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Article

Identification of Characteristic Parameters in Seed Yielding of Selected Varieties of Industrial Hemp (*Cannabis sativa* L.) Using Artificial Intelligence Methods

Dominika Sieracka [1], Maciej Zaborowicz [2] and Jakub Frankowski [1,*]

[1] Department of Bioeconomy, Institute of Natural Fibers and Medicinal Plants—National Research Institute, Wojska Polskiego 71B, 60-630 Poznan, Poland; dominika.sieracka@iwnirz.pl
[2] Department of Biosystems Engineering, Poznan University of Life Sciences, Wojska Polskiego 28, 60-637 Poznan, Poland; maciej.zaborowicz@up.poznan.pl
* Correspondence: jakub.frankowski@iwnirz.pl

Abstract: Currently, there is a significant increase in interest in hemp cultivation and hemp products around the world. The hemp industry is a strongly developing branch of the economies of many countries. Short-term forecasting of the hemp seed and grain yield will provide growers and processors with information useful to plan the demand for employees, technical facilities (including appropriately sized drying houses and crop cleaning lines) and means of transport. This will help to optimize inputs and, as a result, increase the income from cultivation. One of the methods of yield prediction is the use of artificial intelligence (AI) methods. Neural modeling proved to be useful in predicting the yield of many plants, which is why work was undertaken to use it also to predict hemp yield. The research was carried out on selected, popular hemp varieties—Białobrzeskie and Henola. Their aim was to identify characteristic factors: climatic, cultivation and agrotechnical, affecting the size and quality of the yield. The collected data allowed the generation of Artificial Neural Network (ANN) models. It has been shown that based on a set of characteristics obtained during the cultivation process, it is possible to create a predictive neural model. Modeling using one output variable, which is seed yield, can be used in short-time prediction of industrial crops, which are gaining more and more importance.

Keywords: neural modeling; artificial neural networks; sensitivity analysis; hemp cultivation; seed material

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1. Introduction

Due to their properties, Artificial Neural Networks (ANN) perform identification and prediction tasks similarly to the human brain; however, the use of computer methods eliminates subjective analysis and evaluation, which cannot be ruled out when performing similar analyses by a human. ANN are increasingly used in many fields of science, including mechanical and agricultural engineering, and connected problems, especially related to the scope of classification and prediction [1–3]. In the broadly understood agricultural industry, they were used, e.g., in research on starch content in potatoes [4], optimization of methods and parameters of drying willow [5], determination of the moment when crop irrigation should start [6], or the possibility of using unsold cut flowers of the most popular species for energy purposes [7].

For the efficient operation of farms and agricultural enterprises, in addition to the highest possible yield, it is also important to reduce losses associated with the storage of manufactured products. This maximizes the production volume of agricultural crops. This topic also interested scientists using Artificial Intelligence (AI) methods in their research [8,9]. The research that can be used in practice is the work on the possibility of using computer image analysis methods and neural modeling in the process of qualitative assessment of greenhouse tomatoes. Works were carried out by Zaborowicz and his research team. Generated neural model can do this by implementing into a computer system [10].

The hemp industry has been developing very strongly in recent years, and the area of hemp cultivation is constantly growing [11]. In Europe, the number of hectares of hemp plantations increased by 70% between 2013 and 2018 [12]. Hence, in recent years there has also been a lot of interesting research in the field of AI conducted on hemp. The use of ANN was undertaken to assess the effect of different types and concentrations of carbohydrate sources and the potency of nutrients on seed germination rates and morphological features of hemp seedlings grown in vitro [13]. AI methods have been used to detect and classify hemp diseases [14,15]. Mathematical models have also been developed to predict the dry density, compressive strength and thermal conductivity of hemp-based biocomposites using the AI-based gene expression programming (GEP) technique [16].

There have also been many works successfully using ANN in research on forecasting the yield of agricultural plants [17–19]. However, there is currently no objective and easy-to-use system for predicting the yield of industrial hemp seeds. So far, yields have been predicted using average amounts of seeds harvested in previous years, taking into account, e.g., variety or form of harvest. Cultivation of hemp, especially for seed purposes, is difficult, time-consuming and labor intensive. It is also burdened with a high risk of failure, but the market demand for hemp products, and thus for high-quality seed material, is growing dynamically. This indicates the need to undertake scientific research aimed at developing a new, effective method of seed yield prediction of selected industrial hemp varieties.

This topic was raised by Frankowski's team. Data collected from experimental plots were used to study the effect of sowing density and fertilization on the yield of Henola hemp seeds and straw. ANN studies were a supplement to standard research and statistical methods [20]. The results achieved are reported in the discussion section of this article. The achieved results proved to be promising. This prompted researchers to continue to develop them. Analyzing a much larger amount of data coming not from experimental plots but from hemp seed plantations, an attempt was made to identify the cultivation parameters characteristic of the seed yield of selected industrial hemp varieties. The aim of the research was to answer the question whether the ANN model can effectively predict the yield of industrial hemp seeds, based on the information obtained during the cultivation process. The result of the research was the generation of six ANN models. Thanks to the sensitivity analysis of the variables of the created neural models, it was possible to determine the indicators that are most important for their operation. The conducted research allowed the formulation of the main conclusion: based on the set of characteristics obtained during the agrotechnical process, it is possible to create a predictive neural model for assessing the yield of industrial hemp seeds.

2. Materials and Methods

2.1. Research Material

In order to generate training sets, information collected from seed plantations managed in Poland in 2019 and 2020 for Białobrzeskie and Henola varieties was used. The varieties to be tested were selected due to their very high popularity both in Europe and in the world, and the largest number of plantations and batches from them, among other varieties contracted by the Institute of Natural Fibers and Medicinal Plants—National Research Institute (INF&MP-NRI). The Białobrzeskie variety is a monoecious, stabilized variety with a high fiber content, cultivated for textile purposes since the 1960s [21–23]. It belongs to Central European forms and is adapted to Polish climatic and soil conditions [24], but it is successfully cultivated in other European countries, as well as in North America, South America and Australia, among others [25–27]. The Henola variety was bred in response to the growing market demand for hemp seeds and oil. It was bred through the positive selection of monoecious plants characterized by the shortest height, well-developed inflorescences and a short vegetation period. In 2017, it was entered into the national Research Centre for Cultivar Testing (RCCT) register [23,27]. It is characterized by a vegetation period shorter by about a month, the technical length of plants almost twice as long, and significantly larger inflorescences than the Białobrzeskie variety (Figure 1) [28]. It is a Polish variety, but, like Białobrzeskie, popular and cultivated around the world [26,27].

Figure 1. Comparison of hemp plants of Białobrzeskie and Henola varieties [Source: own study based on: [29]].

2.2. Collected Data and Methods

When analyzing hemp agricultural technology [29–32], it was concluded that the input data needed to generate neural models should be: soil class, forecrop, number of seeds sown per hectare, weather conditions, degree of qualification and form of harvest. Yield—weight of seeds collected from one hectare of plantation and yield quality—seed germination of a given batch were taken as the output data.

The following data was collected:

- plantation size (ha);
- weight of seeds sown on the plantation (kg);
- soil class—according to the soil quality classification adopted in Poland [33];
- forecrop—a plant grown on the same field in the growing season preceding the hemp cultivation season;
- category—category of seed material sown on a given plantation, according to the Seed Law [34];
- form of harvesting—one- or two-stage harvesting;
- seed moisture (%)—on the basis of data from the ISTA Certificate;
- crop quality—germination in % given on the ISTA Certificate;
- weather conditions—average monthly temperature and monthly rainfall from April to November, based on data provided by the Institute of Meteorology and Water Management—National Research Institute (IM&WM-NRI) on its website [35].

Ultimately, 24 training variables and 336 seed batch cases were included in the dataset. They constituted a training set for ANN models. For data to be entered into STATISTICA 7.1, the file was converted to Comma-Separated Values (CSV) format.

From the training set prepared in this way, 3 ANN models were generated:

1. "Germination and yield 1", with two output variables: yield per hectare and seed germination (%);
2. "Germination 1", with one output variable: seed germination (%);
3. "Yield 1", with one output variable: yield per hectare.

The STATISTICA 7.1 simulator divided the training set into three subsets:

1. Training subset (U) used to teach the network;
2. Validation subset (W), allowing the control of the effects of the learning algorithm during the learning process;
3. Test subset (T)—which allows the assessment of the quality of the generated neural network.

The division into subsets was carried out in the default way for the program, according to the proportion: 2:1:1.

The ANN simulator in the STATISTICA 7.1 package was used for the neural modeling process. The process was carried out in two stages. The former used the Automatic Designer function and the latter used the User Network Designer function.

Using the Automatic Designer function, neural models were generated and analyzed at the next stages. It was assumed that the simulator should test 20 networks of each type and keep the 10 with the best results. The condition of maintaining the network was considered to be a balance between the error and the diversity of the network in order to obtain a wide range of produced models in order to select the optimal topology [36].

The research was carried out using ANN, as the method has been successfully used in the field of agricultural and life sciences for yield prediction and evaluation, and is also excellent for evaluating characteristic variables. PNN (Probabilistic Neural Networks), GRNN (Generalized Regression Neural Networks), RBF (Radial Basis Function Networks) and MLP (Multi-Layer Perceptrons) were tested. Among the networks generated using the Automatic Designer function, the best characteristics were achieved by RBF networks, followed by MLP networks. They are characteristic of non-linear solutions.

After analyzing the models generated using the Automatic Designer function, it was decided to continue the work related to modeling using the User Network Designer function. It was decided to use two networks (RBF and MLP) which achieved the best characteristics in the first stage of research. The best characteristics were achieved by RBF networks, which are shown in results section.

Using this option, 3 RBF models were generated, containing 10 networks each, in which the output variables were again:

1. "Germination and yield 2";
2. "Germination 2";
3. "Yield 2".

The networks were trained with the following algorithms:

1. SS—SubSample;
2. EX—by user (Explicit)—determination of radial deviation;
3. PI—Pseudoinversion.

The error and quality metrics were used to evaluate the models. The error was assumed to be RMSE (Root Mean Square Error), which is represented by the formula:

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(y_t - y_t^P)^2}$$

Quality is understood as the quality of the network for different subsets obtained during network training. For regression networks, the quotient of standard deviations is given as the network quality.

3. Results

3.1. Qualitative Characteristics and Sensitivity Assessment of the Generated Neural Network Models Created Using the Automatic Designer Function

The 3 best networks were selected for each of the models generated using the *Automatic Designer* function. The number of training cases in the set was 336. The number of training variables was from 23 to 24, depending on the generated model (Table 1).

Table 1. Summary of neural models generated with the Automatic Designer function.

Model	Network	Learning Quality	Validation Quality	Testing Quality	Learning Error	Validation Error	Testing Error	Learning Algorithm
Germination and yield 1	RBF 15:41-3-2:2	0.9626	0.9756	0.9837	0.1359	0.1874	0.1619	KM, KN, PI
Germination 1	RBF 15:41-6-1:1	0.9685	0.9624	0.9252	0.1755	0.1617	0.1742	KM, KN, PI
Yield 1	RBF 17:49-13-1:1	0.7659	1.2494	0.9799	0.0019	0.0035	0.0029	KM, KN, PI

The best results were shown by RBF-type networks. These networks are characterized by one hidden layer with radial neurons. The networks generated using the Automatic Designer function had 3, 6 and 13 neurons in the hidden layer. The networks with 3 and 6 neurons were characterized by low error and high quality. The network with 13 neurons showed signs of overfitting.

In the first model, with two output variables: germination and yield, in the first stage of the research (model: "Germination and yield 1"), for the RBF 15:41-3-2:2 network generated using the Automatic Designer function, the learning quality was 0.9626, validation quality was 0.9756, and test quality was 0.9837. The network learning error for the training set was 0.1359, the validation error was 0.1874, and the test error was 0.1619. KM, KN and PI algorithms were used for the network learning process.

In the model with one output variable, which was germination (model: "Germination 1"), the RBF 15:41-6-1:1 network generated using the Automatic Designer function showed a learning quality of 0.9685, a validation quality of 0.9624, and a test quality of 0.9252. The learning error was 0.1755, the validation error was 0.1617, and the test error was 0.1742. KM, KN and PI algorithms were used for the network learning process.

In the third case, for the network with one output variable: yield (model: "Yield 1"), for the RBF 17:49-15-1:1 model, generated using the Automatic Designer function, the learning quality was 0.7659, the validation quality was 1.2494 and test quality was 0.9799. The learning error was 0.0019, the validation error was 0.0035, and the test error was 0.29. KM, KN and PI algorithms were used for the network learning process.

The "Germination and Yield 1" and "Germination 1" models generated in the first stage of the research, using the Automatic Designer function, were characterized by high quality and low error. The "Yield 1" model showed features of network overfitting, so it was decided to continue the research using the User Network Designer function.

3.2. Qualitative Characteristics and Sensitivity Assessment of the Generated Neural Network Models Created Using the User Network Designer Function

The best 3 networks were selected for each of the models generated using the User Network Designer function. The best characteristics were shown by RBF-type networks. Researchers checked the optimal number of neurons in the hidden layer, gradually increasing it. The best results were obtained with 9 neurons in the hidden layer. With a dozen neurons in the hidden layer, the networks began overfitting.

Networks generated using the User Network Designer function were mostly characterized by higher quality and lower RMSE error than networks generated using the *Automatic Designer* function (Table 2).

Table 2. Comparison of neural models generated with the User Network Designer function.

Model	Network	Learning Quality	Validation Quality	Testing Quality	Learning Error	Validation Error	Testing Error	Learning Algorithm
Germination and yield 2	RBF 22:49-9-2:2	0.9847	0.9934	0.9992	0.1135	0.1096	0.1195	SS, EX, PI
Germination 2	RBF 22:51-9-1:1	0.9841	0.9997	0.9999	0.1867	0.2147	0.2001	SS, EX, PI
Yield 2	RBF 22:45-9-1:1	0.9898	0.9905	0.9790	0.0023	0.0025	0.0020	SS, EX, PI

The RBF 22:49-9-2:2 network, generated in the second stage of the research (model: “Germination and Yield 2”) using the User Network Designer function, was characterized by a learning quality 0.9847, a validation quality of 0.9934 and a test quality of 0.9992. The network learning error for the training set was 0.1135, the validation error was 0.1096 and the test error was 0.1195. The SS, EX and PI algorithms were used for the network learning process.

The RBF 22:51-9-1:1 network, generated using the User Network Designer function (“Germination 2” model), had a learning quality of 0.9841, a validation quality of 0.9997 and a test quality of 0.9999. The training, validation and test errors for this network were 0.1867, 0.2147, 0.2001, respectively. The network was trained with SS, EX and PI algorithms.

For RBF 22:45-9-1:1 networks generated using the User Network Designer function (model: “Yield 2”), the learning quality was 0.9898, the validation quality was 0.9905, and the test quality was 0.9790. The errors: learning error 0.0023, validation error 0.0025 and test error 0.0020. The SS, EX and PI algorithms were also used in the learning process of this network.

The “Germination and Yield 1” and “Germination 1” models generated in the first stage of the research, using the Automatic Designer function, were characterized by high quality and low error. The “Yield 1” model showed features of network overfitting. In the second stage of the research, carried out using the User Network Designer function, the models did not show features of network overfitting. In addition, in the “Germination and Yield 2” model, the network quality was higher and the errors were lower than in the “Germination and Yield 1” model. In the “Germination 2” model, the web qualities were higher than in the “Germination 1” model, but the errors were lower in the “Germination 1” model. The “Yield 2” model had a higher learning and validation quality than the “Yield 1” model, and the test quality of both models differed slightly—by 0.01%. The “Yield 2” model was characterized by a higher learning error, but lower validation and testing errors than the “Yield 1” model.

Figure 2 shows screenshots of all 3 generated RBF models (Figure 2).

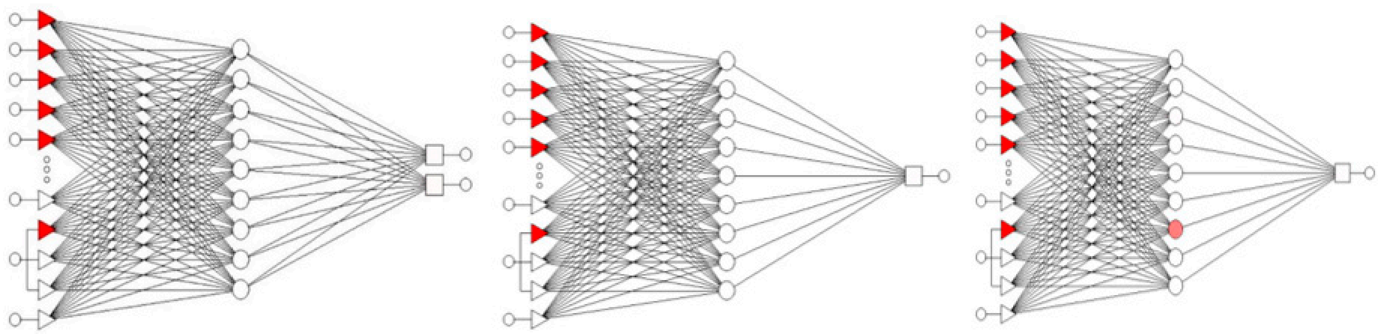

Figure 2. Screenshots of RBF 22:49-9-2:2, RBF 22:51-9-1:1 and RBF 22:45-9-1:1.

3.3. Sensitivity Analysis

An important point in the process of neural modeling is the sensitivity analysis, during which importance ranks are determined for individual variables. This allows the determination of which variables are crucial for the correct learning process and operation of the neural model, and which are of little importance. It is believed that in cases where the error quotient is less than or equal to unity, the removal of the analyzed variable not only has no impact on the operation of the network, but may improve the quality of the generated model. The criterion for the sensitivity analysis was the quotient of the error obtained without the considered variable and the error obtained with the use of all learning variables. On the basis of the quotient, the individual variables were assigned appropriate ranks according to the following rule: the smaller the quotient, the higher the rank. The STATISTICA 7.1 simulator assigns appropriate ranks to individual variables and ranks them, thus supporting the sensitivity analysis process. The lower its rank value, the more important the variable is for the neural modeling process. In the course of the research, a sensitivity analysis of the variables of individual training sets that were involved in the neural modeling process was carried out. Due to this, the information on the level of significance of individual variables was obtained. The results are summarized in Table 3.

Table 3. Sensitivity analysis of the RBF 22:49-9-2:2, RBF 22:45-9-1:1 and RBF 22:51-9-1:1 models.

Network	**RBF 22:49-9-2:2**		**RBF 22:45-9-1:1**		**RBF 22:51-9-1:1**	
Variable	**Quotient**	**Rank**	**Quotient**	**Rank**	**Quotient**	**Rank**
total precipitation _4	1.0622	8	1.0120	6	1.0066	10
total precipitation _5	1.0640	7	1.0120	1	1.0074	2
total precipitation _6	1.0657	2	1.0120	3	1.0074	6
total precipitation _7	1.0657	3	1.0120	4	1.0074	1
total precipitation _8	1.0655	6	1.0112	8	1.0074	5
total precipitation _9	1.0657	1	1.0079	9	1.0074	3
total precipitation _10	1.0657	4	1.0120	2	1.0074	4
total precipitation _11	1.0657	5	1.0120	5	1.0074	7
average monthly temperature _4	1.0221	11	0.9982	18	1.0028	13
average monthly temperature _5	1.0266	10	1.0051	11	1.0039	11
average monthly temperature _6	1.0311	9	1.0079	10	1.0074	8
average monthly temperature _7	1.0207	12	1.0020	12	1.0023	15
average monthly temperature _8	1.0143	15	0.9992	14	1.0016	16
average monthly temperature _9	1.0027	20	0.9979	20	1.0005	21
average monthly temperature _10	1.0057	19	0.9989	15	1.0003	22
average monthly temperature _11	1.0176	14	0.9981	19	1.0014	18
quantity of seeds sown per hectare [kg]	1.0016	21	1.0113	7	1.0071	9
variety	1.0007	22	0.9973	21	1.0006	20
soil class	1.0121	16	0.9967	22	1.0035	12
forecrop	1.0203	13	1.0003	13	1.0027	14
seeds category	1.0078	17	0.9985	16	1.0015	17
harvesting form	1.0062	18	0.9984	17	1.0008	19

On the basis of the performed sensitivity analysis, the ranks of the ANN input variables were determined and they were assigned an appropriate hierarchy. These ranks determine the level of significance of the variables in the context of the quality of operation of the generated neural models.

4. Discussion

Agricultural crops are characterized by frequent non-linearity of processes and phenomena, which makes the relations between them complex and not easy to describe and characterize. Therefore, where traditional statistical methods of describing the studied phenomena fail, the use of artificial intelligence is used [3]. The use of ANN to predict the yield of agricultural plants is more and more often undertaken by researchers from around the world.

Research on the use of ANN in agriculture was conducted, among others, by Medara's team, which worked on data obtained from the Indian Ministry of Agriculture on sugar cane. The studies included data from different regions, which meant differences in the course of weather conditions and sowing dates—similar to the studies presented in this article. Experiments were carried out for 2160 different models. The team was able to successfully model yield with an overall accuracy of 83.49%. The smallest error value achieved was 4.03 [37]. On the other hand, Niedbała and Kozłowski built three independent models for forecasting winter wheat yields. Models were built using ANN with MLP topology based on meteorological data (air temperature and precipitation) and information on applied mineral fertilizers. The lowest error value was 8.85 [38]. The presented research on the prediction of hemp yield quality and quantity is in line with the global trend. RBF-type models generated in the second stage of the research, using the *User Network Designer* function, are characterized by high quality of 97–98%. This quality is higher than the quality of networks generated by researchers conducting research on the yield of, e.g., sugar cane—83.49% [37], and comparable to the quality of the network created by Gandhi's team investigating rice yield—the model of these researchers was characterized by a quality of 97.5% [39].

Research on the use of ANN in forecasting hemp yield was undertaken by Frankowski's team. The results obtained during the experimental plots were used to build a dataset for the ANN. Four input data were adopted: total precipitation, mean temperature, fertilizer and straw yield. Linear, MLP and RBF networks were tested using STATISTICA 7.1. The best results were obtained for linear networks. They were characterized by a quality of 0.910 and a test error of 0.336 [20]. In the research presented in the following article, data from seed orchards were used and the set of input data was significantly expanded. As a result, RBF-type networks were produced with a test quality higher by 0.069 and an error lower by 0.334 than linear networks produced during tests on experimental plots.

A very interesting solution is also the use of AI to predict yields using image analysis. Vijayakumar's team developed three ML-based models for citrus fruit yield prediction based on the use of Unmanned Aerial Vehicle (UAV) imaging and ground imagery. Four ML algorithms were used to generate the models—gradient enhancing regression (GBR), random forest regression (RFR), linear regression (LR) and partial least squares regression (PLSR). The best generated model was characterized by a Mean Absolute Percentage Error (MAPE) of 23.45% [40]. Taking into account the growing popularity of the use of UAV and the opportunities it gives, as well as the often-high variability of, e.g., terrain or soil in one field, the use of this technique supported by ANN seems to be an interesting and legitimate supplement to research on the yielding of agricultural plants, including hemp. They are characterized by the fact that they show differences in development and yield depending on the conditions in the field, which, due to the considerable height of the plants, is practically impossible to determine from the ground level.

As the examples cited show, innovations in the field of technology, including those related to AI methods, are more often and more willingly used in agricultural practice. They are also widely used in crop yield forecasting. Scientists successfully use ANN to forecast the yield of various agricultural crops economically important for a given country or region, and the hemp industry is developing very dynamically around the world.

However, the researchers recognize the limitations of both the use of ANN and those of the current study. For this reason, it is planned to continue the research after extending the dataset with information from the next growing season. Taking into account the variety of available advanced artificial intelligence and machine learning methods, after increasing the dataset, it is also planned to undertake research using other methods, e.g., Deep Learning.

Another problem to solve in yield prediction is the impact of violent weather phenomena, such as hailstorms or exceptionally heavy rains. In the era of progressive climate change, these phenomena are becoming more and more frequent, but at the same time difficult to predict, and their occurrence can significantly mechanically damage or even completely destroy plantations. Therefore, taking up this problem seems to be extremely important and interesting.

5. Conclusions

Based on the conducted research, it was shown that it is possible to create a predictive neural model for assessing the yield of industrial hemp seeds based on a set of characteristics obtained during the agrotechnical process. The information obtained from hemp seed plantations of the Białobrzeskie and Henola varieties was sufficient to build a training set for ANN. The sensitivity analysis carried out showed that in Germination and yield 2 and Germination 2 models, all quotients were higher than unity, and in the Yield 2 model higher or very close to unity, which means that all data from the training set were important for the proper operation of the network.

Modeling using one output variable, which is seed yield, can be used not only in seed orchards, but also in the case of industrial crops, which are gaining more and more importance. Hemp is cultivated on such plantations, e.g., to obtain seeds for food purposes (e.g., for pressing oil or producing dehulled seeds or hemp flour). This branch of the hemp industry is developing very intensively, mainly due to its growing popularity. Therefore, it is extremely important to determine the parameters affecting the yield of seeds.

It is planned to continue the research by extending the dataset with information from the next growing season. This should allow for even better research results and optimization of the set of input data necessary to create a neural model that will be able to forecast the yield of hemp seeds or grains as accurately as possible in the short term.

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