Asian Journal of Plant Sciences

ISSN 1682-3974

Asian Journal of Plant Sciences 3 (3): 340-343, 2004
ISSN 1682-3974

Application of an Artificial Neural Network (ANN) for the Identification of Grapevine (*Vitis vinifera* L.) Genotypes

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Abstract: Neural networks were employed to distinguish between 12 accessions of grapevine found in some viticultural zones of Anatolia. The results show that the artificial neural network succeeded in identifying the unknown variety with certainty, except in the case of Antep Razakısı and Dımışkı, which is obviously a case of synonymy. A considerable similarity between Aydın Razakısı and Çivril Razakısı also appears. Similarity was found between Buca Razakısı and Dumanlı Razakısı and the other vine accessions are clearly differentiated.

Key words: Ampelography, artificial neural networks, grapevine, *Vitis vinifera* L.

INTRODUCTION

Grapes, *Vitis vinifera* L. and other genera of the family Vitaceae, are widely distributed in the tropics and suptropics with ranges extending into the temperate regions. The definition and the identification of varieties are of considerable scientific and practical importance in modern viticulture and ampelography.

In the last years ampelographic data have been used to resolve the complex problem of the definition and identification. An important contribution to the solution of ampelographic problems has been made by the charts[1], not only for the completeness of the descriptors but also having been internationally adopted, they offer the possibility of common terminology. Recently, statistical methods such as multivariate analysis and discriminant functions have been proposed in the area of ampelographic data processing[2,3]. Other interesting perspectives come from the anlysis of isoenzymes[4-8] and of chemical compounds of phenolic nature having taxonomic value[9]. Finally, DNA marker technologies (randomly amplified polymorphic DNA, RAPDs, amplified fragment length polymorphism, AFLP) have proven to be useful tools for characterization of varieties[10-13]. Artificial neural network (ANN) has been applied in many fields of experimental science. In physics for the identification of elemental particles[14], in medicine for diagnostic purposes[15], in Electrical-Electronics Engineering for the classification of electromyographic sigmals[16], in botany for the taxonomic identification of plankton[17] and in vines for the identification of grapevine, olive and chesnut genotypes[18-20]. Moreover, the use of artificial neural networks has been shown to be extremely efficient in the field of handwriting, voice face recognition and to be particularly adapted to the resolution of problems which require the discrimination of different shapes[21].

In this study, it is determined that Artificial Neural Network could be used to present the differences or synonymy that occurs from the heterogeneity characteristic of grapevine genotypes.

MATERIALS AND METHODS

This study was carried out with 12 accessions of grapevines (Table 1) from the grapevine germplasm collection of the Ataturk Central Horticultural Research Institute, which were recently the subject of ampelographic studies[22] and characterization by the analysis of isoenzymes[8].

What is a neural network? The most simple definition of a neural network, more properly referred to as an 'artificial' neural network, is provided by the inventor of one of the first neurocomputers[19-21].

An artificial neural network (ANN) is an information processing paradigm, implemented in hardware or software that is modelled after the biological processes of the brain[16]. Most have had limited real-world application potential. The backpropagation paradigm, however, is an extremely effective learning tool that can be applied to a wide variety of problems. Backpropagation related paradigms require supervised training. This means they must be taught using a set of training data where known solutions are supplied.

Neural networks are typeically organized in layers which are made-up of a number of interconnected 'nodes' containing an 'activation function'. Patterns are presented to the network via the 'input layer', which commincates to one or more 'hidden layers' where the actual processing

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Table 1: List of the grapevine accessions used for neural network technique

Akhisar Razakısı	Antep Razakısı
Aydın Razakı	Besni
Buca Razakısı	Burdur Razakısı
Çivril Razakısı	Deliemin Razakı
Dımışkı	Dumanlı Razakı
Dülekköy Razakı	Foça Razakısı

is done via a system of weighted 'connection'[19,20]. The hidden layers are linked to an 'output layer' where the answer is output. During the 'training phase', the network's response at the output layer is compared to a supplied set of known answers (training targets). The errors are determined and backpropagated through the network in attempt to improve the network's response The nodal weight factors are adjusted by amounts determined by the training algorithm. The iterative procedure of processing inputs through the network, determining the errors and backpropagating the errors through the network to adjust the weights, constitutes the learning process. One trainind iteration is complete when all supplied training cases have been processed through the network. Iteration continues until the network's response error is kept to a minimum. The network can then be tested on new data and if this proves successful it can be used to predict the output for a given set of input values[20,21].

In total, data from 39 characteristic per vine accessions were utilised. The learning for the back-propagation artificial neural network was achieved on a Pentium-4 PC, by using the phyllometric data. The network was designed using a total of 39 inputs represented by the ampelographic parameters[22] and 12 outputs represented by the accessions under examination. Output values were 1 or 0 (true or false).

RESULTS AND DISCUSSION

Figure 1 contains the results of the recognition phase of the neural network. Each graph illustrates the network output for input represented by the phyllometric parameters of a given variety. For example, in diagram

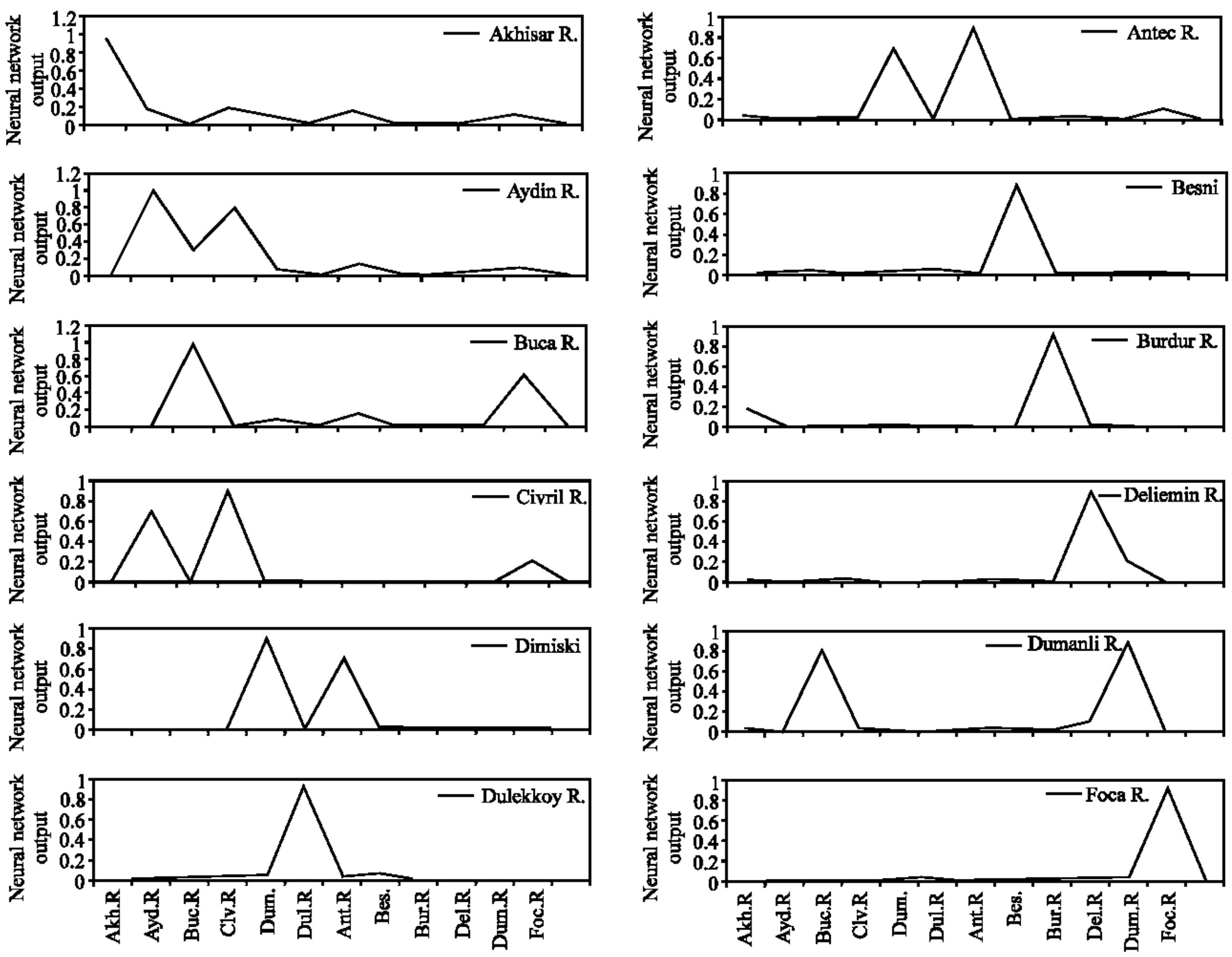

Fig. 1: Output of the neural network recognition phase

Akhisar R. Output values for the recognition test effectuated on the accession Akhisar Razakısı are reported. Each figure present in the abscissa the names of the 12 studied accessions.

Artificial neural network succeeded in identifying the unknown variety with certainly, except in the case of Antep Razakısı (Fig. 1-Antep R.) and Dımışkı (Fig. 1-Dımışkı), which is obviously a case of synonymy. A considerable similarity between Aydın Razakısı (Fig. 1-Aydın R.) and Çivril Razakısı (Fig. 1-Çivril R.) also appears.

In order to optimize the neural network activity, the number of 'hidden neurons' and the number of iterations were modified. Minimum error was reached with a network composed of 60 hidden neurons. The learning phase was carried out 10,000 iterations, at the end of which the RMS (Root Mean Squared error) was 0.065.

This parameter indicates the effectiveness of the article neural network, the smaller the value, the closer the network is to modeling the input data. The artificial neural network was tested by presenting them with inputs for which the output was known, so that the predicted and actual output was known.

It is determined that these are two clones of the same vine variety; the two different denominations are therefore considered to be synonyms. Similarity was found between Buca Razakısı (Fig. 1- Buca R.) and Dumanlı Razakısı (Fig. 1-Dumanlı R.) and the other vine accessions are clearly differentiated.

The results obtained are interesting, above all, because the use of the neural network allowed distinction of the vine accessions, in agreement with the results of studies made on the same genetic material, with ampelographic or molecular marker methods[19,20]. In addition, the experimental method can be further improved by increasing the number of ampelographic parameters to include quantifiable morphologic and physiological traits.

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