_1 2 | Log-sigmoid | Hard-limit | 80 | | | 66 | 10.00% | | 0.00% | 0 | 0 |
| Leaves_1 2 | Log-sigmoid | Linear | | | 10 | 99 | 10.00% | 0 0 | 0.00% | 0 | 0 |
| Leaves_1 2 | Log-sigmoid | Log-sigmoid | Gradient Descent 80 10 | | 10 | 66 | 10.00% | 0 0 | 0.00% | 0 | 0 |
| | | | | | | | | | | | |

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

| | Transfer | Transfer functions | | Ratio | (in percentage %) | şe %) | | | Species | | | Species | |
|--------------|----------------------------|----------------------------|--|-------|-------------------|-------|---------------|-----------|---------|----------|-----------|---------|----------|
| Folder Hidde | 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 | 66 | 0.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_1 2 | Log-sigmoid | Symmetric hard-limit | Gradient Descent | 98 | 10 | 10 | 66 | 20.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_1 2 | Log-sigmoid | None | Gradient Descent | 08 | 10 | 10 | 66 | 30.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_1 2 | Hyperbolic tangent sigmoid | Hard-limit | Gradient Descent | 80 | 10 | 10 | 66 | 10.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_1 2 | Hyperbolic tangent sigmoid | Linear | Gradient Descent | 98 | 10 | 10 | 66 | 0.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_1 2 | Hyperbolic tangent sigmoid | Log-sigmoid | Gradient Descent | 08 | 10 | 10 | 66 | 0.00% | 0 | 0 | 10.00% | 0 | 0 |
| Leaves_1 2 | Hyperbolic tangent sigmoid | Hyperbolic tangent sigmoid | Gradient Descent | 08 | 10 | 10 | 66 | 10.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_1 2 | Hyperbolic tangent sigmoid | Symmetric hard-limit | Gradient Descent | 08 | 10 | 10 | 66 | 10.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_1 2 | Hyperbolic tangent sigmoid | - | Gradient Descent | 08 | 10 | 10 | 66 | 0.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_1 2 | Symmetric hard-limit | Hard-limit | Gradient Descent | 08 | 10 | 10 | 66 | 0.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_1 2 | Symmetric hard-limit | Linear | Gradient Descent | 08 | 10 | 10 | 66 | 30.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_1 2 | Symmetric hard-limit | Log-sigmoid | Gradient Descent | 08 | 10 | 10 | 66 | 20.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_1 2 | Symmetric hard-limit | Hyperbolic tangent sigmoid | Gradient Descent | 98 | 10 | 10 | 66 | 20.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_1 2 | Symmetric hard-limit | Symmetric hard-limit | Gradient Descent | 80 | 10 | 10 | 66 | %00.0 | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_1 2 | Symmetric hard-limit | None | Gradient Descent | 98 | 10 | 10 | 66 | 10.00% | 0 | 0 | 10.00% | 0 | 0 |
| Leaves_1 2 | Hard-limit | Hard-limit | Stochastic Approximation to Gradient Descent | 98 | 10 | 10 | 66 | 0.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_1 2 | Hard-limit | Linear | Stochastic Approximation to Gradient Descent | 80 | 10 | 10 | 66 | 0.00% | 0 | 0 | 10.00% | 0 | 0 |
| Leaves_1 2 | Hard-limit | Log-sigmoid | Stochastic Approximation to Gradient Descent | 98 | 10 | 10 | 66 | 10.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_1 2 | Hard-limit | Hyperbolic tangent sigmoid | Stochastic Approximation to Gradient Descent | 80 | 10 | 10 | 66 | 0.00% | 0 | 0 | 10.00% | 0 | 0 |
| Leaves_1 2 | Hard-limit | Symmetric hard-limit | Stochastic Approximation to Gradient Descent | 98 | 10 | 10 | 66 | 10.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_1 2 | Hard-limit | None | Stochastic Approximation to Gradient Descent | 08 | 10 | 10 | 66 | 20.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_1 2 | Linear | Hard-limit | Stochastic Approximation to Gradient Descent | 08 | 10 | 10 | 66 | %00.0 | 0 | 0 | %00.0 | 0 | 0 |
| Leaves_1 2 | Linear | Linear | Stochastic Approximation to Gradient Descent | Н | 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 | 66 | %00.0 | 0 | 0 | %00.0 | 0 | 0 |
| Leaves_1 2 | Linear | Hyperbolic tangent sigmoid | Stochastic Approximation to Gradient Descent | 80 | 10 | 10 | 66 | %00.0 | 0 | 0 | %00.0 | 0 | 0 |
| Leaves_1 2 | Linear | Symmetric hard-limit | Stochastic Approximation to Gradient Descent | | 10 | 10 | 66 | 30.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_1 2 | Linear | None | Stochastic Approximation to Gradient Descent | 08 | 10 | 10 | 66 | 10.00% | 0 | 0 | %00.0 | 0 | 0 |
| Leaves_1 2 | Log-sigmoid | Hard-limit | Stochastic Approximation to Gradient Descent | | 10 | 10 | 66 | 10.00% | 0 | 0 | %00.0 | 0 | 0 |
| Leaves_1 2 | Log-sigmoid | Linear | Stochastic Approximation to Gradient Descent | 80 | 10 | 10 | 66 | %00:0 | 0 | 0 | %00.0 | 0 | 0 |
| Leaves_1 2 | Log-sigmoid | Log-sigmoid | Stochastic Approximation to Gradient Descent | | 10 | 10 | 99 | 20.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_1 2 | Log-sigmoid | Hyperbolic tangent sigmoid | Stochastic Approximation to Gradient Descent | | 10 | 10 | 66 | 20.00% | 0 | 0 | %00.0 | 0 | 0 |
| Leaves_1 2 | Log-sigmoid | Symmetric hard-limit | Stochastic Approximation to Gradient Descent | 80 | 10 | 10 | 99 | %00.0 | 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 | 08 | 10 | 10 | 66 | %00.0 | 0 | 0 | 10.00% | 0 | 0 |
| Leaves_1 2 | Hyperbolic tangent sigmoid | Linear | Stochastic Approximation to Gradient Descent | 80 | 10 | 10 | 66 | 30.00% | 0 | 0 | %00.0 | 0 | 0 |
| Leaves_1 2 | Hyperbolic tangent sigmoid | Log-sigmoid | Stochastic Approximation to Gradient Descent | 8 | 10 | 10 | 66 | 10.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_1 2 | Hyperbolic tangent sigmoid | Hyperbolic tangent sigmoid | Stochastic Approximation to Gradient Descent | 08 | 10 | 10 | 66 | 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 | 66 | %00.0 | 0 | 0 | %00.0 | 0 | 0 |
| Leaves_1 2 | Hyperbolic tangent sigmoid | - | Stochastic Approximation to Gradient Descent | Н | 10 | 10 | 66 | 20.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_1 2 | Symmetric hard-limit | Hard-limit | Stochastic Approximation to Gradient Descent | | 10 | 10 | 66 | 10.00% | 0 | 0 | %00.0 | 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 $\,$

| | | E | | | | | (3-6) | | | | | Č | | |
|----------|-----------|----------------------------|----------------------------|--|---------|---|-------|--------------|------------|-----------------------|--------------|-----------|---------|----------|
| Folder | Hidden I. | + | Transfer functions | Training algorithm | Ratio (| Katio (in percentage %) Train Validation Tes | _ | Ought images | Success % | Species Fnoch Dura | Duration Suc | Success % | Species | Duration |
| Leaves_1 | 2 | + | Log-sigmoid | Stochastic Approximation to Gradient Descent | + | | + | 66 | 2 | + | + | | + | |
| Leaves_1 | 2 | Symmetric hard-limit | Hyperbolic tangent sigmoid | Stochastic Approximation to Gradient Descent | + | 10 | 10 | 66 | 0.00% | | 10. | 0 %00.01 | | 0 |
| Leaves_1 | 2 | Symmetric hard-limit | Symmetric hard-limit | Stochastic Approximation to Gradient Descent | 08 | 10 | 10 | 66 | 10.00% | | 0.00% | 0 %0 | | 0 |
| Leaves_1 | 2 | Symmetric hard-limit | None | Stochastic Approximation to Gradient Descent | 08 | 10 | 10 | 66 | 30.00% | 0 0 | 0.00% | 0 %0 | | |
| Leaves_1 | 10 | Hard-limit | Hard-limit | Perceptron Training Rule | 20 | 15 | 15 | 66 | 10.00% | 0 0 | 0.00% | 0 %0 | | 0 |
| Leaves_1 | 10 | Hard-limit | Linear | Perceptron Training Rule | 20 | 15 | 15 | 66 | 10.00% | 0 0 | 10. | 10.00% 0 | | 0 |
| Leaves_1 | 10 | Hard-limit | Log-sigmoid | Perceptron Training Rule | 20 | 15 | 15 | 66 | 10.00% | | 0.00% | 0 %0 | | 0 |
| Leaves_1 | 10 | Hard-limit | Hyperbolic tangent sigmoid | Perceptron Training Rule | 20 | 15 | 15 | 66 | 20.00% | 0 0 | 0.00% | 0 %0 | | 0 |
| Leaves_1 | 10 | Hard-limit | Symmetric hard-limit | Perceptron Training Rule | 20 | 15 | 15 | 66 | 30.00% | 0 0 | 0.00% | 0 %0 | | 0 |
| Leaves_1 | 10 | Hard-limit | None | Perceptron Training Rule | 20 | 15 | | 66 | 10.00% | 0 0 | 0.00% | 0 %0 | | 0 |
| Leaves_1 | 10 | Linear | Hard-limit | Perceptron Training Rule | 20 | 15 | | 66 | 10.00% | 0 0 | 0.00% | 0 %0 | | 0 |
| Leaves_1 | 10 | Linear | Linear | Perceptron Training Rule | 20 | 15 | 15 | 66 | 20.00% | 0 0 | 0.00% | 0 %0 | | 0 |
| Leaves-1 | 10 | Linear | Log-sigmoid | Perceptron Training Rule | 20 | 15 | 15 | 66 | 20.00% | 0 0 | 0.00% | 0 %0 | | 0 |
| Leaves_1 | 10 | Linear | Hyperbolic tangent sigmoid | Perceptron Training Rule | 20 | 15 | 15 | 66 | 10.00% | 0 0 | 0.00% | 0 %0 | | 0 |
| Leaves 1 | 10 | Linear | Symmetric hard-limit | Perceptron Training Rule | 20 | 15 | 15 | 66 | 30.00% | 0 0 | 0.00% | 0 %0 | | 0 |
| Leaves_1 | 10 | Linear | None | Perceptron Training Rule | 20 | 15 | 15 | 66 | 20.00% | 0 0 | 0.00% | | | 0 |
| Leaves_1 | 10 | Log-sigmoid | Hard-limit | Perceptron Training Rule | 20 | 15 | 15 | 66 | 10.00% | 0 0 | 0.00% | 0 %0 | | 0 |
| Leaves_1 | 10 | Log-sigmoid | Linear | Perceptron Training Rule | 20 | 15 | 15 | 66 | 20.00% | 0 0 | 0.00% | 0 %0 | | 0 |
| Leaves_1 | 10 | Log-sigmoid | Log-sigmoid | Perceptron Training Rule | 20 | 15 | 15 | 66 | 20.00% | 0 0 | 00.0 | 0 %0 | | 0 |
| Leaves_1 | 10 | Log-sigmoid | Hyperbolic tangent sigmoid | Perceptron Training Rule | 20 | 15 | 15 | 66 | 0.00% | 0 0 | 0.00% | 0 %0 | | 0 |
| Leaves_1 | 10 | Log-sigmoid | Symmetric hard-limit | Perceptron Training Rule | 20 | 15 | | 66 | 10.00% | 0 0 | 00:0 | | | 0 |
| Leaves_1 | 10 | Log-sigmoid | None | Perceptron Training Rule | 02 | 15 | | 66 | 00:001 | 0 0 | 0.00% | 0 %0 | | 0 |
| Leaves_1 | 10 | Hyperbolic tangent sigmoid | Hard-limit | Perceptron Training Rule | 20 | 15 | | 66 | 10.00% (| 0 0 | 0.00% | | | 0 |
| Leaves_1 | 10 | Hyperbolic tangent sigmoid | Linear | Perceptron Training Rule | 02 | 15 | | 66 | 10.00% (| 0 0 | 00:00 | | | 0 |
| Leaves_1 | 10 | Hyperbolic tangent sigmoid | Log-sigmoid | Perceptron Training Rule | 20 | 15 | | 99 | 0.00% | 0 0 | 0.00% | 0 80 | | 0 |
| Leaves_1 | 10 | Hyperbolic tangent sigmoid | Hyperbolic tangent sigmoid | Perceptron Training Rule | 20 | 15 | | 99 | 10.00% | | 10. | 10.00% 0 | | 0 |
| Leaves_1 | 10 | Hyperbolic tangent sigmoid | Symmetric hard-limit | Perceptron Training Rule | 20 | 15 | Н | 66 | | 0 0 | 0.00% | 0 %0 | | 0 |
| Leaves_1 | 10 | Hyperbolic tangent sigmoid | None | Perceptron Training Rule | 20 | 15 | | 66 | 10.00% (| 0 0 | 0.00% | | | 0 |
| Leaves-1 | 10 | Symmetric hard-limit | Hard-limit | Perceptron Training Rule | 20 | 15 | | 66 | | | 0.00% | .0 | | 0 |
| Leaves-1 | 10 | Symmetric hard-limit | Linear | Perceptron Training Rule | 20 | 15 | | 99 | _ | | 0.00% | | | 0 |
| Leaves_1 | 10 | Symmetric hard-limit | Log-sigmoid | Perceptron Training Rule | 20 | 15 | | 99 | | | 0.00% | | | 0 |
| Leaves_1 | 10 | Symmetric hard-limit | Hyperbolic tangent sigmoid | Perceptron Training Rule | 20 | 15 | | 99 | ٠. | | 0.00% | | | 0 |
| Leaves-1 | 10 | Symmetric hard-limit | Symmetric hard-limit | Perceptron Training Rule | 20 | 15 | | 99 | 0.00% | 0 0 | 0.00% | | | 0 |
| Leaves-1 | 10 | Symmetric hard-limit | None | Perceptron Training Rule | 20 | 15 | 15 | 99 | 10.00% | 0 0 | 0.00% | | | 0 |
| Leaves_1 | 10 | Hard-limit | Hard-limit | Gradient Descent | 20 | 15 | 15 | 99 | 10.00% | 0 0 | 0.00% | 0 %0 | | 0 |
| Leaves_1 | 10 | Hard-limit | Linear | Gradient Descent | 20 | 15 | 15 | 66 |) %00:08 | 0 0 | %00·0 | 0 %0 | | 0 |
| Leaves_1 | 10 | Hard-limit | Hyperbolic tangent sigmoid | Gradient Descent | 02 | 15 | 15 | 66 | 20.00% (| 0 0 | %00·0 | | | 0 |
| Leaves_1 | 10 | Hard-limit | Log-sigmoid | Gradient Descent | 02 | 15 | 15 | 66 | 10.00% | 0 0 | 0.00% | 0 %0 | | 0 |
| Leaves_1 | 10 | Hard-limit | Symmetric hard-limit | Gradient Descent | 20 | 15 | 15 | 66 | 20.00% (| 0 0 | %00·0 | 0 80 | | 0 |
| Leaves_1 | 10 | Hard-limit | None | Gradient Descent | 02 | 15 | 15 | 66 | 00:001 | 0 0 | 00:00 | 0 %0 | | 0 |
| Leaves_1 | 10 | Linear | Hard-limit | Gradient Descent | 20 | 15 | 15 | 66 | 10.00% | 0 0 | 00:00 | 0 %0 | | 0 |
| Leaves_1 | 10 | Linear | Linear | Gradient Descent | 02 | 15 | | 66 | | | %00·0 | | | 0 |
| Leaves_1 | 10 | Linear | Log-sigmoid | Gradient Descent | 20 | 15 | | 66 | | 0 0 | 0.00% | 0 %0 | | 0 |
| Leaves_1 | 10 | Linear | Hyperbolic tangent sigmoid | Gradient Descent | 20 | 15 | 15 | 66 | 20.00% | 0 0 | 00:00 | % | | |
| | | | | | | | | | | | | | | |

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

| | | TOTOTOTO | transfer functions | | I rano (m bercemage 70) | , , | 0) | | obecies | | | obecies | |
|----------|-----------|----------------------------|--|--|-------------------------|---------|------------------|--------------|---------|----------|-----------|---------|----------|
| Folder | Hidden L. | 1st | 2nd | Training algorithm | ain | on Test | st Quant. images | % ssaccess % | Epoch | Duration | % ssecons | Epoch | Duration |
| Leaves_1 | 10 | Linear | Symmetric hard-limit | Gradient Descent | 70 15 | 15 | 66 | 20.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_1 | 10 | Linear | None | Gradient Descent | 70 15 | 15 | 66 | 10.00% | 0 | 0 | %00:0 | 0 | 0 |
| Leaves_1 | 10 | Log-sigmoid | Hard-limit | Gradient Descent | | 15 | | %00.0 | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_1 | 10 | Log-sigmoid | Linear | Gradient Descent | 70 15 | 15 | 66 | 10.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_1 | 10 | Log-sigmoid | Log-sigmoid | Gradient Descent | | 15 | | 20.00% | 0 | 0 | %00:0 | 0 | 0 |
| Leaves_1 | 10 | Log-sigmoid | Hyperbolic tangent sigmoid | Gradient Descent | 70 15 | 15 | | 10.00% | 0 | 0 | %00.0 | 0 | 0 |
| Leaves_1 | 10 | Log-sigmoid | Symmetric hard-limit | Gradient Descent | | 15 | | 0.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_1 | 10 | Log-sigmoid | None | Gradient Descent | 70 15 | 15 | 66 | %00.0 | 0 | 0 | %00.0 | 0 | 0 |
| Leaves_1 | 10 | Hyperbolic tangent sigmoid | Hard-limit | Gradient Descent | 70 15 | 15 | 66 | %00.0 | 0 | 0 | %00.0 | 0 | 0 |
| Leaves_1 | 10 | Hyperbolic tangent sigmoid | Linear | Gradient Descent | 70 15 | 15 | 66 | 10.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_1 | 10 | Hyperbolic tangent sigmoid | Log-sigmoid | Gradient Descent | | 15 | 66 | 10.00% | 0 | 0 | %00.0 | 0 | 0 |
| Leaves_1 | 10 | Hyperbolic tangent sigmoid | _ | Gradient Descent | | 15 | | %00.0 | 0 | 0 | %00.0 | 0 | 0 |
| Leaves_1 | 10 | Hyperbolic tangent sigmoid | + | Gradient Descent | 70 15 | 15 | 66 | 0.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_1 | 10 | Hyperbolic tangent sigmoid | None | Gradient Descent | 70 15 | 15 | 66 | 10.00% | 0 | 0 | %00.0 | 0 | 0 |
| Leaves_1 | 10 | Symmetric hard-limit | Hard-limit | Gradient Descent | | 15 | | 10.00% | 0 | 0 | %00.0 | 0 | 0 |
| Leaves_1 | 10 | Symmetric hard-limit | Linear | Gradient Descent | | 15 | | 30.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_1 | 10 | Symmetric hard-limit | Log-sigmoid | Gradient Descent | | 15 | | 20.00% | 0 | 0 | %00.0 | 0 | 0 |
| Leaves_1 | 10 | Symmetric hard-limit | Hyperbolic tangent sigmoid | Gradient Descent | | 15 | | 10.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_1 | 10 | Symmetric hard-limit | Symmetric hard-limit | Gradient Descent | | 15 | | 10.00% | 0 | 0 | %00.0 | 0 | 0 |
| Leaves_1 | 10 | Symmetric hard-limit | None | Gradient Descent | 20 | 15 | | %00.0 | 0 | 0 | %00.0 | 0 | 0 |
| Leaves_1 | 10 | Hard-limit | Hard-limit | Stochastic Approximation to Gradient Descent | 20 | 15 | | %00.0 | 0 | 0 | %00:0 | 0 | 0 |
| Leaves_1 | 10 | Hard-limit | Linear | Stochastic Approximation to Gradient Descent | 20 | 15 | | 20.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_1 | 10 | Hard-limit | Log-sigmoid | Stochastic Approximation to Gradient Descent | 20 | 15 | \neg | 20.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_1 | 10 | Hard-limit | Hyperbolic tangent sigmoid | Stochastic Approximation to Gradient Descent | 20 | 15 | \exists | 10.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_1 | 10 | Hard-limit | Symmetric hard-limit | Stochastic Approximation to Gradient Descent | 20 | 15 | | 0.00% | 0 | 0 | 10.00% | 0 | 0 |
| Leaves_1 | 10 | Hard-limit | None | Stochastic Approximation to Gradient Descent | 20 | 15 | \exists | 10.00% | 0 | 0 | 10.00% | 0 | 0 |
| Leaves_1 | 10 | Linear | Hard-limit | Stochastic Approximation to Gradient Descent | 20 | 15 | | 10.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_1 | 10 | Linear | Linear | Stochastic Approximation to Gradient Descent | 20 | 15 | \neg | 30.00% | 0 | 0 | 10.00% | 0 | 0 |
| Leaves_1 | 10 | Linear | Log-sigmoid | Stochastic Approximation to Gradient Descent | 70 15 | 15 | | 10.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_1 | 10 | Linear | gmoi | Stochastic Approximation to Gradient Descent | 0 | 15 | | 10.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_1 | 10 | Linear | netric hard-limit | Stochastic Approximation to Gradient Descent | | 15 | \dashv | 20.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_1 | 10 | Linear | | Stochastic Approximation to Gradient Descent | 0 9 | 15 | 1 | 0.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_1 | 10 | Log-sigmoid | mnt | Stochastic Approximation to Gradient Descent | 0 9 | 15 | 1 | 10.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_1 | 10 | Log-sigmoid | | Stochastic Approximation to Gradient Descent | | C | \top | 0.00% | 0 | 0 | 0.00% | | 0 |
| Leaves_1 | 10 | Log-sigmoid | Log-sigmoid Hamorholio teneent eiemoid | Stochastic Approximation to Gradient Descent | 70 13 | 5 7 | 66 | 10.00% | 0 0 | 0 | 0.00% | | |
| Leaves_1 | 10 | Log-sigmoid | Symmetric hard-limit | Stochastic Approximation to Gradient Descent 7 | | 2 2 | T | 10.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_1 | 10 | Log-sigmoid | | Stochastic Approximation to Gradient Descent | | 15 | T | 10.00% | 0 | 0 | 10.00% | 0 | 0 |
| Leaves_1 | 10 | Hyperbolic tangent sigmoid | Hard-limit | Stochastic Approximation to Gradient Descent | 0 | 15 | | 10.00% | 0 | 0 | 10.00% | 0 | 0 |
| Leaves_1 | 10 | Hyperbolic tangent sigmoid | Linear | Stochastic Approximation to Gradient Descent | 0 | 15 | 66 | 30.00% | 0 | 0 | 10.00% | 0 | 0 |
| Leaves_1 | 10 | Hyperbolic tangent sigmoid | Log-sigmoid | Stochastic Approximation to Gradient Descent | 0 | 15 | | %00.0 | 0 | 0 | %00.0 | 0 | 0 |
| Leaves_1 | 10 | Hyperbolic tangent sigmoid | Hyperbolic tangent sigmoi | Stochastic Approximation to Gradient Descent | 70 15 | 15 | 66 | 10.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_1 | 10 | Hyperbolic tangent sigmoid | Symmetric hard-limit | Stochastic Approximation to Gradient Descent | 20 | 15 | | %00.0 | 0 | 0 | 10.00% | 0 | 0 |
| Leaves_1 | 10 | Hyperbolic tangent sigmoid | None | Stochastic Approximation to Gradient Descent | 20 | 15 | | %00.0 | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_1 | 10 | Symmetric hard-limit | Hard-limit | Stochastic Approximation to Gradient Descent | 20 | 15 | Н | 10.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_1 | 10 | Symmetric hard-limit | Linear | Stochastic Approximation to Gradient Descent | 20 | 15 | | %00.0 | 0 | 0 | %00:0 | 0 | 0 |
| Leaves_1 | 10 | Symmetric hard-limit | Log-sigmoid | Stochastic Approximation to Gradient Descent | 20 | 15 | | 0.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_1 | 10 | Symmetric hard-limit | Hyperbolic tangent sigmoid | Stochastic Approximation to Gradient Descent | 20 | 15 | | 0.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_1 | 10 | Symmetric hard-limit | Symmetric hard-limit | Stochastic Approximation to Gradient Descent | 2 1 | 12 | \top | 10.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_1 | 10 | Symmetric hard-limit | None | Stochastic Approximation to Gradient Descent | 2 | - | 5. | 2 | | | | | = |

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

| | | Transfer | Transfer functions | Ratio | (in percentage % | (% | | | Species | | Species | |
|----------|-----------|----------------------------|----------------------------|-------------------------------|------------------|----|---------------|-----------|----------------|-----------|---------|----------|
| Folder | Hidden L. | 1st | 2nd | Training algorithm Train | Validation T | +- | Quant. images | Success % | Epoch Duration | % ssacons | 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 | Training Rule | 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 | H | 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 | | 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 | Training Rule | | | 1564 | 10.31% | 0 0 | 2.08% | 0 | 0 |
| Leaves_2 | 2 | Symmetric hard-limit | None | ng Rule | | | 1564 | 11.34% | 0 0 | 1.04% | 0 | 0 |
| Leaves_2 | 2 | Hard-limit | Hard-limit | | | | 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 | | 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% | | 3.13% | 0 | 0 |
| Leaves_2 | 2 | Log-sigmoid | Linear | | 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 | Transfer functions | | Ratio | (in percentage %) | tage %) | | | Species | | | Species | |
|------------------|----------------------------|----------------------------|--|-------|-------------------|----------|---------------|-----------|---------|----------|-----------|---------|----------|
| Folder Hidden L. | 1st | 2nd | Training algorithm | Train | Validation | n Test | Quant. images | % ssecons | Epoch | Duration | % ssecons | Epoch | Duration |
| Leaves_2 2 | Log-sigmoid | Hyperbolic tangent sigmoid | Gradient Descent | 80 | 10 | 10 | 1564 | 14.43% | 0 | 0 | %00.0 | 0 | 0 |
| Leaves_2 2 | Log-sigmoid | Symmetric hard-limit | Gradient Descent | 08 | 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 | 98 | 10 | 10 | 1564 | 9.28% | 0 | 0 | 1.04% | 0 | 0 |
| Leaves_2 2 | Hyperbolic tangent sigmoid | | Gradient Descent | 80 | 10 | 10 | 1564 | 7.22% | 0 | 0 | %00.0 | 0 | 0 |
| Leaves_2 2 | Hyperbolic tangent sigmoid | | 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 | %00.0 | 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 | 98 | 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 | %00.0 | 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 | 8 | 10 | 10 | 1564 | 11.34% | 0 | 0 | 1.04% | 0 | 0 |
| Leaves_2 2 | Hard-limit | Hard-limit | Stochastic Approximation to Gradient Descent | | 10 | 10 | 1564 | 7.22% | 0 | 0 | 1.04% | 0 | 0 |
| Leaves_2 2 | Hard-limit | Linear | Stochastic Approximation to Gradient Descent | 1 80 | 10 | 10 | 1564 | 14.43% | 0 | 0 | 3.13% | 0 | 0 |
| Leaves_2 2 | Hard-limit | Log-sigmoid | Stochastic Approximation to Gradient Descent | 1t 80 | 10 | 10 | 1564 | 11.34% | 0 | 0 | 1.04% | | 0 |
| Leaves_2 2 | Hard-limit | Hyperbolic tangent sigmoid | Stochastic Approximation to Gradient Descent | ıt 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 | 1t 80 | 10 | 10 | 1564 | 10.31% | 0 | 0 | %00.0 | 0 | 0 |
| Leaves_2 2 | Hard-limit | None | Stochastic Approximation to Gradient Descent | 1t 80 | 10 | 10 | 1564 | 12.37% | 0 | 0 | 2.08% | 0 | 0 |
| Leaves_2 2 | Linear | Hard-limit | Stochastic Approximation to Gradient Descent | t 80 | 10 | 10 | 1564 | 8.25% | 0 | 0 | 1.04% | 0 | 0 |
| Leaves_2 2 | Linear | Linear | Stochastic Approximation to Gradient Descent | 1 80 | 10 | 10 | 1564 | 7.22% | 0 | 0 | 1.04% | 0 | 0 |
| Leaves_2 2 | Linear | Log-sigmoid | Stochastic Approximation to Gradient Descent | t 80 | 10 | 10 | 1564 | 8.25% | 0 | 0 | 1.04% | | 0 |
| Leaves_2 2 | Linear | Hyperbolic tangent sigmoid | Stochastic Approximation to Gradient Descent | Н | 10 | 10 | 1564 | 11.34% | 0 | 0 | 1.04% | 0 | 0 |
| Leaves_2 2 | Linear | Symmetric hard-limit | Stochastic Approximation to Gradient Descent | t 80 | 10 | 10 | 1564 | 10.31% | 0 | 0 | 2.08% | 0 | 0 |
| Leaves_2 2 | Linear | None | Stochastic Approximation to Gradient Descent | t 80 | 10 | 10 | 1564 | 4.12% | 0 | 0 | %00.0 | 0 | 0 |
| Leaves_2 2 | Log-sigmoid | Hard-limit | Stochastic Approximation to Gradient Descent | ıt 80 | 10 | 10 | 1564 | 14.43% | 0 | 0 | %00.0 | | 0 |
| Leaves_2 2 | Log-sigmoid | Linear | Stochastic Approximation to Gradient Descent | 1t 80 | 10 | 10 | 1564 | 12.37% | 0 | 0 | %00.0 | 0 | 0 |
| Leaves_2 2 | Log-sigmoid | Log-sigmoid | Stochastic Approximation to Gradient Descent | t 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 | 1t 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 | ıt 80 | 10 | 10 | 1564 | 7.22% | 0 | 0 | 2.08% | 0 | 0 |
| Leaves_2 2 | Log-sigmoid | None | Stochastic Approximation to Gradient Descent | ıt 80 | 10 | 10 | 1564 | 12.37% | 0 | 0 | 2.08% | 0 | 0 |
| | Hyperbolic tangent sigmoid | Hard-limit | Stochastic Approximation to Gradient Descent | | 10 | 10 | 1564 | 16.49% | 0 | 0 | 1.04% | 0 | 0 |
| Leaves_2 2 | Hyperbolic tangent sigmoid | Linear | Stochastic Approximation to Gradient Descent | | 10 | 10 | 1564 | 15.46% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_2 2 | Hyperbolic tangent sigmoid | Log-sigmoid | Stochastic Approximation to Gradient Descent | | 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 | ıt 80 | 10 | 10 | 1564 | 87.6 | 0 | 0 | 3.13% | 0 | 0 |
| Leaves_2 2 | Hyperbolic tangent sigmoid | Symmetric hard-limit | Stochastic Approximation to Gradient Descent | 1 80 | 10 | 10 | 1564 | 13.40% | 0 | 0 | 3.13% | 0 | 0 |
| Leaves_2 2 | Hyperbolic tangent sigmoid | None | Stochastic Approximation to Gradient Descent | 1 80 | 10 | 10 | 1564 | 16.49% | 0 | 0 | %00.0 | 0 | 0 |
| Leaves_2 2 | Symmetric hard-limit | Hard-limit | Stochastic Approximation to Gradient Descent | t 80 | 10 | 10 | 1564 | 10.31% | 0 | 0 | 1.04% | 0 | 0 |
| Leaves_2 2 | Symmetric hard-limit | Linear | Stochastic Approximation to Gradient Descent | 1 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 | t 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 | | 10 | 10 | 1564 | 11.34% | 0 | 0 | 0.00% | 0 | 0 |
| | Symmetric hard-limit | Symmetric hard-limit | Stochastic Approximation to Gradient Descent | H | 10 | 10 | 1564 | 6.19% | 0 | 0 | 1.04% | 0 | 0 |
| Leaves_2 2 | Symmetric hard-limit | None | Stochastic Approximation to Gradient Descent | 1t 80 | 10 | 10 | 1564 | 10.31% | 0 | 0 | 1.04% | 0 | |
| | | | | | | | | | | | | | |

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

| | Transfer | Transfer functions | Ratio | Ratio (in percentage % | (% e) | | | Species | | | Species | |
|---------------|----------------------------|----------------------------|-------------------------------|------------------------|-------|---------------|-----------|---------|----------|-----------|---------|----------|
| Folder Hidden | L. 1st | 2nd | Training algorithm Train | Validation | Test | Quant. images | % ssecons | Epoch | Duration | % ssecons | Epoch | Duration |
| Leaves_2 10 | Hard-limit | Hard-limit | Perceptron Training Rule 70 | 15 | 15 | 1564 | 12.37% | 0 | + | 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 | | 15 | 15 | 1564 | 15.46% | 0 | 0 | 2.08% | 0 | 0 |
| Leaves_2 10 | Log-sigmoid | Linear | | 15 | 15 | 1564 | 13.40% | 0 | 0 | 2.08% | 0 | 0 |
| Leaves_2 10 | Log-sigmoid | Log-sigmoid | Training | 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 | | 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 | | 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 | | 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 | | 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 | Training Rule | 15 | 15 | 1564 | 6.19% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_2 10 | Symmetric hard-limit | None | Perceptron Training Rule 70 | 15 | 12 | 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 | | 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 | | 15 | 15 | 1564 | 6.19% | 0 | 0 | 1.04% | 0 | 0 |
| Leaves_2 10 | Linear | None | | 15 | 15 | 1564 | 8.25% | 0 | 0 | 2.08% | 0 | 0 |
| \vdash | Log-sigmoid | Hard-limit | | 15 | 15 | 1564 | 4.12% | 0 | 0 | 1.04% | 0 | 0 |
| - | Log-sigmoid | Linear | | 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

| Folder | | | | | | | | | | | | | | |
|----------|-----------|----------------------------|----------------------------|--|----------|-----------------|-----------|------------------|-----------|-------|----------|-----------|-------|----------|
| , | Hidden L. | Ist | 2nd | Training algorithm | Train | in Validation | tion Test | st Quant. images | Success % | Epoch | Duration | Success % | Epoch | Duration |
| Feaves-2 | 10 | Log-sigmoid | Hyperbolic tangent sigmoid | Gradient Descent | 20 | 15 | 15 | 1564 | 12.37% | 0 | 0 | | 0 | 0 |
| Leaves_2 | 10 | Log-sigmoid | Symmetric hard-limit | Gradient Descent | 20 | 15 | 15 | 1564 | 12.37% | 0 | 0 | 2.08% | 0 | 0 |
| Leaves_2 | 10 | Log-sigmoid | None | Gradient Descent | 20 | 15 | 15 | 1564 | 9.28% | 0 | 0 | 2.08% | 0 | 0 |
| Leaves_2 | 10 | Hyperbolic tangent sigmoid | Hard-limit | Gradient Descent | 20 | 15 | 15 | | 7.22% | 0 | 0 | %00:0 | 0 | 0 |
| Leaves 2 | 10 | Hyperbolic tangent sigmoid | Linear | Gradient Descent | 20 | 15 | 15 | 1564 | 8.25% | 0 | 0 | %00.0 | 0 | 0 |
| Leaves_2 | 10 | Hyperbolic tangent sigmoid | Log-sigmoid | Gradient Descent | 20 | 15 | 15 | | 7.22% | 0 | 0 | 2.08% | | 0 |
| Leaves_2 | 10 | Hyperbolic tangent sigmoid | Hyperbolic tangent sigmoid | Gradient Descent | 20 | 15 | 15 | 1564 | 11.34% | 0 | 0 | 1.04% | | 0 |
| Leaves 2 | 10 | Hyperbolic tangent sigmoid | Symmetric hard-limit | Gradient Descent | 20 | 15 | 15 | 1564 | 7.22% | 0 | 0 | %00.0 | 0 | 0 |
| Leaves_2 | 10 | Hyperbolic tangent sigmoid | None | Gradient Descent | 20 | 15 | 15 | 1564 | 10.31% | 0 | 0 | 1.04% | 0 | 0 |
| Leaves 2 | 10 | Symmetric hard-limit | Hard-limit | Gradient Descent | 20 | 15 | 15 | 1564 | 10.31% | 0 | 0 | %00.0 | 0 | 0 |
| Leaves_2 | 10 | Symmetric hard-limit | Linear | Gradient Descent | 20 | 15 | 15 | 1564 | 4.12% | 0 | 0 | 1.04% | 0 | 0 |
| Leaves_2 | 10 | Symmetric hard-limit | Log-sigmoid | Gradient Descent | 20 | 15 | 15 | 1564 | 12.37% | 0 | 0 | 1.04% | 0 | 0 |
| Leaves 2 | 10 | Symmetric hard-limit | Hyperbolic tangent sigmoid | Gradient Descent | 20 | 15 | 15 | | 9.28% | 0 | 0 | 2.08% | 0 | 0 |
| Leaves_2 | 10 | Symmetric hard-limit | Symmetric hard-limit | Gradient Descent | 20 | 15 | 15 | 1564 | 13.40% | 0 | 0 | 1.04% | 0 | 0 |
| Leaves_2 | 10 | Symmetric hard-limit | None | Gradient Descent | | 15 | 15 | | 12.37% | 0 | 0 | %00:0 | 0 | 0 |
| Leaves_2 | 10 | Hard-limit | Hard-limit | Stochastic Approximation to Gradient Descen | | 15 | 15 | | 9.28% | 0 | 0 | %00.0 | | 0 |
| Leaves_2 | 10 | Hard-limit | Linear | Stochastic Approximation to Gradient Descent | nt 70 | 15 | 15 | 1564 | 15.46% | 0 | 0 | %00.0 | 0 | 0 |
| Leaves 2 | 10 | Hard-limit | Log-sigmoid | Stochastic Approximation to Gradient Descen | | 15 | 15 | | 7.22% | 0 | 0 | 2.08% | 0 | 0 |
| Leaves_2 | 10 | Hard-limit | Hyperbolic tangent sigmoid | Stochastic Approximation to Gradient Descent | nt 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 | nt 70 | 15 | 15 | 1564 | 9.28% | 0 | 0 | 3.13% | 0 | 0 |
| Leaves 2 | 10 | Hard-limit | None | Stochastic Approximation to Gradient Descent | nt 70 | 15 | 15 | 1564 | 6.19% | 0 | 0 | 3.13% | 0 | 0 |
| Leaves_2 | 10 | Linear | Hard-limit | Stochastic Approximation to Gradient Descent | nt 70 | 15 | 15 | 1564 | 8.25% | 0 | 0 | %00.0 | 0 | 0 |
| Leaves_2 | 10 | Linear | Linear | Stochastic Approximation to Gradient Descent | nt 70 | 15 | 15 | 1564 | 4.12% | 0 | 0 | 1.04% | 0 | 0 |
| Leaves_2 | 10 | Linear | Log-sigmoid | Stochastic Approximation to Gradient Descent | | 15 | 15 | | 9.28% | 0 | 0 | 1.04% | 0 | 0 |
| Leaves_2 | 10 | Linear | Hyperbolic tangent sigmoid | Stochastic Approximation to Gradient Descent | Н | 15 | 15 | | 5.15% | 0 | 0 | %00:0 | | 0 |
| Leaves 2 | 10 | Linear | Symmetric hard-limit | Stochastic Approximation to Gradient Descen | nt 70 | 15 | 15 | | 9.28% | 0 | 0 | %00.0 | | 0 |
| Leaves_2 | 10 | Linear | None | Stochastic Approximation to Gradient Descen | | 15 | 15 | 1564 | 9.28% | 0 | 0 | 3.13% | | 0 |
| Leaves_2 | 10 | Log-sigmoid | Hard-limit | Stochastic Approximation to Gradient Descen | nt 70 | 15 | 15 | 1564 | 10.31% | 0 | 0 | %00:0 | 0 | 0 |
| Leaves_2 | 10 | Log-sigmoid | Linear | Stochastic Approximation to Gradient Descen | nt 70 | 15 | 15 | 1564 | 13.40% | 0 | 0 | 1.04% | 0 | 0 |
| Leaves_2 | 10 | Log-sigmoid | Log-sigmoid | Stochastic Approximation to Gradient Descent | nt 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 | nt 70 | 15 | 15 | | 15.46% | 0 | 0 | 2.08% | 0 | 0 |
| Leaves_2 | 10 | Log-sigmoid | Symmetric hard-limit | Stochastic Approximation to Gradient Descent | | 15 | 15 | | 9.28% | 0 | 0 | 3.13% | | 0 |
| Leaves_2 | 10 | Log-sigmoid | None | Stochastic Approximation to Gradient Descent | - | 15 | 15 | | 7.22% | 0 | 0 | 1.04% | 0 | 0 |
| Leaves 2 | 10 | Hyperbolic tangent sigmoid | Hard-limit | Stochastic Approximation to Gradient Descent | \dashv | 15 | 15 | | 9.28% | 0 | 0 | 1.04% | | 0 |
| Leaves_2 | 10 | Hyperbolic tangent sigmoid | Linear | Stochastic Approximation to Gradient Descen | - | 15 | 15 | | 13.40% | 0 | 0 | 0.00% | | 0 |
| Leaves_2 | 10 | Hyperbolic tangent sigmoid | Log-sigmoid | Stochastic Approximation to Gradient Descent | | 15 | 15 | | 8.25% | 0 | 0 | | | 0 |
| Leaves_2 | 10 | Hyperbolic tangent sigmoid | Hyperbolic tangent sigmoid | Stochastic Approximation to Gradient Descent | nt 70 | 15 | 15 | 1564 | 9.28% | 0 | 0 | %00:0 | 0 | 0 |
| Leaves_2 | 10 | Hyperbolic tangent sigmoid | Symmetric hard-limit | Stochastic Approximation to Gradient Descent | nt 70 | 15 | 15 | 1564 | 7.22% | 0 | 0 | 2.08% | 0 | 0 |
| Leaves_2 | 10 | Hyperbolic tangent sigmoid | None | Stochastic Approximation to Gradient Descent | nt 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 | nt 70 | 15 | 15 | 1564 | 12.37% | 0 | 0 | 1.04% | 0 | 0 |
| Leaves_2 | 10 | Symmetric hard-limit | Linear | Stochastic Approximation to Gradient Descent | nt 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 | nt 70 | 15 | 15 | | 7.22% | 0 | 0 | 1.04% | 0 | 0 |
| Leaves_2 | 10 | Symmetric hard-limit | Hyperbolic tangent sigmoid | Stochastic Approximation to Gradient Descent | | 15 | 15 | | 14.43% | 0 | 0 | 1.04% | 0 | 0 |
| Leaves_2 | 10 | Symmetric hard-limit | Symmetric hard-limit | Stochastic Approximation to Gradient Descent | | 15 | 15 | | 11.34% | 0 | 0 | 1.04% | | 0 |
| Leaves_2 | 10 | Symmetric hard-limit | None | Stochastic Approximation to Gradient Descent | nt 10 | 12 | 15 | 1564 | 7.22% | 0 | 0 | 1.04% | 0 | 0 |

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

| | | Transfer | Transfer functions | Ratio | (in percentage % | (9) | | Species | | Species | |
|----------|-----------|----------------------------|----------------------------|-------------------------------|------------------|-----|-------------|----------------|-----------|---------|----------|
| Folder | Hidden L. | 1st | 2nd | orithm Train | Validation Te | + | s Success % | Epoch Duration | % ssəcons | Epoch | Duration |
| Leaves_3 | 2 | Hard-limit | Hard-limit | Perceptron Training Rule 80 | 10 10 | | 100.00% | | %00.0 | 0 | 0 |
| Leaves_3 | 2 | Hard-limit | Linear | Perceptron Training Rule 80 | 10 10 | | %00.0 | 0 0 | 0.00% | 0 | 0 |
| Leaves_3 | 2 | Hard-limit | Log-sigmoid | Perceptron Training Rule 80 | 10 10 | | 20.00% | 0 0 | %00'0 | 0 | 0 |
| Leaves_3 | 2 | Hard-limit | Hyperbolic tangent sigmoid | Perceptron Training Rule 80 | 10 10 | 20 | %00.0 | 0 0 | 0.00% | 0 | 0 |
| Leaves_3 | 2 | Hard-limit | Symmetric hard-limit | Perceptron Training Rule 80 | 10 10 | | %00.0 | 0 0 | %00.0 | 0 | 0 |
| Leaves_3 | 2 | Hard-limit | None | Perceptron Training Rule 80 | 10 10 | | %00.0 | 0 0 | %00.0 | 0 | 0 |
| Leaves_3 | 2 | Linear | Hard-limit | Perceptron Training Rule 80 | 10 10 | 20 | %00.0 | 0 0 | 0.00% | 0 | 0 |
| Leaves_3 | 2 | Linear | Linear | Perceptron Training Rule 80 | 10 10 | | %00.0 | 0 0 | %00.0 | 0 | 0 |
| Leaves_3 | 2 | Linear | Log-sigmoid | Perceptron Training Rule 80 | 10 10 | | %00.0 | 0 0 | 0.00% | 0 | 0 |
| Leaves_3 | 2 | Linear | Hyperbolic tangent sigmoid | Training Rule | 10 10 | | 20.00% | 0 0 | %00.0 | 0 | 0 |
| Leaves_3 | 2 | Linear | Symmetric hard-limit | Perceptron Training Rule 80 | 10 10 | | 100.00% | 0 0 | 0.00% | 0 | 0 |
| Leaves_3 | 2 | Linear | None | Perceptron Training Rule 80 | 10 10 | | 20.00% | 0 0 | 0.00% | 0 | 0 |
| Leaves_3 | 2 | Log-sigmoid | Hard-limit | Perceptron Training Rule 80 | 10 10 | | %00.0 | 0 0 | 0.00% | 0 | 0 |
| Leaves_3 | 2 | Log-sigmoid | Linear | Perceptron Training Rule 80 | 10 10 | 20 | %00.0 | 0 0 | 0.00% | 0 | 0 |
| Leaves_3 | 2 | Log-sigmoid | Log-sigmoid | Perceptron Training Rule 80 | 10 10 | | %00.0 | | 0.00% | 0 | 0 |
| Leaves_3 | 2 | Log-sigmoid | Hyperbolic tangent sigmoid | Perceptron Training Rule 80 | 10 10 | 20 | 20.00% | 0 0 | 0.00% | 0 | 0 |
| Leaves_3 | 2 | Log-sigmoid | Symmetric hard-limit | Perceptron Training Rule 80 | 10 10 | | %00.0 | 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 | %00.0 | 0 0 | 0.00% | 0 | 0 |
| Leaves_3 | 2 | Hyperbolic tangent sigmoid | Linear | Perceptron Training Rule 80 | 10 10 | | 20.00% | 0 0 | 0.00% | 0 | 0 |
| Leaves_3 | 2 | Hyperbolic tangent sigmoid | Log-sigmoid | Perceptron Training Rule 80 | 10 10 | | 100.00% | 0 0 | 0.00% | 0 | 0 |
| Leaves_3 | 2 | Hyperbolic tangent sigmoid | Hyperbolic tangent sigmoid | | 10 10 | 20 | %00.0 | 0 0 | 0.00% | 0 | 0 |
| Leaves_3 | 2 | Hyperbolic tangent sigmoid | Symmetric hard-limit | Perceptron Training Rule 80 | 10 10 | 20 | %00.0 | 0 0 | 0.00% | 0 | 0 |
| Leaves_3 | 2 | Hyperbolic tangent sigmoid | None | | 10 10 | | 20.00% | 0 0 | 0.00% | 0 | 0 |
| Leaves_3 | 2 | Symmetric hard-limit | Hard-limit | Perceptron Training Rule 80 | 10 10 | | %00.0 | 0 0 | 0.00% | 0 | 0 |
| Leaves_3 | 2 | Symmetric hard-limit | Linear | | 10 10 | | 20.00% | 0 0 | %00.0 | 0 | 0 |
| Leaves_3 | 2 | Symmetric hard-limit | Log-sigmoid | Perceptron Training Rule 80 | 10 10 | | 20.00% | 0 0 | %00.0 | 0 | 0 |
| Leaves_3 | 2 | Symmetric hard-limit | Hyperbolic tangent sigmoid | Perceptron Training Rule 80 | 10 10 | | 20.00% | 0 0 | %00.0 | 0 | 0 |
| Leaves_3 | 2 | Symmetric hard-limit | Symmetric hard-limit | Training Rule | | | 20.00% | | %00.0 | 0 | 0 |
| Leaves_3 | 2 | Symmetric hard-limit | None | ng Rule | | | %00.0 | 0 0 | 0.00% | 0 | 0 |
| Leaves_3 | 2 | Hard-limit | Hard-limit | | | | %00:0 | 0 0 | %00.0 | 0 | 0 |
| Leaves_3 | 2 | Hard-limit | Linear | Gradient Descent 80 | 10 10 | | 0.00% | 0 0 | 0.00% | 0 | 0 |
| Leaves_3 | 2 | Hard-limit | Log-sigmoid | Gradient Descent 80 | 10 10 | | %00:0 | 0 0 | %00.0 | 0 | 0 |
| Leaves_3 | 2 | Hard-limit | Hyperbolic tangent sigmoid | Gradient Descent 80 | 10 10 | | 20.00% | 0 0 | %00.0 | 0 | 0 |
| Leaves_3 | 2 | Hard-limit | Symmetric hard-limit | Gradient Descent 80 | 10 10 | | 100.00% | 0 0 | %00'0 | 0 | 0 |
| Leaves_3 | 2 | Hard-limit | None | Gradient Descent 80 | 10 10 | | 20.00% | 0 0 | %00.0 | 0 | 0 |
| Leaves_3 | 2 | Linear | Hard-limit | Gradient Descent 80 | 10 10 | 20 | %00.0 | 0 0 | 0.00% | 0 | 0 |
| Leaves_3 | 2 | Linear | Linear | Gradient Descent 80 | 10 10 | | %00.0 | 0 0 | 0.00% | 0 | 0 |
| Leaves_3 | 2 | Linear | Log-sigmoid | Gradient Descent 80 | 10 10 | | 20.00% | 0 0 | 0.00% | 0 | 0 |
| Leaves_3 | 2 | Linear | Hyperbolic tangent sigmoid | Gradient Descent 80 | 10 10 | | 20.00% | 0 0 | %00.0 | 0 | 0 |
| Leaves_3 | 2 | Linear | Symmetric hard-limit | | 10 10 | | %00:0 | | %00.0 | 0 | 0 |
| Leaves_3 | 2 | Linear | None | Gradient Descent 80 | 10 10 | | 50.00% | 0 0 | 0.00% | 0 | 0 |
| Leaves_3 | 2 | Log-sigmoid | Hard-limit | Gradient Descent 80 | 10 10 | | %00:0 | 0 0 | %00.0 | 0 | 0 |
| Leaves_3 | 2 | Log-sigmoid | Linear | Gradient Descent 80 | 10 10 | | 0.00% | 0 0 | 0.00% | 0 | 0 |
| Leaves_3 | 2 | Log-sigmoid | Log-sigmoid | Gradient Descent 80 | 10 10 | 20 | 20.00% | 0 0 | 0.00% | 0 | 0 |
| | | | | | | | | | | | |

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

| idden L. | 1st 2nd Log-sigmoid Hyperbol Log-sigmoid Symmet Log-sigmoid None Hyperbolic tangent sigmoid Hard-lin Hyperbolic tangent sigmoid Linear Hyperbolic tangent sigmoid Log-sign Hyperbolic tangent sigmoid Hyperbol Hyperbolic tangent sigmoid Symmetric hard-limit Hyperbolic tangent sigmoid Hyperbol Symmetric hard-limit Linear Symmetric hard-limit Linear Symmetric hard-limit Log-sign Hyperbolic hard-limit Hyperbol | olic tangent sigmoid ric hard-limit nit | Training algorithm | Train 80 | + | n Test | t Quant. images | Success % | Epoch 0 | Duration 0 | % ss | Epoch | Duration |
|---|---|---|--|-------------|----|--------|-----------------|-----------|------------|---------------|-------|-------|----------|
| | | - | , | 8 | 10 | 10 | 06 | 10.00% | 0 | 0 | 7,000 | _ | |
| | | | Gradient Descent | | | | 24 | , , , | | _ | 0.00% | 0 | 0 |
| | | | Gradient Descent | 8 | 10 | 10 | 20 | 20.00% | 0 | 0 | %00.0 | 0 | 0 |
| | | | Gradient Descent | 98 | 10 | 10 | 20 | %00.0 | 0 | 0 | %00.0 | 0 | 0 |
| | | | Gradient Descent | 80 | 10 | 10 | 20 | 20.00% | 0 | 0 | %00.0 | 0 | 0 |
| | | Linear | Gradient Descent | 98 | 10 | 10 | 20 | %00.0 | 0 | 0 | %00.0 | 0 | 0 |
| | | Log-sigmoid | Gradient Descent | 80 | 10 | 10 | 20 | %00.0 | 0 | | %00.0 | 0 | 0 |
| | | Hyperbolic tangent sigmoid | Gradient Descent | 08 | 10 | 10 | 20 | %00.0 | 0 | | %00.0 | 0 | 0 |
| | | \vdash | Gradient Descent | 80 | 10 | 10 | 20 | %00.0 | 0 | 0 | %00.0 | 0 | 0 |
| | | None | Gradient Descent | 8 | 10 | 10 | 20 | 20.00% | 0 | 0 | %00.0 | 0 | 0 |
| | | Hard-limit | Gradient Descent | 8 | 10 | 10 | 20 | %00.0 | 0 | 0 | %00.0 | 0 | 0 |
| | | Linear | Gradient Descent | 80 | 10 | 10 | 20 | %00.0 | 0 | 0 | %00.0 | 0 | 0 |
| | | Log-sigmoid | Gradient Descent | 98 | 10 | 10 | 20 | %00.0 | 0 | 0 | %00.0 | 0 | 0 |
| | | Hyperbolic tangent sigmoid | Gradient Descent | 08 | 10 | 10 | 20 | 20.00% | 0 | 0 | %00.0 | 0 | 0 |
| | Symmetric hard-limit | Symmetric hard-limit | Gradient Descent | 8 | 10 | 10 | 20 | 20.00% | 0 | 0 | %00.0 | 0 | 0 |
| | Symmetric hard-limit | None | Gradient Descent | 98 | 10 | 10 | 20 | %00.0 | 0 | 0 | %00.0 | 0 | 0 |
| | Hard-limit | Hard-limit | Stochastic Approximation to Gradient Descent | 08 | 10 | 10 | 20 | %00.0 | 0 | 0 | %00.0 | 0 | 0 |
| | Hard-limit | Linear | Stochastic Approximation to Gradient Descent | 280 | 10 | 10 | 20 | %00.0 | 0 | 0 | %00.0 | 0 | 0 |
| | Hard-limit | Log-sigmoid | Stochastic Approximation to Gradient Descent | | 10 | 10 | 20 | %00.0 | 0 | | %00.0 | 0 | 0 |
| | Hard-limit | Hyperbolic tangent sigmoid | Stochastic Approximation to Gradient Descent | 2 | 10 | 10 | 20 | %00.0 | 0 | 0 | %00.0 | 0 | 0 |
| | Hard-limit | Symmetric hard-limit | Stochastic Approximation to Gradient Descent | 98 | 10 | 10 | 20 | %00.0 | 0 | | %00.0 | 0 | 0 |
| | Hard-limit | None | Stochastic Approximation to Gradient Descent | 08 | 10 | 10 | 20 | %00.0 | 0 | 0 | %00.0 | 0 | 0 |
| | Linear | Hard-limit | Stochastic Approximation to Gradient Descent | 98 | 10 | 10 | 20 | 100.00% | 0 | 0 | %00.0 | 0 | 0 |
| | Linear | Linear | Stochastic Approximation to Gradient Descent | 08 | 10 | 10 | 20 | 20.00% | 0 | 0 | %00.0 | 0 | 0 |
| | | | Stochastic Approximation to Gradient Descent | | 10 | 10 | 20 | 100.00% | 0 | | %00.0 | 0 | 0 |
| | Linear | Hyperbolic tangent sigmoid | Stochastic Approximation to Gradient Descent | | 10 | 10 | 20 | %00.0 | 0 | | %00.0 | 0 | 0 |
| 2 | Linear | Symmetric hard-limit | Stochastic Approximation to Gradient Descent | : 80 | 10 | 10 | 20 | 50.00% | 0 | 0 | 0.00% | 0 | 0 |
| 2 2 2 2 2 2 2 2 2 2 | Linear | | Stochastic Approximation to Gradient Descent | 2 80 | 10 | 10 | 20 | %00.0 | 0 | 0 | %00.0 | 0 | 0 |
| 0 0 0 0 0 0 0 0 | Log-sigmoid | Hard-limit | Stochastic Approximation to Gradient Descent | 2 80 | 10 | 10 | 20 | 0.00% | 0 | | %00.0 | 0 | 0 |
| 00000000 | Log-sigmoid | Linear | Stochastic Approximation to Gradient Descent | 08 | 10 | 10 | 20 | %00.0 | 0 | 0 | %00.0 | 0 | 0 |
| 0 0 0 0 0 0 | Log-sigmoid | - | Stochastic Approximation to Gradient Descent | 2 | 10 | 10 | 20 | 0.00% | 0 | 0 | %00.0 | 0 | 0 |
| 2 2 2 2 2 | Log-sigmoid | Hyperbolic tangent sigmoid | Stochastic Approximation to Gradient Descent | : 80 | 10 | 10 | 20 | 0.00% | 0 | 0 | 0.00% | 0 | 0 |
| 2 | Log-sigmoid | etric hard-limit | Stochastic Approximation to Gradient Descent | | 10 | 10 | 20 | 0.00% | 0 | | %00.0 | 0 | 0 |
| 2 2 2 | | | Stochastic Approximation to Gradient Descent | | 10 | 10 | 20 | 20.00% | 0 | 0 | %00.0 | 0 | 0 |
| 2 2 | Hyperbolic tangent sigmoid | Hard-limit | Stochastic Approximation to Gradient Descent | | 10 | 10 | 20 | %00.0 | 0 | | %00.0 | 0 | 0 |
| 2 | | Linear | Stochastic Approximation to Gradient Descent | | 10 | 10 | 20 | 50.00% | 0 | | %00.0 | 0 | 0 |
| | Hyperbolic tangent sigmoid | Log-sigmoid | Stochastic Approximation to Gradient Descent | 08 | 10 | 10 | 20 | %00.0 | 0 | | %00.0 | 0 | 0 |
| Leaves_3 2 H | Hyperbolic tangent sigmoid | Hyperbolic tangent sigmoid | Stochastic Approximation to Gradient Descent | 08 | 10 | 10 | 20 | %00.0 | 0 | 0 | %00.0 | 0 | 0 |
| Leaves_3 2 H | Hyperbolic tangent sigmoid | Symmetric hard-limit | Stochastic Approximation to Gradient Descent | 98 13 | 10 | 10 | 20 | 20.00% | 0 | | %00.0 | 0 | 0 |
| Leaves_3 2 H | \vdash | None | Stochastic Approximation to Gradient Descent | 08 | 10 | 10 | 20 | 20.00% | 0 | 0 | %00.0 | 0 | 0 |
| Leaves_3 2 Sy | | Hard-limit | Stochastic Approximation to Gradient Descent | 98 | 10 | 10 | 20 | %00.0 | 0 | 0 | %00.0 | 0 | 0 |
| Leaves_3 2 Sy | Symmetric hard-limit | Linear | Stochastic Approximation to Gradient Descent | 28 | 10 | 10 | 20 | %00.0 | 0 | 0 | %00.0 | 0 | 0 |
| Leaves_3 2 Sy | | | Stochastic Approximation to Gradient Descent | 08 | 10 | 10 | 20 | %00.0 | 0 | 0 | %00.0 | 0 | 0 |
| 2 | | Hyperbolic tangent sigmoid | Stochastic Approximation to Gradient Descent | 08 | 10 | 10 | 20 | 20.00% | 0 | 0 | %00.0 | 0 | 0 |
| 2 | | netric hard-limit | Stochastic Approximation to Gradient Descent | | 10 | 10 | 20 | 0.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_3 2 Sy | Symmetric hard-limit | None | Stochastic Approximation to Gradient Descent | 08 | 10 | 10 | 20 | 20.00% | 0 | 0 | %00.0 | 0 | 0 |

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

| Success % Epoch Duration Success % Epoch 0.00% 0 0.00% 0 0.00% 0 0.00% 0 0.00% 0 0.00% 0 0.00% 0 0.00% 0 0.00% 0 0.00% 0 0.00% 0 0.00% 0 0.00% 0 0.00% 0 0.00% 0 0.00% 0 0.00% 0 0.00% 0 0.00% 0 0.00% 0 0.00% 0 0.00% 0 0.00% 0 0.00% 0 0.00% 0 0.00% 0 0.00% 0 0.00% 0 0.00% 0 0.00% 0 0.00% 0 0.00% 0 0.00% 0 0.00% 0 0.00% 0 0.00% 0 0.00% 0 | | Transfer | Transfer functions | | Ratio | in percentage | age %) | | | Species | | | Species | |
|---|----------|----------------------------|----------------------------|--------------------------|----------|---------------|--------|----|---------|----------|----------|-------|---------|----------|
| (1) Hand-lating Hand-lating Program Thating Rule 70 15 20 6000% 0 0 0 0 0 10 0 (1) Hand-lating Local-lating Local-lating Local-lating Local-lating Procession Thating Rule 71 5 20 0.00% 0 | | | 2nd | Training algorithm | Train | | _ | | Success | \vdash | Duration | | Epoch | Duration |
| Hard-bunith Liborator Liborator Proception Planting Rule 70 15 15 30 10,00% 0 0 0 0.0% 0 0 0 0 0 0 0 0 0 | | Hard-limit | Hard-limit | Perceptron Training Rule | | 15 | 15 | 20 | %00.0 | 0 | 0 | %00.0 | 0 | 0 |
| 10 Hard-lanth Log-signod Processor Processor 11 10 600% 0 0 100% 0 10 Hard-lanth Hyperbolic tangen signod Proception Thating Rule 7 15 50 600% 0 0 0.00% 0 10 Hard-lanth Symmetric hard-lanth Proception Thating Rule 7 15 50 600% 0 0 0.00% 0 0 0.00% 0 0 0.00% 0 0 0.00% 0 0 0.00% 0 0 0.00% 0 0 0.00% 0 0 0.00% 0 0 0.00% 0 0 0.00% 0 0 0.00% 0 0 0.00% 0 0 0.00% 0 0 0.00% 0 0 0.00% 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 | \vdash | Hard-limit | Linear | Perceptron Training Rule | - | 15 | 15 | 20 | 50.00% | 0 | 0 | %00.0 | 0 | 0 |
| 10 Hard-linit Pyte-belic tangent eigenoff Perception Thailing Rule 70 16 15 20 6000% 0 0 10 0 10 Hard-linit Symmetric band-linit Perception Thailing Rule 70 15 20 6000% 0 0 10 000% 10 Ideac Inched-linit Perception Thailing Rule 70 15 20 6000% 0 0 10 000% 0 10 Likear Likear Hope Paper and Paper Annual Paper An | | Hard-limit | Log-sigmoid | Training | | 15 | 15 | 20 | %00.0 | 0 | 0 | %00.0 | 0 | 0 |
| 10. Hard-Burtt Numerate band-Jamit Preception Thanks Rule 70 15 20 0.00% 0 0 0.00% 0 10. Hard-Burtt Numerate band-Jamit Preception Thanks Rule 70 15 20 0.00% 0 0 0.00% 0 10. Innear Linear Linear Preception Thanks Rule 70 15 20 0.00% 0 | | Hard-limit | Hyperbolic tangent sigmoid | Perceptron Training Rule | | 15 | 15 | 20 | 0.00% | 0 | 0 | 0.00% | 0 | 0 |
| Hard-limit Numeri | | Hard-limit | Symmetric hard-limit | Perceptron Training Rule | | 15 | 15 | 20 | 20.00% | 0 | 0 | 0.00% | 0 | 0 |
| 10 Linear Have thank Proceptor Thinking Rule 70 15 23 0.00% 0 0.00% 0 10 Linear Linear Linear Linear Linear Proceptor Thinking Rule 70 15 22 0.00% 0 0.00% 0 10 Linear Standard Proceptor Thinking Rule 70 15 22 610.00% 0 0 0.00% 0 10 Linear Standard Manuer's bard-limit Proceptor Thinking Rule 70 15 22 610.00% 0 0 0.00% 0 10 Linear None Proceptor Thinking Rule 70 15 22 610.00% 0 0 0.00% 0 | | Hard-limit | None | Perceptron Training Rule | | 15 | 15 | 20 | %00.0 | 0 | 0 | 0.00% | 0 | 0 |
| 10 Linear Linear Linear Perceptor Training Bule 70 15 23 10.00% 0 0.00% 0 10 Linear Hope and the control of the control of Perceptor Training Bule 70 15 15 20 10.00% 0 0.00% 0 10 Linear Symmetric hand-limit Perceptor Training Bule 70 15 20 60.00% 0 0.00% 0 10 Linear No. 15 20 60.00% 0 0 0.00% 0 10 Linear No. 15 20 60.00% 0 0 0.00% 0 10 Lee-signoid Barch Imag Perceptor Training Bule 70 15 15 20 60.00% 0 0 0.00% 10 Lee-signoid Expendent signoid Perceptor Training Rule 70 15 15 20 0.00% 0 0.00% 10 Perceptor Training Rule 70 15 15 20 0.00% 0 0.0 | \vdash | Linear | Hard-limit | Perceptron Training Rule | \vdash | 15 | 15 | 20 | 0.00% | 0 | 0 | 0.00% | 0 | 0 |
| 10 Linear Logs-gamed signed signed benefator Thining Rule (2002) 15 2.0 100.00% 0 0.00% 0 10 Linear Experience band-limit Perceptor Thining Rule (2002) 15 2.0 30.00% 0 0.00% 0 10 Linear Name of the Chinat Perceptor Thining Rule (2002) 15 2.0 0.00% 0 0.00% 0 10 Linear Name of the Chinat Perceptor Thining Rule (2002) 15 2.0 0.00% 0 0 0.00% 0 10 Log-signoid Broad (2002) Perceptor Thining Rule (2002) 15 2.0 0.00% 0 | 1 | Linear | Linear | Training | - | 15 | 15 | 20 | 0.00% | 0 | 0 | 0.00% | 0 | 0 |
| 10 Linear Hyperbolic tangent signal Preceptor Thining Rule 70 15 20 30,00% 0 0,00% 0 10 Linear Symmetric land-limit Preceptor Thining Rule 70 15 20 0,00% 0 0,00% 0 10 Linear Name Preceptor Thining Rule 70 15 20 0,00% 0 0 00% 0 10 Loce-Signoid Hord-Imit Preceptor Thining Rule 70 15 20 0,00% 0 | | Linear | Log-sigmoid | Training | - | 15 | 15 | 20 | 100.00% | 0 | 0 | 0.00% | 0 | 0 |
| 10 Linear None Perceptoral Training Rule 70 15 15 20 60.00% 0 0 0.00% 0 10 Linear None Month Perceptoral Training Rule 70 15 15 20 0.00% 0 0 0.00% 0 10 Log-signoid Inter-limit Perceptoral Training Rule 70 15 15 20 0.00% 0 0 0.00% 0 10 Log-signoid Log-signoid Log-signoid Perceptoral Training Rule 70 15 15 20 0.00% 0 0 0.00% 0 10 Log-signoid Log-signoid Everytoral Training Rule 70 15 15 20 0.00% 0 0 0.00% 0 10 Hyperbolic tangent signoid Brack Index I | | Linear | Hyperbolic tangent sigmoid | Training | | 15 | 15 | 20 | 20.00% | 0 | 0 | %00.0 | 0 | 0 |
| 10 Log-signoid Mone Perceptron' Training Rule 70 15 15 20 0.00% 0 0 0.00% 0 10 Log-signoid Interest Perceptron' Training Rule 70 15 15 20 0.00% 0 0 0.00% 0 10 Log-signoid Log-signoid Reverpton' Training Rule 70 15 15 20 0.00% 0 0 0.00% 0 10 Log-signoid Ryper-loir Langum signoid Breveptron' Training Rule 70 15 15 20 0.00% 0 0 0.00% 0 10 Hyper-loir Langum signoid Breveptron' Training Rule 70 15 15 20 0.00% 0 0 0.00% 0< | | Linear | Symmetric hard-limit | Perceptron Training Rule | - | 15 | 15 | 20 | 20.00% | 0 | 0 | 0.00% | 0 | 0 |
| 10 Log-signoid Linear Perception Thaning Rale 70 15 21 0.00% 0 0 0.00% 0 10 Log-signoid Linear Perception Thaning Rale 70 15 21 20 0.00% 0 0 0.00% 0 10 Log-signoid Experience Lease and Annual Control Thaning Rale 70 15 20 0.00% 0 0 0.00% 0 10 Log-signoid Symmetric bunchlinit Perception Thaning Rale 70 15 20 0.00% 0 0 0.00% 0 10 Hyperbolic tangent signoid Perception Thaning Rale 70 15 20 0.00% 0 0 0.00% 0 10 Hyperbolic tangent signoid Perception Thaning Rale 70 15 20 0.00% 0 0 0.00% 0 10 Hyperbolic tangent signoid Perception Thaning Rale 70 15 20 0.00% 0 0 0 0 0 0 0 0 | | Linear | None | | | 15 | 15 | 20 | 0.00% | 0 | 0 | 0.00% | 0 | 0 |
| 10 Log-signoid Linear Perceptor Thaning Rule 70 15 20 300% 0 0 0.00% 0 10 Log-signoid Lice-signoid Lice-signoid Log-signoid Lice-signoid Perceptor Thaning Rule 70 15 20 1000% 0 0 0.00% 0 10 Log-signoid Hyperbolic tangent signoid March Perceptor Thaning Rule 70 15 20 0.00% 0 0 0.00% 0 10 Log-signoid Name Perceptor Thaning Rule 70 15 20 0.00% 0 0 0.00% 0 <td></td> <td>Log-sigmoid</td> <td>Hard-limit</td> <td>Perceptron Training Rule</td> <td></td> <td>15</td> <td>15</td> <td>20</td> <td>%00.0</td> <td>0</td> <td>0</td> <td>0.00%</td> <td>0</td> <td>0</td> | | Log-sigmoid | Hard-limit | Perceptron Training Rule | | 15 | 15 | 20 | %00.0 | 0 | 0 | 0.00% | 0 | 0 |
| 10 Log-signoid Log-signoid Log-signoid Perceptron Training Rule 70 15 15 20 1000% 0 0 0 10 Log-signoid Spannetric land-limit Perceptron Training Rule 70 15 15 20 0.00% 0 0 0.00% 0 10 Log-signoid Symmetric land-limit Perceptron Training Rule 70 15 20 0.00% 0 0 0.00% 0 | \vdash | Log-sigmoid | Linear | | \vdash | 15 | 15 | 20 | 20.00% | 0 | 0 | 0.00% | 0 | 0 |
| 110 Log-signoid Hyperbolic tangent signoid Perceptron Training Rule 70 15 20 0.00% 0 0 0.00% 0 10 Log-signoid Symmetric bard-limit Perceptron Training Rule 70 15 15 20 0.00% 0 0 0.00% 0 10 Hyperbolic tangent signoid Innear Perceptron Training Rule 70 15 15 20 0.00% 0 0 0.00% 0 10 Hyperbolic tangent signoid Hard-limit Perceptron Training Rule 70 15 15 20 0.00% 0 0 0.00% 0 10 Hyperbolic tangent signoid Hyperbolic tangent signoid Hyperbolic tangent signoid Perceptron Training Rule 70 15 15 20 0.00% 0 0 0.00% 0 10 Hyperbolic tangent signoid Perceptron Training Rule 70 15 15 20 0.00% 0 0 0.00% 0 0 0< | \vdash | Log-sigmoid | Log-sigmoid | Perceptron Training Rule | | 15 | 15 | 20 | 100.00% | 0 | 0 | 0.00% | 0 | 0 |
| 10 Logs/ground Symmetric hard-limit Perceptron Training Rule 70 15 20 0.00% 0 0 0 10 Logs/ground Name-tric hard-limit Perceptron Training Rule 70 15 20 0.00% 0 0 0.00% 0 10 Hyperbolic tangent sigmoid Hard-limit Perceptron Training Rule 71 15 20 0.00% 0 0 0.00% 0 10 Hyperbolic tangent sigmoid Assigmoid Perceptron Training Rule 70 15 20 0.00% 0 0 0.00% 0 10 Hyperbolic tangent sigmoid Symmetric hard-limit Hard-limit Perceptron Training Rule 70 15 20 0.00% 0 0 0.00% 0 10 Hyperbolic tangent sigmoid Perceptron Training Rule 70 15 20 0.00% 0 0 0.00% 0 0 0.00% 0 0 0 0 0 0 0 | _ | Log-sigmoid | Hyperbolic tangent sigmoid | Perceptron Training Rule | \vdash | 15 | 15 | 20 | 0.00% | 0 | 0 | 0.00% | 0 | 0 |
| 10 Log-signoid None Perceptron Training Rule 70 15 15 20 0.00% 0 0 0.00% 0 10 Hyperbolic augent sigmoid Hard-limit Perceptron Training Rule 70 15 15 20 0.00% 0 0 0.00% 0 10 Hyperbolic augent sigmoid Linear Perceptron Training Rule 70 15 15 20 0.00% 0 0 0.00% 0 10 Hyperbolic tangent sigmoid Perceptron Training Rule 70 15 15 20 0.00% 0 0 0.00% 0 10 Hyperbolic tangent sigmoid Perceptron Training Rule 70 15 20 0.00% 0 0 0.00% 0 10 Symmetric bard-limit Barcelling Perceptron Training Rule 70 15 20 0.00% 0 0 0.00% 0 10 Symmetric bard-limit Barcelling Perceptron Training Rule 70 | | Log-sigmoid | Symmetric hard-limit | Training | | 15 | 15 | 20 | %00.0 | 0 | 0 | %00.0 | 0 | 0 |
| 10 Hyperbolic tangent signoid Investignent Hard-limit Perceptron Training Rule 70 15 15 20 0.00% 0 0 0.00% 0 10 Hyperbolic tangent signoid Log-signoid Perceptron Training Rule 70 15 20 0.00% 0 0 0.00% 0 10 Hyperbolic tangent signoid Perceptron Training Rule 70 15 20 0.00% 0 0 0.00% 0 | \vdash | Log-sigmoid | None | | - | 15 | 15 | 20 | 0.00% | 0 | 0 | 0.00% | 0 | 0 |
| 10 Hyperbolic tangent sigmoid Perceptron Training Rale 70 15 20 0.00% 0 0 0.00% 0 10 Hyperbolic tangent sigmoid Hyperbolic tangent sigmoid Perceptron Training Rale 70 15 20 0.00% 0 0 0.00% 0 10 Hyperbolic tangent sigmoid Hyperbolic tangent sigmoid Hyperbolic tangent sigmoid Perceptron Training Rale 70 15 20 0.00% 0 0 0.00% 0 10 Symmetric bard-limit Long-sigmoid Perceptron Training Rale 70 15 20 0.00% 0 0 0.00% 0 < | | Hyperbolic tangent sigmoid | Hard-limit | Training | | 15 | 15 | 20 | 0.00% | 0 | 0 | 0.00% | 0 | 0 |
| 10 Hyperbolic tangent sigmoid Perceptron Training Rale 70 15 20 0.00% 0 0.00% 0 10 Hyperbolic tangent sigmoid Perceptron Training Rale 70 15 20 0.00% 0 0 0.00% 0 10 Hyperbolic tangent sigmoid Perceptron Training Rale 70 15 20 0.00% 0 0 0.00% 0 10 Hyperbolic tangent sigmoid Perceptron Training Rale 70 15 20 0.00% 0 0 0.00% 0 10 Symmetric hard-limit Lard-limit Location Training Rale 70 15 15 20 0.00% 0 0 0.00% 10 Symmetric hard-limit Symmetric hard-limit Perceptron Training Rale 70 15 15 20 0.00% 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 <t< td=""><td></td><td>Hyperbolic tangent sigmoid</td><td>Linear</td><td></td><td>-</td><td>15</td><td>15</td><td>20</td><td>%00.0</td><td>0</td><td>0</td><td>0.00%</td><td>0</td><td>0</td></t<> | | Hyperbolic tangent sigmoid | Linear | | - | 15 | 15 | 20 | %00.0 | 0 | 0 | 0.00% | 0 | 0 |
| 10 Hyperbolic tangent sigmoid Hyperbolic tangent sigmoid Perceptron Training Rule 70 15 15 20 0.00% 0 0 0 10 Hyperbolic tangent sigmoid Symmetric hard-limit Perceptron Training Rule 70 15 15 20 0.00% 0 </td <td></td> <td>Hyperbolic tangent sigmoid</td> <td>Log-sigmoid</td> <td></td> <td>-</td> <td>15</td> <td>15</td> <td>20</td> <td>%00.0</td> <td>0</td> <td>0</td> <td>0.00%</td> <td>0</td> <td>0</td> | | Hyperbolic tangent sigmoid | Log-sigmoid | | - | 15 | 15 | 20 | %00.0 | 0 | 0 | 0.00% | 0 | 0 |
| 10 Hyperbolic tangent sigmoid Symmetric hard-limit Perceptron Training Rule 70 15 15 20 0.00% 0 0.00% 0 10 Hyperbolic tangent sigmoid Receptron Training Rule 70 15 15 20 0.00% 0 0 0.00% 0 10 Symmetric hard-limit Innear Perceptron Training Rule 70 15 20 0.00% 0 0 0.00% 0 10 Symmetric hard-limit Linear Perceptron Training Rule 70 15 20 0.00% 0< | - | Hyperbolic tangent sigmoid | Hyperbolic tangent sigmoid | Perceptron Training Rule | | 15 | 15 | 20 | %00.0 | 0 | 0 | %00.0 | 0 | 0 |
| 10 Hyperbolic tangent sigmoid None Perceptron Training Rule 70 15 20 0.00% 0 0 0.00% 0 10 Symmetric hard-limit Hard-limit Hard-limit Linear Perceptron Training Rule 70 15 20 0.00% 0 0 0.00% 0 10 Symmetric hard-limit Linear-limit Hyperbolic tangent signoid Perceptron Training Rule 70 15 20 0.00% 0 0 0.00% 0 | _ | Hyperbolic tangent sigmoid | Symmetric hard-limit | | - | 15 | 15 | 20 | %00.0 | 0 | 0 | %00.0 | 0 | 0 |
| 10 Symmetric hard-limit Description Training Rule 70 15 20 0.00% 0 0 0.00% 0 10 Symmetric hard-limit Log-signoid Perceptron Training Rule 70 15 20 0.00% 0 0 0.00% 0 10 Symmetric hard-limit Hyperbolic tangent signoid Perceptron Training Rule 70 15 20 0.00% 0 0 0.00% 0 10 Symmetric hard-limit Perceptron Training Rule 70 15 20 0.00% 0 0 0.00% 0 10 Hard-limit Mard-limit Perceptron Training Rule 70 15 20 0.00% 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 <t< td=""><td></td><td>Hyperbolic tangent sigmoid</td><td>None</td><td>Perceptron Training Rule</td><td></td><td>15</td><td>15</td><td>20</td><td>0.00%</td><td>0</td><td>0</td><td>%00.0</td><td>0</td><td>0</td></t<> | | Hyperbolic tangent sigmoid | None | Perceptron Training Rule | | 15 | 15 | 20 | 0.00% | 0 | 0 | %00.0 | 0 | 0 |
| 10 Symmetric hard-limit Linear Perceptron Training Rule 70 15 15 20 0.00% 0 0 0.00% 0 10 Symmetric hard-limit Hyperbolic tangent sigmoid Perceptron Training Rule 70 15 15 20 0.00% 0 0 0.00% 0 10 Symmetric hard-limit Hyperbolic tangent sigmoid Perceptron Training Rule 70 15 20 0.00% 0 0 0.00% 0 10 Symmetric hard-limit None Perceptron Training Rule 70 15 15 20 0.00% 0 0 0.00% 0 <t< td=""><td>-</td><td>Symmetric hard-limit</td><td>Hard-limit</td><td>Perceptron Training Rule</td><td>-</td><td>15</td><td>15</td><td>20</td><td>20.00%</td><td>0</td><td>0</td><td>%00.0</td><td>0</td><td>0</td></t<> | - | Symmetric hard-limit | Hard-limit | Perceptron Training Rule | - | 15 | 15 | 20 | 20.00% | 0 | 0 | %00.0 | 0 | 0 |
| 10 Symmetric hard-limit Log-sigmoid Perceptron Training Rule 70 15 15 20 0.00% 0 0 0.00% 0 10 Symmetric hard-limit Hyperbolic tangent sigmoid Perceptron Training Rule 70 15 15 20 0.00% 0 0 0.00% 0 10 Symmetric hard-limit Hyperbolic tangent sigmoid Perceptron Training Rule 70 15 15 20 0.00% 0 0 0.00% 0 10 Hard-limit Hard-limit Designoid Gradient Descent 70 15 15 20 0.00% 0 0 0.00% 0 10 Hard-limit Log-sigmoid Gradient Descent 70 15 15 20 0.00% 0 0 0.00% 0 10 Hard-limit Gradient Descent 70 15 15 20 0.00% 0 0 0.00% 0 10 Innear Gradient Descent <td></td> <td>Symmetric hard-limit</td> <td>Linear</td> <td>Perceptron Training Rule</td> <td></td> <td>15</td> <td>15</td> <td>20</td> <td>%00.0</td> <td>0</td> <td>0</td> <td>%00'0</td> <td>0</td> <td>0</td> | | Symmetric hard-limit | Linear | Perceptron Training Rule | | 15 | 15 | 20 | %00.0 | 0 | 0 | %00'0 | 0 | 0 |
| 10 Symmetric hard-limit Hyperbolic tangent sigmoid Perceptron Training Rule 70 15 15 20 0.00% 0 | | Symmetric hard-limit | Log-sigmoid | Perceptron Training Rule | | 15 | 15 | 20 | %00.0 | 0 | 0 | %00.0 | 0 | 0 |
| 10 Symmetric hard-limit Symmetric hard-limit Perceptron Training Rule 70 15 15 20 0.00% 0 0 0.00% 0 10 Symmetric hard-limit None Perceptron Training Rule 70 15 15 20 0.00% 0 | | Symmetric hard-limit | Hyperbolic tangent sigmoid | Training | | 15 | 15 | 20 | %00.0 | 0 | 0 | %00'0 | 0 | 0 |
| 10 Symmetric hard-limit None Perceptron Training Rule 70 15 20 0.00% 0 0 0.00% 0 10 Hard-limit Hard-limit Hard-limit Linear Gradient Descent 70 15 15 20 50.00% 0 | | Symmetric hard-limit | Symmetric hard-limit | Training | | 15 | 15 | 20 | %00.0 | 0 | 0 | %00.0 | 0 | 0 |
| 10 Hard-limit Hard-limit Gradient Descent 70 15 16 50.00% 0 0 0 10 Hard-limit Linear Gradient Descent 70 15 15 20 50.00% 0 0 0 0 10 Hard-limit Log-signoid Gradient Descent 70 15 15 20 50.00% 0 <t< td=""><td>-</td><td>Symmetric hard-limit</td><td>None</td><td>Training</td><td>-</td><td>15</td><td>15</td><td>20</td><td>%00.0</td><td>0</td><td>0</td><td>%00'0</td><td>0</td><td>0</td></t<> | - | Symmetric hard-limit | None | Training | - | 15 | 15 | 20 | %00.0 | 0 | 0 | %00'0 | 0 | 0 |
| 10 Hard-limit Linear Gradient Descent 70 15 15 20 0.00% 0 0.00% 0 10 Hard-limit Log-sigmoid Gradient Descent 70 15 15 20 50.00% 0 0 0 0 10 Hard-limit Log-sigmoid Gradient Descent 70 15 15 20 50.00% 0 | | Hard-limit | Hard-limit | Gradient Descent | 20 | 15 | 15 | 20 | 20.00% | 0 | 0 | %00.0 | 0 | 0 |
| 10 Hard-limit Log-sigmoid Gradient Descent 70 15 15 20 50.00% 0 0 0.00% 0 10 Hard-limit Hyperbolic tangent sigmoid Gradient Descent 70 15 15 20 0.00% 0 <t< td=""><td>_</td><td>Hard-limit</td><td>Linear</td><td>Gradient Descent</td><td>20</td><td>15</td><td>15</td><td>20</td><td>%00.0</td><td>0</td><td>0</td><td>%00.0</td><td>0</td><td>0</td></t<> | _ | Hard-limit | Linear | Gradient Descent | 20 | 15 | 15 | 20 | %00.0 | 0 | 0 | %00.0 | 0 | 0 |
| 10 Hard-limit Hyperbolic tangent signoid Gradient Descent 70 15 20 0.00% 0 0 0.00% 0 10 Hard-limit Symmetric hard-limit Gradient Descent 70 15 20 50.00% 0 0 0.00% 0 10 Hard-limit None Gradient Descent 70 15 15 20 50.00% 0 0 0.00% 0 10 Linear Hard-limit Gradient Descent 70 15 15 20 0.00% 0 </td <td></td> <td> Hard-limit</td> <td>Log-sigmoid</td> <td>Gradient Descent</td> <td>20</td> <td>15</td> <td>15</td> <td>20</td> <td> 20.00%</td> <td>0</td> <td>0</td> <td>%00'0</td> <td>0</td> <td>0</td> | | Hard-limit | Log-sigmoid | Gradient Descent | 20 | 15 | 15 | 20 | 20.00% | 0 | 0 | %00'0 | 0 | 0 |
| 10 Hard-limit Symmetric hard-limit Gradient Descent 70 15 20 50.00% 0 0.00% 0 10 Hard-limit None Gradient Descent 70 15 20 50.00% 0 0 0.00% 0 10 Linear Hard-limit Gradient Descent 70 15 15 20 0.00% 0 | | Hard-limit | Hyperbolic tangent sigmoid | Gradient Descent | 20 | 15 | 15 | 20 | %00.0 | 0 | 0 | %00'0 | 0 | 0 |
| 10 Hard-limit None Gradient Descent 70 15 20 50.00% 0 0.00% 0 10 Linear Hard-limit Gradient Descent 70 15 20 0.00% 0 0 0.00% 0 10 Linear Linear Log-signoid Gradient Descent 70 15 15 20 0.00% 0 0 0.00% 0 10 Linear Log-signoid Gradient Descent 70 15 15 20 0.00% 0 | \vdash | Hard-limit | Symmetric hard-limit | Gradient Descent | 20 | 15 | 15 | 20 | 20.00% | 0 | 0 | %00'0 | 0 | 0 |
| 10 Linear Hard-limit Gradient Descent 70 15 20 0.00% 0 0.00% 0 10 Linear Linear Linear Linear Gradient Descent 70 15 15 20 0.00% 0 0 0.00% 0 10 Linear Log-signoid Gradient Descent 70 15 15 20 0.00% 0 0 0.00% 0 10 Linear Symmetric hard-limit Gradient Descent 70 15 15 20 0.00% 0 | | Hard-limit | None | Gradient Descent | 20 | 15 | 15 | 20 | 20.00% | 0 | 0 | %00.0 | 0 | 0 |
| 10 Linear Linear Linear Gradient Descent 70 15 20 0.00% 0 0 0.00% 0 10 Linear Log-sigmoid Gradient Descent 70 15 20 50.00% 0 0 0.00% 0 10 Linear Hyperbolic tangent sigmoid Gradient Descent 70 15 15 20 0.00% 0 </td <td>\vdash</td> <td>Linear</td> <td>Hard-limit</td> <td>Gradient Descent</td> <td>20</td> <td>15</td> <td>15</td> <td>20</td> <td>0.00%</td> <td>0</td> <td>0</td> <td>0.00%</td> <td>0</td> <td>0</td> | \vdash | Linear | Hard-limit | Gradient Descent | 20 | 15 | 15 | 20 | 0.00% | 0 | 0 | 0.00% | 0 | 0 |
| 10 Linear Log-sigmoid Gradient Descent 70 15 20 50.00% 0 0.00% 0 10 Linear Hyperbolic tangent sigmoid Gradient Descent 70 15 20 0.00% 0 0 0.00% 0 10 Linear Symmetric hard-limit Gradient Descent 70 15 20 0.00% 0 | | Linear | Linear | Gradient Descent | 20 | 15 | 15 | 20 | 0.00% | 0 | 0 | 0.00% | 0 | 0 |
| 10 Linear Hyperbolic tangent signoid Gradient Descent 70 15 20 0.00% 0 0.00% 0 10 Linear Symmetric hard-limit Gradient Descent 70 15 20 0.00% 0 0 0.00% 0 10 Linear None Gradient Descent 70 15 20 0.00% 0 </td <td></td> <td>Linear</td> <td>Log-sigmoid</td> <td>Gradient Descent</td> <td>20</td> <td>15</td> <td>15</td> <td>20</td> <td>20.00%</td> <td>0</td> <td>0</td> <td>0.00%</td> <td>0</td> <td>0</td> | | Linear | Log-sigmoid | Gradient Descent | 20 | 15 | 15 | 20 | 20.00% | 0 | 0 | 0.00% | 0 | 0 |
| 10 Linear Symmetric hard-limit Gradient Descent 70 15 20 0.00% 0 0.00% 0 10 Linear None Gradient Descent 70 15 20 0.00% 0 </td <td></td> <td>Linear</td> <td>Hyperbolic tangent sigmoid</td> <td>Gradient Descent</td> <td>20</td> <td>15</td> <td>15</td> <td>20</td> <td>%00.0</td> <td>0</td> <td>0</td> <td>%00'0</td> <td>0</td> <td>0</td> | | Linear | Hyperbolic tangent sigmoid | Gradient Descent | 20 | 15 | 15 | 20 | %00.0 | 0 | 0 | %00'0 | 0 | 0 |
| 10 Linear None Gradient Descent 70 15 20 0.00% 0 0.00% 0 10 Log-sigmoid Hard-limit Gradient Descent 70 15 20 0.00% 0 0 0.00% 0 10 Log-sigmoid Linear Gradient Descent 70 15 20 0.00% 0 0 0.00% 0 10 Log-sigmoid Log-sigmoid Gradient Descent 70 15 20 0.00% 0 0 0.00% 0 | | Linear | Symmetric hard-limit | Gradient Descent | 20 | 15 | 15 | 20 | %00.0 | 0 | 0 | %00.0 | 0 | 0 |
| 10 Log-sigmoid Hard-limit Gradient Descent 70 15 20 0.00% 0 0 0.00% 0 10 Log-sigmoid Linear Gradient Descent 70 15 15 20 0.00% 0 0 0.00% 0 10 Log-sigmoid Log-sigmoid Gradient Descent 70 15 15 20 0.00% 0 0 0.00% 0 | | Linear | None | Gradient Descent | 20 | 15 | 15 | 20 | %00.0 | 0 | 0 | %00'0 | 0 | 0 |
| 10 Log-sigmoid Linear Gradient Descent 70 15 20 0.00% 0 0 0.00% 0 10 Log-sigmoid Log-sigmoid Gradient Descent 70 15 15 20 0.00% 0 0 0.00% 0 | | Log-sigmoid | Hard-limit | Gradient Descent | 20 | 15 | 15 | 20 | %00.0 | 0 | 0 | %00.0 | 0 | 0 |
| 10 Log-sigmoid Log-sigmoid Gradient Descent 70 15 15 20 0.00% 0 0 | - | Log-sigmoid | Linear | Gradient Descent | 20 | 15 | 15 | 20 | 0.00% | 0 | 0 | 0.00% | 0 | 0 |
| | +- | Log-sigmoid | Log-sigmoid | Gradient Descent | 20 | 15 | 15 | 20 | %00.0 | 0 | 0 | 0.00% | 0 | 0 |

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

| | | Transfer 1 | Transfer functions | | Ratio | | (in percentage % | (2) | | Species | | 51 | Species | |
|------------|-----------|----------------------------|----------------------------|--|-------|----|------------------|--------------------|-----------|---------|----------|-----------|---------|----------|
| Folder | Hidden L. | 1st | 2nd | Training algorithm | Train | | tion Te | Test Quant. images | % ssacons | Epoch | Duration | Success % | Epoch | Duration |
| Leaves_3 | 10 | Log-sigmoid | Hyperbolic tangent sigmoid | Gradient Descent | 20 | 15 | 15 | 20 | %00.0 | 0 | 0 | %00.0 | 0 | 0 |
| Leaves_3 | 10 | Log-sigmoid | Symmetric hard-limit | Gradient Descent | 2 | 15 | 15 | | %00.0 | 0 | 0 | %00.0 | 0 | 0 |
| Leaves_3 | 10 | Log-sigmoid | None | Gradient Descent | 20 | 15 | 15 | 20 | %00.0 | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_3 | 10 | Hyperbolic tangent sigmoid | Hard-limit | Gradient Descent | 20 | 15 | 15 | 20 | 20.00% | 0 | 0 | %00.0 | 0 | 0 |
| Leaves_3 | 10 | Hyperbolic tangent sigmoid | Linear | Gradient Descent | 20 | 15 | 15 | | 20.00% | 0 | 0 | %00.0 | 0 | 0 |
| _ | 10 | Hyperbolic tangent sigmoid | Log-sigmoid | Gradient Descent | 20 | 15 | 15 | | %00:0 | 0 | | %00.0 | 0 | 0 |
| Leaves_3 | 10 | Hyperbolic tangent sigmoid | Hyperbolic tangent sigmoid | Gradient Descent | 22 | 15 | 15 | | %00.0 | 0 | | %00.0 | 0 | 0 |
| Leaves_3 | 10 | Hyperbolic tangent sigmoid | Symmetric hard-limit | Gradient Descent | 20 | 15 | 15 | 20 | 20.00% | 0 | 0 | %00.0 | 0 | 0 |
| Leaves_3 1 | 10 | Hyperbolic tangent sigmoid | None | Gradient Descent | 2 | 15 | 15 | | 100.00% | 0 | | %00.0 | 0 | 0 |
| Leaves_3 | 10 | Symmetric hard-limit | Hard-limit | Gradient Descent | 20 | 15 | 15 | 20 | %00.0 | 0 | 0 | %00.0 | 0 | 0 |
| Leaves_3 | 10 | Symmetric hard-limit | Linear | Gradient Descent | 20 | 15 | 15 | | 100.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_3 | 10 | Symmetric hard-limit | Log-sigmoid | Gradient Descent | 22 | 15 | 15 | 20 | %00.0 | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_3 | 10 | Symmetric hard-limit | Hyperbolic tangent sigmoid | Gradient Descent | 20 | 15 | 15 | | %00.0 | 0 | 0 | %00.0 | 0 | 0 |
| Leaves_3 | 10 | Symmetric hard-limit | Symmetric hard-limit | Gradient Descent | 20 | 15 | 15 | | %00.0 | 0 | 0 | %00.0 | 0 | 0 |
| Leaves_3 | 10 | Symmetric hard-limit | None | Gradient Descent | 2 | 15 | 15 | | 20.00% | 0 | 0 | %00.0 | 0 | 0 |
| Leaves_3 | 10 | Hard-limit | Hard-limit | Stochastic Approximation to Gradient Descent | | 15 | 15 | | 20.00% | 0 | 0 | %00.0 | 0 | 0 |
| Leaves_3 1 | 10 | Hard-limit | Linear | Stochastic Approximation to Gradient Descent | t 70 | 15 | 15 | | %00.0 | 0 | 0 | %00.0 | 0 | 0 |
| Leaves_3 | 10 | Hard-limit | Log-sigmoid | Stochastic Approximation to Gradient Descent | | 15 | 15 | | %00.0 | 0 | | %00.0 | 0 | 0.01 |
| Leaves_3 | 10 | Hard-limit | Hyperbolic tangent sigmoid | Stochastic Approximation to Gradient Descent | t 70 | 15 | 15 | 20 | %00.0 | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_3 | 10 | Hard-limit | Symmetric hard-limit | Stochastic Approximation to Gradient Descent | t 70 | 15 | 15 | 20 | %00.0 | 0 | | 0.00% | 0 | 0 |
| Leaves_3 | 10 | Hard-limit | None | Stochastic Approximation to Gradient Descent | t 70 | 15 | 15 | 20 | 20.00% | 0 | 0 | %00.0 | 0 | 0 |
| Leaves_3 1 | 10 | Linear | Hard-limit | Stochastic Approximation to Gradient Descent | t 70 | 15 | 15 | | %00.0 | 0 | 0 | %00.0 | 0 | 0 |
| Leaves_3 | 10 | Linear | Linear | Stochastic Approximation to Gradient Descent | t 70 | 15 | 15 | 20 | %00.0 | 0 | 0 | %00.0 | 0 | 0 |
| _ | 10 | Linear | Log-sigmoid | Stochastic Approximation to Gradient Descent | | 15 | 15 | | 20.00% | 0 | | %00.0 | 0 | 0 |
| | 10 | Linear | Hyperbolic tangent sigmoid | Stochastic Approximation to Gradient Descent | | 15 | 15 | | %00.0 | 0 | | 0.00% | 0 | 0 |
| Leaves_3 | 10 | Linear | Symmetric hard-limit | Stochastic Approximation to Gradient Descent | t 70 | 15 | 15 | | 20.00% | 0 | 0 | %00.0 | 0 | 0 |
| Leaves_3 | 10 | Linear | None | Stochastic Approximation to Gradient Descent | t 70 | 15 | 15 | | 100.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_3 | 10 | Log-sigmoid | Hard-limit | Stochastic Approximation to Gradient Descent | t 70 | 15 | 15 | 20 | %00.0 | 0 | 0 | %00.0 | 0 | 0 |
| Leaves_3 | 10 | Log-sigmoid | Linear | Stochastic Approximation to Gradient Descent | t 70 | 15 | 15 | | 20.00% | 0 | 0 | %00.0 | 0 | 0 |
| Leaves_3 1 | 10 | Log-sigmoid | Log-sigmoid | Stochastic Approximation to Gradient Descent | t 70 | 15 | 15 | | 20.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_3 1 | 10 | Log-sigmoid | Hyperbolic tangent sigmoid | Stochastic Approximation to Gradient Descent | t 70 | 15 | 15 | | %00:0 | 0 | 0 | %00.0 | 0 | 0 |
| Leaves_3 | 10 | Log-sigmoid | Symmetric hard-limit | Stochastic Approximation to Gradient Descent | t 70 | 15 | 15 | | 20.00% | 0 | 0 | %00.0 | 0 | 0 |
| | 10 | Log-sigmoid | None | Stochastic Approximation to Gradient Descent | t 70 | 15 | 15 | | %00.0 | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_3 1 | 10 | Hyperbolic tangent sigmoid | Hard-limit | Stochastic Approximation to Gradient Descent | | 15 | 15 | | 100.00% | 0 | | %00.0 | 0 | 0 |
| | 10 | Hyperbolic tangent sigmoid | Linear | Stochastic Approximation to Gradient Descent | | 15 | 15 | | %00.0 | | | 0.00% | 0 | 0 |
| Leaves_3] | 10 | Hyperbolic tangent sigmoid | Log-sigmoid | Stochastic Approximation to Gradient Descent | H | 15 | 15 | | %00.0 | 0 | | %00.0 | 0 | 0 |
| Leaves_3 1 | 10 | Hyperbolic tangent sigmoid | Hyperbolic tangent sigmoid | Stochastic Approximation to Gradient Descent | t 70 | 15 | 15 | 20 | 100.00% | 0 | 0 | %00.0 | 0 | 0 |
| Leaves_3 | 10 | Hyperbolic tangent sigmoid | Symmetric hard-limit | Stochastic Approximation to Gradient Descent | t 70 | 15 | 15 | | 20.00% | 0 | | %00.0 | 0 | 0 |
| Leaves_3 | 10 | Hyperbolic tangent sigmoid | None | Stochastic Approximation to Gradient Descent | t 70 | 15 | 15 | 20 | 20.00% | 0 | 0 | %00.0 | 0 | 0 |
| Leaves_3 | 10 | Symmetric hard-limit | Hard-limit | Stochastic Approximation to Gradient Descent | t 70 | 15 | 15 | | %00.0 | 0 | 0 | %00.0 | 0 | 0 |
| Leaves_3 | 10 | Symmetric hard-limit | Linear | Stochastic Approximation to Gradient Descent | t 70 | 15 | 15 | 20 | %00.0 | 0 | 0 | %00.0 | 0 | 0 |
| Leaves_3 | 10 | Symmetric hard-limit | Log-sigmoid | Stochastic Approximation to Gradient Descent | t 70 | 15 | 15 | | %00.0 | 0 | 0 | %00.0 | 0 | 0 |
| - | 10 | Symmetric hard-limit | Hyperbolic tangent sigmoid | Stochastic Approximation to Gradient Descent | | 15 | 15 | Н | 20.00% | 0 | 0 | 0.00% | 0 | 0 |
| | 10 | Symmetric hard-limit | Symmetric hard-limit | Stochastic Approximation to Gradient Descent | Н | 15 | 15 | П | 0.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_3 1 | 10 | Symmetric hard-limit | None | Stochastic Approximation to Gradient Descent | t 70 | 15 | 15 | 20 | 20.00% | 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 | Transfer functions | Rati | Ratio (in percentage % | ;e %) | | | Species | | | Species | |
|----------|-----------|----------------------------|----------------------------|-------------------------------|------------------------|-------|---------------|-----------|---------|----------|-----------|---------|----------|
| Folder | Hidden L. | 1st | 2nd | Training algorithm Train | n Validation | Test | Quant. images | % ssəcons | Epoch | Duration | Success % | Epoch | Duration |
| Leaves_1 | 2 | Hard-limit | Hard-limit | Perceptron Training Rule 80 | 10 | 10 | 66 | 0.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_1 | 2 | Hard-limit | Linear | Perceptron Training Rule 80 | 10 | 10 | 66 | 0.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_1 | 2 | Hard-limit | Log-sigmoid | | 10 | 10 | 66 | 10.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_1 | 2 | Hard-limit | Hyperbolic tangent sigmoid | Perceptron Training Rule 80 | 10 | 10 | 66 | 10.00% | 0 | 0 | %00.0 | 0 | 0 |
| Leaves_1 | 2 | Hard-limit | Symmetric hard-limit | Perceptron Training Rule 80 | 10 | 10 | 66 | 0.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_1 | 2 | Hard-limit | None | Perceptron Training Rule 80 | 10 | 10 | 66 | 20.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_1 | 2 | Linear | Hard-limit | Perceptron Training Rule 80 | 10 | 10 | 66 | 0.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_1 | 2 | Linear | Linear | Perceptron Training Rule 80 | 10 | | 66 | 20.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_1 | 2 | Linear | Log-sigmoid | Perceptron Training Rule 80 | 10 | 10 | 66 | 10.00% | 0 | 0 | %00.0 | 0 | 0 |
| Leaves_1 | 2 | Linear | Hyperbolic tangent sigmoid | Perceptron Training Rule 80 | 10 | 10 | 66 | 10.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_1 | 2 | Linear | Symmetric hard-limit | Perceptron Training Rule 80 | 10 | 10 | 66 | 10.00% | 0 | 0 | %00.0 | 0 | 0 |
| Leaves_1 | 2 | Linear | None | Perceptron Training Rule 80 | 10 | 10 | 66 | 20.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_1 | 2 | Log-sigmoid | Hard-limit | Perceptron Training Rule 80 | 10 | 10 | 66 | 0.00% | 0 | 0 | %00.0 | 0 | 0 |
| Leaves_1 | 2 | Log-sigmoid | Linear | Perceptron Training Rule 80 | 10 | 10 | 66 | 20.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_1 | 2 | Log-sigmoid | Log-sigmoid | Perceptron Training Rule 80 | 10 | 10 | 66 | 10.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_1 | 2 | Log-sigmoid | Hyperbolic tangent sigmoid | Perceptron Training Rule 80 | 10 | 10 | 66 | 10.00% | 0 | 0 | 10.00% | 0 | 0 |
| Leaves_1 | 2 | Log-sigmoid | Symmetric hard-limit | Perceptron Training Rule 80 | 10 | 10 | 66 | 10.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_1 | 2 | Log-sigmoid | None | Perceptron Training Rule 80 | 10 | 10 | 66 | 20.00% | 0 | 0 | %00.0 | 0 | 0 |
| Leaves_1 | 2 | Hyperbolic tangent sigmoid | Hard-limit | Perceptron Training Rule 80 | 10 | 10 | 66 | 10.00% | 0 | 0 | 10.00% | 0 | 0 |
| Leaves_1 | 2 | Hyperbolic tangent sigmoid | Linear | Perceptron Training Rule 80 | 10 | 10 | 66 | 0.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_1 | 2 | Hyperbolic tangent sigmoid | Log-sigmoid | Perceptron Training Rule 80 | 10 | | 66 | 20.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_1 | 2 | Hyperbolic tangent sigmoid | Hyperbolic tangent sigmoid | Perceptron Training Rule 80 | 10 | 10 | 66 | 10.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_1 | 2 | Hyperbolic tangent sigmoid | Symmetric hard-limit | Perceptron Training Rule 80 | 10 | 10 | 66 | 10.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_1 | 2 | Hyperbolic tangent sigmoid | None | Perceptron Training Rule 80 | 10 | | 66 | 0.00% | 0 | 0 | 10.00% | 0 | 0 |
| Leaves_1 | 2 | Symmetric hard-limit | Hard-limit | Perceptron Training Rule 80 | 10 | 10 | 66 | 0.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_1 | 2 | Symmetric hard-limit | Linear | Rule | 10 | | 66 | 20.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_1 | 2 | Symmetric hard-limit | Log-sigmoid | Training Rule | 10 | | 99 | 10.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_1 | 2 | Symmetric hard-limit | Hyperbolic tangent sigmoid | Perceptron Training Rule 80 | 10 | | 66 | 0.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_1 | 2 | Symmetric hard-limit | Symmetric hard-limit | Perceptron Training Rule 80 | 10 | 10 | 66 | 0.00% | 0 | 0 | %00.0 | 0 | 0 |
| Leaves_1 | 2 | Symmetric hard-limit | None | ing Rule | 10 | | 66 | 0.00% | 0 | 0 | 10.00% | 0 | 0 |
| Leaves_1 | 2 | Hard-limit | Hard-limit | Gradient Descent 80 | 10 | | 66 | 10.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_1 | 2 | Hard-limit | Linear | Gradient Descent 80 | 10 | | 66 | 10.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_1 | 2 | Hard-limit | Log-sigmoid | | 10 | | 66 | 0.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_1 | 2 | Hard-limit | Hyperbolic tangent sigmoid | | 10 | | 66 | 10.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_1 | 2 | Hard-limit | Symmetric hard-limit | Gradient Descent 80 | 10 | 10 | 66 | 30.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_1 | 2 | Hard-limit | None | Gradient Descent 80 | 10 | 10 | 66 | 0.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_1 | 2 | Linear | Hard-limit | Gradient Descent 80 | 10 | | 66 | 0.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_1 | 2 | Linear | Linear | Gradient Descent 80 | 10 | | 66 | 20.00% | 0 | 0 | %00.0 | 0 | 0 |
| Leaves_1 | 2 | Linear | Log-sigmoid | Gradient Descent 80 | 10 | | 66 | 0.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_1 | 2 | Linear | Hyperbolic tangent sigmoid | | 10 | | 66 | 10.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_1 | 2 | Linear | Symmetric hard-limit | | 10 | | 66 | 0.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_1 | 2 | Linear | None | Gradient Descent 80 | 10 | 10 | 66 | 10.00% | 0 | 0 | 0.00% | 0 | 0 |
| | | | | | | | | | | | | | |

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

| top 200 Conferent Descent Town Multation | | | Transfer functions | functions | | Ratio | Ratio (in percentage %) | nge %) | | | Species | | | Species | |
|---|----------|-----------|----------------------------|------------------------------|--|----------|-------------------------|--------|---------------|---------|----------|----------|-----------|---------|----------|
| 2 Confesionabel Hurb-limit Confesionabel Linearizational | Folder | Hidden L. | 1st | 2nd | Training algorithm | Train | \vdash | ш | Quant. images | Success | \vdash | Duration | Success % | Epoch | Duration |
| 2 Importantial Limon Clarical Descript State of the part of | Leaves_1 | 2 | Log-sigmoid | Hard-limit | Gradient Descent | <u>8</u> | 10 | 10 | 66 | 20.00% | 0 | 0 | 0.00% | 0 | 0 |
| 2 Disperigational Ingestigned Ingestignated Gradient Descent 81 10 | Leaves_1 | 2 | Log-sigmoid | Linear | Gradient Descent | 80 | 10 | 10 | 66 | %00.0 | 0 | 0 | 0.00% | 0 | 0 |
| 2 Ione-element Pyther foliation to import a lighted of Christiant Descent 80 10 10 99 10.00% 0 2 Hope-element Symmetric bard-light and control of the co | Leaves_1 | 2 | Log-sigmoid | Log-sigmoid | Gradient Descent | 98 | 10 | 10 | 66 | 10.00% | 0 | 0 | 0.00% | 0 | 0 |
| 2 Local-claused Symmetric bard-lating Graduent Decent 89 10 99 10.00% 0 2 Hope-claused angued March-lating Graduent Decent 81 10 10 99 10.00% 0 0 2 Hyper-lock engoned Spruncture land-lating Graduent Decent 81 10 10 99 10.00% 0 0 2 Hyper-lock engoned Spruncture land-lating Graduent Decent 81 10 10 99 10.00% 0 0 2 Hyper-lock engoned Spruncture land-lating Graduent Decent 81 10 10 99 10.00% 0 0 2 Hyper-lock engoned Spruncture land-lating Graduent Decent 81 10 10 99 10.00% 0 0 2 Hyper-lock engoned Spruncture land-lating Graduent Decent 81 10 10 99 10.00% 0 0 2 Hyper-lock engoned Spruncture land-lating Graduent Decent 81 10 10 <td>Leaves_1</td> <td>2</td> <td>Log-sigmoid</td> <td>Hyperbolic tangent sigmoid</td> <td>Gradient Descent</td> <td>98</td> <td>10</td> <td>10</td> <td>66</td> <td>10.00%</td> <td>0</td> <td>0</td> <td>%00.0</td> <td>0</td> <td>0</td> | Leaves_1 | 2 | Log-sigmoid | Hyperbolic tangent sigmoid | Gradient Descent | 98 | 10 | 10 | 66 | 10.00% | 0 | 0 | %00.0 | 0 | 0 |
| 2 Hoperbolic unique signael Anna Gradient Decents 80 10 99 10000% 0 2 Hyperbolic unique signael Anna Gradient Decents Gradient Decents 81 10 99 10000% 0 0 2 Hyperbolic unique signael A limes Gradient Decents 81 10 99 10000% 0 0 2 Hyperbolic unique signael A greenband Interaction of the control | Leaves_1 | 2 | Log-sigmoid | Symmetric hard-limit | Gradient Descent | 80 | 10 | 10 | 66 | %00.0 | 0 | 0 | 0.00% | 0 | 0 |
| 2 Hyperbold tangent algoard I Lunear Gradient Descent 81 10 10 99 1000W 0 2 Hyperbold tangent algoard I Lunear Gradient Descent 81 10 10 99 1000W 0 2 Hyperbold tangent algoard I Lungar Ingential Cardient Descent 81 10 10 99 1000W 0 2 Hyperbold tangent algoard I Lungar Ingential Cardient Descent 81 10 10 99 1000W 0 2 Symmetric Inach Innt Lunear Gradient Descent 81 10 10 99 1000W 0 2 Symmetric Inach Innt Hunch Innt Lunear Gradient Descent 81 10 10 99 1000W 0 2 Symmetric Inach Innt Hunch Innt Annual Innt | Leaves_1 | 2 | Log-sigmoid | None | Gradient Descent | 98 | 10 | 10 | 66 | 10.00% | 0 | 0 | %00.0 | 0 | 0 |
| 2 Hyperbolk tungust signoid Log-signoid Log-signoid Log-signoid Log-signoid Log-signoid Log-signoid Log-signoid Log-signoid Log-signoid Conferent Descent 81 10 10 99 1000% 0 2 Hyperbolk tungust signoid Log-signoid Conferent Descent 80 10 10 99 1000% 0 0 2 Hyperbolk tungust signoid Symmetric Including Conferent Descent 80 10 10 99 1000% 0 0 2 Hyperbolk tungust signoid Symmetric Including Conferent Descent 80 10 10 99 1000% 0 0 2 Symmetric Including Signoid Symmetric Including Conference Conferen | Leaves_1 | 2 | Hyperbolic tangent sigmoid | Hard-limit | Gradient Descent | 8 | 10 | 10 | 66 | 10.00% | 0 | 0 | 0.00% | 0 | 0 |
| 2 Hyperbolic inquient signated (Exciliant Descent 81 10 10 99 10.00% 0 2 Hyperbolic inquient signated (Exciliant Descent 80 10 10 99 10.00% 0 0 2 Hyperbolic inquient signated (Superior State Descent 80 10 10 99 0.00% 0 0 2 Symmetric barchinat Lucor Gradient Descent 80 10 10 99 0.00% 0 0 2 Symmetric barchinat Lucor Gradient Descent 80 10 10 99 0.00% 0 0 2 Symmetric barchinat Lucor Gradient Descent 80 10 99 0.00% 0 0 2 Symmetric barchinat Lucor Symmetric barchinat Symmetric barchina | Leaves_1 | 2 | Hyperbolic tangent sigmoid | Linear | Gradient Descent | 08 | 10 | 10 | 66 | 10.00% | 0 | 0 | 0.00% | 0 | 0 |
| 2 Hyperbolic tangenst signood Symmetric bard-land of Condatur Descent 83 10 10 99 0.00% 0 0 2 Symmetric bard-land Condatur Descent 83 10 10 99 0.00% 0 0 2 Symmetric bard-lant Gradual Descent 83 10 10 99 0.00% 0 0 2 Symmetric bard-lant Log-signoid Gradual Descent 83 10 10 99 0.00% 0 0 2 Symmetric bard-lant Gradual Descent 80 10 10 99 0.00% 0 0 2 Symmetric bard-lant Symmetric bard-lant Symmetric bard-lant Symmetric bard-lant 80 10 10 99 0.00% 0 0 2 Symmetric bard-lant Symmetric bard-lant Symmetric bard-lant Symmetric bard-lant 80 10 10 99 10.00% 0 0 2 Symmetric bard-lant Symmetric bard-lant <td>Leaves_1</td> <td>2</td> <td>Hyperbolic tangent sigmoid</td> <td>Log-sigmoid</td> <td>Gradient Descent</td> <td>80</td> <td>10</td> <td>10</td> <td>66</td> <td>10.00%</td> <td>0</td> <td>0</td> <td>0.00%</td> <td>0</td> <td>0</td> | Leaves_1 | 2 | Hyperbolic tangent sigmoid | Log-sigmoid | Gradient Descent | 80 | 10 | 10 | 66 | 10.00% | 0 | 0 | 0.00% | 0 | 0 |
| 2 Ripochelle tangent signand Numeric bard-limit Graduen Descut 81 10 10 99 1000% 0 0 2 Symmetric bard-limit Graduen Descut 81 10 10 99 1000% 0 0 2 Symmetric bard-limit Linear Graduen Descut 81 10 10 99 1000% 0 0 2 Symmetric bard-limit Linear Graduen Descut 81 10 10 99 1000% 0 0 2 Symmetric bard-limit Linear Graduen Descut 81 10 10 99 1000% 0 0 2 Symmetric bard-limit Graduen Descut 81 10 10 99 1000% 0 0 2 Symmetric bard-limit Graduen Descut 81 10 10 99 1000% 0 0 2 Arter Limit Brock-limit Stock-land Descut 81 10 10 99 | Leaves_1 | 2 | _ | Hyperbolic tangent sigmoid | Gradient Descent | 08 | 10 | 10 | 66 | %00.0 | 0 | 0 | %00.0 | 0 | 0 |
| 2 Hyporkolist unggen signored Concional Descent 80 10 99 30.00% 0 2 Symmetric hard-limit Linard-limit Concional Descent 80 10 99 10.00% 0 0 2 Symmetric hard-limit Linard-limit Concional Descent 80 10 0 99 10.00% 0 0 2 Symmetric hard-limit Symmetric hard-limit March-limit March-limit 10 99 10.00% 0 0 2 Symmetric hard-limit March-limit March-limit March-limit 10 99 10.00% 0 0 2 Symmetric hard-limit March-limit March-limit March-limit 10 99 10.00% 0 0 2 Symmetric hard-limit Stochastic Approximation to Gradient Descent 80 10 10 99 10.00% 0 0 2 Symmetric hard-limit Gradient Descent 80 10 10 99 10 | Leaves_1 | 2 | + | Symmetric hard-limit | Gradient Descent | 08 | 10 | 10 | 66 | 0.00% | 0 | 0 | %00.0 | 0 | 0 |
| 2 Symmetric hard-limit Gradient Descent 80 10 99 10.00% 0 2 Symmetric hard-limit Linear Gradient Descent 80 10 10 99 10.00% 0 0 2 Symmetric hard-limit Linear Gradient Descent 80 10 10 99 10.00% 0 0 2 Symmetric hard-limit Symmetric parel-limit Symmetric hard-limit 10 99 10.00% 0 | Leaves 1 | 2 | Hyperbolic tangent sigmoid | None | Gradient Descent | 08 | 10 | 10 | 66 | 30.00% | 0 | 0 | 0.00% | 0 | 0 |
| 2 Symmetric bard-limit Linear Cerelisar Descent 80 10 10 99 0.00% 0 0 2 Symmetric bard-limit Gredient Descent 80 10 10 99 0.00% 0 0 2 Symmetric bard-limit Gredient Descent 80 10 10 99 0.00% 0 0 2 Symmetric bard-limit Hard-limit Mayer-limit Gredient Descent 80 10 10 99 0.00% 0 0 2 Hard-limit Hord-limit Symmetric bard-limit Symmetric bard-limit Symmetric bard-limit 10 99 10.00% 0 0 2 Hard-limit Symmetric bard-limit Symmetric | Leaves_1 | 2 | Symmetric hard-limit | Hard-limit | Gradient Descent | 08 | 10 | 10 | 66 | 10.00% | 0 | 0 | 0.00% | 0 | 0 |
| 2 Symmetric hard-limit Log-signoid Gredient Descent 80 10 10 99 1000% 0 2 Symmetric hard-limit Symmetric land-limit Gredient Descent 80 10 10 99 1000% 0 0 2 Symmetric hard-limit Symmetric land-limit Gredient Descent 80 10 10 99 1000% 0 0 2 Hard-limit Innat Storiestic Approximation to Gradient Descent 80 10 10 99 1000% 0 0 2 Hard-limit Innat Storiestic Approximation to Gradient Descent 80 10 10 99 1000% 0 0 2 Hard-limit Storiestic Approximation to Gradient Descent 80 10 10 99 1000% 0 0 2 Hard-limit Storiestic Approximation to Gradient Descent 80 10 10 99 1000% 0 0 2 Linear Incept | Leaves_1 | 2 | | Linear | Gradient Descent | 8 | 10 | 10 | 66 | 0.00% | 0 | 0 | 0.00% | 0 | 0 |
| 2 Symmetric band-limit Springetic band-limit Symmetric band-limit Gradient Descent 80 10 99 30.00% 0 0 2 Symmetric band-limit Linear Hard-limit Linear 10 99 10.00% 0 0 0 2 Hard-limit Linear Linear 10 99 10.00% 0 </td <td>Leaves_1</td> <td>2</td> <td></td> <td>Log-sigmoid</td> <td>Gradient Descent</td> <td>98</td> <td>10</td> <td>10</td> <td>66</td> <td>0.00%</td> <td>0</td> <td>0</td> <td>0.00%</td> <td>0</td> <td>0</td> | Leaves_1 | 2 | | Log-sigmoid | Gradient Descent | 98 | 10 | 10 | 66 | 0.00% | 0 | 0 | 0.00% | 0 | 0 |
| 2 Symmetric bard-limit Genérate Decent Grafient Decent 81 10 10 99 30,00% 0 0 2 Symmetric bard-limit Stochastic Approximation to Cardent Decent 80 10 99 20,00% 0 0 2 Hard-limit Linear Stochastic Approximation to Cardent Decent 80 10 99 10,00% 0 0 2 Hard-limit Linear Stochastic Approximation to Cardent Decent 80 10 99 10,00% 0 0 2 Hard-limit Stochastic Approximation to Cardent Decent 80 10 99 10,00% 0 0 2 Hard-limit Stochastic Approximation to Cardent Decent 80 10 99 10,00% 0 0 2 Linear Hard-limit Stochastic Approximation to Cardent Decent 80 10 99 10,00% 0 0 2 Linear Mycrobial Linear Approximation to Cardent Decent 80 10 99 | Leaves_1 | 2 | Symmetric hard-limit | Hyperbolic tangent sigmoid | Gradient Descent | 08 | 10 | 10 | 66 | 10.00% | 0 | 0 | 10.00% | 0 | 0 |
| 2 Symmetric bard-limit None Gordenite Approximation to Gradent Descent 89 10 99 900% 0 2 Hard-limit Linear Linear Stochastic Approximation to Gradent Descent 89 10 99 0.00% 0 0 2 Hard-limit Long 10 99 10.00% 0 0 0 2 Hard-limit Long 10 99 10.00% 0 <td>Leaves_1</td> <td>2</td> <td>Symmetric hard-limit</td> <td>Symmetric hard-limit</td> <td>Gradient Descent</td> <td>08</td> <td>10</td> <td>10</td> <td>66</td> <td>30.00%</td> <td>0</td> <td>0</td> <td>0.00%</td> <td>0</td> <td>0</td> | Leaves_1 | 2 | Symmetric hard-limit | Symmetric hard-limit | Gradient Descent | 08 | 10 | 10 | 66 | 30.00% | 0 | 0 | 0.00% | 0 | 0 |
| 2 Hard-limit Hard-limit Stochastic Approximation to Gradient Descent 80 10 99 1000% 0 2 Hard-limit Linear Log-signoid Stochastic Approximation to Gradient Descent 80 10 99 1000% 0 0 2 Hard-limit Stochastic Approximation to Gradient Descent 80 10 99 1000% 0 0 0 2 Hard-limit Symmetric hard-limit Stochastic Approximation to Gradient Descent 80 10 99 1000% 0 0 0 2 Linear Linear Linear Linear Linear 10 99 1000% 0 </td <td>Leaves_1</td> <td>2</td> <td>Symmetric hard-limit</td> <td>None</td> <td>Gradient Descent</td> <td>08</td> <td>10</td> <td>10</td> <td>66</td> <td>20.00%</td> <td>0</td> <td>0</td> <td>0.00%</td> <td>0</td> <td>0</td> | Leaves_1 | 2 | Symmetric hard-limit | None | Gradient Descent | 08 | 10 | 10 | 66 | 20.00% | 0 | 0 | 0.00% | 0 | 0 |
| 2 Hard-limit Linear Stochastic Approximation to Gradient Descent 80 10 99 1000% 0 2 Hard-limit Log-signoid Stochastic Approximation to Gradient Descent 80 10 99 10.00% 0 0 2 Hard-limit Symmetric hard-limit Stochastic Approximation to Gradient Descent 80 10 99 10.00% 0 0 2 Hard-limit None Stochastic Approximation to Gradient Descent 80 10 99 10.00% 0 0 2 Linear Linear Stochastic Approximation to Gradient Descent 80 10 10 99 10.00% 0 0 2 Linear Linear Stochastic Approximation to Gradient Descent 80 10 10 99 10.00% 0 0 2 Linear Stochastic Approximation to Gradient Descent 80 10 10 99 10.00% 0 0 2 Linear Stochastic Approximation to Gradient Desc | Leaves 1 | 2 | Hard-limit | Hard-limit | Stochastic Approximation to Gradient Desce | ╫ | 10 | 10 | 66 | 0.00% | 0 | 0 | 0.00% | 0 | 0 |
| 2 Hard-limit Log-sigmoid Stochastic Approximation to Gradient Descent 80 10 99 0.00% 0 2 Hard-limit Hyperbolic tangent sigmoid Stochastic Approximation to Gradient Descent 80 10 99 10.00% 0 0 2 Hard-limit None Sprumetric land-limit Stochastic Approximation to Gradient Descent 80 10 99 10.00% 0 0 2 Linear Log-sigmoid Stochastic Approximation to Gradient Descent 80 10 99 10.00% 0 0 2 Linear Brochastic Approximation to Gradient Descent 80 10 99 10.00% 0 0 2 Linear Stochastic Approximation to Gradient Descent 80 10 99 10.00% 0 | Leaves 1 | 1 6 | Hard-limit | Linear | Stochastic Approximation to Gradient Desce | + | 10 | 10 | 66 | 10.00% | 0 | | %00.0 | 0 | 0 |
| 2 Hard-limit Hyperbolic tangent sigmoid Stochastic Approximation to Gradient Descent 80 10 99 10.00% 0 2 Hard-limit Symmetric bard-limit Stochastic Approximation to Gradient Descent 80 10 10 99 10.00% 0 0 2 Linear Hard-limit Nome Stochastic Approximation to Gradient Descent 80 10 10 99 20.00% 0 0 2 Linear Linear Linear 10 99 20.00% 0 0 2 Linear Linear Linear 10 99 20.00% 0 0 2 Linear Hyperbolic tangent signoid Stochastic Approximation to Gradient Descent 80 10 10 99 20.00% 0 0 2 Linear Symmetric bard-limit Stochastic Approximation to Gradient Descent 80 10 10 99 0.00% 0 0 2 Linear Symmetric bard-limit Stocha | Leaves 1 | 1 6 | Hard-limit | Log-sigmoid | Stochastic Approximation to Gradient Desce | + | 10 | 10 | 66 | 2000 | 0 | 0 | %00.0 | 0 | |
| 2 Hard-limit Symmetric bard-limit Stochastic Approximation to Gradient Descent 80 10 99 10.00% 0 2 Hard-limit Symmetric bard-limit Stochastic Approximation to Gradient Descent 80 10 99 10.00% 0 0 2 Linear Hard-limit Stochastic Approximation to Gradient Descent 80 10 10 99 0.00% 0 0 2 Linear Hard-limit Stochastic Approximation to Gradient Descent 80 10 10 99 0.00% 0 0 2 Linear Exclusive Approximation to Gradient Descent 80 10 10 99 0.00% 0 0 2 Linear Stochastic Approximation to Gradient Descent 80 10 10 99 0.00% 0 0 2 Linear Stochastic Approximation to Gradient Descent 80 10 10 99 0.00% 0 0 2 Linear Stochastic Approximation to Gradient Descent 80 10 10 99 0.00% 0 | Leaves 1 | - C | Hard-limit | Hymerbolic tangent sigmoid | Stochastic Approximation to Gradient Desce | + | 10 | 10 | 00 | 10.00% | | | 2000 | | |
| 2 Hard-limit Stochastic Approximation to Gradient Descent 80 10 95 20.0% 0 2 Linear Hard-limit Stochastic Approximation to Gradient Descent 80 10 99 20.0% 0 0 2 Linear Linear Linear Linear 10.9 10.0% 0 | Leaves 1 | 4 6 | Hard-limit | Symmetric hard-limit | Stochastic Approximation to Gradient Desce | + | 10 | 10 | 00 | 10.00% | 0 | 0 | 2,00.0 | 0 | |
| z Integration Footbasite Approximation to Gradient Descent 80 10 95 50.00% 0 0 2 Linear Linear Linear Stochastic Approximation to Gradient Descent 80 10 99 0.00% 0 0 2 Linear Ryperbolic tangent sigmoid Stochastic Approximation to Gradient Descent 80 10 99 0.00% 0 0 2 Linear Symmetric bard-limit Stochastic Approximation to Gradient Descent 80 10 99 0.00% 0 0 2 Linear Symmetric bard-limit Stochastic Approximation to Gradient Descent 80 10 99 0.00% 0 0 2 Log-sigmoid Lard-limit Stochastic Approximation to Gradient Descent 80 10 10 99 0.00% 0 0 2 Log-sigmoid Linear Symmetric bard-limit Stochastic Approximation to Gradient Descent 80 10 10 99 10.00% 0 0 | Leaves 1 | 1 0 | Hard-limit | None | Stochastic Approximation to Gradient Desce | + | 10 | 101 | 00 | 20.00% | | | 20000 | 0 | |
| z Interest Stochastic Approximation to Gradient Descent 80 10 99 0.00% 0 0 2 Linear Log-sigmoid Hyper-bolic tangent sigmoid Stochastic Approximation to Gradient Descent 80 10 10 99 20.00% 0 0 2 Linear None Stochastic Approximation to Gradient Descent 80 10 10 99 0.00% 0 0 2 Linear None Stochastic Approximation to Gradient Descent 80 10 10 99 0.00% 0 0 0 2 Log-sigmoid Linear Stochastic Approximation to Gradient Descent 80 10 10 99 0.00% 0 0 0 2 Log-sigmoid Stochastic Approximation to Gradient Descent 80 10 10 99 0.00% 0 <td>Leaves-1</td> <td>4 6</td> <td>Timoon</td> <td>Hond limit</td> <td>Stochastic Approximation to Gradient Description to Gr</td> <td>+</td> <td>10</td> <td>101</td> <td>99</td> <td>0.00%</td> <td></td> <td>60.0</td> <td>0.00%</td> <td></td> <td></td> | Leaves-1 | 4 6 | Timoon | Hond limit | Stochastic Approximation to Gradient Description to Gr | + | 10 | 101 | 99 | 0.00% | | 60.0 | 0.00% | | |
| z Linear Hyperbolic tangent sigmoid Stochastic Approximation to Gradient Descent 80 10 10 99 20.00% 0 0 2 Linear Symmetric hard-limit Stochastic Approximation to Gradient Descent 80 10 99 0.00% 0 0 2 Log-sigmoid Brachlimit Stochastic Approximation to Gradient Descent 80 10 99 0.00% 0 0 2 Log-sigmoid Brachlimit Stochastic Approximation to Gradient Descent 80 10 10 99 0.00% 0 0 2 Log-sigmoid Stochastic Approximation to Gradient Descent 80 10 10 99 0.00% 0 0 2 Log-sigmoid Stochastic Approximation to Gradient Descent 80 10 10 99 0.00% | Leaves 1 | 2 6 | Linear | Times. | Stochastic Approximation to Gradient Description to Chadient Description to Ch | + | 10 | 101 | 99 | 0.00% | | 0.02 | 0.00% | | |
| z Linear Conclusion Physical production to Gradient Descent 80 10 10 99 20.00% 0 2 Linear Symmetric hard-limit Stochastic Approximation to Gradient Descent 80 10 10 99 0.00% 0 0 2 Linear Symmetric hard-limit Stochastic Approximation to Gradient Descent 80 10 10 99 0.00% 0 0 2 Log-sigmoid Linear Stochastic Approximation to Gradient Descent 80 10 10 99 0.00% 0 0 2 Log-sigmoid Hyperbolic tangent sigmoid Stochastic Approximation to Gradient Descent 80 10 10 99 10.00% 0 0 2 Log-sigmoid Hyperbolic tangent sigmoid Stochastic Approximation to Gradient Descent 80 10 10 99 10.00% 0 0 2 Log-sigmoid Stochastic Approximation to Gradient Descent 80 10 10 99 10.00% 0 0 2 Log-sigmoid Hyperbolic tangent sigm | Leaves-1 | 4]0 | Linear | Log-ejamoid | Stochastic Approximation to Gradient Desce | + | 101 | 101 | 00 | 20000 | | | 20000 | | |
| 2 Linear Hyperbolic tangent sigmoid Stochastic Approximation to Gradient Descent 90 10 10 99 20.00 0 0 2 Linear None Marchimit Stochastic Approximation to Gradient Descent 80 10 10 99 0.00% 0 0 2 Log-sigmoid Harchimit Stochastic Approximation to Gradient Descent 80 10 10 99 0.00% 0 0 0 2 Log-sigmoid Log-sigmoid Log-sigmoid Log-sigmoid Stochastic Approximation to Gradient Descent 80 10 10 99 0.00% 0 0 2 Log-sigmoid Hyperbolic tangent sigmoid Stochastic Approximation to Gradient Descent 80 10 10 99 0.00% 0 0 2 Log-sigmoid Stochastic Approximation to Gradient Descent 80 10 10 99 0.00% 0 0 0 2 Log-sigmoid Barchimit Stochastic Approximation to Gradient Descent | Leaves_1 | 4 C | Linear | Urn onbolio tongent giornoid | Stochastic Approximation to Gradient Description to Chadient Description | + | 10 | 10 | 99 | 20.00% | | | 0.00% | | |
| 2 Linear Synthetic nari-man Stochastic Approximation to Gradient Descent 80 10 10 99 0.00% 0 2 Log-sigmoid Hard-limit Stochastic Approximation to Gradient Descent 80 10 99 0.00% 0 0 2 Log-sigmoid Log-sigmoid Log-sigmoid Log-sigmoid 10 99 10.00% 0 0 0 2 Log-sigmoid Log-sigmoid Log-sigmoid Expression Approximation to Gradient Descent 80 10 99 10.00% 0 0 2 Log-sigmoid Hyperbolic tangent sigmoid Stochastic Approximation to Gradient Descent 80 10 99 10.00% 0 0 0 2 Log-sigmoid Brochastic Approximation to Gradient Descent 80 10 10 99 10.00% 0 0 0 2 Log-sigmoid Incelastic Approximation to Gradient Descent 80 10 10 99 10.00% 0 0 2 <td>Leaves-1</td> <td>4 c</td> <td>Linear</td> <td>Cressotuic band limit</td> <td>Stochastic Approximation to Gradient Description to Chadient Description</td> <td>+</td> <td>10</td> <td></td> <td>99</td> <td>20.00%</td> <td></td> <td></td> <td>0.00%</td> <td></td> <td></td> | Leaves-1 | 4 c | Linear | Cressotuic band limit | Stochastic Approximation to Gradient Description to Chadient Description | + | 10 | | 99 | 20.00% | | | 0.00% | | |
| 2 Long-signaid Hard-limit Stochastic Approximation to Gradient Descent 80 10 99 0.00% 0 2 Log-signoid Linear Stochastic Approximation to Gradient Descent 80 10 10 99 10.00% 0 0 2 Log-signoid Linear Stochastic Approximation to Gradient Descent 80 10 10 99 10.00% 0 0 2 Log-signoid Log-signoid Symmetric hard-limit Stochastic Approximation to Gradient Descent 80 10 10 99 10.00% 0 0 2 Log-signoid None Symmetric hard-limit Stochastic Approximation to Gradient Descent 80 10 10 99 10.00% 0 0 2 Log-signoid Hyperbolic tangent signoid Stochastic Approximation to Gradient Descent 80 10 10 99 10.00% 0 0 2 Hyperbolic tangent signoid Stochastic Approximation to Gradient Descent 80 10 10 99 </td <td>reaves_1</td> <td>7 0</td> <td>Linear</td> <td>Symmetric nard-innit</td> <td>Stochastic Approximation to Gradient Descr</td> <td>+</td> <td>10</td> <td>10</td> <td>66</td> <td>0.00%</td> <td></td> <td></td> <td>0.00%</td> <td>0</td> <td></td> | reaves_1 | 7 0 | Linear | Symmetric nard-innit | Stochastic Approximation to Gradient Descr | + | 10 | 10 | 66 | 0.00% | | | 0.00% | 0 | |
| 2 Log-sigmoid Hard-limit Stochastic Approximation to Gradient Descent 80 10 99 0.00% 0 2 Log-sigmoid Linear Stochastic Approximation to Gradient Descent 80 10 10 99 10.00% 0 0 2 Log-sigmoid Linear Stochastic Approximation to Gradient Descent 80 10 99 10.00% 0 0 2 Log-sigmoid Hyperbolic tangent sigmoid Stochastic Approximation to Gradient Descent 80 10 10 99 10.00% 0 0 2 Log-sigmoid Hard-limit Stochastic Approximation to Gradient Descent 80 10 10 99 10.00% 0 0 2 Hyperbolic tangent sigmoid Hard-limit Stochastic Approximation to Gradient Descent 80 10 10 99 10.00% 0 0 2 Hyperbolic tangent sigmoid Log-sigmoid Stochastic Approximation to Gradient Descent 80 10 10 99 10.00% 0 | Leaves_1 | 2 | Linear | None | Stochastic Approximation to Gradient Desce | + | 10 | 01 | 99 | 0.00% | 0 | 0 | 0.00% | 0 | 0 |
| 2 Log-sigmoid Linear Stochastic Approximation to Gradient Descent 80 10 99 10.00% 0 0 2 Log-sigmoid Hoperbolic tangent sigmoid Hoperbolic tangent sigmoid Stochastic Approximation to Gradient Descent 80 10 10 99 10.00% 0 0 2 Log-sigmoid Hyperbolic tangent sigmoid Hyperbolic tangent sigmoid Stochastic Approximation to Gradient Descent 80 10 10 99 10.00% 0 0 2 Log-sigmoid Hyperbolic tangent sigmoid Hard-limit Stochastic Approximation to Gradient Descent 80 10 10 99 10.00% 0 0 2 Hyperbolic tangent sigmoid Linear Stochastic Approximation to Gradient Descent 80 10 10 99 0.00% 0 0 0 2 Hyperbolic tangent sigmoid Linear Stochastic Approximation to Gradient Descent 80 10 10 99 0.00% 0 0 0 0 2 | Leaves_1 | 2 | Log-sigmoid | Hard-limit | Stochastic Approximation to Gradient Desce | - | 10 | 0 | 66 | 0.00% | 0 | 0 | 0.00% | 0 | 0 |
| 2 Log-sigmoid Log-sigmoid Stochastic Approximation to Gradient Descent 80 10 99 10.00% 0 0 2 Log-sigmoid Hyperbolic tangent sigmoid Stochastic Approximation to Gradient Descent 80 10 10 99 10.00% 0 0 0 2 Log-sigmoid None Stochastic Approximation to Gradient Descent 80 10 10 99 10.00% 0 0 0 2 Log-sigmoid None Stochastic Approximation to Gradient Descent 80 10 10 99 10.00% 0 0 0 2 Hyperbolic tangent sigmoid Linear Stochastic Approximation to Gradient Descent 80 10 10 99 20.00% 0 0 0 2 Hyperbolic tangent sigmoid Stochastic Approximation to Gradient Descent 80 10 10 99 20.00% 0 0 0 2 Hyperbolic tangent sigmoid Stochastic Approximation to Gradient Descent 80 10 <td>Leaves_1</td> <td>2</td> <td>Log-sigmoid</td> <td>Linear</td> <td>Stochastic Approximation to Gradient Desce</td> <td>-</td> <td>10</td> <td>10</td> <td>66</td> <td>10.00%</td> <td>0</td> <td>0</td> <td>0.00%</td> <td>0</td> <td>0</td> | Leaves_1 | 2 | Log-sigmoid | Linear | Stochastic Approximation to Gradient Desce | - | 10 | 10 | 66 | 10.00% | 0 | 0 | 0.00% | 0 | 0 |
| 2 Log-sigmoid Hyperbolic tangent sigmoid Stochastic Approximation to Gradient Descent 80 10 99 0.00% 0 0 2 Log-sigmoid Symmetric hard-limit Stochastic Approximation to Gradient Descent 80 10 10 99 0.00% 0 0 2 Hyperbolic tangent sigmoid Hard-limit Stochastic Approximation to Gradient Descent 80 10 10 99 0.00% 0 0 2 Hyperbolic tangent sigmoid Linear Stochastic Approximation to Gradient Descent 80 10 10 99 0.00% 0 0 2 Hyperbolic tangent sigmoid Linear Stochastic Approximation to Gradient Descent 80 10 10 99 0.00% 0 0 2 Hyperbolic tangent sigmoid Symmetric hard-limit Stochastic Approximation to Gradient Descent 80 10 10 99 0.00% 0 0 2 Hyperbolic tangent sigmoid Stochastic Approximation to Gradient Descent 80 10 10 | Leaves_1 | 2 | Log-sigmoid | Log-sigmoid | Stochastic Approximation to Gradient Desce | \dashv | 10 | 10 | 66 | 10.00% | 0 | 0 | 0.00% | 0 | 0 |
| 2 Log-sigmoid Symmetric hard-limit Stochastic Approximation to Gradient Descent 80 10 99 30.00% 0 0 2 Log-sigmoid None Stochastic Approximation to Gradient Descent 80 10 10 99 10.00% 0 0 0 2 Hyperbolic tangent sigmoid Hard-limit Stochastic Approximation to Gradient Descent 80 10 10 99 20.00% 0 0 0 2 Hyperbolic tangent sigmoid Log-sigmoid Stochastic Approximation to Gradient Descent 80 10 10 99 20.00% 0 0 0 2 Hyperbolic tangent sigmoid Hyperbolic tangent sigmoid Stochastic Approximation to Gradient Descent 80 10 10 99 0.00% 0 0 0 2 Hyperbolic tangent sigmoid None Stochastic Approximation to Gradient Descent 80 10 10 99 0.00% 0 0 0 2 Hyperbolic tangent sigmoid Stochastic Approxi | Leaves_1 | 2 | Log-sigmoid | Hyperbolic tangent sigmoid | Stochastic Approximation to Gradient Desce | - | 10 | 10 | 66 | 0.00% | 0 | 0 | 0.00% | 0 | 0 |
| 2 Log-sigmoid None Stochastic Approximation to Gradient Descent 80 10 99 10.00% 0 0 2 Hyperbolic tangent sigmoid Hard-limit Stochastic Approximation to Gradient Descent 80 10 10 99 0.00% 0 0 0 2 Hyperbolic tangent sigmoid Linear Stochastic Approximation to Gradient Descent 80 10 10 99 20.00% 0 | Leaves_1 | 2 | Log-sigmoid | Symmetric hard-limit | Stochastic Approximation to Gradient Desce | | 10 | 10 | 66 | 30.00% | 0 | 0 | 0.00% | 0 | 0 |
| 2 Hyperbolic tangent sigmoid Hard-limit Stochastic Approximation to Gradient Descent 80 10 99 0.00% 0 0 2 Hyperbolic tangent sigmoid Linear Stochastic Approximation to Gradient Descent 80 10 10 99 20.00% 0 0 2 Hyperbolic tangent sigmoid Symmetric hard-limit Stochastic Approximation to Gradient Descent 80 10 10 99 0.00% 0 | Leaves_1 | 2 | Log-sigmoid | None | Stochastic Approximation to Gradient Desce | - | 10 | 10 | 66 | 10.00% | 0 | 0 | 0.00% | 0 | 0 |
| 2 Hyperbolic tangent sigmoid Linear Stochastic Approximation to Gradient Descent 80 10 99 20.00% 0 0 2 Hyperbolic tangent sigmoid Log-sigmoid Stochastic Approximation to Gradient Descent 80 10 10 99 20.00% 0 0 0 2 Hyperbolic tangent sigmoid Symmetric hard-limit Stochastic Approximation to Gradient Descent 80 10 10 99 0.00% 0 | Leaves_1 | 2 | Hyperbolic tangent sigmoid | Hard-limit | Stochastic Approximation to Gradient Desce | - | 10 | 10 | 66 | 0.00% | 0 | 0 | 0.00% | 0 | 0 |
| 2 Hyperbolic tangent sigmoid Stochastic Approximation to Gradient Descent 80 10 99 20.00% 0 0 2 Hyperbolic tangent sigmoid Symmetric hard-limit Stochastic Approximation to Gradient Descent 80 10 10 99 0.00% 0 0 2 Hyperbolic tangent sigmoid None Stochastic Approximation to Gradient Descent 80 10 10 99 10.00% 0 0 0 2 Symmetric hard-limit Hard-limit Stochastic Approximation to Gradient Descent 80 10 10 99 0.00% 0< | Leaves_1 | 2 | Hyperbolic tangent sigmoid | Linear | Stochastic Approximation to Gradient Desce | | 10 | 10 | 66 | 20.00% | 0 | 0 | 0.00% | 0 | 0 |
| 2 Hyperbolic tangent sigmoid Hyperbolic tangent sigmoid Stochastic Approximation to Gradient Descent 80 10 99 0.00% 0 0 2 Hyperbolic tangent sigmoid Symmetric hard-limit Stochastic Approximation to Gradient Descent 80 10 10 99 0.00% 0 <td>Leaves_1</td> <td>2</td> <td></td> <td>Log-sigmoid</td> <td>Stochastic Approximation to Gradient Desce</td> <td></td> <td>10</td> <td>10</td> <td>66</td> <td>20.00%</td> <td>0</td> <td>0</td> <td>%00.0</td> <td>0</td> <td>0</td> | Leaves_1 | 2 | | Log-sigmoid | Stochastic Approximation to Gradient Desce | | 10 | 10 | 66 | 20.00% | 0 | 0 | %00.0 | 0 | 0 |
| 2 Hyperbolic tangent sigmoid Symmetric hard-limit Stochastic Approximation to Gradient Descent 80 10 99 10.00% 0 0 0 2 Hyperbolic tangent sigmoid None Stochastic Approximation to Gradient Descent 80 10 10 99 0.00% 0 0 0 2 Symmetric hard-limit Log-sigmoid Stochastic Approximation to Gradient Descent 80 10 10 99 20.00% 0 | Leaves_1 | 2 | - | Hyperbolic tangent sigmoid | Stochastic Approximation to Gradient Desce | \vdash | 10 | 10 | 66 | %00.0 | 0 | 0 | 0.00% | 0 | 0 |
| 2 Hyperbolic tangent sigmoid None Stochastic Approximation to Gradient Descent 80 10 99 0.00% 0 0 0 2 Symmetric hard-limit Linear Stochastic Approximation to Gradient Descent 80 10 10 99 20.00% 0 0 0 2 Symmetric hard-limit Log-sigmoid Stochastic Approximation to Gradient Descent 80 10 10 99 20.00% 0 0 0 2 Symmetric hard-limit Hyperbolic tangent sigmoid Stochastic Approximation to Gradient Descent 80 10 10 99 0.00% 0 0 0 2 Symmetric hard-limit Stochastic Approximation to Gradient Descent 80 10 10 99 10.00% 0 0 0 0 2 Symmetric hard-limit Stochastic Approximation to Gradient Descent 80 10 10 99 10.00% 0 0 0 0 0 2 Symmetric hard-limit None | Leaves_1 | 2 | Hyperbolic tangent sigmoid | Symmetric hard-limit | Stochastic Approximation to Gradient Desce | | 10 | 10 | 66 | 10.00% | 0 | 0 | 0.00% | 0 | 0 |
| 2 Symmetric hard-limit Hard-limit Stochastic Approximation to Gradient Descent 80 10 99 20.00% 0 0 0 2 Symmetric hard-limit Log-sigmoid Stochastic Approximation to Gradient Descent 80 10 10 99 20.00% 0 0 0 2 Symmetric hard-limit Hyperbolic tangent sigmoid Stochastic Approximation to Gradient Descent 80 10 10 99 0.00% 0 0 0 2 Symmetric hard-limit Stochastic Approximation to Gradient Descent 80 10 10 99 10.00% 0 0 0 0 2 Symmetric hard-limit Stochastic Approximation to Gradient Descent 80 10 10 99 10.00% 0 0 0 0 0 2 Symmetric hard-limit None Stochastic Approximation to Gradient Descent 80 10 10 99 10.00% 0 0 0 0 0 0 0 0 | Leaves_1 | 2 | _ | None | Stochastic Approximation to Gradient Desce | | 10 | 10 | 66 | %00.0 | 0 | 0 | 0.00% | 0 | 0 |
| 2 Symmetric hard-limit Linear Stochastic Approximation to Gradient Descent 80 10 99 20.00% 0 0 0 2 Symmetric hard-limit Log-sigmoid Stochastic Approximation to Gradient Descent 80 10 10 99 20.00% 0 <td>Leaves_1</td> <td>2</td> <td>Symmetric hard-limit</td> <td>Hard-limit</td> <td>Stochastic Approximation to Gradient Desce</td> <td></td> <td>10</td> <td>10</td> <td>66</td> <td>20.00%</td> <td>0</td> <td>0</td> <td>%00.0</td> <td>0</td> <td>0</td> | Leaves_1 | 2 | Symmetric hard-limit | Hard-limit | Stochastic Approximation to Gradient Desce | | 10 | 10 | 66 | 20.00% | 0 | 0 | %00.0 | 0 | 0 |
| Symmetric hard-limit Log-sigmoid Stochastic Approximation to Gradient Descent 80 10 10 99 20.00% 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 | Leaves_1 | 2 | Symmetric hard-limit | Linear | Stochastic Approximation to Gradient Desce | | 10 | 10 | 66 | 20.00% | 0 | 0 | 0.00% | 0 | 0 |
| Symmetric hard-limit Hyperbolic tangent sigmoid Stochastic Approximation to Gradient Descent 80 10 99 0.00% 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 | Leaves_1 | 2 | Symmetric hard-limit | Log-sigmoid | Stochastic Approximation to Gradient Desce | \vdash | 10 | 10 | 66 | 20.00% | 0 | 0 | 0.00% | 0 | 0 |
| 2 Symmetric hard-limit Stochastic Approximation to Gradient Descent 80 10 10 99 10.00% 0 0 0 1 Symmetric hard-limit None Stochastic Approximation to Gradient Descent 80 10 10 99 20.00% 0 0 0 | Leaves_1 | 2 | Symmetric hard-limit | Hyperbolic tangent sigmoid | Stochastic Approximation to Gradient Desce | | 10 | 10 | 66 | %00.0 | 0 | 0 | 10.00% | 0 | 0 |
| 2 Symmetric hard-limit None Stochastic Approximation to Gradient Descent 80 10 10 99 20.00% 0 0 | Leaves_1 | 2 | Symmetric hard-limit | Symmetric hard-limit | Stochastic Approximation to Gradient Desce | | 10 | 10 | 66 | 10.00% | 0 | 0 | %00.0 | 0 | 0 |
| | Leaves_1 | 2 | Symmetric hard-limit | None | Stochastic Approximation to Gradient Desce | - | 10 | 10 | 66 | 20.00% | 0 | 0 | 10.00% | 0 | 0 |

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

| | | Transfer functions | functions | | Katio | (in percentage % | e %) | | | Species | | | Species | |
|----------|-----------|----------------------------|----------------------------|--------------------------|-------|------------------|------|---------------|-----------|---------|----------|-----------|---------|----------|
| Folder | Hidden L. | 1st | 2nd | Training algorithm | Train | Validation | Test | Quant. images | % ssacons | Epoch | Duration | % ssəcons | Epoch | Duration |
| Leaves_1 | 10 | Hard-limit | Hard-limit | Perceptron Training Rule | 20 | 15 | 15 | 66 | %00.0 | 0 | 0.01 | 0.00% | 0 | 0 |
| Leaves_1 | 10 | Hard-limit | Linear | Perceptron Training Rule | 20 | 15 | 15 | 66 | %00.0 | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_1 | 10 | Hard-limit | Log-sigmoid | Perceptron Training Rule | 20 | 15 | 15 | 66 | 20.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_1 | 10 | Hard-limit | Hyperbolic tangent sigmoid | Perceptron Training Rule | 20 | 15 | 15 | 66 | 20.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_1 | 10 | Hard-limit | Symmetric hard-limit | Perceptron Training Rule | 20 | 15 | | 66 | %00.0 | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_1 | 10 | Hard-limit | None | Perceptron Training Rule | 20 | 15 | 15 | 66 | %00.0 | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_1 | 10 | Linear | Hard-limit | Perceptron Training Rule | 20 | 15 | 15 | 66 | %00.0 | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_1 | 10 | Linear | Linear | Perceptron Training Rule | 20 | 15 | 15 | 66 | 10.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_1 | 10 | Linear | Log-sigmoid | Perceptron Training Rule | 20 | 15 | 15 | 66 | 10.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_1 | 10 | Linear | Hyperbolic tangent sigmoid | Perceptron Training Rule | 20 | 15 | 15 | 66 | %00.0 | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_1 | 10 | Linear | Symmetric hard-limit | Perceptron Training Rule | 20 | 15 | 15 | 66 | 30.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_1 | 10 | Linear | None | Perceptron Training Rule | 20 | 15 | 15 | 66 | 10.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_1 | 10 | Log-sigmoid | Hard-limit | Perceptron Training Rule | 20 | 15 | 15 | 66 | %00.0 | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_1 | 10 | Log-sigmoid | Linear | Perceptron Training Rule | 20 | 15 | 15 | 66 | 20.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_1 | 10 | Log-sigmoid | Log-sigmoid | Perceptron Training Rule | 20 | 15 | | 66 | 20.00% | 0 | 0 | %00.0 | 0 | 0 |
| Leaves_1 | 10 | Log-sigmoid | Hyperbolic tangent sigmoid | Perceptron Training Rule | 20 | 15 | 15 | 66 | %00.0 | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_1 | 10 | Log-sigmoid | Symmetric hard-limit | Perceptron Training Rule | 20 | 15 | | 66 | 10.00% | 0 | 0 | %00.0 | 0 | 0 |
| Leaves_1 | 10 | Log-sigmoid | None | Perceptron Training Rule | 20 | 15 | 15 | 66 | %00.0 | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_1 | 10 | Hyperbolic tangent sigmoid | Hard-limit | Perceptron Training Rule | 20 | 15 | 15 | 66 | 20.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_1 | 10 | Hyperbolic tangent sigmoid | Linear | Perceptron Training Rule | 20 | 15 | | 66 | 20.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_1 | 10 | Hyperbolic tangent sigmoid | Log-sigmoid | Perceptron Training Rule | 20 | 15 | 15 | 66 | 20.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_1 | 10 | Hyperbolic tangent sigmoid | Hyperbolic tangent sigmoid | Perceptron Training Rule | 20 | 15 | 15 | 66 | %00.0 | 0 | 0 | 10.00% | 0 | 0 |
| Leaves_1 | 10 | Hyperbolic tangent sigmoid | Symmetric hard-limit | Perceptron Training Rule | 20 | 15 | 15 | 66 | 10.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_1 | 10 | Hyperbolic tangent sigmoid | None | Perceptron Training Rule | 20 | 15 | | 66 | 20.00% | 0 | 0 | 300.01 | 0 | 0 |
| Leaves_1 | 10 | Symmetric hard-limit | Hard-limit | Perceptron Training Rule | 20 | 15 | 15 | 66 | 10.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_1 | 10 | Symmetric hard-limit | Linear | Perceptron Training Rule | 20 | 15 | 15 | 66 | 10.00% | 0 | 0 | 300.01 | 0 | 0 |
| Leaves_1 | 10 | Symmetric hard-limit | Log-sigmoid | Perceptron Training Rule | 20 | 15 | | 66 | 10.00% | 0 | 0 | 10.00% | 0 | 0 |
| Leaves_1 | 10 | Symmetric hard-limit | Hyperbolic tangent sigmoid | Perceptron Training Rule | 20 | 15 | | 66 | 20.00% | 0 | 0 | %00'0 | 0 | 0 |
| Leaves_1 | 10 | Symmetric hard-limit | Symmetric hard-limit | Perceptron Training Rule | 20 | 15 | | 66 | 20.00% | 0 | 0 | %00'0 | 0 | 0 |
| Leaves_1 | 10 | Symmetric hard-limit | None | Perceptron Training Rule | 20 | 15 | | 66 | 20.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_1 | 10 | Hard-limit | Hard-limit | Gradient Descent | 20 | 15 | | 66 | 20.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_1 | 10 | Hard-limit | Linear | Gradient Descent | 20 | 15 | | 66 | 10.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_1 | 10 | Hard-limit | Log-sigmoid | Gradient Descent | 20 | 15 | | 66 | 0.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_1 | 10 | Hard-limit | Hyperbolic tangent sigmoid | Gradient Descent | 20 | 15 | | 66 | %00:0 | 0 | 0 | %00'0 | 0 | 0 |
| Leaves_1 | 10 | Hard-limit | Symmetric hard-limit | Gradient Descent | 20 | 15 | 15 | 66 | 10.00% | 0 | 0 | %00'0 | 0 | 0 |
| Leaves_1 | 10 | Hard-limit | None | Gradient Descent | 20 | 15 | | 66 | 10.00% | 0 | 0 | %00'0 | 0 | 0 |
| Leaves_1 | 10 | Linear | Hard-limit | Gradient Descent | 20 | 15 | 15 | 66 | 20.00% | 0 | 0 | %00.0 | 0 | 0 |
| Leaves_1 | 10 | Linear | Linear | Gradient Descent | 20 | 15 | | 66 | 10.00% | 0 | 0 | 300.01 | 0 | 0 |
| Leaves_1 | 10 | Linear | Log-sigmoid | Gradient Descent | 20 | 15 | 15 | 66 | 10.00% | 0 | 0 | 10.00% | 0 | 0 |
| Leaves_1 | 10 | Linear | Hyperbolic tangent sigmoid | Gradient Descent | 20 | 15 | 15 | 66 | %00:0 | 0 | 0 | %00'0 | 0 | 0 |
| Leaves_1 | 10 | Linear | Symmetric hard-limit | Gradient Descent | 20 | 15 | 15 | 66 | 10.00% | 0 | 0 | %00.0 | 0 | 0 |
| Leaves_1 | 10 | Linear | None | Gradient Descent | 20 | 15 | 15 | 66 | 10.00% | 0 | 0 | %00.0 | 0 | 0 |
| Leaves_1 | 10 | Log-sigmoid | Hard-limit | Gradient Descent | 20 | 15 | 15 | 66 | 10.00% | 0 | 0 | %00.0 | 0 | 0 |

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

| | | Transfer functions | functions | | Ratio | Ratio (in percentage %) | se %) | | | Species | | Spe | Species | |
|---------------|-----------|----------------------------|----------------------------|--|----------|-------------------------|-------|---------------|-----------|----------------|--------------|-----|---------|----------|
| Folder Hid | Hidden L. | 1st | 2nd | Training algorithm | Train | Validation | Test | Quant. images | Saccess % | Epoch Duration | tion Success | % | Epoch D | Duration |
| Leaves_1 10 | | Log-sigmoid | Linear | Gradient Descent | 20 | 15 | 15 | 66 | %00.0 | 0 0 | 0.00% | 0 9 | 0 | |
| Leaves_1 10 | | Log-sigmoid | Log-sigmoid | Gradient Descent | 20 | 15 | 15 | 66 | 10.00% | 0 0 | %00·0 | 0 9 | 0 | |
| Leaves_1 10 | | Log-sigmoid | Hyperbolic tangent sigmoid | Gradient Descent | 20 | 15 | 15 | 66 | %00.0 | 0 0 | 0.00% | 0 % | 0 | |
| Leaves_1 10 | | Log-sigmoid | Symmetric hard-limit | Gradient Descent | 20 | 15 | 15 | 66 | 10.00% | 0 0 | 0.00% | 0 % | 0 | |
| Leaves_1 10 | | Log-sigmoid | None | Gradient Descent | 02 | 15 | 15 | 66 | 10.00% | 0 0 | 10.00% | 0 % | 0 | |
| Leaves_1 10 | | Hyperbolic tangent sigmoid | Hard-limit | Gradient Descent | 20 | 15 | 15 | 66 | 30.00% | 0 0 | 0.00% | 0 % | 0 | |
| Leaves_1 10 | | Hyperbolic tangent sigmoid | Linear | Gradient Descent | 20 | 15 | 15 | 66 | 20.00% | 0 0 | 0.00% | 0 % | 0 | |
| Leaves_1 10 | | Hyperbolic tangent sigmoid | Log-sigmoid | Gradient Descent | 20 | 15 | 15 | 66 | 10.00% | 0 0 | 0.00% | 0 | 0 | |
| Leaves_1 10 | | Hyperbolic tangent sigmoid | Hyperbolic tangent sigmoid | Gradient Descent | 20 | 15 | 15 | 66 | 10.00% | 0 0 | 0.00% | 0 | 0 | |
| Leaves_1 10 | | - | Symmetric hard-limit | Gradient Descent | 20 | 15 | 15 | 66 | 20.00% | 0 0 | 0.00% | 0 % | 0 | |
| \vdash | | + | None | Gradient Descent | 20 | 15 | 15 | 66 | 0.00% | 0 0 | 0.00% | 0 % | 0 | |
| Leaves_1 10 | | Symmetric hard-limit | Hard-limit | Gradient Descent | 70 | 15 | 15 | 66 | 20.00% | 0 0 | 0.00% | 0 % | 0 | |
| Leaves_1 10 | | Symmetric hard-limit | Linear | Gradient Descent | 20 | 15 | 15 | 66 | 10.00% | 0 0 | 0.00% | 0 % | 0 | |
| Leaves_1 10 | | Symmetric hard-limit | Log-sigmoid | Gradient Descent | 20 | 15 | 15 | 66 | 10.00% | 0 0 | 0.00% | 0 % | 0 | |
| Leaves_1 10 | | Symmetric hard-limit | angent sigmoid | Gradient Descent | 20 | 15 | 15 | 66 | 10.00% | 0 0 | 0.00% | 0 % | 0 | |
| Leaves_1 10 | | Symmetric hard-limit | Symmetric hard-limit | Gradient Descent | 20 | 15 | 15 | 66 | 10.00% | 0 0 | 0.00% | 0 % | 0 | |
| Leaves_1 10 | | Symmetric hard-limit | None | Gradient Descent | 20 | 15 | 15 | 66 | 20.00% | 0 0 | 0.00% | 0 % | 0 | |
| Leaves_1 10 | | Hard-limit | Hard-limit | Stochastic Approximation to Gradient Descent | t 70 | 15 | 15 | 66 | 10.00% | 0 0 | 0.00% | 0 , | 0 | |
| Leaves_1 10 | | Hard-limit | Linear | Gradient | + | 15 | 15 | 66 | 20.00% | 0 0 | 0.00% | | 0 | |
| L | | Hard-limit | Log-sigmoid | Stochastic Approximation to Gradient Descent | + | 15 | 15 | 66 | 10.00% | | 0.00% | | 0 | |
| - | | Hard-limit | Hyperbolic tangent sigmoid | Stochastic Approximation to Gradient Descent | + | 15 | 15 | 66 | 0.00% | | 0.00% | | 0 | |
| ۲. | | Hard-limit | Symmetric hard-limit | Stochastic Approximation to Gradient Descent | + | 15 | 15 | 66 | 0.00% | | 0.00% | | 0 | |
| Leaves_1 10 | | Hard-limit | None | Stochastic Approximation to Gradient Descent | - | 15 | 15 | 66 | 0.00% | 0 0 | 0.00% | | 0 | |
| Leaves_1 10 | | Linear | Hard-limit | Stochastic Approximation to Gradient Descent | t 70 | 15 | 15 | 66 | 30.00% | 0 0 | 0.00% | 0 % | 0 | |
| Leaves_1 10 | | Linear | Linear | Stochastic Approximation to Gradient Descent | t 70 | 15 | 15 | 66 | 0.00% | 0 0 | 0.00% | 0 % | 0 | |
| Leaves_1 10 | | Linear | Log-sigmoid | Stochastic Approximation to Gradient Descent | t 70 | 15 | 15 | 66 | 10.00% | 0 0 | 0.00% | 0 % | 0 | |
| Leaves_1 10 | | Linear | Hyperbolic tangent sigmoid | Stochastic Approximation to Gradient Descent | t 70 | 15 | 15 | 66 | %00.0 | 0 0 | 0.00% | 0 | 0 | |
| Leaves_1 10 | | Linear | Symmetric hard-limit | Stochastic Approximation to Gradient Descent | t 70 | 15 | 15 | 66 | %00.0 | 0 0 | 0.00% | 0 % | 0 | |
| Leaves_1 10 | | Linear | None | Stochastic Approximation to Gradient Descent | t 70 | 15 | 15 | 66 | %00.0 | 0 0 | 0.00% | 0 % | 0 | |
| Leaves_1 10 | | Log-sigmoid | Hard-limit | Stochastic Approximation to Gradient Descent | t 70 | 15 | 15 | 66 | 20.00% | 0 0 | 0.00% | 0 % | 0 | |
| Leaves_1 10 | | Log-sigmoid | Linear | Stochastic Approximation to Gradient Descent | t 70 | 15 | 15 | 66 | %00.0 | 0 0 | 0.00% | 0 % | 0 | |
| Leaves_1 10 | | Log-sigmoid | Log-sigmoid | Stochastic Approximation to Gradient Descent | t 70 | 15 | 15 | 66 | 20.00% | 0 0 | 0.00% | 0 0 | 0 | |
| Leaves_1 10 | | Log-sigmoid | gmoi | Stochastic Approximation to Gradient Descent | t 70 | 15 | 15 | 66 | 10.00% | 0 0 | 0.00% | | 0 | |
| | | Log-sigmoid | netric hard-limit | Stochastic Approximation to Gradient Descent 7 | t 70 | 15 | 15 | 66 | 10.00% | | 0.00% | | 0 | |
| Leaves_1 10 | | - | | Stochastic Approximation to Gradient Descent | t 20 | 15 | 15 | 66 | 0.00% | | 0.00% | | 0 | |
| \dashv | | - | Hard-limit | Stochastic Approximation to Gradient Descent | t 20 | 15 | 15 | 66 | %00.0 | 0 0 | 0.00% | | 0 | |
| Leaves_1 10 | | Hyperbolic tangent sigmoid | | Stochastic Approximation to Gradient Descent | t 70 | 15 | 15 | 66 | 20.00% | 0 0 | 0.00% | | 0 | |
| Leaves_1 10 | | Hyperbolic tangent sigmoid | Log-sigmoid | Stochastic Approximation to Gradient Descent | t 70 | 15 | 15 | 66 | 20.00% | 0 0 | 0.00% | 0 9 | 0 | |
| Leaves_1 10 | | Hyperbolic tangent sigmoid | cangent sigmoi | Stochastic Approximation to Gradient Descent | t 70 | 15 | 15 | 66 | %00.0 | 0 0 | 0.00% | 0 % | 0 | |
| Leaves_1 10 | | - | Symmetric hard-limit | Stochastic Approximation to Gradient Descent | t 70 | 15 | 15 | 66 | 10.00% | 0 0 | 0.00% | 0 | 0 | |
| Leaves_1 10 | | \vdash | None | Stochastic Approximation to Gradient Descent | t 70 | 15 | 15 | 66 | %00.0 | 0 0 | 10.00 | 0 % | 0 | |
| Leaves_1 10 | | Symmetric hard-limit | Hard-limit | Stochastic Approximation to Gradient Descent | t 70 | 15 | 15 | 66 | 10.00% | 0 0 | 0.00% | | 0 | |
| Leaves_1 10 | | Symmetric hard-limit | Linear | Stochastic Approximation to Gradient Descent | t 70 | 15 | 15 | 66 | %00.0 | 0 0 | 0.00% | 0 | 0 | |
| Leaves_1 10 | | Symmetric hard-limit | Log-sigmoid | Stochastic Approximation to Gradient Descent | t 70 | 15 | 15 | 66 | 10.00% | 0 0 | 0.00% | 0 % | 0 | |
| Leaves_1 10 | | Symmetric hard-limit | Hyperbolic tangent sigmoid | Stochastic Approximation to Gradient Descent | t 70 | 15 | 15 | 66 | 0.00% | 0 0 | 0.00% | 0 % | 0 | |
| | | Symmetric hard-limit | Symmetric hard-limit | Stochastic Approximation to Gradient Descent | \vdash | 15 | 15 | 66 | 10.00% | 0 0 | 0.00% | | 0 | |
| Leaves_1 10 | | Symmetric hard-limit | None | Stochastic Approximation to Gradient Descent | t 70 | 15 | 15 | 66 | 10.00% | 0 0 | 0.00% | 0 % | 0 | |
| | | | | | | | | | | | | | | |

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

| | Transfer | Transfer functions | Ratio (in | (in percentage % | (% | | | Species | | Species | |
|------------------|----------------------------|----------------------------|------------------------------------|------------------|------|---------------|-----------|------------------|-------------|---------|----------|
| Folder Hidden L. | 1st | 2nd | Training algorithm Train V | Validation | Test | Quant. images | % ssəcons | Epoch Duration | n Success % | Epoch | Duration |
| Leaves_2 2 | Hard-limit | Hard-limit | g Rule | 0 | 10 | | 6.19% | 0 0 | 0.00% | 0 | 0 |
| Leaves_2 2 | Hard-limit | Linear | 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 11 | 10 | 10 | 1564 | 4.12% | 0 0.01 | 4.17% | 0 | 0 |
| Leaves_2 2 | Hard-limit | Hyperbolic tangent sigmoid | Perceptron Training Rule 80 1 | 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 1 | 10 | 1564 | 7.22% | 0 0 | 0.00% | 0 | 0 |
| Leaves_2 2 | Hard-limit | None | Perceptron Training Rule 80 1 | 10 | 10 | 1564 | 6.19% | 0 0 | 1.04% | 0 | 0 |
| Leaves_2 2 | Linear | Hard-limit | Perceptron Training Rule 80 11 | 10 | 10 | 1564 | 9.28% | 0 0 | 1.04% | 0 | 0 |
| Leaves_2 2 | Linear | Linear | Rule 80 | 10 | 10 | 1564 | 11.34% | 0 0 | 3.13% | 0 | 0 |
| Leaves_2 2 | Linear | Log-sigmoid | Perceptron Training Rule 80 11 | 10 | 10 | 1564 | 10.31% | 0 0 | 1.04% | 0 | 0 |
| Leaves_2 2 | Linear | Hyperbolic tangent sigmoid | Perceptron Training Rule 80 11 | 10 | 10 | 1564 | 8.25% | 0 0 | 1.04% | 0 | 0 |
| Leaves_2 2 | Linear | Symmetric hard-limit | Perceptron Training Rule 80 11 | 10 | 10 | 1564 | 7.22% | 0 0 | 0.00% | 0 | 0 |
| Leaves_2 2 | Linear | None | Perceptron Training Rule 80 11 | 10 | 10 | 1564 | 10.31% | 0 0 | 3.13% | 0 | 0 |
| Leaves_2 2 | Log-sigmoid | Hard-limit | Perceptron Training Rule 80 11 | 10 | 10 | 1564 | 8.25% | 0 0 | 0.00% | 0 | 0 |
| Leaves_2 2 | Log-sigmoid | Linear | 80 | 10 | 10 | 1564 | 4.12% | 0 0 | 0.00% | 0 | 0 |
| - | Log-sigmoid | Log-sigmoid | 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 1 | 10 | 10 | 1564 | 8.25% | 0 0 | 2.08% | 0 | 0 |
| - | Log-sigmoid | Symmetric hard-limit | Perceptron Training Rule 80 10 | 10 | 10 | 1564 | 7.22% | 0 0 | 2.08% | 0 | 0 |
| Leaves_2 2 | Log-sigmoid | None | 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 1 | 10 | 10 | 1564 | 12.37% | 0 0 | 1.04% | 0 | 0 |
| Leaves_2 2 | Hyperbolic tangent sigmoid | Linear | Perceptron Training Rule 80 1 | 10 | 10 | 1564 | 10.31% | 0 0 | 1.04% | 0 | 0 |
| Leaves_2 2 | Hyperbolic tangent sigmoid | Log-sigmoid | Perceptron Training Rule 80 1 | 10 | 10 | 1564 | 8.25% | 0 0 | 1.04% | 0 | 0 |
| Leaves_2 2 | Hyperbolic tangent sigmoid | Hyperbolic tangent sigmoid | Perceptron Training Rule 80 11 | 10 | 10 | 1564 | 6.19% | 0 0 | 1.04% | 0 | 0 |
| Leaves_2 2 | Hyperbolic tangent sigmoid | Symmetric hard-limit | Rule 80 | 10 | 10 | 1564 | 6.19% | 0 0 | 0.00% | 0 | 0 |
| | Hyperbolic tangent sigmoid | | 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 1 | 10 | 10 | 1564 | 12.37% | 0 0 | 1.04% | 0 | 0 |
| Leaves_2 2 | Symmetric hard-limit | Linear | Rule 80 | 10 | 10 | 1564 | 80.00 | 0 0 | 0.00% | 0 | 0 |
| Leaves_2 2 | Symmetric hard-limit | Log-sigmoid | Rule 80 | 10 | 10 | 1564 | 7.22% | 0 0 | 0.00% | 0 | 0 |
| Leaves_2 2 | Symmetric hard-limit | Hyperbolic tangent sigmoid | | 10 | 10 | 1564 | 12.37% | 0 0 | 0.00% | 0 | 0 |
| Leaves_2 2 | Symmetric hard-limit | Symmetric hard-limit | Training Rule 80 | | 10 | 1564 | 4.12% | 0 0 | 0.00% | 0 | 0 |
| Leaves_2 2 | Symmetric hard-limit | None | ng Rule 80 | | 10 | 1564 | 10.31% | 0 0 | 1.04% | 0 | 0 |
| Leaves_2 2 | Hard-limit | Hard-limit | | | 10 | 1564 | 13.40% | | 1.04% | 0 | 0 |
| Leaves_2 2 | Hard-limit | Linear | Gradient Descent 80 1 | 10 | 10 | 1564 | 8.25% | 0 0 | 0.00% | 0 | 0 |
| Leaves_2 2 | Hard-limit | Log-sigmoid | | 10 | 10 | 1564 | 7.22% | 0 0 | 1.04% | 0 | 0 |
| Leaves_2 2 | Hard-limit | Hyperbolic tangent sigmoid | 08 | | 10 | 1564 | 5.15% | 0 0 | 2.08% | 0 | 0 |
| Leaves_2 2 | Hard-limit | Symmetric hard-limit | 80 | 10 | 10 | 1564 | 2.06% | 0 0 | 0.00% | 0 | 0 |
| Leaves_2 2 | Hard-limit | None | | 10 | 10 | 1564 | 11.34% | 0 0 | 0.00% | 0 | 0 |
| Leaves_2 2 | Linear | Hard-limit | 08 | 10 | 10 | 1564 | 7.22% | 0 0 | 2.08% | 0 | 0 |
| Leaves_2 2 | Linear | Linear | 80 | | 10 | 1564 | 12.37% | 0 0 | 2.08% | 0 | 0 |
| Leaves_2 2 | Linear | Log-sigmoid | | 10 | 10 | 1564 | 7.22% | 0 0 | 0.00% | 0 | 0 |
| Leaves_2 2 | Linear | Hyperbolic tangent sigmoid | 08 | | 10 | 1564 | 14.43% | | 1.04% | 0 | 0 |
| Leaves_2 2 | Linear | Symmetric hard-limit | | 10 1 | 10 | 1564 | 6.19% | 0 0 | 3.13% | 0 | 0 |
| Leaves_2 2 | Linear | None | 80 | | 10 | 1564 | 7.22% | 0 0 | 0.00% | 0 | 0 |
| | Log-sigmoid | Hard-limit | 80 | | 10 | 1564 | 5.15% | 0 0 | 0.00% | 0 | 0 |
| | Log-sigmoid | Linear | 80 | 10 | 10 | 1564 | 8.25% | 0 0 | 2.08% | 0 | 0 |
| Leaves_2 2 | Log-sigmoid | Log-sigmoid | Gradient Descent 80 11 | 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 1 | Transfer functions | | Ratio | o (in percentage % | (% e.2) | | | Species | | S | Species | |
|----------|-----------|----------------------------|----------------------------|--|---------|--------------------|---------|---------------|-----------|----------|----------|---------------|----------|----------|
| Folder | Hidden L. | 1st | 2nd | Training algorithm | Train | | Test | Quant. images | Success % | \vdash | Duration | Success % I | \vdash | Duration |
| Leaves_2 | 2 | Log-sigmoid | Hyperbolic tangent sigmoid | Gradient Descent | 8 | 10 | 10 | 1564 | 11.34% | 0 | 0 | 1.04% | 0 | 0 |
| Leaves_2 | 2 | Log-sigmoid | Symmetric hard-limit | Gradient Descent | 8 | 10 | 10 | 1564 | 10.31% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_2 | 2 | Log-sigmoid | None | Gradient Descent | 08 | 10 | 10 | 1564 | 10.31% | 0 | 0 | 3.13% 0 | | 0 |
| Leaves_2 | 2 | Hyperbolic tangent sigmoid | Hard-limit | Gradient Descent | 98 | 10 | 10 | 1564 | 8.25% | 0 | 0 | 0.00% | 0 | |
| Leaves 2 | 2 | Hyperbolic tangent sigmoid | Linear | Gradient Descent | 8 | 10 | 10 | 1564 | 9.28% | 0 | 0 | 0.00% | 0 | |
| Leaves_2 | 2 | Hyperbolic tangent sigmoid | Log-sigmoid | Gradient Descent | 8 | 10 | 10 | 1564 | 14.43% | 0 | 0 | 0.00% | 0 | |
| Leaves_2 | 2 | Hyperbolic tangent sigmoid | Hyperbolic tangent sigmoid | Gradient Descent | 8 | 10 | 10 | 1564 | 8.25% | 0 | 0 | 1.04% 0 | 0 | |
| Leaves 2 | 2 | Hyperbolic tangent sigmoid | Symmetric hard-limit | Gradient Descent | 8 | 10 | 10 | 1564 | 8.25% | 0 | 0 | 0.00% | 0 | |
| Leaves_2 | 2 | Hyperbolic tangent sigmoid | None | Gradient Descent | 98 | 10 | 10 | 1564 | 8.25% | 0 | 0 | 2.08% 0 | 0 | |
| Leaves_2 | 2 | Symmetric hard-limit | Hard-limit | Gradient Descent | 8 | 10 | 10 | 1564 | 8.25% | 0 | 0 | 2.08% 0 | 0 | |
| Leaves_2 | 2 | Symmetric hard-limit | Linear | Gradient Descent | 08 | 10 | 10 | 1564 | 10.31% | 0 | 0 | 2.08% | 0 0 | |
| Leaves_2 | 2 | Symmetric hard-limit | Log-sigmoid | Gradient Descent | 8 | 10 | 10 | 1564 | 7.22% | 0 | 0 | 0.00% | 0 | |
| Leaves 2 | 2 | Symmetric hard-limit | Hyperbolic tangent sigmoid | Gradient Descent | 8 | 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 | 8 | 10 | 10 | 1564 | 6.19% | 0 | 0 | 1.04% | 0 0 | |
| Leaves_2 | 2 | Hard-limit | Hard-limit | Stochastic Approximation to Gradient Descent | | 10 | | 1564 | 8.25% | 0 | 0 | 2.08% | 0 0 | |
| Leaves_2 | 2 | Hard-limit | Linear | Stochastic Approximation to Gradient Descent | e 80 | 10 | 10 | 1564 | 7.22% | 0 | 0 | 0.00% | 0 (| |
| Leaves 2 | 2 | Hard-limit | Log-sigmoid | Stochastic Approximation to Gradient Descent | 98 1 | 10 | 10 | 1564 | 11.34% | 0 | 0 | 2.08% | 0 | |
| Leaves_2 | 2 | Hard-limit | Hyperbolic tangent sigmoid | Stochastic Approximation to Gradient Descent | e 80 | 10 | 10 | 1564 | 11.34% | 0 | 0 | 0.00% | 0 (| |
| Leaves_2 | 2 | Hard-limit | Symmetric hard-limit | Stochastic Approximation to Gradient Descent | 8 | 10 | 10 | 1564 | 7.22% | 0 | 0 | 1.04% 0 | 0 | |
| Leaves 2 | 2 | Hard-limit | None | Stochastic Approximation to Gradient Descent | 98 1 | 10 | 10 | 1564 | 8.25% | 0 | 0 | 1.04% 0 | 0 | |
| Leaves_2 | 2 | Linear | Hard-limit | Stochastic Approximation to Gradient Descent | t 80 | 10 | 10 | 1564 | 14.43% | 0 | 0 | 0.00% | 0 0 | |
| Leaves_2 | 2 | Linear | Linear | Stochastic Approximation to Gradient Descent | 98 | 10 | 10 | 1564 | 7.22% | 0 | 0 | 2.08% | 0 0 | |
| Leaves_2 | 2 | Linear | Log-sigmoid | Stochastic Approximation to Gradient Descent | t 80 | 10 | 10 | 1564 | 16.49% | 0 |) 0 | | 0 0 | |
| Leaves_2 | 2 | Linear | Hyperbolic tangent sigmoid | Stochastic Approximation to Gradient Descent | - | 10 | 10 | 1564 | 10.31% | | | | 0 (| |
| Leaves_2 | 2 | Linear | Symmetric hard-limit | Stochastic Approximation to Gradient Descent | | 10 | 10 | 1564 | 7.22% | 0 | 0 | 0.00% 0 | 0 (| |
| Leaves_2 | 2 | Linear | None | Stochastic Approximation to Gradient Descent | | 10 | | 1564 | 9.28% | 0 | | 1.04% 0 | 0 (| |
| Leaves_2 | 2 | Log-sigmoid | Hard-limit | Stochastic Approximation to Gradient Descent | 98 | 10 | 10 | 1564 | 8.25% | 0 | 0 | 1.04% 0 | 0 (| |
| Leaves_2 | 2 | Log-sigmoid | Linear | Stochastic Approximation to Gradient Descent | t 80 | 10 | | 1564 | 10.31% | 0 |) 0 | 0 %00.0 | 0 (| |
| Leaves_2 | 2 | Log-sigmoid | Log-sigmoid | Stochastic Approximation to Gradient Descent | - | 10 | | 1564 | 8.25% | 0 | 0 | | 0 0 | |
| Leaves 2 | 2 | Log-sigmoid | Hyperbolic tangent sigmoid | Stochastic Approximation to Gradient Descent | | 10 | 10 | 1564 | 13.40% | 0 | | | 0 0 | |
| Leaves_2 | 2 | Log-sigmoid | Symmetric hard-limit | Stochastic Approximation to Gradient Descent | | 10 | 10 | 1564 | 7.22% | | | | | |
| Leaves_2 | 2 | Log-sigmoid | None | Stochastic Approximation to Gradient Descent | t 80 | 10 | 10 | 1564 | 9.28% | 0 | 0 1 | 1.04% 0 | 0 (| |
| Leaves_2 | 2 | Hyperbolic tangent sigmoid | Hard-limit | Stochastic Approximation to Gradient Descent | t 80 | 10 | 10 | 1564 | 12.37% | 0 |) 0 | 0.00% | 0 (| |
| Leaves_2 | 2 | Hyperbolic tangent sigmoid | Linear | Stochastic Approximation to Gradient Descent | t 80 | 10 | 10 | 1564 | 8.25% | 0 |) 0 | 0.00% | 0 (| |
| Leaves_2 | 2 | Hyperbolic tangent sigmoid | Log-sigmoid | Stochastic Approximation to Gradient Descent | e 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 | 98 | 10 | 10 | 1564 | 11.34% | 0 | 0 | 0.00% | 0 | |
| Leaves_2 | 2 | Hyperbolic tangent sigmoid | Symmetric hard-limit | Stochastic Approximation to Gradient Descent | 98 | 10 | 10 | 1564 | 12.37% | 0 | 0.02 | 1.04% 0 | 0 | |
| Leaves 2 | 2 | Hyperbolic tangent sigmoid | None | Stochastic Approximation to Gradient Descent | e 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 | 8 | 10 | 10 | 1564 | 5.15% | 0 | | | 0 | |
| Leaves_2 | 2 | Symmetric hard-limit | Linear | Stochastic Approximation to Gradient Descent | 8 | 10 | 10 | 1564 | 10.31% | 0 | 0 | 1.04% 0 | 0 | |
| Leaves 2 | 2 | Symmetric hard-limit | Log-sigmoid | Stochastic Approximation to Gradient Descent | 98 | 10 | 10 | 1564 | 10.31% | 0 | 0 | 0.00% | 0 | |
| Leaves_2 | 2 | Symmetric hard-limit | Hyperbolic tangent sigmoid | Stochastic Approximation to Gradient Descent | t 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 | | 10 | | 1564 | 10.31% | | 0 | | 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 | |

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

| | | Transfer | Transfer functions | Ratio | Ratio (in percentage %) | ;e %) | | | Species | | | Species | |
|----------|-----------|----------------------------|----------------------------|-------------------------------|-------------------------|-------|---------------|-----------|---------|----------|-----------|---------|----------|
| Folder | Hidden L. | 1st | 2nd | Training algorithm Train | Validation | Test | Quant. images | % ssecons | 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 |
| _ | 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 |
| + | 10 | Linear | Linear | | 15 | 15 | 1564 | 8.25% | 0 | 0 | 1.04% | 0 | 0 |
| Leaves_2 | 10 | Linear | Log-sigmoid | | 15 | 15 | 1564 | 5.15% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_2 | 10 | Linear | Hyperbolic tangent sigmoid | | 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 |
| _ | 10 | Linear | None | Perceptron Training Rule 70 | 15 | 15 | 1564 | 13.40% | 0 | 0 | 0.00% | 0 | 0 |
| - | 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 |
| + | 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 |
| + | 10 | Hyperbolic tangent sigmoid | Log-sigmoid | | 15 | 15 | 1564 | 9.28% | 0 | 0 | 0.00% | 0 | 0 |
| + | 10 | Hyperbolic tangent sigmoid | Hyperbolic tangent sigmoid | | 15 | 15 | 1564 | 8.25% | 0 | 0 | 1.04% | 0 | 0 |
| + | 10 | Hyperbolic tangent sigmoid | Symmetric hard-limit | Perceptron Training Rule 70 | 15 | 15 | 1564 | 9.28% | 0 | 0 | 2.08% | 0 | 0 |
| + | 10 | Hyperbolic tangent sigmoid | None | Training Rule | 15 | 15 | 1564 | 8.25% | 0 | 0 | 0.00% | 0 | 0 |
| + | 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 |
| | 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 $4\,$

| | | E | | | | ., | É | | | | ŀ | | - | |
|----------|-----------|----------------------------|----------------------------|--|-------|----|----------|------|--------|---------|---------|-------|----------|----------|
| [] | Hidden I | 101 | Transfer functions | The interest of the second sec | Katio | ニト | age %) | 1 | 00 | Species | + | ·- H | \vdash | |
| roider | nidden L. | + | ZIIQ | Training algorithm | TLa | + | \dashv | + | Ω | + | Duranon | 02 20 | росп | Duration |
| Leaves_2 | 10 | Log-sigmoid | Hyperbolic tangent sigmoid | Gradient Descent | 20 | 15 | 15 | 1564 | 8.25% | 0 0 | | 1.04% | | |
| Leaves_2 | 10 | Log-sigmoid | Symmetric hard-limit | Gradient Descent | 20 | 15 | 15 | 1564 | 5.15% | 0 0 | 0 | 0.00% | 0 | 0 |
| Leaves_2 | 10 | Log-sigmoid | None | Gradient Descent | 20 | 15 | 15 | 1564 | 7.22% | 0 0 | | 1.04% | 0 | 0 |
| Leaves_2 | 10 | Hyperbolic tangent sigmoid | Hard-limit | Gradient Descent | 20 | 15 | 15 | 1564 | 6.19% | 0 0 | | 1.04% | 0 | 0 |
| Leaves_2 | 10 | Hyperbolic tangent sigmoid | Linear | Gradient Descent | 20 | 15 | 15 | 1564 | 13.40% | 0 | | %00.0 | 0 | 0 |
| Leaves_2 | 10 | Hyperbolic tangent sigmoid | Log-sigmoid | Gradient Descent | 20 | 15 | 15 | 1564 | 6.19% | 0 0 | | | 0 | 0 |
| Leaves_2 | 10 | Hyperbolic tangent sigmoid | Hyperbolic tangent sigmoid | Gradient Descent | 20 | 15 | 15 | 1564 | 6.19% | 0 | | 0.00% | 0 | 0 |
| Leaves_2 | 10 | Hyperbolic tangent sigmoid | Symmetric hard-limit | Gradient Descent | 20 | 15 | 15 | 1564 | 15.46% | 0 0 | | 0.00% | 0 | 0 |
| Leaves_2 | 10 | Hyperbolic tangent sigmoid | None | Gradient Descent | 20 | 15 | 15 | 1564 | 8.25% | 0 | | 0.00% | 0 | 0 |
| Leaves_2 | 10 | Symmetric hard-limit | Hard-limit | Gradient Descent | 20 | 15 | 15 | 1564 | 12.37% | 0 0 | | 1.04% | 0 | 0 |
| Leaves_2 | 10 | Symmetric hard-limit | Linear | Gradient Descent | 20 | 15 | 15 | 1564 | 5.15% | 0 0 | | 0.00% | 0 | 0 |
| Leaves_2 | 10 | Symmetric hard-limit | Log-sigmoid | Gradient Descent | 20 | 15 | 15 | 1564 | 6.19% | 0 0 | | 0.00% | 0 | 0 |
| Leaves_2 | 10 | Symmetric hard-limit | Hyperbolic tangent sigmoid | Gradient Descent | 20 | 15 | 15 | 1564 | 4.12% | 0 0 | | 1.04% | 0 | 0 |
| Leaves_2 | 10 | Symmetric hard-limit | Symmetric hard-limit | Gradient Descent | 20 | 15 | 15 | 1564 | 9.28% | 0 0 | | 0.00% | 0 | 0 |
| Leaves_2 | 10 | Symmetric hard-limit | None | Gradient Descent | 20 | 15 | 15 | 1564 | 8.25% | 0 0 | | 1.04% | 0 | 0 |
| Leaves_2 | 10 | Hard-limit | Hard-limit | Stochastic Approximation to Gradient Descent | | 15 | 15 | 1564 | 9.28% | 0 0 | | 2.08% | 0 | 0 |
| Leaves_2 | 10 | Hard-limit | Linear | Stochastic Approximation to Gradient Descent | | 15 | 15 | 1564 | 8.25% | 0 | | | 0 | 0 |
| Leaves_2 | 10 | Hard-limit | Log-sigmoid | Stochastic Approximation to Gradient Descent | ıt 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 | ıt 20 | 15 | 15 | 1564 | 6.19% | 0 0 | | 0.00% | 0 | 0 |
| Leaves_2 | 10 | Hard-limit | Symmetric hard-limit | Stochastic Approximation to Gradient Descent | t 70 | 15 | 15 | 1564 | 6.19% | 0 0 | | 1.04% | 0 | 0 |
| Leaves 2 | 10 | Hard-limit | None | Stochastic Approximation to Gradient Descent | rt 70 | 15 | 15 | 1564 | 3.09% | 0 0 | | 1.04% | 0 | 0 |
| Leaves_2 | 10 | Linear | Hard-limit | Stochastic Approximation to Gradient Descent | t 70 | 15 | 15 | 1564 | 11.34% | 0 0 | | 0.00% | 0 | 0 |
| Leaves_2 | 10 | Linear | Linear | Stochastic Approximation to Gradient Descent | t 70 | 15 | 15 | 1564 | 8.25% | 0 0 | | 1.04% | 0 | 0 |
| Leaves_2 | 10 | Linear | Log-sigmoid | Stochastic Approximation to Gradient Descent | ıt 20 | 15 | 15 | 1564 | 12.37% | 0 0 | | 2.08% | 0 | 0 |
| Leaves_2 | 10 | Linear | Hyperbolic tangent sigmoid | Stochastic Approximation to Gradient Descent | 1 70 | 15 | 15 | 1564 | 12.37% | 0 | | 1.04% | 0 | 0 |
| Leaves_2 | 10 | Linear | Symmetric hard-limit | Stochastic Approximation to Gradient Descent | t 70 | 15 | 15 | 1564 | 10.31% | 0 0 | | 0.00% | 0 | 0 |
| Leaves_2 | 10 | Linear | None | Stochastic Approximation to Gradient Descent | 1t 20 | 15 | 15 | 1564 | 6.19% | 0 0 | | 1.04% | 0 | 0 |
| Leaves_2 | 10 | Log-sigmoid | Hard-limit | Stochastic Approximation to Gradient Descent | t 70 | 15 | 15 | 1564 | 7.22% | 0 0 | | 0.00% | 0 | 0 |
| Leaves_2 | 10 | Log-sigmoid | Linear | Stochastic Approximation to Gradient Descent | t 70 | 15 | 15 | 1564 | 7.22% | 0 0 | | 1.04% | 0 | 0 |
| Leaves_2 | 10 | Log-sigmoid | Log-sigmoid | Stochastic Approximation to Gradient Descent | 1 70 | 15 | 15 | 1564 | 11.34% | 0 | | 1.04% | 0 | 0 |
| Leaves_2 | 10 | Log-sigmoid | Hyperbolic tangent sigmoid | Stochastic Approximation to Gradient Descent | ıt 70 | 15 | 15 | 1564 | 8.25% | 0 | | 1.04% | 0 | 0 |
| Leaves_2 | 10 | Log-sigmoid | Symmetric hard-limit | Stochastic Approximation to Gradient Descent | | 15 | 15 | 1564 | 10.31% | 0 0 | | | | 0 |
| Leaves_2 | 10 | Log-sigmoid | None | Stochastic Approximation to Gradient Descent | | 15 | 15 | 1564 | 8.25% | 0 0 | | 0.00% | | 0 |
| Leaves_2 | 10 | Hyperbolic tangent sigmoid | Hard-limit | Stochastic Approximation to Gradient Descent | | 15 | 15 | 1564 | 3.09% | | | 0.00% | | 0 |
| Leaves_2 | 10 | Hyperbolic tangent sigmoid | Linear | Stochastic Approximation to Gradient Descent | ıt 20 | 15 | 15 | 1564 | 12.37% | 0 0 | | 0.00% | 0 | 0 |
| Leaves_2 | 10 | Hyperbolic tangent sigmoid | Log-sigmoid | Stochastic Approximation to Gradient Descent | ıt 20 | 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 | | 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 | ıt 20 | 15 | 15 | 1564 | 11.34% | 0 0 | | 0.00% | 0 | 0 |
| Leaves_2 | 10 | Hyperbolic tangent sigmoid | None | Stochastic Approximation to Gradient Descent | ıt 70 | 15 | 15 | 1564 | 7.22% | 0 0 | | %00.0 | 0 | 0 |
| Leaves_2 | 10 | Symmetric hard-limit | Hard-limit | Stochastic Approximation to Gradient Descent | ıt 70 | 15 | 15 | 1564 | 14.43% | 0 0 | | 1.04% | 0 | 0 |
| Leaves_2 | 10 | Symmetric hard-limit | Linear | Stochastic Approximation to Gradient Descent | | 15 | 15 | 1564 | 7.22% | 0 0 | | | 0 | 0 |
| Leaves_2 | 10 | Symmetric hard-limit | Log-sigmoid | Stochastic Approximation to Gradient Descent | | 15 | 15 | 1564 | 8.25% | 0 0 | | 1.04% | | 0 |
| Leaves_2 | 10 | Symmetric hard-limit | Hyperbolic tangent sigmoid | Stochastic Approximation to Gradient Descent | ıt 20 | 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 | | 15 | 15 | 1564 | 6.19% | 0 0 | | 1.04% | 0 | 0 |
| Leaves_2 | 10 | Symmetric hard-limit | None | Stochastic Approximation to Gradient Descent | ıt 20 | 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 | Transfer functions | Ratio (in | (in percentage | (% | | | Species | | | Species | |
|----------|-----------|----------------------------|----------------------------|--------------------------------|----------------|------|---------------|-----------|---------|----------|-----------|---------|----------|
| Folder | Hidden L. | 1st | 2nd | corithm Train | Validation | Test | Quant. images | % ssecons | Epoch | Duration | % ssəcons | Epoch | Duration |
| Leaves_3 | 2 | Hard-limit | Hard-limit | 80 | | 10 | 20 | 20.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_3 | 2 | Hard-limit | Linear | Perceptron Training Rule 80 10 | | 10 | 20 | %00.0 | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_3 | 2 | Hard-limit | Log-sigmoid | Perceptron Training Rule 80 10 | | 10 | 20 | 20.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_3 | 2 | Hard-limit | Hyperbolic tangent sigmoid | Perceptron Training Rule 80 10 | | 10 | 20 | %00.0 | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_3 | 2 | Hard-limit | Symmetric hard-limit | Perceptron Training Rule 80 10 | | 10 | 20 | 20.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_3 | 2 | Hard-limit | None | Perceptron Training Rule 80 10 | | 10 | 20 | %00.0 | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_3 | 2 | Linear | Hard-limit | Perceptron Training Rule 80 10 | | 10 | 20 | %00.0 | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_3 | 2 | Linear | Linear | Perceptron Training Rule 80 10 | | 10 | 20 | 20.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_3 | 2 | Linear | Log-sigmoid | Perceptron Training Rule 80 10 | | 10 | 20 | 20.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_3 | 2 | Linear | Hyperbolic tangent sigmoid | Perceptron Training Rule 80 10 | | 10 | 20 | %00.0 | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_3 | 2 | Linear | Symmetric hard-limit | Perceptron Training Rule 80 10 | | 10 | 20 | %00.0 | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_3 | 2 | Linear | None | Perceptron Training Rule 80 10 | | 10 | 20 | %00.0 | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_3 | 2 | Log-sigmoid | Hard-limit | Perceptron Training Rule 80 10 | | 10 | 20 | 20.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_3 | 2 | Log-sigmoid | Linear | Perceptron Training Rule 80 10 | | 10 | 20 | 20.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_3 | 2 | Log-sigmoid | Log-sigmoid | | | 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 | %00:0 | 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 | 20.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_3 | 2 | Hyperbolic tangent sigmoid | Log-sigmoid | Perceptron Training Rule 80 10 | | 10 | 20 | %00.0 | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_3 | 2 | Hyperbolic tangent sigmoid | _ | | | 10 | 20 | 20.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_3 | 2 | Hyperbolic tangent sigmoid | - | Training Rule 80 | | 10 | 20 | 0.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_3 | 2 | Hyperbolic tangent sigmoid | _ | Training Rule 80 | | 10 | 20 | %00.0 | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_3 | 2 | Symmetric hard-limit | Hard-limit | Perceptron Training Rule 80 10 | | 10 | 20 | %00.0 | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_3 | 2 | Symmetric hard-limit | Linear | Perceptron Training Rule 80 10 | | 10 | 20 | 20.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_3 | 2 | Symmetric hard-limit | Log-sigmoid | Perceptron Training Rule 80 10 | | 10 | 20 | 20.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_3 | 2 | Symmetric hard-limit | Hyperbolic tangent sigmoid | Perceptron Training Rule 80 10 | 10 | 10 | 20 | 20.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_3 | 2 | Symmetric hard-limit | Symmetric hard-limit | Training Rule 80 | | | 20 | %00.0 | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_3 | 2 | Symmetric hard-limit | None | | | | 20 | %00.0 | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_3 | 2 | Hard-limit | Hard-limit | 08 | | 10 | 20 | %00'0 | 0 | 0 | %00:0 | 0 | 0 |
| Leaves_3 | 2 | Hard-limit | Linear | | | 10 | 20 | %00.0 | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_3 | 2 | Hard-limit | Log-sigmoid | | | 10 | 20 | %00'0 | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_3 | 2 | Hard-limit | Hyperbolic tangent sigmoid | | | 10 | 20 | 20.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_3 | 2 | Hard-limit | Symmetric hard-limit | Gradient Descent 80 10 | | 10 | 20 | 20.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_3 | 2 | Hard-limit | None | | | 10 | 20 | 20.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_3 | 2 | Linear | Hard-limit | | | 10 | 20 | %00.0 | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_3 | 2 | Linear | Linear | | | 10 | 20 | %00.0 | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_3 | 2 | Linear | Log-sigmoid | | | 10 | 20 | %00.0 | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_3 | 2 | Linear | Hyperbolic tangent sigmoid | | | 10 | 20 | 20.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_3 | 2 | Linear | Symmetric hard-limit | | | 10 | 20 | %00.0 | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_3 | 2 | Linear | None | | | 10 | 20 | 50.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_3 | 2 | Log-sigmoid | Hard-limit | | | 10 | 20 | %00.0 | 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 | %00.0 | 0 | 0 | %00.0 | 0 | 0 |
| | | | | | | | | | | | | | |

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

| | | Transfer | Transfer functions | | Ratio (in | (in percentage % | e %) | | | Species | | | Species | |
|------------|-----------|----------------------------|----------------------------|--|--------------|------------------|-------|---------------|-----------|---------|----------|-----------|---------|----------|
| Folder | Hidden L. | 1st | 2nd | Training algorithm | Train Va | Validation | بد | Quant. images | Success % | Epoch | Duration | Success % | Epoch | Duration |
| Leaves_3 2 | 2 | Log-sigmoid | Hyperbolic tangent sigmoid | Gradient Descent | 80 10 | | 10 20 | 0 | 0.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_3 2 | 2 | Log-sigmoid | Symmetric hard-limit | Gradient Descent | 80 10 | | 10 20 | 0 | 20.00% | 0 | 0 | %00.0 | 0 | 0 |
| Leaves_3 2 | 2 | Log-sigmoid | None | Gradient Descent | 80 10 | | 10 20 | 0 | 20.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_3 2 | 2 | Hyperbolic tangent sigmoid | Hard-limit | Gradient Descent | | | 10 20 | 0 | 0.00% | 0 | 0 | %00.0 | 0 | 0 |
| Leaves_3 2 | 2 | Hyperbolic tangent sigmoid | Linear | Gradient Descent | 80 10 | | 10 20 | 0 | %00.0 | 0 | 0 | %00.0 | 0 | 0 |
| Leaves_3 2 | 2 | Hyperbolic tangent sigmoid | Log-sigmoid | Gradient Descent | | | 10 20 | 0 | 20.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_3 2 | 2 | Hyperbolic tangent sigmoid | Hyperbolic tangent sigmoid | Gradient Descent | | | | 0 | 0.00% | 0 | 0 | %00.0 | 0 | 0 |
| Leaves_3 2 | 2 | Hyperbolic tangent sigmoid | Symmetric hard-limit | Gradient Descent | 80 10 | | 10 20 | 0 | 20.00% | 0 | 0 | %00.0 | 0 | 0 |
| Leaves_3 2 | 2 | Hyperbolic tangent sigmoid | None | Gradient Descent | 80 10 | | 10 20 | 0 | 100.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_3 2 | 2 | Symmetric hard-limit | Hard-limit | Gradient Descent | 80 10 | | 10 20 | 0 | 0.00% | 0 | 0 | %00.0 | 0 | 0 |
| Leaves_3 2 | 2 | Symmetric hard-limit | Linear | Gradient Descent | | | | 0 | 0.00% | 0 | 0 | %00.0 | 0 | 0 |
| Leaves_3 2 | 2 | Symmetric hard-limit | Log-sigmoid | Gradient Descent | 80 10 | | 10 20 | 0 | 20.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_3 2 | 2 | Symmetric hard-limit | Hyperbolic tangent sigmoid | Gradient Descent | 80 10 | | 10 20 | 0 | 0.00% | 0 | 0 | %00.0 | 0 | 0 |
| Leaves_3 2 | 2 | Symmetric hard-limit | Symmetric hard-limit | Gradient Descent | 80 10 | | 10 20 | 0 | 20.00% | 0 | 0 | %00.0 | 0 | 0 |
| Leaves_3 2 | 2 | Symmetric hard-limit | None | Gradient Descent | <u>&</u> | | | 0 | 0.00% | 0 | 0 | %00.0 | 0 | 0 |
| Leaves_3 2 | 2 | Hard-limit | Hard-limit | Stochastic Approximation to Gradient Descent | 80 | | 10 20 | 0 | 20.00% | 0 | 0 | %00.0 | 0 | 0 |
| Leaves_3 2 | 2 | Hard-limit | Linear | Stochastic Approximation to Gradient Descent | t 80 10 | | 10 20 | 0 | 0.00% | 0 | 0 | %00.0 | 0 | 0 |
| Leaves_3 2 | 2 | Hard-limit | Log-sigmoid | Stochastic Approximation to Gradient Descent | <u>&</u> | | 10 20 | 0 | %00.0 | 0 | 0 | %00.0 | 0 | 0 |
| Leaves_3 2 | 2 | Hard-limit | Hyperbolic tangent sigmoid | Stochastic Approximation to Gradient Descent | t 80 10 | | 10 20 | 0 | 20.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_3 2 | 2 | Hard-limit | Symmetric hard-limit | Stochastic Approximation to Gradient Descent | t 80 10 | | 10 20 | 0 | 0.00% | 0 | 0 | %00.0 | 0 | 0 |
| Leaves_3 2 | 2 | Hard-limit | None | Stochastic Approximation to Gradient Descent | t 80 10 | | 10 20 | 0 | %00.0 | 0 | 0 | %00.0 | 0 | 0 |
| Leaves_3 2 | 2 | Linear | Hard-limit | Stochastic Approximation to Gradient Descent | <u>&</u> | | 10 20 | 0 | 100.00% | 0 | 0 | %00.0 | 0 | 0 |
| Leaves_3 2 | 2 | Linear | Linear | Stochastic Approximation to Gradient Descent | t 80 10 | | 10 20 | 0 | 0.00% | 0 | 0 | %00.0 | 0 | 0 |
| Leaves_3 2 | 2 | Linear | Log-sigmoid | Stochastic Approximation to Gradient Descent | 90 | | 10 20 | 0 | 0.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_3 2 | 2 | Linear | Hyperbolic tangent sigmoid | Stochastic Approximation to Gradient Descent | 92 | | | 0 | 20.00% | 0 | 0 | %00.0 | 0 | 0 |
| Leaves_3 2 | 2 | Linear | Symmetric hard-limit | Stochastic Approximation to Gradient Descent | 98 | | 10 20 | 0 | 20.00% | 0 | 0 | %00.0 | 0 | 0 |
| Leaves_3 2 | 2 | Linear | None | Stochastic Approximation to Gradient Descent | 98 | | | 0 | 0.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_3 2 | 2 | Log-sigmoid | Hard-limit | Stochastic Approximation to Gradient Descent | 98 | | 10 20 | 0 | 20.00% | 0 | 0 | %00.0 | 0 | 0 |
| Leaves_3 2 | 2 | Log-sigmoid | Linear | Stochastic Approximation to Gradient Descent | 98 | | 10 20 | 0 | %00.0 | 0 | 0 | %00.0 | 0 | 0 |
| Leaves_3 2 | 2 | Log-sigmoid | Log-sigmoid | Stochastic Approximation to Gradient Descent 8 | t 80 10 | | 10 20 | 0 | 20.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_3 2 | 2 | Log-sigmoid | Hyperbolic tangent sigmoid | Stochastic Approximation to Gradient Descent | t 80 10 | | 10 20 | 0 | %00.0 | 0 | 0 | %00.0 | 0 | 0 |
| Leaves_3 2 | 2 | Log-sigmoid | Symmetric hard-limit | Stochastic Approximation to Gradient Descent 8 | 30 | (| | 0 | %00.0 | 0 | 0 | 0.00% | 0 | 0 |
| | 2 | Log-sigmoid | | Stochastic Approximation to Gradient Descent | 30 | _ | 10 20 | 0 | 0.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_3 2 | 2 | Hyperbolic tangent sigmoid | Hard-limit | Stochastic Approximation to Gradient Descent | 30 | | | 0 | %00:0 | 0 | 0 | %00.0 | 0 | 0 |
| Leaves_3 2 | 2 | Hyperbolic tangent sigmoid | Linear | Stochastic Approximation to Gradient Descent | 30 | | | 0 | 20.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_3 2 | 2 | Hyperbolic tangent sigmoid | Log-sigmoid | Stochastic Approximation to Gradient Descent | 30 | | | 0 | 20.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_3 2 | 2 | Hyperbolic tangent sigmoid | Hyperbolic tangent sigmoid | Stochastic Approximation to Gradient Descent | t 80 10 | | 10 20 | 0 | 20.00% | 0 | 0 | %00.0 | 0 | 0 |
| Leaves_3 2 | 2 | Hyperbolic tangent sigmoid | Symmetric hard-limit | Stochastic Approximation to Gradient Descent | 8 | | 10 20 | 0 | 0.00% | 0 | 0 | %00.0 | 0 | 0 |
| Leaves_3 2 | 2 | Hyperbolic tangent sigmoid | None | Stochastic Approximation to Gradient Descent | t 80 10 | | 10 20 | 0 | %00.0 | 0 | 0 | %00.0 | 0 | 0 |
| Leaves_3 2 | 2 | Symmetric hard-limit | Hard-limit | Stochastic Approximation to Gradient Descent | 8 | | 10 20 | 0 | 20.00% | 0 | 0 | %00.0 | 0 | 0 |
| Leaves_3 2 | 2 | Symmetric hard-limit | Linear | Stochastic Approximation to Gradient Descent | t 80 10 | | 10 20 | 0 | 0.00% | 0 | 0 | %00.0 | 0 | 0 |
| Leaves_3 2 | 2 | Symmetric hard-limit | Log-sigmoid | Stochastic Approximation to Gradient Descent | 08 | | 10 20 | 0 | 20.00% | 0 | 0 | %00.0 | 0 | 0 |
| Leaves_3 2 | 2 | Symmetric hard-limit | Hyperbolic tangent sigmoid | Stochastic Approximation to Gradient Descent | t 80 10 | | 10 20 | 0 | 100.00% | 0 | 0 | %00.0 | 0 | 0 |
| \vdash | 2 | Symmetric hard-limit | Symmetric hard-limit | Stochastic Approximation to Gradient Descent | 80 | | | 0 | 20.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_3 2 | 2 | Symmetric hard-limit | None | Stochastic Approximation to Gradient Descent | t 80 10 | | 10 20 | 0 | 20.00% | 0 | 0 | %00.0 | 0 | 0 |
| | | | | | | | | | | | | | | |

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

| | _ | Transfer | Transfer functions | | Katio | (in percentage %) | _ S S | | | Species | S 8 | | Species | |
|----------|-----------|----------------------------|----------------------------|--------------------------|-------|-------------------|----------------|---------------|---------|-----------|------------|-------------|---------|----------|
| Folder | Hidden L. | 1st | 2nd | Training algorithm | Train | | Test | Quant. images | Success | % Epoch | h Duration | η Success % | Epoch | Duration |
| Leaves_3 | 10 | Hard-limit | Hard-limit | Perceptron Training Rule | 20 | 15 | 15 | 20 | 0.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_3 | 10 | Hard-limit | Linear | Perceptron Training Rule | 20 | 15 | 15 | 20 | 0.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_3 | 10 | Hard-limit | Log-sigmoid | Perceptron Training Rule | | 15 | 15 | 20 | 0.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_3 | 10 | Hard-limit | Hyperbolic tangent sigmoid | Perceptron Training Rule | 20 | 15 | 15 | 20 | 0.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_3 | 10 | Hard-limit | Symmetric hard-limit | Perceptron Training Rule | 20 | 15 | 15 | 20 | 0.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_3 | 10 | Hard-limit | None | Perceptron Training Rule | 20 | 15 | 15 | 20 | 20.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_3 | 10 | Linear | Hard-limit | Perceptron Training Rule | 20 | 15 | 15 | 20 | 50.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_3 | 10 | Linear | Linear | Perceptron Training Rule | 20 | 15 | 15 | 20 | 20.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_3 | 10 | Linear | Log-sigmoid | Perceptron Training Rule | 20 | 15 | 15 | 20 | 20.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_3 | 10 | Linear | Hyperbolic tangent sigmoid | | 20 | 15 | 15 | 20 | 0.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_3 | 10 | Linear | Symmetric hard-limit | Perceptron Training Rule | 20 | 15 | 15 | 20 | 20.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_3 | 10 | Linear | None | Perceptron Training Rule | 20 | 15 | 15 | 20 | 50.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_3 | 10 | Log-sigmoid | Hard-limit | Perceptron Training Rule | 20 | 15 | 15 | 20 | 0.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_3 | 10 | Log-sigmoid | Linear | Perceptron Training Rule | 20 | 15 | 15 | 20 | 20.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_3 | 10 | Log-sigmoid | Log-sigmoid | Perceptron Training Rule | 20 | 15 | 15 | 20 | 0.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_3 | 10 | Log-sigmoid | Hyperbolic tangent sigmoid | Perceptron Training Rule | 20 | 15 | 15 | 20 | 20.00% | 0 | 0 | %00.0 | 0 | 0 |
| Leaves_3 | 10 | Log-sigmoid | Symmetric hard-limit | Perceptron Training Rule | 20 | 15 | 15 | 20 | 0.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_3 | 10 | Log-sigmoid | None | Perceptron Training Rule | 20 | 15 | 15 | 20 | 50.00% | 0 | 0 | %00.0 | 0 | 0 |
| Leaves_3 | 10 | Hyperbolic tangent sigmoid | Hard-limit | Perceptron Training Rule | 20 | 15 | 15 | 20 | 0.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_3 | 10 | Hyperbolic tangent sigmoid | Linear | Perceptron Training Rule | 20 | 15 | 15 | 20 | 20.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_3 | 10 | Hyperbolic tangent sigmoid | Log-sigmoid | Perceptron Training Rule | 20 | 15 | 15 | 20 | 20.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_3 | 10 | Hyperbolic tangent sigmoid | Hyperbolic tangent sigmoid | | 20 | 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 | | 20 | 15 | 15 | 20 | 20.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_3 | 10 | Symmetric hard-limit | Hard-limit | Perceptron Training Rule | 20 | 15 | 15 | 20 | 0.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_3 | 10 | Symmetric hard-limit | Linear | Perceptron Training Rule | 20 | 15 | 15 | 20 | 0.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_3 | 10 | Symmetric hard-limit | Log-sigmoid | Perceptron Training Rule | 20 | 15 | 15 | 20 | 20.00% | 0 | 0 | %00.0 | 0 | 0 |
| Leaves_3 | 10 | Symmetric hard-limit | Hyperbolic tangent sigmoid | Perceptron Training Rule | 20 | 15 | 15 | 20 | 0.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_3 | 10 | Symmetric hard-limit | Symmetric hard-limit | Perceptron Training Rule | 20 | 15 | 15 | 20 | 0.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_3 | 10 | Symmetric hard-limit | None | Perceptron Training Rule | 20 | 15 | 15 | 20 | 20.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_3 | 10 | Hard-limit | Hard-limit | Gradient Descent | 02 | 15 | 15 | 20 | 20.00% | 0 | 0 | %00.0 | 0 | 0 |
| Leaves_3 | 10 | Hard-limit | Linear | Gradient Descent | 20 | 15 | 15 | 20 | 100.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_3 | 10 | Hard-limit | Log-sigmoid | Gradient Descent | 20 | 15 | 15 | 20 | 0.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_3 | 10 | Hard-limit | Hyperbolic tangent sigmoid | Gradient Descent | 20 | 15 | 15 | 20 | 20.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_3 | 10 | Hard-limit | Symmetric hard-limit | Gradient Descent | 20 | 15 | 15 | 20 | 0.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_3 | 10 | Hard-limit | None | Gradient Descent | 20 | 15 | 15 | 20 | 20.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_3 | 10 | Linear | Hard-limit | Gradient Descent | 20 | 15 | 15 | 20 | 0.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_3 | 10 | Linear | Linear | Gradient Descent | 20 | 15 | 15 | 20 | %00.0 | 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 | 20 | 15 | 15 | 20 | 0.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_3 | 10 | Linear | Symmetric hard-limit | Gradient Descent | 20 | 15 | 15 | 20 | 100.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_3 | 10 | Linear | None | Gradient Descent | 20 | 15 | 15 | 20 | 20.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_3 | 10 | Log-sigmoid | Hard-limit | Gradient Descent | 20 | 15 | 15 | 20 | 20.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves_3 | 10 | Log-sigmoid | Linear | Gradient Descent | 20 | 15 | 15 | 20 | 0.00% | 0 | 0 | 0.00% | 0 | 0 |
| Leaves 3 | 10 | | | J | 1 | , | | | /// | | | | | |

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

| Polity (1987) Hybrid (1987) Polity (| | | E | | | - | | (4) | | | | | | | |
|--|----------|---------------|----------------------------|----------------------------|--|----------|----|--------|-------|---------|----------|----------|-----------|---------|----------|
| 10 Indee@gounded Experience of Long-Signoud Gradient Descent 70 15 15 10 20 6000000 0 10 Hope-Schoole taggerst signoudd Symunetric bander agroadd Candient Descent 70 15 15 20 6000000 0 10 Hyper-Choic taggerst signoudd Long-Signoudd Candient Descent 70 15 15 20 6000000 0 10 Hyper-Choic taggerst signoudd Long-Signoud Candient Descent 70 15 15 20 6000000 0 10 Hyper-Choic taggerst signoudd Long-Bescut 70 15 15 20 6000000 0 10 Hyper-Choic taggerst signoudd Candient Descent 70 15 15 20 6000000 0 0 10 Hyper-Choic taggerst signoudd Candient Descent 70 15 15 20 6000000 0 0 0 0 0 0 0 0 0 0 | Folder | Hidden I. | 1st | runctions 2nd | Training algorithm | Trail | _ | rage % | Onant | | \vdash | Duration | Success % | Species | Duration |
| 10 Liegesfignoed Symmetre band-limit Gradent Doesent 70 15 20 20,000% 0 10 Liegesfignoed Anne Alley District Gradent Doesent 70 15 20 50,000% 0 10 Hyperbole means algoried Increase Gradent Doesent 70 15 22 50,000% 0 10 Hyperbole means algoried Increase Gradent Doesent 70 15 22 50,000% 0 10 Hyperbole means algoried Hyperbolic stagents Gradent Doesent 70 15 22 50,000% 0 10 Hyperbolic means algoried Gradent Doesent 70 15 22 50,000% 0 10 Symmetric back-hunt Lorest Gradent Doesent 70 15 22 50,000% 0 10 Symmetric back-hunt Lorest Gradent Doesent 70 15 22 50,000% 0 10 Symmetric back-hunt Lorest Doesent | Leaves_3 | + | + | Hyperbolic tangent sigmoid | Gradient Descent | 02 | + | + | 20 | | + | + | | 0 | 0 |
| 10 Hyperbolic numbers of graduard Doscott 70 15 35 20 60.00% 0 10 Hyperbolic numbers of graduard brown Graduard Doscott 70 15 15 20 60.00% 0 10 Hyperbolic numbers of gradual brown 70 15 15 20 60.00% 0 10 Hyperbolic numbers of gradual grand brown Graduard Doscott 70 15 15 20 60.00% 0 10 Hyperbolic numbers of gradual grand brown Graduard Doscott 70 15 20 60.00% 0 10 Symmetric back hunt Graduard Doscott 70 15 20 60.00% 0 10 Symmetric back hunt Graduard Doscott 70 15 20 60.00% 0 10 Symmetric back hunt Graduard Doscott 70 15 20 60.00% 0 10 Symmetric back hunt Graduard Doscott 70 15 20 60.00% 0 <t< th=""><th>Leaves_3</th><td>+</td><td>Log-sigmoid</td><td>Symmetric hard-limit</td><td>Gradient Descent</td><td>202</td><td>15</td><td>15</td><td>20</td><td>20.00%</td><td>0</td><td></td><td>0.00%</td><td>0</td><td>0</td></t<> | Leaves_3 | + | Log-sigmoid | Symmetric hard-limit | Gradient Descent | 202 | 15 | 15 | 20 | 20.00% | 0 | | 0.00% | 0 | 0 |
| (b) Hyperbolic magnetia standal filterial Gendrach Descent (b) (b | Leaves_3 | + | Log-sigmoid | None | Gradient Descent | 20 | 15 | 15 | 20 | 20.00% | 0 | | 0.00% | 0 | 0 |
| 10 Hyperbolic tangent signoid Locale and Descent 70 15 15 20 0.00% 0 10 Hyperbolic tangent signoid Locale and Descent 70 15 15 20 0.00% 0 10 Hyperbolic tangent signoid Symmetric band-limit Condent Descent 70 15 15 20 0.00% 0 10 Symmetric band-limit Linear Condent Descent 70 15 15 20 0.00% 0 10 Symmetric band-limit Linear Condent Descent 70 15 15 20 0.00% 0 10 Symmetric band-limit Linear Condent Descent 70 15 15 20 0.00% 0 10 Symmetric band-limit Linear Condent Descent 70 15 15 20 0.00% 0 10 Symmetric band-limit Linear Condent Descent 70 15 15 20 0.00% 0 <t< th=""><th>Leaves_3</th><td>_</td><td>Hyperbolic tangent sigmoid</td><td>Hard-limit</td><td>Gradient Descent</td><td>20</td><td>15</td><td>15</td><td>20</td><td>20.00%</td><td>0</td><td></td><td>0.00%</td><td>0</td><td>0</td></t<> | Leaves_3 | _ | Hyperbolic tangent sigmoid | Hard-limit | Gradient Descent | 20 | 15 | 15 | 20 | 20.00% | 0 | | 0.00% | 0 | 0 |
| 10 Hyperbolk tangent signand Hyperbolk tangent signand Grachent Descent 70 15 15 20 10.00% 0 10 Hyperbolk tangent signand Hyperbolk tangent signand Grachent Descent 70 15 15 20 0.00% 0 10 Hyperbolk tangent signand Hyperbolk tangent signand Hyperbolk tangent signand Hyperbolk tangent signand Grachent Descent 70 15 15 20 0.00% 0 10 Symmetric bard-limit Innext Grachent Descent 70 15 15 20 0.00% 0 10 Symmetric bard-limit Hyperbolk tangent signand Grachent Descent 70 15 15 20 0.00% 0 10 Symmetric bard-limit Hyperbolk tangent signand Grachent Descent 70 15 15 20 0.00% 0 10 Symmetric bard-limit Grachent Descent 70 15 15 20 0.00% 0 10 Hard-limit Hyperbolk tangent signand Grachent Descent 70 15 15 20 0.00% 0 | Leaves_3 | - | Hyperbolic tangent sigmoid | Linear | Gradient Descent | 20 | 15 | 15 | 20 | 20.00% | 0 | | %00:0 | 0 | 0 |
| 10 Hyperbolic tangent signoid of Conferint Descent 70 15 15 20 0.00% 0 10 Hyperbolic tangent signoid of Symmetric land-limit Gradient Descent 70 15 15 20 10.00% 0 10 Symmetric hard-limit Inflament Gradient Descent 70 15 15 20 10.00% 0 10 Symmetric hard-limit Inflament Gradient Descent 70 15 15 20 10.00% 0 10 Symmetric hard-limit Inprecipalic tangent signoid Gradient Descent 70 15 15 20 10.00% 0 10 Symmetric hard-limit Symmetric hard-limit Symmetric hard-limit Gradient Descent 70 15 15 20 10.00% 0 10 Symmetric hard-limit | Leaves_3 | _ | Hyperbolic tangent sigmoid | Log-sigmoid | Gradient Descent | 20 | 15 | 15 | 20 | %00.0 | 0 | | %00.0 | 0 | 0 |
| 10 Hyperbolk tangent signoid Summetric hard-limit Gradiant Descrit 70 15 20 10 0.00% 0 10 Symmetric hard-limit Linchell Descrit 70 15 20 0.00% 0 10 Symmetric hard-limit Linchell Descrit 70 15 20 0.00% 0 10 Symmetric hard-limit Appealone tangent signed Gendlint Descrit 70 15 20 0.00% 0 10 Symmetric hard-limit Appealone tangent signed Gendlint Descrit 70 15 15 20 0.00% 0 10 Symmetric hard-limit Symmetric bard-limit Symmetric hard-limit Symmetric | Leaves_3 | \vdash | Hyperbolic tangent sigmoid | Hyperbolic tangent sigmoid | Gradient Descent | 20 | 15 | 15 | 20 | 0.00% | 0 | | %00.0 | 0 | 0 |
| 10 Symmetric bard-limit Hard-limit Gradient Descent 70 15 15 20 0.00% 0 10 Symmetric bard-limit Hard-limit Hard-limit Gradient Descent 70 15 15 20 60.00% 0 10 Symmetric bard-limit Log-signoid Gradient Descent 70 15 15 20 60.00% 0 10 Symmetric bard-limit Log-signoid Gradient Descent 70 15 15 20 60.00% 0 10 Symmetric bard-limit March-limit March-limit Symmetric bard-limit Symmetric bard-limit 30 15 15 20 60.00% 0 10 Hard-limit Symmetric bard-limit | Leaves_3 | | Hyperbolic tangent sigmoid | Symmetric hard-limit | Gradient Descent | 20 | 15 | 15 | 20 | 100.00% | | | %00.0 | 0 | 0 |
| 10 Symmetric bard-limit Hand-limit Gradient Descut 70 15 15 20 50.00% 0 10 Symmetric bard-limit Linear Gradient Descut 70 15 15 20 60.00% 0 10 Symmetric bard-limit Hape-big Linear 15 15 15 20 60.00% 0 10 Symmetric bard-limit Hyper-big Hyper-big 15 15 15 20 60.00% 0 10 Symmetric bard-limit Hyper-big Hyper-big 15 15 15 20 60.00% 0 10 Hard-limit Hard-limit Hard-limit Hard-limit Symmetric bard-limit 50.00% 0 10.00% 0 10 Hard-limit Hard-limit Hard-limit Hard-limit 10 15 15 20 60.00% 0 10 Libear Symmetric bard-limit Symmetric bard-limit Symmetric bard-limit Symmetric bard-limit Sy | Leaves_3 | \vdash | Hyperbolic tangent sigmoid | None | Gradient Descent | 20 | 15 | 15 | 20 | 0.00% | | | 0.00% | 0 | 0 |
| 10 Symmetric hard-limit Linear Gradient Descent 70 15 15 20 0.00% 0 10 Symmetric hard-limit Expeginded Gradient Descent 70 15 15 20 0.00% 0 10 Symmetric hard-limit Symmetric bard-limit Symmetric bard-limit 15 15 20 0.00% 0 10 Symmetric bard-limit Bard-limit Bard-limit Bard-limit 15 15 20 0.00% 0 10 Hard-limit Linear Stochastic Approximation to Gradient Descent 70 15 15 20 0.00% 0 10 Hard-limit Linear Stochastic Approximation to Gradient Descent 70 15 15 20 0.00% 0 10 Hard-limit Stochastic Approximation to Gradient Descent 70 15 20 0.00% 0 10 Hard-limit Stochastic Approximation to Gradient Descent 70 15 15 20 0.00% | Leaves_3 | \vdash | Symmetric hard-limit | Hard-limit | Gradient Descent | 20 | 15 | 15 | 20 | 20.00% | | | %00.0 | 0 | 0 |
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| 10 Symmetric hard-limit Hard-limit Stochastic Approximation to Gradient Descent 70 15 20 50.00% 0 10 Symmetric hard-limit Linear Stochastic Approximation to Gradient Descent 70 15 20 100.00% 0 10 Symmetric hard-limit Log-sigmoid Stochastic Approximation to Gradient Descent 70 15 20 50.00% 0 10 Symmetric hard-limit Symmetric hard-limit Stochastic Approximation to Gradient Descent 70 15 20 50.00% 0 10 Symmetric hard-limit Symmetric hard-limit None Stochastic Approximation to Gradient Descent 70 15 20 50.00% 0 10 Symmetric hard-limit None Stochastic Approximation to Gradient Descent 70 15 20 50.00% 0 | Leaves_3 | | Hyperbolic tangent sigmoid | None | Stochastic Approximation to Gradient Descent | | 15 | 15 | 20 | %00.0 | 0 | | %00.0 | 0 | 0 |
| 10 Symmetric hard-limit Linear Stochastic Approximation to Gradient Descent 70 15 20 100.00% 0 10 Symmetric hard-limit Log-sigmoid Stochastic Approximation to Gradient Descent 70 15 15 20 50.00% 0 10 Symmetric hard-limit Hyperbolic tangent sigmoid Stochastic Approximation to Gradient Descent 70 15 15 20 50.00% 0 10 Symmetric hard-limit Symmetric hard-limit Stochastic Approximation to Gradient Descent 70 15 15 20 50.00% 0 10 Symmetric hard-limit None Stochastic Approximation to Gradient Descent 70 15 15 20 50.00% 0 | Leaves_3 | | Symmetric hard-limit | Hard-limit | Stochastic Approximation to Gradient Descent | | 15 | 15 | 20 | 20.00% | 0 | | 0.00% | 0 | 0 |
| 10 Symmetric hard-limit Log-sigmoid Stochastic Approximation to Gradient Descent 70 15 20 50.00% 0 10 Symmetric hard-limit Hyperbolic tangent sigmoid Stochastic Approximation to Gradient Descent 70 15 15 20 50.00% 0 10 Symmetric hard-limit Symmetric hard-limit Stochastic Approximation to Gradient Descent 70 15 15 20 50.00% 0 10 Symmetric hard-limit None Stochastic Approximation to Gradient Descent 70 15 15 20 50.00% 0 | Leaves_3 | - | Symmetric hard-limit | Linear | Stochastic Approximation to Gradient Descent | | 15 | 15 | 20 | 100.00% | | | 0.00% | 0 | 0 |
| Symmetric hard-limit Hyperbolic tangent sigmoid Stochastic Approximation to Gradient Descent 70 15 15 20 50.00% 0 Symmetric hard-limit Symmetric hard-limit Symmetric hard-limit Symmetric hard-limit None Symmetric hard-limit N | Leaves_3 | | Symmetric hard-limit | Log-sigmoid | Stochastic Approximation to Gradient Descent | \dashv | 15 | 12 | 20 | 20.00% | | | 0.00% | 0 | 0 |
| 10 Symmetric hard-limit Symmetric hard-limit Stochastic Approximation to Gradient Descent 70 15 15 20 50.00% 0 10 Symmetric hard-limit None Stochastic Approximation to Gradient Descent 70 15 15 20 50.00% 0 | Leaves_3 | \rightarrow | Symmetric hard-limit | Hyperbolic tangent sigmoid | Stochastic Approximation to Gradient Descent | \dashv | 15 | 15 | 20 | 20.00% | | | %00.0 | 0 | 0 |
| 10 Symmetric hard-limit None Stochastic Approximation to Gradient Descent 70 15 15 20 | Leaves_3 | _ | Symmetric hard-limit | Symmetric hard-limit | Stochastic Approximation to Gradient Descent | | 15 | 15 | 20 | 50.00% | | | 0.00% | 0 | 0 |
| | Leaves_5 | | Symmetric hard-limit | None | Stochastic Approximation to Gradient Descent | - | 15 | 15 | 20 | 20.00% | 0 | 0 | 0.00% | 0 | 0 |