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Artificial Neural Networks application in the identification of three species of *Rollinia* (Annonaceae)

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Artificial neural networks (ANN) are capable of modelling functional relations between both dependent and independent variables. In this work, we propose the application of ANN as a complementary method of botanical identification which uses vegetative characters. In order to complete this objective, the development of a multilayer neural model to identification for three species of the genus *Rollinia* (Annonaceae) is presented.

Key words: Annonaceae, Artificial Neural Networks, multilayer neural model, *Rollinia*

Introduction

Parallel calculation and neural networks are new computing paradigms that are becoming increasingly appealing among scientists interested in computer and artificial intelligence. The key element of these paradigms is a novel computational structure composed of a large number of highly interconnected neurons working in parallel. Therefore, many operations can be performed simultaneously as opposed to traditional serial processing, in which computations were performed sequentially. Artificial Neural Networks (ANN) methods were introduced as alternative calculation structures, for the purpose of reproducing the functions of the human brain (Castillo *et al*. 1998). The brain basically learns from experience. Neural networks are sometimes called machine learning algorithms. The strengths of the connections between neurons are stored as a weight-value for a given specific connection. The system acquires new knowledge by adjusting the weights of these connections (Klerfors & Huston 1998).

Neural networks (NN) as an analytic tool allow data to be analysed in order to discover and model the functional relationships among the recorded variables (Rzempoluck 1997). The current research effort in neural networks has attracted researchers trained in engineering, physics, mathematics, neuroscience, biology, computer science, and psychology (Lippmann 1987).

The identification of taxa plays an important role in botanical taxonomy, and it is an essential prerequisite in several research areas.

The use of diagnostic keys for the identification of plants is widespread among botanists. Currently there exists a great variety of diagnostic keys made with computers. As for flowering plants, the keys are generally based on features of flowers and/or fruits. The lack of reproductive structures is, therefore, a limiting factor in the identification of specimens. In ecological and botanical studies it is generally important to be able to recognise the species *in situ*, and specimens with flowers and/or fruit are not always available. It is often difficult to identify sterile specimens with the traditional method of diagnostic keys.

Facing this problem, we propose that the properties of Neural Networks would allow them to be used in the identification, given the fact that they are capable of discovering not directly apparent relations between the variables, and thus, they give meaning to incomplete data.

In order to evaluate the power of this method, the following three Argentinean species of *Rollinia* were selected: *R. emarginata, R. salicifolia* and *R. rugulosa*. These species, described by Schlechtendal (1835) from Brazil, are found in the forests of NE Argentina. Souren (1983) and Maas *et al*. (1992) reduced *R. salicifolia* and *R. rugulosa* into the synonymy of *R. emarginata*. However, Záchia and Irgang (1996) maintained them as distinct species. Záchia and Tressens (1999) added new information, which reinforces the reinstallation of *R. salicifolia*.

In the present work, the application of Artificial Neural Networks is proposed as a complementary method of botanical identification and, as a case study, is employed to separate the three above-mentioned species of *Rollinia*, using vegetative characters.

Materials and methods

Artificial Neural Networks

The type of Artificial Neural Network implemented is a Multilayer Perceptron (MLP), feed-forward, error propagation network. Multilayer perceptrons are feed-forward networks with one or more layers of nodes between the input units and the output nodes. These additional layers contain hidden units or nodes that are neither directly connected to the input nor to the output nodes (Lippmann 1987, Castillo *et al*. 1998).

The error back-propagation or simply back-propagation is an algorithm that is commonly used to train neural networks (Rzempoluck 1997). It is an iterative gradient algorithm designed to minimise the mean square error between the actual output of a MLP and the desired output. It requires differentiable activation functions (Lippmann 1987). The term feed-forward refers to the manner in which information is propagated through the network (Rzempoluck 1997).

In this work, the program NNDT was used, where the MLP networks are trained with the Levenberg-Marquardt method. This method minimises the squares of the residuals (differences between desired outputs and network outputs) by modifying the network weights. The parameter λ determines the weighting of the searching methods (Gauss-Newton and the steepest descent methods). The first method dominates when λ is low (close to zero) while the second method dominates when λ is high (Saxén 1995).

In supervised learning, a measure of the quality may be given in terms of some standard error measures as: sum of square errors (SSQ) (Eq. 1) and root mean square error (RMS) (Eq. 2) (Castillo *et al*. 1998).

$$\mathrm{SSQ} = \sum_{p=1}^{r} \left\| b_p - \overline{b_p} \right\|^2 \quad (1)$$

$$\mathrm{RMS} = \sqrt{\frac{\sum_{p=1}^{r} \left\| b_p - \overline{b_p} \right\|^2}{r}} \quad (2)$$

where $\overline{b_p}$ = network output for input vector, b_p =

desired output for input vector, and r = number of residuals.

Examples

Each one of the studied leaves constitutes a pattern for the MLP. The measurements were always carried out for mature leaves located on the middle or distal parts of the branches. Due to the marked difference in size of the proximal leaves (first and/or second leaf at the base of the branch), we did not include them in the measurements. The number of the patterns reserved for training and testing is summarised in Table 1.

Network structures

The network was organised with as many input nodes as independent variables, and with as many output nodes as dependent variables (Rzempoluck 1997). To be able to define the input nodes it was necessary to previously select the vegetative characters with a taxonomic value.

Each input node corresponds to a single attribute. The value of an attribute is the input to the network. The input nodes were the following: leaf blade length (LonLam), leaf blade width (LatLam), petiole length (PecLam), number of secondary veins (Nven), gap between the centermost two secondary veins (InVen1 and InVen2; two opposite or subopposite intervals were considered on each leaf). The measurements were expressed in millimetres. The established output nodes were *R. salicifolia, R. emarginata* and *R. rugulosa*.

In the training mode the following assignation took place: code 1 for the output variable, indicating the taxon is positively identified; and code 0 for the rest of the output variables.

Data files

The files for training and testing of the data were organised in the same fashion, where a row of the matrix contains an example of the relationship that the ANN has to learn or check. The training data and the testing data were kept in separate files.

The data used for training and validating were obtained from fertile herbarium specimens, which were reliably identified. These were selected to make sure that the quality of the results would be as good as possible.

We developed two kinds of validation sets. One of them consisted of measurements of fertile herbarium specimens and it was "validation set". Due to the small size of the validation set (Table 1), we developed a "caricature set" consisting of the following steps: For each species (1) determine the minimum and maximum values of each input variable used to train the network, (2) consider all combinations of minimum and maximum values of input parameters. We obtained 64 combinations for each species.

Output files

For every MLP model ".log" and ".out" files were created. The ".log" file contains information about real time (from a computer clock), iteration number, sum squared quadratic error (SSQ), root mean squared error (RMS) (Castillo *et al*. 1998), and Marquardt parameter (Saxén 1995). The ".out" file contains information about input signals, desired output signals, network output signals, and internal node activations.

Activation functions and parameters

The following activation function and different parameters, which determine the learning process, were defined:

— "Sigmoidal from 0 to 1" (Castillo *et al*. 1998) was selected as an activation function.

Table 1. Number of patterns reserved for training and validating for each of the *Rollinia* species.

R. salicifolia		*R. emarginata*		*R. rugulosa*	
Train	Validate	Train	Validate	Train	Validate
33	5	44	8	40	9

— The maximum number of training events was set to 2500.
— In each one of the training sessions the weights, biases and initial states were set with pseudorandom numbers uniformly distributed in the range $[-\alpha, \alpha]$. Although a separate initialisation range can be given for each layer (Saxén 1995), in this work the α value is the same for all layers of weights (Table 2). In many cases the initial values are important in determining the length and efficiency of the training.
— In order to obtain more exact results the "analytical derivations" option was activated. These derivations were obtained from the Jacobian matrix calculation (Saxén 1995).

Training and validating neural networks models

The program executes a learning algorithm with the aim of minimizing the differences between the proposed values and the ones obtained from the model (error signal). When the error signal does not improve in terms of the RMS, the learning process stops.

Table 2. Configurations of proposed neural networks models. Topology specifies the number of nodes of the first layer, the hidden layers and the output layer, which are separated colons. The numbers in the columns "Seed" and "α" represent the values used to initialised weights and α parameter respectively. Models that could not be improved are indicated with asterisks.

Models	Topology	Seed	α
Mod1	6:5:3	0	0.001
Mod2	6:5:3	10	0.01
Mod3	6:5:3	20	0.01*
Mod4	6:5:3	30	0.01
Mod5	6:5:3	50	0.001
Mod6	6:5:3	50	0.01*
Mod7	6:4:3	0	0.001
Mod8	6:4:3	10	0.01
Mod9	6:4:3	20	0.01*
Mod10	6:4:3	30	0.01
Mod11	6:4:3	50	0.001
Mod12	6:4:3	50	0.01

Analysis of neural models

The following analyses were carried out:

— For each convergent models three graphs were made: (1) progress in terms of RMS error for the last training period; (2) observed values with respect to predicted network values; (3) weight values.
— A comparative analysis between both measured and predicted values of the output nodes RS, RE and RR was made for every one of the patterns.

Specimens examined

Rollinia emarginata. — **Argentina**. Corrientes: Dep. Capital, Perichón, 31.X.1975 *Anzótegui et Schinini 278* (CTES). Dep. San Cosme, Paso de la Patria, 19.XI.1971 *Tressens et al. 146* (CTES). Dep. San Luis del Palmar, Ea. Garabatá, 18 km SE de S.L. del Palmar y 3 km S de ruta 5, 2.XI.1975 *Cristóbal et al. 1371* (CTES); 35 km SE de S.L. del Palmar, ruta 5, 2.XI.1975 *Cristóbal et al. 1414* (CTES). Dep. Ituzaingó, Isla Apipé Grande, Puerto San Antonio, 8.XII.1973 *Krapovickas et al. 23934* (CTES). Dep. Empedrado, Estancia "Las Tres Marías", 12.X.1979 *Pedersen 12487* (CTES); Empedrado, Mansión de Inviernom, 20.IV.1972 *Carnevali 3039* (CTES). Dep. Concepción, Tabay, 1.XI.1965 *Krapovickas et Cristóbal 11677* (CTES). Dep. Santo Tomé, Ea. Bertrán (Infrán Cué), 23 km SW de Virasoro, 7.IV.1992 *Tressens et al. 4012* (CTES). **Paraguay**. Concepción: prope Concepción, IX.1901–1902 *Hassler 7294* (G, NY, S); prope Concepcion, IX.1901–1902 *Hassler 7407* (Isotipo de *Rollinia longipetala* R.E. Fries, NY). Cordillera: prope Nueva Columbia, 18.XI.1978 *Bernardi 18803* (G); pr. San Bernardino, VIII.1895 *Hassler 806* (G, K); San Bernardino, X.1915 *Hassler 1494* (G); San Bernardino, XI.1898–1899 *Hassler 3523* (BM, G, K, NY); in regione lacus Ypacaraí, IX.1913 *Hassler 12276* (C, K, Z). Guairá: Villarrica, XI.1931 *Jörgensen 3434* (NY, S). Caazapá: ad viam de Artigas 10 km ante Yuty, 15.XI.1978 *Bernardi 18678* (G). Paraguarí: Paraguarí, III.1881 *Balansa 3268* (G); Cordillera de Altos, IX.1902 *Fiebrig 180* (G); prope Cerro-Hu, X.1885–1895 *Hassler 1215* (BM, G); prope Paraguay, XII.1900 *Hassler 6669* (G); Paraguarí, 7.VIII.1893 *Malme 874* (S); Région des Cerros, Nord Paraguarí, 25.III.1983 *Stutz 1545* (G). Central: environs de l'Assomption, 1875 *Balansa 2296* (K); Centurión, X.1908–1909 Asunción, 11.VII.1893 *Lindman A.1671* (S); Asunción, Recoleta, 4.X.1893 *Lindman A.2177* (S); near Asunción, XI–XII.1888–1890 *Morong 99* (G, K). Ñeembucú: Curupayty, Humaitá, 9.XI.1978 *Bernardi 18424* (G). Canindeyú: pr. Igatimí, XI.1898–1899 *Hassler 5482* (G).

Rollinia salicifolia. — **Argentina**. Corrientes: Dep. Ituzaingó, ruta 38 y río Aguapey, 7.I.1985 *Tressens et al. 3003* (CTES). Dep. Santo Tomé, Ruta 38, 17 km NW de ruta 14, 7.XII.1980 *Tressens 1223* (CTES); Forestadora Caabí Porá S.A., Ea. Timbauva, 9.VI.1994 *Tressens et al. 5057* (CTES); Colonia Garabí, 3.XII.1970 *Krapovickas et al. 17025* (CTES). Dep. Alvear, ruta 40 y bañado Cuay Chico, 11.III.1982 *Tressens et al. 1986* (CTES). **Paraguay**. Alto Paraná: Colonia Mayntzhusen, 1909–1910 *Fiebrig 5396* (G, K). Canendiyu: prope Igatimí, Sierra Maracayú, X.1898–1899 *Hassler 4791* (BM, G); In campo Igatimí, Sierra Maracayú, X.1898–1899 *Hassler 5202* (Sintipos de *Rollinia intermedia* R.E. Fries, BM, NY). Central: Villa Elisa, *Pedersen 4209* (C). Cordillera: in regione lacus Ypacaray, IX.1913 *Hassler 12275* (BM, K, G, NY, S, Z); in regione lacus Ypacaraí, San Bernardino, X.1913 *Hassler 12305* (BM); San Bernardino, 3.XI.1950 *Rojas 14313* (GB); Camino Gruta, San Bernardino, 18.IX.1945 *Teague 228* (BM). Guairá: Santa Barbara, près de Villa Rica, 26.II.1876 *Balansa 2297* (G); Villarrica, *Jörgensen 3433* (NY). Paraguarí: circa La Rosada, Ybicuí, 17.X.1978 *Bernardi 18085* (G); La Rosada, Ybicuí, 17.X.1978 *Bernardi 18088* (G); in silvis pr. Cord. de Altos, X.1885–1895 *Hassler 1720* (holotype of *Rollinia longifolia* A.St.-Hil var. *paraguariensis* Chodat, G); Cordillera de Altos, XI.1898–1899, *Hassler 3475* (Lectotype of *Rollinia intermedia* R.E. Fries, G). San Pedro: Alto Paraguay, Primavera, 5.XI.1955 *Woolston 608* (C, NY).

Rollinia rugulosa. — **Argentina**. Corrientes: Dep. Ituzaingó, río Aguapey y ruta 38, 4.XII.1980 *Tressens 1174 A* (CTES). Dep. Santo Tomé, Ea. Timbó, 1.III.1983 *Schinini et al. 23516* (CTES). Misiones: Dep. Iguazú, Parque Nacional Iguazú, 8 km E de Pto. de las Canoas. 18.XII.1991 *Vanni et al. 2974* (CTES). Dep. Guaraní, Predio Guaraní, 25.XI.1993 *Tressens et al. 4743* (CTES); ídem, 8.IX.1994 *Schinini et al. 28737* (CTES), ídem, 2.XI.99 *Tressens et al. 6448*. Dep. San Pedro, San Pedro, monte vivero Yabotí, 480 m s.m., 17.XI.1995 *Guaglianone et al. 2902* (CTES). Salta: Dep. Orán, camino a Isla de Cañas, 10–30 km al W de ruta 50, ribera N del Río Iruya, 25.X.1991 *Novara et al. 10408* (CTES). **Bolivia**. Santa Cruz: Cordillera, 5 km N de Yatarenda, 17.IV.1977 *Krapovickas et Schinini 31491*(CTES). Tarija: El Sivingal, 10 km N de San Simón, 30.IV.1983 *Krapovickas et Schinini 39016* (CTES). **Brazil**. Paraná: Mun. União da Vitoria, Rio Iguaçu, 1.XI.1970 *Koczicki 263* (CTES); Mun. Pato Branco, Independência, 5.XI.1990 *Ribas et Giberti 312* (CTES); Mun. Curitiba, Pilarzinho, 7.II.1993 *Ribas 499* (CTES); Mun. Cerro Azul, Rio Turvo, 5.X.1977 *Hatschbach 40342* (CTES). Rio Grande do Sul: vale do Rio Ibitiria ca. 30 km NE de Vacaria, *J.C. et F.M. Lindeman et al. 9482* (CTES). Rio Grande do Sul: Santo Antonio da Patrulha, Picaca do Karaá, 21.III.1993 *Záchia 1275* (CTES).

Results

The 12 neural models are given in Table 2. Important considerations were the number of neurons and the number of layers to be used. Once the learning process had finished and the weights of the neural networks had been calculated, it was important to check the quality of the resulting MLP neural model (Table 3).

In order to select the best neural configuration of the converging models (Table 2), the values obtained from SSQ and RMS (Table 3) were placed in order from the smallest to the

Table 3. Analysis of the measures of quality in the supervised learning: sum squared quadratic error (SSQ), root mean squared error (RMS), number of iterations, and the Marquardt parameter λ during a training process.

Models	Iterations	SSQ	RMS	λ
Mod1	884	1	5.33760512683624E–02	0.00000000001
Mod2	121	9.12207500727814E–21	5.09792287942384E–12	0.000001
Mod3	1323	4.80107166506084.	0.116954122851763	10000000
Mod4	1457	9.9140165937725E–22	1.6806267140778E–12	0.000000000001
Mod5	244	1.62568460819741	6.80557130616858E–02	1000000
Mod6	138	6.67866932200278	0.137940378156412	1000000
Mod7	352	10.0920852892207	0.169565266907375	10000
Mod8	356	5.61388684605581	0.126467306519877	1000000
Mod9	978	8.75270700362818	0.157912910142977	100000
Mod10	346	3.76912548523073	0.103625524103242	100000
Mod11	413	13.1609781133353	0.193637971845804	1000000
Mod12	634	9.12960741087326E–21	5.10002720814854E–12	0.001

highest.

The analysis of the measures of quality as sum squared quadratic error (SSQ) and root mean squared error (RMS) was carried out in order to select neural models. Models "mod2.mlp", "mod4.mlp" and "mod12.mlp" seem to be the best.

If the numbers of erroneous or confusing cases and exact predictions during the training process (Table 4) are compared, three neural models can be selected as the optimum ones due to the fact that for all patterns, the species predicted by the model coincides with the proposed one.

The results provided by the validation process were taken into account for the selection of a model (Tables 5 and 6).

In Table 5, if the numbers of erroneous and uncertain are compared, "mod4.mlp" can be excluded. The other ones present similar predictions, so in selecting between them it is necessary to increase the number of test samples. In Table 6 "mod2.mlp" seems to be the best because it has fewer erroneous cases than the others. Also, it even required more iteration, the addition of a neuron to the first hidden layer (Table 2) assured the good predictability of this model. The topology of "mod2.mlp" is displayed in Fig. 1.

Table 7 presents the species that have characteristics in the corners of a six-dimensional space. This table includes those patterns where network output was equal with desired output and it excludes those where the relation between the characters' values are impossible (e.g. leaf length is less than leaf width).

It is also desirable to perform the cross-validation to obtain a measure of the predicted quality (Castillo *et al.* 1998) of the selected MLP neural model. It was carried out comparing the RMS training (RMSE) and RMS testing (RMST). During the validation process the RMSE obtained was equal to 5.09792287942572E-12, in the cross-validation using the test data (with fertile herbarium specimens measurements) the

Table 4. Analysis of the predictions provided by each convergent model during training process. Number of exact predictions (Ex), number of uncertain cases (*U*) and erroneous cases (*E*) of each of the species with respect to the rest. RR = *Rollinia rugulosa*, RE = *R. emarginata*, RS = *R. salicifolia*.

Neurals	RR					RE					RS				
Models		RS		RE			RS		RR			RR		RE	
	Ex	*U*	*E*	*U*	*E*	Ex	*U*	*E*	*U*	*E*	Ex	*U*	*E*	*U*	*E*
Mod2	40	–	–	–	–	44	–	–	–	–	33	–	–	–	–
Mod4	40	–	–	–	–	44	–	–	–	–	33	–	–	–	–
Mod12	40	–	–	–	–	44	–	–	–	–	33	–	–	–	–

Table 5. Analysis of the predictions provided by each convergent model used to validate a data set achieved from herbarium specimens. Number of exact predictions (Ex), number of uncertain cases (*U*) and erroneous cases (*E*) of each of the species with respect to the rest. RR = *Rollinia rugulosa*, RE = *R. emarginata*, RS = *R. salicifolia*.

Neurals	RR					RE					RS				
Models		RS		RE			RS		RR			RR		RE	
	Ex	*U*	*E*	*U*	*E*	Ex	*U*	*E*	*U*	*E*	Ex	*U*	*E*	*U*	*E*
Mod2	9	–	–	–	–	8	–	–	–	–	5	–	–	–	–
Mod4	7	–	2	–	–	8	–	–	–	–	5	–	–	–	–
Mod12	8	–	1	–	–	8	–	–	–	–	4	1	–	–	–

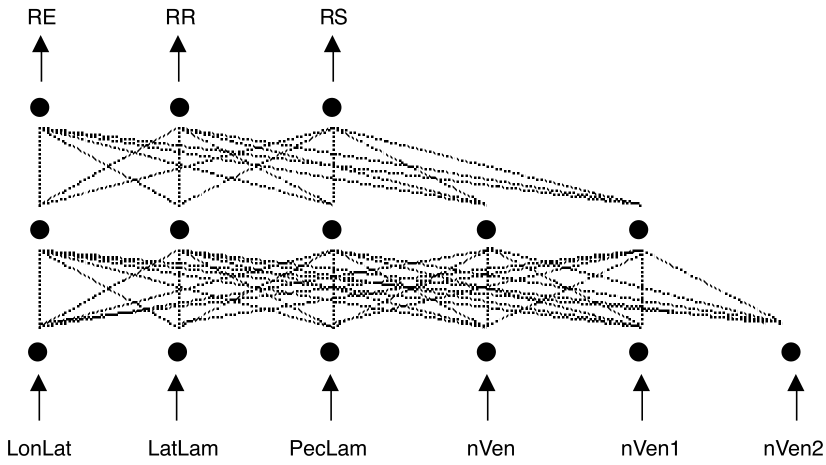

Fig. 1. Proposed topology for the selected neural model "mod2.mlp"; 6:5:3.

RMST obtained was equal to 1.11951642702488E-10, and using the "caricature set" equal to 0.590639179061818. In both analyses the training error and testing error decrease to a minimum.

Conclusions

Among the twelve proposed neural models developed to simulate the identification of *R. salicifolia*, *R. emarginata* and *R. rugulosa*, the model "mod2.mlp" was selected as the most appropriate on the basis of the following arguments:

— The values of the output nodes provided by the network matched for all of the training patterns.
— It gives the minimum number of hidden nodes and layers which, together with the activation functions, provide a convergent configuration.
— Convergence requires a minimum number of iterations to obtain a minimum number of SSQ and RMS.
— After the training process, networks predictions correspond to the desired values specified by the botanist for all three species.

The convergence models indicate that the selection of the morphological characters was adequate, which corroborated their diagnostic value.

The validation process shows a number of erroneous cases, probably due to the small test sample (Table 5). On the other hand, the amount of erroneous cases present in Table 6 could be due to the overlapping of characters' values for different species. After the analysis presented in Table 7, we propose the typical leaves for the three species (Fig. 2).

Table 6. Analysis of the predictions provided by each convergent model used to validate a "caricature set". Number of exact predictions (Ex), number of uncertain cases (*U*) and erroneous cases (*E*) of each of the species with respect to the rest. RR = *Rollinia rugulosa*, RE = *R. emarginata*, RS = *R. salicifolia*.

Neurals	RR						RE						RS					
Models		RS		RE		RS–RE		RS		RR		RS–RR		RR		RE		RR–RE
	Ex	*U*	*E*	*U*	*E*	*E*	Ex	*U*	*E*	*U*	*E*	*E*	Ex	*U*	*E*	*U*	*E*	*E*
Mod2	33	–	9	14	7	1	33	2	2	14	13	–	20	–	23	3	10	10
Mod4	30	–	8	18	8	–	21	–	–	27	16	–	12	13	28	13	11	–
Mod12	16	–	17	–	25	–	39	–	23	–	3	–	26	–	13	1	25	1

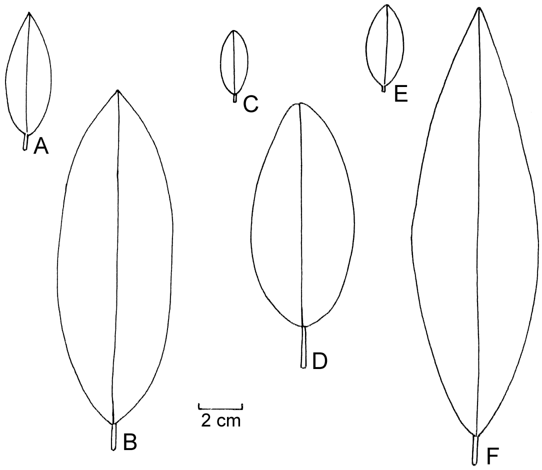

Fig. 2. Schematic representation of leaves from three species considering minimum and maximum values from Table 7 (examples in boldface). **A**–**B**: *Rollinia salicifolia*, **C**–**D**: *R. emarginata*, **E**–**F**: *R. rugulosa*. **A**, **C** and **E**: Leaves made with minimum values. **B**, **D** and **F**: Leaves made with maximum values.

The comparison of the RMS training and the RMS testing allowed checking that the selected model can generalise from the utilised training data, that is, when faced with new patterns, the model is capable of inferring to which species of *Rollinia* it corresponds.

The obtained results suggest that the type of neural network called Multilayer Perceptron (MLP) is appropriate for solving botanical identification problems. This method has the advantage of being able to discover not easily recognised associations between characters, and of making incomplete data useful. It can be used to identify specimens with only vegetative parts.

Even though the development of an optimal model requires a large process and knowledge about the appropriate methodology, once developed, an instructive document could be implemented to make it accessible to botanists in general, who would in turn gain an accurate identification tool.

Table 7. Input setting and output predictions provided by "mod2.mlp" neural model using a "caricature set" during validation process. LonLam = leaf blade length, LatLam = leaf blade width, PecLam = petiole length, Nven = number of secondary veins, InVen1 and InVen2 = gap between the centermost two secondary veins.

LonLam	LatLam	PecLam	NVen	InVen1	InVen2	Network Output/Desired
55.5	20	5	8	5.5	0	RS
55.5	20	12	19	5.5	0	RS
55.5	51	12	8	5.5	0	RS
55.5	51	12	8	5.5	25	RS
55.5	51	12	8	24	0	RS
55.5	51	12	19	24	0	RS
150	20	5	8	5.5	0	RS
150	20	5	8	24	0	RS
150	20	12	8	5.5	0	RS
150	20	12	8	5.5	25	RS
150	20	12	8	24	0	RS
150	20	12	8	24	25	RS
150	20	12	19	5.5	0	RS
150	20	12	19	5.5	25	RS
150	20	12	19	24	0	RS
150	51	12	8	5.5	0	RS
150	51	12	8	5.5	25	RS
150	51	12	8	24	0	RS
150	51	12	8	24	25	RS
150	51	12	19	5.5	0	RS
27	12	4	8	4	3	RE

Continued

Table 7. (Continued)

LonLam	LatLam	PecLam	NVen	InVen1	InVen2	Network Output/Desired
27	12	4	8	15	3	RE
27	12	18.5	8	4	3	RE
27	12	18.5	8	4	18.5	RE
27	12	18.5	8	15	3	RE
27	12	18.5	8	15	18.5	RE
27	12	18.5	16	4	3	RE
27	12	18.5	16	4	18.5	RE
27	12	18.5	16	15	18.5	RE
100	12	18.5	8	4	3	RE
100	12	18.5	8	4	18.5	RE
100	12	18.5	8	15	3	RE
100	12	18.5	8	15	18.5	RE
100	12	18.5	16	4	3	RE
100	12	18.5	16	4	18.5	RE
100	12	18.5	16	15	3	RE
100	12	18.5	16	15	18.5	RE
100	47	18.5	8	4	3	RE
100	47	18.5	8	4	18.5	RE
100	47	18.5	8	15	3	RE
100	47	18.5	8	15	18.5	RE
100	47	18.5	16	4	3	RE
100	47	18.5	16	4	18.5	RE
100	47	18.5	16	15	3	RE
100	47	18.5	16	15	18.5	RE
36	18	2	9	5	21	RR
36	18	2	9	21	5.5	RR
36	18	2	9	21	21	RR
36	18	2	25	5	5.5	RR
36	18	2	25	5	21	RR
36	18	2	25	21	5.5	RR
36	18	2	25	21	21	RR
36	58	12	25	21	5.5	RR
36	58	12	25	21	21	RR
190	18	2	9	21	5.5	RR
190	18	2	9	21	21	RR
190	18	2	25	5	5.5	RR
190	18	2	25	5	21	RR
190	18	2	25	21	5.5	RR
190	18	2	25	21	21	RR
190	18	12	25	5	21	RR
190	18	12	25	21	5.5	RR
190	18	12	25	21	21	RR
190	58	2	25	5	5.5	RR
190	58	2	25	5	21	RR
190	58	2	25	21	5.5	RR
190	58	2	25	21	21	RR
190	58	12	25	5	5.5	RR
190	58	12	25	5	21	RR
190	58	12	25	21	5.5	RR
190	58	12	25	21	21	RR

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