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# Prediction of semen quality using artificial neural network

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**Abstract**

Examination of semen characteristics is routinely performed for fertility status investigation of the male partner of an infertile couple as well as for evaluation of the sperm donor candidate. A useful tool for preliminary assessment of semen characteristics might be an artificial neural network. Thus, the aim of the present study was to construct an artificial neural network, which could be used for predicting the result of semen analysis based on the basic questionnaire data.

On the basis of eleven survey questions two models of artificial neural networks to predict semen parameters were developed. The first model aims to predict the overall performance and profile of semen. The second network was developed to predict the concentration of sperm.

The network to evaluate sperm concentration proved to be the most efficient. 92.93% of the patients in the learning process were properly qualified for the group with a correct or incorrect result, while the result for the test set was 85.71%. This study suggests that an artificial neural network based on eleven survey questions might be a valuable tool for preliminary evaluation and prediction of the semen profile.

**Keywords:** Artificial neural network; Concentration; Semen analysis; Semen characteristics; Spermatozoa

**Highlights:**

- We build two models of ANNs to predict (1) the overall performance and quality of semen, and (2) the concentration of sperm.
- Evaluation of semen quality and sperm parameters might be performed on the basis of eleven survey questions.
- Both models of ANNs are characterized by high values of evaluation indicators of effectiveness of the method.

## Introduction

Examination of semen characteristics is a basic test of male fertility (Cooper et al., 2010). Semen analysis is a noninvasive and inexpensive evaluation of such parameters as concentration, motility and morphology of spermatozoa. Additionally, analysis of semen measures the volume of ejaculate, the viability and maturity of spermatozoa and the concentration of leukocyte and others (WHO, 2010). When the results of semen examinations of three sperm parameters – concentration, motility and morphology – are normal according to WHO criteria, semen is classified as normozoospermia. A concentration of spermatozoa lower than 15 million/ml is described as oligozoospermia. If the percentage of normal forms of spermatozoa is below 4%, it is called teratozoospermia. And if the percentage of progressively motile spermatozoa stays below 32%, then it is defined as asthenozoospermia. Often, two or three of these abnormalities occur simultaneously, which is described as e.g. oligoasthenoteratozoospermia (WHO, 2010). Seminal characteristics might be affected by several factors, including age, weight, psychological stress, environmental and occupational factors (e.g. air pollution, heavy metals), or a certain lifestyle (e.g. recreational and prescription substances, exercise)

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(Marzec-Wróblewska et al., 2011, 2015b; Sharma et al., 2013). It should be emphasized, that analysis of sperm characteristics alone cannot determine whether a man is fertile, but it still can be a good indicator of male fertility potential (Milardi et al., 2012).

An artificial neural network – ANN – is nonlinear mathematical model analysis inspired by the function of biological nervous systems. ANNs are capable of modeling relationships between inputs and outputs as well as finding patterns in them (Buscema, 2002; Zou et al., 2008). Artificial neural networks are used in environmental toxicology, physical sciences, engineering as well as in medicine and clinical research (Buciński et al., 2009; Iraji, 2019a, b; Saritas et al., 2010; Wnuk et al., 2013). Fertility studies also used the ANN to prediction, e.g. results of zona-free hamster egg sperm penetration assay, IVF outcomes or the presence of spermatozoa in the testes of men with nonobstructive azoospermia (Samli and Dogan, 2004; Siristatidis et al., 2011).

Semen analysis is routinely performed for fertility status investigation of the male partner of an infertile couple (Cooper et al., 2010), however, is psychologically difficult for half of the men (Lalos et al., 1985). Examination of semen characteristics is also performed for assessment of the sperm donor candidate and low quality of semen is the main reason for potential candidate rejection (Garrido et al., 2002). While artificial neural networks have been successfully used in same fertility studies (Ma et al., 2011; Vickram et al., 2016), surprisingly, their use in the preliminary diagnosis of male infertility is a lot less than we expected. Actually, only two teams of researchers have worked on this issue: Girela et al. (2013) and Gil et al. (2012), and Sahoo and Kumar (2014). The question we asked ourselves was whether an extensive survey, such as the one used in the studies of, both Girela et al. (2013) and Gil et al. (2012), (34 questions) is necessary. Thus, the aim of the present study was to construct an artificial neural network, which could be used for predicting the result of semen analysis based on the basic questionnaire data.

## Materials and methods

### *Data*

This study was designed to verify whether ANN based on eleven survey questions might be a valuable tool for preliminary evaluation and prediction of the semen profile, and only the inclusion criteria were used. The inclusion criteria were a man aged 18–50 years from an infertile couple and attending infertility clinic for a fertility evaluation. Results of semen examination presented as a semen evaluation category were obtained from 141 men undergoing routine infertility evaluation in two infertility clinics. The following semen evaluation categories were used in the study: normozoospermia (normal semen characteristic value), oligozoospermia (sperm concentration < $15 \times 10^6$/ml of semen), asthenozoospermia (motility < 32% spermatozoa with progressive motility) and teratozoospermia (morphologically normal spermatozoa < 4%); (WHO, 2010). All participants were aged between 21 and 50 years and fulfilling inclusion criteria.

Each of the participants filled up a questionnaire to assess the following data (in brackets are given the original questionnaire variables and their conversion into a range of normalization of the input parameters):

1. Age at the time of analysis (years: 21–30, 31–40, 41–50; prearranged with values 1, 2, 3; respectively).
2. Urbanization level – area (rural area, urban area; prearranged with binary values 0, 1; respectively).
3. Urbanization level – area/population (rural area; urban area smaller than 1000 inhabitants; cities of 1000 to 10000 inhabitants; cities of 10000 or more inhabitants; prearranged with values 0, 1, 2, 3; respectively).
4. Coffee consumption (No, Yes; prearranged with binary values 0, 1; respectively).
5. Alcohol consumption, (No, Yes; prearranged with binary values 0, 1; respectively).
6. Smoking habit (No, Yes; prearranged with binary values 0, 1; respectively).
7. Smoking habit – amount (0 cigarettes per day, 1–5 cigarettes per day, 6–10 cigarettes per day, 11–20 cigarettes per day, more than 20 cigarettes per day; prearranged with values 0, 1, 2, 3, 4; respectively).
8. Smoking habit – duration (never, less than one year, from 1 to 5 years, over 5 to 10 years, more than 10 years; prearranged with values 0, 1, 2, 3, 4; respectively).
9. Occupational exposure to agents that are known to affect spermatogenesis (heat, radiation, solvents, pesticides, heavy metals, traffic exhaust fumes) (No, Yes; prearranged with binary values 0, 1; respectively).
10. Occupational exposure to agents that are known to affect spermatogenesis – intensification (none, low: less than 5 hours per week, medium: from 5 to 15 hours per week, high: more than 15 hours per week; prearranged with values 0, 1, 2, 3; respectively).
11. Sexual abstinence before semen collection (3–7 days).

### *ANN analysis*

Analogously to the human nervous system, an essential element of the artificial neural network is the artificial neuron. Neural computing takes effect after the merger of neurons in the network. There are many types of artificial neural networks with different architectures and principles of operation. In the initial phase of the research, various types of neural networks were built including radial bases functions RBF and MLP multilayer perceptron. A decision to choose MLP as a method of classification was due to higher predictive accuracy of this method. A multilayer perceptron is used for classification and prediction. In the model regression at the output of the network, we expect the result will be a numerical value. In the classification models, based on the input, the network assigns the case to one of the possible classes. In this type of tasks, the results are in a nominal value. In practice, the classification models are created more often, because they are easier to build, but also effectively they learn the correct answers. This type of network is built from the input layer, an output and at least one hidden layer (Fig. 1). In the input layer signals are multiplied by the weighting factors and then summed. The next layer is a layer of hidden neurons, where signals are processed and the data between them compiled. Then, on the basis of their activation function, the signals are calculated and sent to the output layer neurons. Collected and processed signals in the output layer create solutions for network output. The architecture of artificial neural networks is determined by the number of layers and number of neurons contained therein (Buciński et al., 2005; Knyazev and Lashuk, 2007; Luenberger and Ye, 2008).

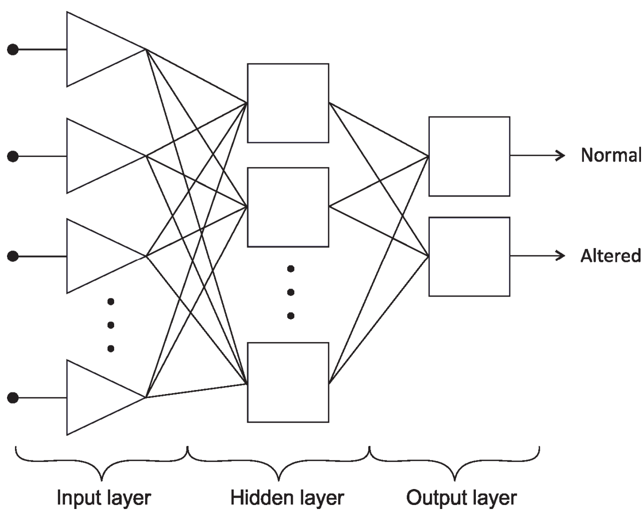


**Fig. 1.** Prediction of the seminal profile using the Multilayer Perceptron Network

Based on the survey data, two classification models for artificial neural networks were developed. Model building and all statistical analyses were done using v.12 Statistica (StatSoft, Tulsa, OK, USA).

The aim of the first artificial neural network model (ANN1) was to predict the general semen profile. The second network (ANN2) was developed to predict the class of one the sperm parameters – concentration. Although sperm parameters are quantitative continuous data, the results of the artificial neural network classification model are in the nominal value. For this reason, it was necessary to determine sharp cutoff values and use the semen evaluation category in this study. Therefore, the classification models, based on the survey data, qualify the study participants for the group of men with either normal or altered sperm parameters according to the WHO criteria (WHO, 2010). In this study, a network output will give two types of answer: normal or altered (in the case of the general semen profile it means that at least one of the three semen parameters is altered). A number of cases ($n$ = 42) of the entire dataset ($n$ = 141) were randomly assigned to a separate file called test and were not used during the learning process. The set of test was used for independent control of the learning network. The resulting output value was compared to the expected value. The difference between these values was calculated by fault functions. The error committed by the network during the learning was minimized by adjusting the weights of each input layer neuron. The learning process was stopped at the optimum time when the error value was the smallest, to avoid over-fitting the network. Over-fitting the network means losing the ability to generalize knowledge due to excessive adjustment to the input data (Goryński et al., 2014). The predictive values of the networks were calculated on the basis of the results of the classification process:

a) classification accuracy ($\frac{\text{TP+TN}}{(\text{TP+FN+TN+TP})} \cdot 100$),

b) sensitivity (True Positive Frequency, TPF); ($\frac{\text{TP}}{\text{TP+FN}} \cdot 100$),

c) specificity (True Negative Frequency, TNF); ($\frac{\text{TN}}{\text{TN+FP}} \cdot 100$),

d) positive predictive value (PPV); ($\frac{\text{TP}}{\text{TP+FP}} \cdot 100$),

e) negative predictive value (NPV); ($\frac{\text{TN}}{\text{TN+FN}} \cdot 100$),

(where: TP, true positive: the profile of semen or sperm concentration was normal and was properly classified; FP, false positive: the profile of semen or sperm concentration was altered and was improperly classified; FN, false negative: the profile of semen or sperm concentration was normal and was improperly classified; TN, true negative: the profile of semen or sperm concentration was changed and was properly classified).

### *Patient and public involvement*

The development of the main research question, i.e. whether there is a possibility to determine the quality of semen without conducting its analysis, was based on information that many patients report that semen analysis is psychologically difficult for them.

The patients were not involved in the design, in the recruitment to and conduct of this study. The patients attending one of the infertility clinics: "Almed – Genito-Urinary Medicine Clinic, dr G. Ludwikowski" (Bydgoszcz, Kuyavian-Pomeranian Voivodeship, Poland) and "NZOZ Medical Center Co. Prof. dr hab. med. Wiesław Szymański, dr med. Marek Szymański" (Bydgoszcz, Kuyavian-Pomeranian Voivodeship, Poland).

The results of this study will be disseminated to study participants in the form of this article.

The study received required permission from the Local Committee for Bioethical Research of Nicolaus Copernicus University Collegium Medicum in Bydgoszcz (Ref. No. KB/538/2007).

## Results

The demographic characteristics of men and number of participants in one of used in the study semen evaluation categories are presented in Table 1 and Table 2, respectively.

The structure of an artificial neural network has a huge impact on its optimal work, that is why the architecture of the ANN has been specified in this paper. Determination of the number of neurons in the hidden layer is one of the most important stages in ANN modeling – if the number of neurons in the hidden layer is too small the neural network will not solve a given problem. Moreover, if the ANN is too complicated it makes the ANN correspond too closely to the data set – the ANN loses its ability to generalize. That phenomenon is called over-fitting. The optimal structure of the ANN model has been selected experimentaly by trial and error method. After many attempts to create the perfect network with different structures and functions activation, we have chosen two optimal network models that allowed the correct classification of patients with normal or altered general semen profile and sperm concentration. The classification models created by us consist of 11 input neurons (11 questions from the questionnaire), one layer of hidden neurons and two neurons in the output layer. In this study, a network output gives two types of answer: normal or altered. The backpropagation algorithm: Broyden-Fletcher-Godfrab-Shanno (BFGS) was used to train the network. The learning process was stopped at the optimum cycle when the error value committed by the network was the smallest. The exact parameters of the network are presented in Table 3.

The network developed to evaluate the characteristic of sperm concentration (ANN2) proved to be the most efficient. 92.929% of the patients in the learning process was correctly qualified for the group with a normal or altered sperm concentration profile, while in the test set – 85.714% for the network constructed to assess the general semen profile (ANN1). The rate of correct answers was 85.859% for the training set, and

**Table 1.** Demographic characteristics of men

| Variable | All individuals |
|---|---|
| Age (years, *N*, %) | |
| 21–30 | 57 (40.4) |
| 31–40 | 77 (54.6) |
| 41–50 | 7 (5.0) |
| Urbanization level – area (N, %) | |
| rural | 37 (26.2) |
| urban | 104 (73.8) |
| Urbanization level – area/population (*N*, %) | |
| rural area | 37 (26.2) |
| urban area smaller than 1000 inhabitants | 7 (5.0) |
| cities of 1000 to 10000 inhabitants | 9 (6.4) |
| cities of 10000 or more inhabitants | 88 (62.4) |
| Coffee consumption (*N*, %) | |
| yes | 100 (70.9) |
| no | 41 (29.1) |
| Alcohol consumption (*N*, %) | |
| yes | 107 (75.9) |
| no | 34 (24.1) |
| Smoking habit (*N*, %) | |
| yes | 39 (27.7) |
| no* | 102 (72.3) |
| Smoking habit – amount cigarettes per day (*N*, %) | |
| 0** | 76 (53.9) |
| 1–5 | 6 (4.3) |
| 6–10 | 20 (14.2) |
| 11–20 | 31 (22.0) |
| more than 20 | 8 (5.7) |
| Smoking habit – duration (*N*, %) | |
| never | 76 (53.9) |
| less than one year | 14 (9.9) |
| from 1 to 5 years | 14 (9.9) |
| over 5 to 10 years | 18 (12.8) |
| more than 10 years | 19 (13.5) |
| Occupational exposure (*N*, %) | |
| yes | 51 (36.2) |
| no | 90 (63.8) |
| Occupational exposure – intensification (*N*, %) | |
| none | 90 (63.8) |
| low | 33 (23.4) |
| medium | 12 (8.5) |
| high | 6 (4.3) |

The data are presented as the number (*N*) and percentage (%) of patients.
* The number of patients who declared to be a non-smoker for at least 3 months prior to the survey.
** The number of patients who never smoked.

**Table 2.** The number of participants in one of used in the study semen evaluation categories

| Semen evaluation categories | *N* | % |
|---|---|---|
| Normozoospermia | 73 | 51.77 |
| Oligozoospermia | 30 | 21.28 |
| Asthenozoospermia | 54 | 38.30 |
| Teratozoospermia | 1 | 0.71 |

The data are presented as the number (*N*) and percentage (%) of patients.

**Table 3.** Characteristics of artificial neural networks

| Seminal parameter predicted | MLP network architecture | Hidden activation function | Output activation function | Number of cycles BFGS algorithm |
|---|---|---|---|---|
| General semen profile (ANN1) | 11-8-2 | logistic | exponential | 46 |
| Sperm concentration (ANN2) | 11-7-2 | logistic | softmax | 29 |

**Table 4.** The performance of developed networks is determined by the percentage of properly qualified patients

| Artificial neural network | Learning set | Testing set |
|---|---|---|
| General semen profile ANN1 | 85.859 % | 80.952 % |
| Sperm concentration ANN2 | 92.929 % | 85.714 % |

**Table 5.** The results of the classification process

| | Predicted | |
|---|---|---|
| | Normal | Altered |
| General semen profile (ANN1) | | |
| normal (*n* = 73) | TP = 62 | FN = 11 |
| altered (*n* = 68) | FP = 10 | TN = 58 |
| Sperm concentration (ANN2) | | |
| normal (*n* = 111) | TP = 105 | FN = 6 |
| altered (*n* = 30) | FP = 7 | TN = 23 |

TP, true positive; FP, false positive; FN, false negative; TN, true negative.

**Table 6.** Accuracy measures achieved by both MLP (ANN1 and ANN2) models

| Parameter | General semen profile (ANN1) | Sperm concentration (ANN2) |
|---|---|---|
| sensitivity | 84.93% | 94.59% |
| specificity | 85.29% | 76.67% |
| positive predictive value | 86.11% | 93.75% |
| negative predictive value | 84.06% | 79.31% |
| classification accuracy | 85.12% | 90.78% |

80.952% for the test set (Table 4). The results of the classification process are shown in Table 5, while the predictive values of the classification accuracy, sensitivity (TPF), specificity (TNF), positive predictive value (PPV) and negative predictive value (NPV) networks are shown in Table 6. The area under the receiver operating curve (ROC; Fig. 2) was also calculated to assess the quality of our artificial neural network models (Table 7). These results indicated that in this work network good classifiers are created.

The sensitivity analysis for the eleven input variables was implemented and the results are shown in Table 8. This procedure allows evaluating the suitability of each variable. The variables with a rank close to 1 are the most, while those with a rank close to 11 the least significant.

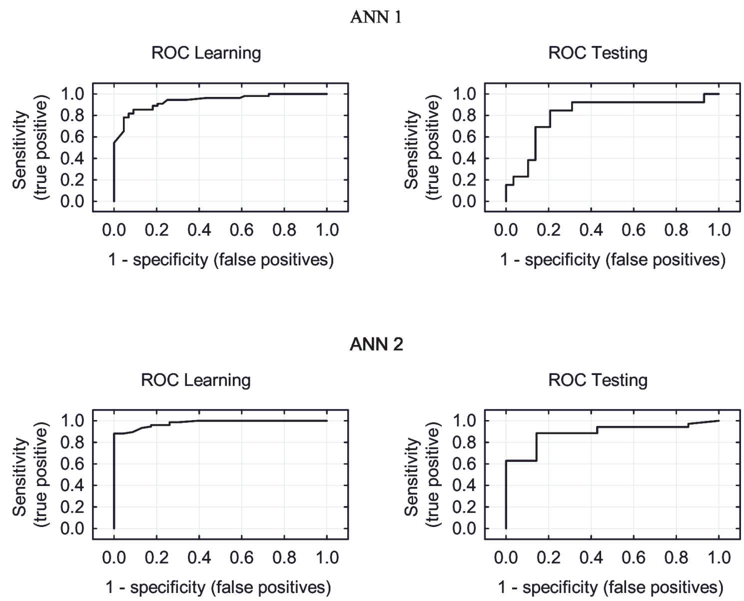


**Fig. 2.** The receiver operator characteristic curves (ROC) show true positive results (sensitivity) relative to false-positive results (1-specificity) for each cut-off point

**Table 7.** The area under the ROC

| Artificial neural network | The area under the ROC | | |
|---|---|---|---|
| | Learning set | Testing set | Learning and testing set |
| ANN1 | 0.936 | 0.812 | 0.892 |
| ANN2 | 0.979 | 0.888 | 0.948 |

**Table 8.** Sensitivity analysis results for the input variables used for prediction semen parameters in ANN analysis

| Variable | ANN 1 | | ANN 2 | |
|---|---|---|---|---|
| | Rank | Error | Rank | Error |
| Age at the time of analysis | 8 | 1.224 | 6 | 3.367 |
| Alcohol consumption | 10 | 1.032 | 8 | 1.836 |
| Coffee consumption | 3 | 18.531 | 1 | 6.113 |
| Smoking habit | 1 | 422.283 | 2 | 4.425 |
| Smoking habit-amount | 6 | 2.396 | 9 | 1.652 |
| Smoking habit-duration | 4 | 7.258 | 5 | 3.523 |
| Occupational exposure to agents that are known to affect spermatogenesis | 5 | 6.531 | 3 | 4.277 |
| Occupational exposure to agents that are known to affect spermatogenesis – intensification | 7 | 1.602 | 10 | 1.270 |
| Sexual abstinence before semen collection | 11 | 0.939 | 11 | 0.956 |
| Urbanization level-area | 2 | 60.154 | 4 | 3.652 |
| Urbanization level-area/ population | 9 | 1.166 | 7 | 2.580 |

## Discussion

Artificial neural networks are widely applied in medical fields. They are often used as an effective diagnostic tool for many diseases or as a help to predict treatment outcomes. Many studies have described the use of ANN to predict the survival of patients with liver cancer (Spelt et al., 2013), pancreas cancer (Ansari et al., 2013) or breast cancer (Bhardwaj and Tiwari, 2015). Application of neural network for the psychosomatic and psychiatric evaluation as well as in the field of epidemiology also are developed (Mekruksavanich, 2016).

Among many examples of applications of ANN in medicine, special attention should be given to their utility in andrology. Artificial neural networks have been used to predict mainly the particular issues such as the presence of spermatozoa in the testes of men with nonobstructive azoospermia or sperm retrieval before testicular sperm extraction in those men (Samli and Dogan, 2004). Furthermore, Vickram et al. (2013) used the ANN for the prediction of Zn concentration in seminal plasma, while Siristatidis et al. (2011) attempted to construct an ANN for the prediction of the IVF outcome.

This statistical tool might be also used for prediction of seminal parameters. In the present study, we construct two artificial neural networks, one to predict the overall seminal profile, and a second for the prediction of characteristics of sperm concentration. Similar studies were conducted only by Girela et al. (2013), Gil et al. (2012) and Sahoo and Kumar (2014). In their study, Sahoo and Kumar (2014) created the MLP model to predict the general semen profile. The value of the achieved accuracy of classification reached as much as 92%, however, with a relatively low sensitivity of 41.67% and the area under the ROC was 0.728. The values in the current article are 85.12%, 84.93% and 0.812, respectively (Table 9).

**Table 9.** Performance comparison of researches

| | Gil et al. (2012) | | | Sahoo and Kumar (2014) | Girela et al. (2013) | | Actual results | |
|---|---|---|---|---|---|---|---|---|
| | Sperm morphology | Sperm concentration | Sperm motility | General semen profile | Sperm concentration | Sperm motility | Sperm concentration | General semen profile |
| Classification accuracy (%) | 69.00 | 86.00 | 73.00 | 92.00 | 90.00 | 82.00 | **90.78** | **85.12** |
| Specifity (%) | 25.00 | 94.10 | 44.80 | 98.86 | 50.00 | 43.75 | **76.67** | **85.29** |
| Sensitivity (%) | 72.80 | 40.00 | 84.50 | 41.67 | 95.00 | 89.29 | **94.59** | **84.93** |
| Positive predictive value (%) | 91.00 | 89.90 | 79.00 | 92.55 | 93.03 | 89.29 | **93.75** | **86.11** |
| Negative predictive value (%) | 7.40 | 54.50 | 54.20 | 83.33 | 60.00 | 43.75 | **79.31** | **84.06** |

Girela et al. (2013), based on survey responses developed two MLP models to predict the motility and sperm concentration. On the basis of the factors used to evaluate the effectiveness of the test, it can be concluded that we were able to create more effective predictive models. This means that the most likely men with expected normal sperm characteristics actually had a normal semen profile. In this paper, we have obtained a higher value for specificity model (76.67%) and negative predictive value – 79.30%, while Girela and colleagues achieved 50% and 60%, respectively (Table 9). Gil et al. (2012) have evaluated the efficiency of three artificial intelligence methods: Decision Trees (DT), Support Vector Machines (SVM) and Multilayer Perceptron (MLP), to the prediction of semen profile and sperm parameters, i.e. sperm concentration; and all of these methods achieved the high accuracy measurement parameters. However, with good overall measurement parameters, they received a low value of specificity and positive predictive value. Probably, this is resulted from the uneven groups of the people with the normal and the altered sperm parameters in the study population. Notwithstanding, their paper showed that the MLP is a statistical tool that achieves the highest value indicators of the method effectiveness. For predictions of sperm concentration, the value of obtained classification accuracy has reached 86% and the specificity 40%, while the values in this paper are 90.78% and 76.67%, respectively (Table 9). Additionally, it should be emphasized that both Girela et al. (2013) and Gil et al. (2012) created predictors of sperm parameters on the basis of 34 survey questions, then they have identified the relevant information using the DT. In our study, the patient answered only an 11 basic survey questions. However, interpreting the results supplied by the network, one should bear in mind that they are approximate.

According to sensitivity analysis, smoking habit, coffee consumption, urbanization level and occupational exposure are the most significant parameters to the proper classification of men in both developed ANNs. Environmental tobacco smoke is one of the most essential factor affecting indoor air quality and is considered as being carcinogenic to humans (Office on Smoking and Health (US), 2006; WHO and International Agency for Research on Cancer, 2009). Both mainstream and sidestream smoke contain many toxic elements including heavy metals and rare earth elements (Böhlandt et al., 2012; Slezakova et al., 2009). The components of tobacco smoke are known as affecting both the semen characteristics and the individual sperm parameters (Böhlandt et al., 2012; Marzec-Wróblewska et al., 2015a; Pant et al., 2015).

Another important factor affecting the characteristics of semen and sperm concentration was the coffee consumption. On one hand, coffee, one of the most favored non-alcoholic beverage in the world, used to be associated with negative impacts, mainly on cardiovascular systems, on the other hand, recent research results emphasized the beneficial effect of drinking coffee to our health (Dirks-Naylor, 2015; Grioni et al., 2015). The certain number of studies have shown a relationship between coffee intake with characteristics of semen and male fertility potential. In the study of Yang et al. (2015) coffee consumption (and tobacco smoking) was one of the lifestyle habits which affect semen characteristics. An increase in the progressive and nonprogressive motility was found to be associated with the coffee consumption. Jurewicz et al. (2014a) show a similar effect of coffee consumption. Drinking coffee was associated with an increase in the percentage of motile sperm cells. However, an increase in sperm head or neck abnormalities also has been shown. Sperm concentration also could be affected by coffee intake, which was confirmed by Jensen et al. (2010) study.

The place where we live is not indifferent to our health. Urbanization has been linked with changes in our diet, physical activity, a risk level of certain diseases and, obviously, male fertility. For example, Wang et al. (2016) provided data that urbanization links with endocrine disruptors, which were ubiquitously present in the studied urban river (Panlong River). The concentrations of endocrine disrupting chemicals in the urban section of the river were greatly higher than those in sections of suburban areas. Findings of Zhou et al. (2014) associated exposure to higher concentrations of air pollution in urban areas in Chongqing, China with decreased semen quality in urban residents, contrasted with the lower air pollutants level and better semen quality in the rural males. In an experimental study of Zou et al. (2008) the differentiated impact of the rural/urban area on semen characteristics and sperm parameters has been confirmed. Data provided by Swan et al. (2003) showed that both motility and concentration of spermatozoa might be decreased in agricultural and semirural areas relative to less agriculturally exposed and more urban areas. It might be connected with herbicides, pesticides or fertilizers which were applied to all (or most) of this agricultural areas. Also in the developed artificial neural network, urbanization level was one of the most important factors for the prediction of semen profile and characteristics of sperm parameters.

Occupational exposure to agents which might have an influence on spermatogenesis and semen characteristics has been studied by many researches. They examined the effect of various elements, heavy metals, chemical compounds, etc. Their works are shown a generally negative effect on semen characteristics and value of particular sperm parameters (Jurewicz et al., 2014b).

Taking into account the fact, that many patients were influenced by several factors (smoking habit, alcohol or coffee consumption, urbanization level, and occupational exposure, etc.), it is necessary to consider the possibility of their synergistic or additive effect on semen quality. For example, Martini et al. (2004) study shown deterioration in the semen quality of those patients who were both tobacco and alcohol consumers with respect to those without these habits or those with one of them. This possible synergistic or additive effect of several factors needs additional research.

## Conclusions

1. This paper proved that the artificial neural network might be an effective tool for the initial evaluation of some sperm parameters.
2. Evaluation of semen quality and sperm parameters might be performed on the basis of eleven survey questions.
3. Both models of ANNs are characterized by high values of evaluation indicators of effectiveness of the method.
4. The sensitivity analysis allowed to estimate which factors have the greatest impact on sperm parameters.
5. It has been shown that the created networks are an ideal multidimensional statistical method, and are superior predictive models in this knowledge area.

It should be emphasized, although ANN will never be able to replace a standardized diagnostic examination, however, might be a valid instrument to a preliminary evaluation of the patient, performed either during the fertility study of the potentially infertile couple and for sperm donor selection.

### *Conflict of interests*

The authors have no conflict of interests to declare.

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