Neural Identification of Chosen Apple Pests Using Algorithm LVQ

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Abstract. The aim of this work was a neural identification of selected apple tree orchard pests in Poland. The classification was conducted on the basis of graphical information coded in the form of selected geometric characteristics of agrofags, presented on digital images. A neural classification model is presented in this paper, optimized using learning files acquired on the basis of information contained in digital photographs of pests. There has been identified 6 selected apple pests, the most commonly encountered in Polish orchards, has been addressed. In order to classify the chosen agrofags, neural networks type SOFM (Self-Organizing Feature Map) methods supported LVQ (Learning Vector Quantization) algorithms were utilized, supported by digital analysis of image techniques.

Keywords: classification of apple pests, neural modelling, computer analysis of the digital image

1 Introduction

Apples are one of the more important horticultural commodities, mass produced in Poland. Apple production, comprising roughly 70% of fruit crops (over 80% of tree fruit crops) is conducted by approximately 242 thousand specialized firms [15]. It is worth to notice that Poland is among the leading producers and exporters of apple concentrate worldwide. An important issue related to apple production is the matter of effectively protecting the plantation against pests [18][11]. Efficient plant protection is possible only after correctly identified the pests and their feeding[16][19].

Neural image analysis is a relatively new branch of information technology [27][28][2][26][21]. With increasing frequency it finds practical employment, as computer assistance for processes performed during recognition of objects displayed in graphic form, among others. In the above context, methods and techniques of extracting information coded in digital images, performed mostly on the basis of previously defined characteristic attributes, become important [17]. During

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identification, and then extracting the data embedded in digital images, an important role is played by artificial neural networks SOFM (Self-Organizing Feature Map) type, taught without supervision (unsupervision), i.e. generated using the "without teacher" technique [1][12][20]. It is worth noting that in the process of taught of neural networks new input signals providing the output of results in real time. Due to their properties, neural models more and more commonly find practical applications [25][10][17][5][6].

In this work research was conducted with the aim of assisting decision-making processes occurring during apple production [13]. With crop protection in mind, the problem of identifying 6 selected apple pests, commonly occurring in Polish orchards, was considered. Chosen graphical parameters characterizing only the geometric properties were assumed as characteristic properties allowing for identification of a given pest.

The aim of the work was to using a SOFM neural classifier and LVQ algorithm designed to recognize apple orchard pests based on digital photographs. Accordingly, a set of neural classification models was designed and constructed.

2 Materials and methods

2.1 Materials

Apple trees can be infested with numerous kinds of pests, but only a few of them occur in production orchards. The research material used in order to solve the established problem was a group of 6 pests most commonly feeding on apple orchards and posing the greatest threat to apple trees. For the purpose of capturing feeding pests, pheromone traps were utilized [8][23]. Next, a series of pictures and the binary representation of the 6 selected pests was taken (Fig. 1):

Fig. 1. The 6 selected apple pests (1…6) [24]

1) Apple bossom weevil [Anthonomus pomorum (L.)] COLEOPTERA, CURCULIONIDAE
2) Apple leaf sucker [Cacopsylla mali (Schmidb.)] HEMIPTERA, PSYLLIDA
3) Apple moth [Yponomeuta malinellus (Zell.)] LEPIDOPTERA, GRACILLARIIDAE
4) Codling moth [Cydia pomonella (L.)] LEPIDOPTERA, TORTRICIDAE
5) Apple clearwing [Synanthedon myopaeformis (Borkh.)] LEPIDOPTERA, SESIIDAE
6) Apple aphid [Aphis pomi (De Geer)] HEMIPTERA, APHIDIDAE

2.2 Methods

The pattern of conduct is shown (Fig. 2.):

Fig. 2. The pattern of conduct

For the purpose of constructing the neural classification model Kohonen type, the neural network simulator implemented in the Statistica v.10 suite was used

A neural LVQ (Learning Vector Quantization) model

Neural networks type LVQ (introduced by Tuevo Kohonen) are modeled on the typological properties of the human brain, in particular in cortex and is an example of neural networks teaching with forcing [3]. Because of their unsupervised learning methods, such networks are also known as SOFMs (Self-Organizing Feature Maps). By transforming output values (in the course of post processing), LVQ networks produce a nominal output variable which, for better perception, is commonly presented in the form of a two-dimensional grid of nodes. Each value of the variable represents a single class with its corresponding adequate neurons found in the network output layer. The link between a neuron and a given class is indicated by the a priori prescribed label containing class name. Each time a taught network is used and an input signal appears, a winning neuron (one with the highest level of activation and the best match between the weight vector and the input vector presented to the network) is designated. The structure allows for defining the output layer of the LVQ network in the form of a two-dimensional "map" which models a multidimensional set of input data [3].

The structure of a LVQ network is usually defined as a two-layer network. It comprises an input and two-dimensional output layer in which the data presented on the input are processed. The output layer (Kohonen layer) is made up solely of radial neurons which are seen as nodes in the two-dimensional grid (Fig. 3).

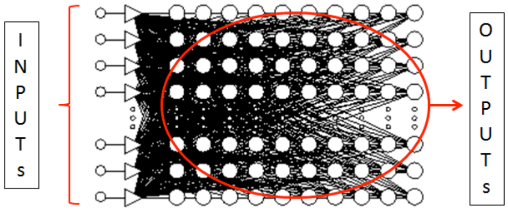

Fig. 3. A sample structure of LVQ type artificial neural network with Kohonen output layer

Learning LVQ

LVQ is essentially a controlled version of the Kohonen learning algorithm. In the basic version of the LVQ network, the distance between the input vector and the weights of the i - weight of this neuron is calculated for each $i = 1, \ldots, m$

$$d_i = \|w_i - x\| = \sqrt{\sum_{j=1}^{N} \left(w_{ij} - w_j\right)^2} \tag{1}$$

where:

w_i - vector weights,
x - input vector.

The weight of the winning neuron is modified according to the pattern:

$$W' = \begin{cases} w + \propto, & (x - w) \text{ if the neuron belongs to the correct class} \\ w - \gamma, & (x - w) \text{if the neuron does NOT belong to the correct cl} \end{cases} \tag{2}$$

where:

w' – weight of winning neuron.

Learning file design

The most important stage of generating ANN (Artificial Neural Network) is creating proper learning files that contain coded data, including empirical data [3][4]. Therefore, numerical input variables and a nominal output variable were specified that were a consequence of the established scientific problem structure. As a group of representative input parameters, a file of selected 5 standard shape coefficients. These measurements mostly regard the description of objects presented on binary images and are adequate for the insects displayed in the photographs [22][20][2][3]. As the 5 input variables for the created neural network, the following representative characteristics were accepted:

[1] dimensionless shape factor marked in the learning data file designated table 1 as **[1]**:

$$W_b = \frac{L^2}{4\pi S} \tag{3}$$

where:

L – stands for circumference of the object,

S - stands for surface area of the object.

[2] factor of circulation R_{C1} marked in the learning data file (it determines the diameter of circle with a circumference equal to the circumference of the analyzed object) designated table 1as **[2]**:

$$R_{C1} = 2 \cdot \sqrt{\frac{S}{\pi}} \tag{4}$$

where:

S - stands for surface area of the object

[3] factor of circulation R_{C2} marked in the learning data file (it determines the diameter of circle of which field is equal for field of the analyzed object) designated table 1 as **[3]**:

$$R_{C2} = \frac{L}{\pi} \tag{5}$$

where:

L - stands for circumference of the object

[4] Malinowska factor marked in the learning data file designated table 1 as **[4]**:

$$R_M = \frac{L}{2 \cdot \sqrt{\pi \cdot S}} - 1 \tag{6}$$

where:

L - stands for circumference of the object
S - stands for surface area of the object

[5] field S marked in the learning data file whose measurement refers to counting pixels belonging to the area of interest designated in table 1 as **[5]**. This feature is sensitive to errors that resulted from the improper binarization. On the other hand, however, it is insensitive to translations and rotations.

As one variable output, designed for labeling response LVQ network, adds was adopted:

- 6-state variable with nominal values of: **1)** *Anthonomus pomorum*, **2)** *Cacopsylla mali*, **3)** *Yponomeuta malinellus*, **4)** *Cydia pomonella*, **5)** *Synanthedon myopaeformis*, **6)** *Aphis pomi*.

Using the acquired research material and applying image analysis methods, a data (learning) file was generated that contained 2600 cases. The created file was conventionally divided into:

- training file, containing 1300 cases,
- validating file, containing 650 cases,
- testing file, containing 650 cases.

The structure of the learning file comprised 5 uninterrupted, numerical input variables and one nominal (6-state) output variable necessary in the process of labeling Kohonen neural network model using LVQ algorithm. A structure and fragment of the learning file is presented (Tab. 1.):

Table 1. Fragment of learning file

Input variables						Output variable
Case number	W_b **[1]**	R_{C1} **[2]**	R_{C2} **[3]**	R_M **[4]**	S **[5]**	Pests (Fig. 1) (**1…6**).
…	…	…	…	…	…	…
311	14.309	0.890	244.066	4.166	2995	**1)**
312	12.161	1.677	333.998	0.072	1298	**3)**
313	17.311	0.578	258.126	3.324	3367	**3)**
314	10.121	1.122	354.123	0.067	1378	**5)**
315	18.099	1.123	367.990	0.083	1265	**6)**
316	17.359	0.777	278.066	3.166	3122	**5)**
317	17.171	0.574	280.948	3.082	3267	**4)**
318	17.359	0.786	244.066	3.166	3123	**1)**
…	…	…	…	…	…	**…**
2600	16.22	0.589	282.933	3.182	3444	**4)**

For designing the neural models, an artificial neural network simulator, implemented in the statistical package Statistica v.10 suite, was utilized. Creating the neural models was conducted in two stages. Initially the efficient option assisting neural network designing ("Automatic network designer"), implemented in the statistical information system. This tool allowed for automation and simplification of initial network set searching procedures that would best model the studied process. During the second stage, the "User network designer" tool was used. This tool was utilized repeatedly, modifying initial parameter-related settings, learning algorithms and the network structure itself.

3 Results and discussion

The author has constructed teaching file containing 1600 learning cases. The adopted representative variables comprised such 5 distinctive input parameters (Tab. 1.) The "Pests" parameter was not used in generating the Kohonen networks (unsupervised learning). The variable was used to label the topological Kohonen map using LVQ method optimization.

The generated topology map was optimized with the use of Kohonen's algorithm implemented in Statistica v.10. The learning process was carried out conventionally in two stages. The preliminary learning stage involved using a high value of initial learning ratio (between 0.9 and 0.1) together with a broad neighbourhood range (between 2 and 1). Learning was carried out during only 200 cycles. The second stage involved use of a low value of learning ratio (between 0.1. and 0.01) together with a limited neighbourhood (equal to 0) over 10000 epochs. The generated Kohonen topology map (10×10) had a quadratic structure consisting of 100 nodes (Fig. 4).

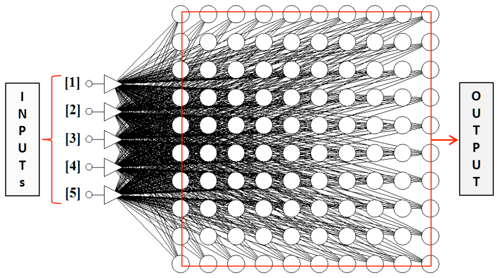

Fig. 4. Generated topology Kohonen map

The quality of neural model for the purpose of classification issues is typically fixed for the test subset. The quality for the classification networks is contractually fixed through the percentage of consistent classifications. The selected network achieved a quality level of 0.899833. In this context the generated network should be qualified as appropriate.

Commonly recognized measure of the qualitative estimation of the ANN is an error value *RMS* (*Root Mean Squared*) generated by the network model during operation on a file not used in the learning process of the network (e.g., the testing file). This measure is defined as a total error made by the network on a data file (training, testing and validation data). It is derived from the formula:

$$RMS = \sqrt{\frac{\sum_{i=1}^{n}(y_i - z_i)^2}{n}} \quad (7)$$

(7)

where:

n - number of cases,
y_i - real values,
z_i - values determined with the use of the network.

The *RMS* error was respectively:

- 0.139 for the training file,
- 0.122 for the validation file,
- 0.123 for the testing file.

The obtained approximate and small value of the *RMS* error implies appropriate classification properties of the generated neural model. The standard classification statistics for the testing file are given in table 2.

Table 2. Classification statistics

	[1]	[2]	[3]	[4]	[5]
Total	520	520	520	520	520
Correct	500	508	509	504	490
Incorrect	20	12	11	16	19
Unknown	0	0	0	0	11

4 Conclusions

The following conclusions can be derived from the completed empirical studies, computer simulations of LVQ neural networks and analysis of the results:

1. The results acquired confirm the hypothesis that artificial neural networks type SOFM using LVQ algorithm and image analysis techniques are efficient tools assisting in the quick and reliable identification of pests feeding on apple tree orchards.

2. The best classification properties were found in the SOFM network model, whose *RMS* error for the training file was 0.139, for the validating file: 0.122, and for the test file: 0.123.

3. The non-parametric classification technique performed by the LVQ method turned out to be well-suited for the quality-based identification of apple pests with the use of the graphic information encoded in digital photographs.
4. The study conducted indicates that the designed model is a useful instrument that efficiently assists in the decision-making processes occurring during apple production.

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