Prediction Model Based on Neural Networks for Microwave Drying Process of Amaranth Seeds

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ABSTRACT

In this work, a model has been developed for the prediction of the fundamental variables of the microwave oven drying of amaranth seeds, using the initial mass of the seeds and the temperature of the process as input data. The model was developed by using the Python programming language, the Sklearn machine learning library for data analysis, and the MLPRegressor predictor for model training. The data used in the created dataset was obtained from the measurements made of the drying time and the energy consumption in the drying experiments carried out at three temperatures (35, 45, 55 ℃) in a domestic microwave oven, as well as the germination rate of amaranth seeds obtained in the germination tests. The accuracy achieved in the predictions made by the model is 99.5% for the drying time, 98.2% for energy consumption and between 89.2% and 84.1% for the germination rate of the seeds.

CCS Concepts

• Computing methodologies ~ Neural networks

Keywords

Artificial neural network (ANN); Prediction model; Microwave drying; Amaranth seeds.

1. INTRODUCTION

With the emergence and use of modern computers, in the 80s of the 20th century, and the development of software and computer applications, science and engineering found a very powerful and effective tool for the resolution of difficult and complex problems in all its areas [1]. In most of the industrial sector, specialists use software every day to perform their calculations and design tasks. The software, correctly designed and evaluated, contributes to improve the efficiency and productivity of industrial processes and is a very powerful tool to develop academic and research processes [2].

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In the last 40 years, several software have been developed for application to the drying process of different products [3, 4, 5, 6, 7, 8, 9, 10, 11, 12]. However, commercially few software have been used successfully or are well accepted at the industrial level [9, 10]. Moreover, taking into account that drying is a unitary operation that consumes a large amount of energy, the industry and the scientific and academic community need software to predict the drying process, improve their energy efficiency and reduce the carbon footprint and the costs of dried products.

There is a general consensus that the drying of wet materials is a very complex, dynamic, unstable, highly non-linear, highly interactive, successively interconnected and multivariable process, whose mechanisms are not yet fully understood [13, 14]. These characteristics mean that the identification of the relationships between the inputs and outputs of a drying process using mathematical, statistical, numerical and analytical techniques are much more complex, cumbersome and problematic and, therefore, its application is not recommended [13, 14]. On the other hand, Artificial neural networks (ANN) have found many applications as a superior tool for modeling scientific, engineering, complex, dynamic, highly non-linear, and ill-defined problems. For this reason, ANN have been widely used in drying applications, due to their favorable characteristics, such as: efficiency, generalization and simplicity [13].

In general, ANN have been used in drying technology to model, predict and optimize heat and mass transfer processes, performance and thermodynamic parameters, quality indicators, as well as the physicochemical properties of dry products. However, there is a limited number of works on the application of RNA to the microwave drying process to predict the main parameters of the process and the quality of dry products. Therefore, the main objective of this work is to develop a model, using neural networks, for the prediction of drying time, energy consumption and germination rate of dried amaranth seeds in a microwave oven.

2. RELATED WORK

Microwave assisted drying, alone or combined with other procedures, has emerged and developed as an alternative method to conventional drying methods and is currently used in many industrial processes for the drying of various materials and products [15]. This is due to the advantages associated with heating with this form of energy, including, among others, a greater energy efficiency of the process and quality of the product to be dried; and a decrease in time and temperature, required to carry out the drying process [15].

However, this method of drying is very complex because it involves the interaction of the electromagnetic field with the wet product to be dried, the absorption and penetration of the electromagnetic wave in it and its conversion into thermal energy (heat), the transfer of heat by conduction through the product, and the diffusion and transfer of mass (moisture) from the inside of the product to its surface [15]. For this reason, the use of standard physical, mathematical and statistical approaches for the precise modeling of the microwave assisted drying process is very laborious from the computational point of view [13]. Therefore, there is great potential for the application of ANN to the microwave-assisted drying process to achieve different objectives.

The ANN have been widely applied, since the 90s of the last century, to the different drying methods to model, predict and optimize different aspects and parameters of the process and some physicochemical properties of dry products. Some papers have been published [13, 14, 16, 17] that perform a thorough review on the application of RNA to drying technology. Table 1 summarizes the main results obtained in the application of ANN to microwave drying process published in recent years. As it can be observed in Table 1, all the proposed models show high coefficients of determination, in most of the cases greater than 0.99, when using the validation data to predict the output parameters. These results show that neural networks have been applied successfully to predict different parameters of the drying process of different products. However, no models have been developed to predict the energy consumption required in said process or to predict quality parameters of seed drying, such as its germination rate, mainly for crops typical of the Andean region, such as amaranth and the quinoa.

Table 1. ANNs applications in microwave-assisted drying

Authors [Ref.]	**Aims/Model inputs/Model outputs**	**Coefficient of determination (R^2)**
Motevali *et al*. (2010) [18]	Aim: To compare thin layer drying equations and ANN. Model inputs: Temperature and velocity of the drying air, pre-treatment, and drying time Model outputs: Moisture ratio	0.99988
Momenzadeh *et al*. (2011) [19]	Aim: To model the drying kinetics in a microwave assisted fluidized bed dryer. Model inputs: Drying air temperature, grain moisture content, and microwave power. Model outputs: Drying time	0.998
Krishna Murthy and Manohar (2012) [20]	Aim: To model the moisture content. Model inputs: Drying time and microwave power. Model outputs: Moisture content	0.989
Balbay *et al*. (2012) [21]	Aim: To predict the drying kinetics. Model inputs: Temperature and flow rate of the drying air. Model outputs: Moisture content	0.993
Motavali *et al*. (2013) [22]	Aim: To model the microwave–vacuum drying kinetics. Model inputs: Microwave power, absolute pressure, and drying time. Model outputs: Moisture ratio and drying rate	0.9958
Sarimeseli *et al*. (2014) [23]	Aim: To model the drying kinetics. Model inputs: Microwave power, sample mass, and drying time. Model outputs: Moisture ratio	0.9999
Yousefi *et al*. (2014) [24]	Aim: To model the impact of microwave fluidized bed drying process on the physiochemical properties. Model inputs: Temperature and flow rate of the inlet air, microwave power, starting time of the microwave impingement, and sample mass. Model outputs: Phenolic and anthocyanins contents, antioxidant and water activities, density, porosity, hardness, rehydration capacity, and drying time.	0.92

3. MATERIALS AND METHODS

3.1 Process of Drying and Germination of Seeds

Figure 1 shows a diagram of the drying process of the amaranth seeds used in this work. The drying process of these seeds was carried out in a rotary plate domestic microwave oven (Marca LACOR Model 69330), with 30 liters of capacity and 900 W of power, which has a built-in PID temperature controller Eurotherm 3216 L, which allows control the temperature of the drying process. In this oven, a seed mass of 100 g was placed, with an initial humidity of approximately 20%; and these were dried, at 3 temperatures (35, 45 and 55 °C), until a final humidity of 12% was obtained. For each temperature studied, 5 experiments were carried out. In each experiment, the electrical energy consumption was measured using a FLUKE 1735 energy analyzer.

The germination tests of the seeds, dried at the different temperatures under study, were carried out in a germination chamber, designed and built at the Technical University of Cotopaxi, under controlled conditions of temperature (22 ℃) and relative humidity (70%). To perform these tests in the germination chamber, a Petri dish was placed for each of the experiments carried out at the different temperatures under study. In each Petri dish a total of 50 seeds were placed on a wet filter paper. The germination process of the seeds was observed daily, establishing a record with the amount of seeds germinated, not germinated and contaminated; and from this record the germination rate of the seeds was calculated.

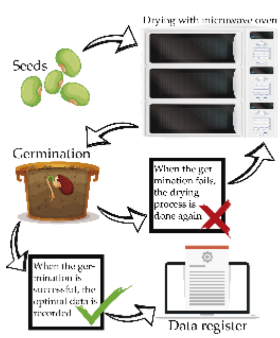

Figure 1. Seeds drying process.

3.2 Dataset

Table 2 shows a description of the three dependent variables (drying time, energy consumption and germination rate of the seeds) that were measured in each of the drying experiments carried out at the three drying temperatures under study. (Independent variable). With the data collected from each of these variables, the dataset that was used to train and test the prepared prediction model was elaborated.

Table 2. Description of the variables used in the dataset

Variables	Description
Drying temperature (T_d)	Seed drying temperature (℃).
Drying time (t_d)	Time required for drying the seeds up to a humidity of 12% (min).
Energy consumption (E_c)	Electric energy consumed by the microwave oven to dry the seeds up to 12% humidity (Wh).
Germination rate (G_r)	Percentage of germinated seeds (%)

For the elaboration of the dataset, the data stored in an Excel sheet was first converted to a CSV file, through the use of the online tool Zamzar. This step is essential for the data to be recognized and analyzed by the MLPRegressor predictor. Subsequently, by means of this predictor, the data was pre-processed.

3.3 Selection of the Neural Network

For the analysis and prediction of the experimental data obtained in the drying process of amaranth seeds in a microwave oven, the multilayer perceptron neuron network (MLP) was selected. [25]. This neural network was selected because it allows the creation of several hidden layers to generate several models, from which MLP is responsible for selecting the best option [26]. MLP is a type of artificial neural network feedforward, which uses a non-linear activation and a supervised learning technique known as backpropagation for coaching [27]. This neural network is found in the Scikit Learn library of the Python programming language [28]. Scikit learn allows the creation of algorithms and training or machine learning to perform the prediction using the MLPRegressor predictor, which is a multilayer perceptron and is trained using back propagation without an activation function of the output layer [29].

4. PREDICTION MODEL

4.1 Architecture of the Model

Figure 2 shows the architecture of the prediction model developed for microwave drying of amaranth seeds. As can be seen, the first process is the entry of the data records, which are in CSV format. Then, in the pre-processing stage, the unnecessary data are eliminated and those qualitative data are transformed into a numerical format. Once this stage is completed, a dataset is available to perform its analysis [30]. To perform the prediction process using the MLPRegressor predictor, the drying temperature is used as input. This data is entered through the trained neural network (see prediction algorithm), and as a result of the prediction process the drying time, energy consumption and germination rate are obtained. The prediction algorithm is shown in section 4.2, while the details of the training and prediction procedures are shown in section 4.3.

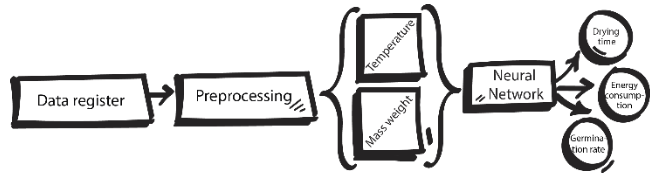

Figure 2. Architecture of the prediction method

```
Input: T_d
Output: Final predicted (t_d, E_c , G_r)
x=Dataset ( T_d )
y=Dataset (t_d, E_c , G_r)
X= array x
Loop maximum_score
        X_train, X_test, y_train, y_test=Split (X,y)
        mlr=MLPRegressor→alpha=1e-5, hidden_layer=10
        mlr→fit (X_train, y_train)
        mlr→score (X_train, y_train)
end Loop
Calculate final prediction
mlr→score (X_train, y_train)
mlr→predict ( T_d )
```

Figure 3. Prediction algorithm

4.2 Prediction Algorithm

Figure 3 shows the algorithm developed to perform the prediction of the drying process. As it can be observed in this figure in the algorithm, the drying temperature of the seeds is input as input and, as a result of the prediction process, the drying time, the energy consumption and the germination rate of seeds are obtained.

To make the prediction, the independent variable (drying temperature) is stored in the variable x, while the dependent variables (drying time, energy consumption and germination rate) are stored in the variable and, as can be seen in the prediction algorithm. Next, the variable X is assigned an array of data of type x. Subsequently, a repetitive cycle (While) is created until the maximum value of the percentage of accuracy of the model (Score) is found. The dataset is divided to 50% for training data and the rest for testing. Next, the neural network is trained by MLP calibration with alpha = 1e-5 and 3 hidden layers to predict the drying time and energy consumption and 10 layers for the germination rate. Next, the model is adjusted to the data matrix X and to the objectives y. Finally, at the end of the While cycle, the result of the highest percentage reached by the model and the values of drying time, energy consumption and garbage rate, predicted by MLP according to a drying temperature entered, is obtained.

4.3 Training and Prediction

MLP is one of the most used training algorithms. In it, the number of prediction algorithm executions and the prediction time depend significantly on the degree of learning of the predictor and the problem under study. [31].

The reverse propagation learning rule (regressor) was established to determine a relationship between inputs and outputs. To do this, it was established that the MLPRegressor creates networks randomly and then updates them by having a comparison between the iterative results of the network and the desired values [32]. For the prediction of the state sequences, the most probable state was taken as the predicted state. Once the most probable state was reached, its value gradually increased until reaching the new predicted state. This process was carried out until the algorithm did not find a better predicted state. For all the above, this method is easy to implement, due to its lower computational complexity.

4.4 Evaluation

The Python 3 programming language was used to carry out the model evaluation process. A 3-neuron calibrated neuronal network was created through the sklearn.neural_network module to predict the drying time and energy consumption; and of 10 neurons for the prediction of the germination rate of the seeds and a tolerance of 1.0E-5. To evaluate the model, 50% of the dataset data was used, following the procedure described in the previous section.

5. RESULTS AND DISCUSSION

The results of the prediction of the microwave oven drying time, the energy consumption and the germination rate of the amaranth seeds, for the 3 temperatures under study, obtained with the elaborated model, are shown in Table 3.

Table 3. Results of the model prediction

Drying temp.	**Drying time**		**Energy consumption**		**Germination rate**	
(℃)	**(min)**	**(%)**	**(Wh)**	**(%)**	**(%)**	**(%)**
35	330	99.5	906.6	98.5	82.0	84.1
45	205	99.5	469.7	98.5	74.5	89.2
55	153.8	99.5	264.0	98.5	30.0	84.1

As can be seen in said Table, the model predicts a decrease in the drying time of the seeds, from 330 min to 153.8 min, by increasing the drying temperature from 35 ℃ to 55 ℃. This prediction is made, for the 3 temperatures under study, with a very high accuracy of 99.5%. A high precision in the prediction of the drying time, as obtained in this work, has also been obtained with the model presented by Momenzadeh et al. [19] for drying of shelled corn in a microwave-assisted fluidized bed dryer. However, the model developed by these authors requires 3 input variables to make the prediction, which increases the computational complexity of the model, with the disadvantages that this causes. On the other hand, the model developed by Yousefi et al. [24], for the drying of raspberries in a microwave-assisted fluidized bed dryer, has a lower accuracy (0.92) than that elaborated in this work for the microwave drying of amaranth seeds, possibly due to the prediction of a greater number of output variables.

The model performed in this work also predicts a decrease in energy consumption by the microwave oven and a decrease in the rate of germination of amaranth seeds as the drying temperature increases, from 35 ℃ to 55 ℃, as can be seen in the Table 3. The energy consumption predicts it with an accuracy of 98.5%, slightly lower than with the one that predicts the drying time but higher than the one that predicts the germination rate. Finally, the germination rate of the seeds is the variable that the model predicts with lower precision, between 84.1 and 89.2%, depending on the drying temperature. The lower precision of the model elaborated in the prediction of the energy consumption and the germination rate of the seeds is due to the greater dispersion of the data of these variables obtained in the experiments of drying and germination of the seeds made. However, the trend observed in the predictions made by the model, that is, the reduction of the drying time, the energy consumption and the germination rate of the seeds with the increase in the drying temperature, from 35 ℃ up to 55 ℃, corresponds to that observed in the drying and germination experiments carried out.

Finally, it is important to point out that in relation to the energy consumption incurred in the drying process of seeds in a microwave oven and the germination rate of the same to date, no model has been published that predicts them.

6. CONCLUSIONS

In this work a model has been developed for the prediction of the fundamental variables of the microwave drying process of amaranth seeds with the use of the artificial neural network Multilayer Perceptron (MLP). The model predicts a decrease in drying time, energy consumption and seed germination rate with an increase in drying temperature, from 35 °C to 55 °C. The accuracy achieved in the predictions made by the model is 99.5% for the drying time, 98.2% for energy consumption and between 89.2% and 84.1% for the germination rate of the seeds. The trend shown in the predictions of the three variables studied by the model corresponds to that observed in the drying and germination experiments carried out.

7. ACKNOWLEDGMENTS

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8. REFERENCES

[1] Campbell-Kelly, M., Aspray, W., Ensmenger, N. and Yost , J. R. 2018. Computer, Student Economy Edition: A History of the Information Machine. 3rd Edition. Routledge, Taylor & Francis Group, New York.

[2] Ali, N. B., Petersen, K. and Wohlin, C. 2014. A systematic literature review on the industrial use of software process simulation. J. of Syst. Softw. 97, (Nov. 2014), 65-85. DOI= https://doi.org/10.1016/j.jss.2014.06.059.

[3] Kudra, T. 1991. Dryer calculations. Drying Technology. 9, 5 (Dec. 1991), 1337-1339. DOI= https://doi.org/10.1080/07373939108916757.

[4] Pakowski, Z. and Zylla, R. 1996. Construction of Integrated Software for Drying Calculations. Drying Technology. 14, 2 (Jan. 1996), 463-472. DOI= https://doi.org/10.1080/07373939608917108.

[5] Marinos-Kouris, D., Maroulis, Z. B. and Kiranoudis, C. T. 1996. Computer Simulation of Industrial Dryers. Drying Technology. 14, 5 (Jan. 1996), 971-1010. DOI= https://doi.org/10.1080/07373939608917137.

[6] Marinos-Kouris, D., Maroulis, Z. B. and Kiranoudis, C. T. 1998. Modeling, Simulation and Design of Convective Industrial Dryers. Drying Technology. 16, 6 (Jan. 1998), 993-1026. DOI= https://doi.org/10.1080/07373939808917451.

[7] Baker, C. G. J. and Lababidi, H. M. S. 2001. Developments in computer-aided dryer selection. Drying Technology. 19, 8 (Aug. 2001), 1851-1873. DOI= https://doi.org/10.1081/DRT-100107276.

[8] Menshutina, N. V. and Kudra, T. 2001. Computer aided drying tecnologies. Drying Technology. 19, 8 (Aug. 2001), 1825-1849. DOI= https://doi.org/10.1081/DRT-100107275.

[9] Kemp, I. C. 2007. Drying Software: Past, Present, and Future. Drying Technology. 25, 7-8 (Aug. 2007), 1249-1263. DOI= https://doi.org/10.1080/07373930701438709.

[10] Gong, Z.-X. and Mujumdar, A. S. 2008. Software for Design and Analysis of Drying Systems. Drying Technology. 26, 7 (2008/07/01 2008), 884-894. DOI= https://doi.org/10.1080/07373930802142390.

[11] Gong, Z.-X. and Mujumdar, A. S. 2014. Process Simulation of Combustion Drying with Simprosys Software. Drying Technology, 32, 4 (Feb. 2014), 447-454. DOI= https://doi.org/10.1080/07373937.2013.835319.

[12] Maroulis, Z. B., Saravacos, G. D. and Mujumdar, A. S. 2015. Spreadsheet-Aided Dryer Design, A. S. Mujumdar, Ed. Advances in Drying Science and Technology Series. CRC Press, Taylor & Francis Group, Boca Raton, FL, 111-123.

[13] Aghbashlo, M., Hosseinpour, S. and Mujumdar, A. S. 2015. Application of Artificial Neural Networks (ANNs) in Drying Technology: A Comprehensive Review. Drying Technology. 33, 12 (Sep. 2015), 1397-1462. DOI= https://doi.org/10.1080/07373937.2015.1036288.

[14] Sun, Q., Zhang, M. and Mujumdar, A. S. 2018. Recent developments of artificial intelligence in drying of fresh food: A review. Critical Reviews in Food Science and Nutrition. 1-18. DOI= https://doi.org/10.1080/10408398.2018.1446900.

[15] Moreno, Á. H., Hernández-Maqueda, R. and Ballesteros, I. 2017. Secado industrial con energía microondas. J. A. Menendez and Á.H Moreno, Ed. Universidad Técnica de Cotopaxi, Latacunga, 85-118.

[16] Ttayagarajan, T., Ponnavaikko, M., Shanmugam, J., Panda, R. C. and Rao, P. G. 1998. Artificial Neural Networks: Principles and Application to Model based Control of Drying Systems - A Review. Drying Technology. 16, 6 (Jan. 1998), 931-966. DOI= https://doi.org/10.1080/07373939808917449.

[17] Farkas, I. 2013. Use of Artificial Intelligence for the Modelling of Drying Processes. Drying Technology, 31, 7 (May. 2013), 848-855. DOI= https://doi.org/10.1080/07373937.2013.769002.

[18] Motevali, A., Minaei, S., Khoshtaghaza Mohamad, H., Kazemi, M. and Mohamad Nikbakht, A. 2010. Drying of Pomegranate Arils: Comparison of Predictions from Mathematical Models and Neural Networks. International Journal of Food Engineering. 6, 3 (2010). Article 15. DOI= https://doi.org/10.2202/1556-3758.1889.

[19] Momenzadeh, L., Zomorodian, A. and Mowla, D. 2011. Experimental and theoretical investigation of shelled corn drying in a microwave-assisted fluidized bed dryer using Artificial Neural Network. Food and Bioproducts Processing. 89, 1 (Jan. 2011), 15-21. DOI= https://doi.org/10.1016/j.fbp.2010.03.007.

[20] Krishna Murthy, T. P. and Manohar, B. 2012. Microwave drying of mango ginger (Curcuma amada Roxb): prediction of drying kinetics by mathematical modelling and artificial neural network. International Journal of Food Science & Technology. 47, 6 (2012), 1229-1236. DOI= https://doi.org/10.1111/j.1365-2621.2012.02963.x.

[21] Balbay, A., Kaya, Y. and Sahin, O. 2012. Drying of black cumin (Nigella sativa) in a microwave assisted drying system and modeling using extreme learning machine. Energy, 44, 1 (Aug. 2012), 352-357. DOI= https://doi.org/10.1016/j.energy.2012.06.022.

[22] Motavali, A., Najafi, G. H., Abbasi, S., Minaei, S. and Ghaderi, A. 2013. Microwave–vacuum drying of sour cherry: comparison of mathematical models and artificial neural networks. Journal of Food Science and Technology. 50, 4 (Aug. 2013), 714-722. DOI= https://doi.org/10.1007/s13197-011-0393-1.

[23] Sarimeseli, A., Coskun, M. A. and Yuceer, M. 2014. Modeling Microwave Drying Kinetics of Thyme (Thymus Vulgaris L.) Leaves Using ANN Methodology and Dried Product Quality. Journal of Food Processing and Preservation. 38, 1 (2014), 558-564. DOI= https://doi.org/10.1111/jfpp.12003.

[24] Yousefi, G., Emam-Djomeh, Z., Omid, M. and Askari, G. R. 2014. Prediction of Physicochemical Properties of Raspberry Dried by Microwave-Assisted Fluidized Bed Dryer Using Artificial Neural Network. Drying Technology. 32, 1 (Jan. 2014), 4-12. DOI= https://doi.org/10.1080/07373937.2013.801849.

[25] Pham, B. T., Tien Bui, D., Prakash, I. and Dholakia, M. B. 2017. Hybrid integration of Multilayer Perceptron Neural Networks and machine learning ensembles for landslide susceptibility assessment at Himalayan area (India) using GIS. CATENA, 149 (Feb. 2017), 52-63. DOI= https://doi.org/10.1016/j.catena.2016.09.007.

[26] Chaphalkar, N. B., Iyer, K. C. and Patil, S. K. 2015. Prediction of outcome of construction dispute claims using multilayer perceptron neural network model. International Journal of Project Management. 33, 8 (Nov. 2015), 1827-1835. DOI= https://doi.org/10.1016/j.ijproman.2015.09.002.

[27] Wang, L., Zeng, Y. and Chen, T. 2015. Back propagation neural network with adaptive differential evolution algorithm for time series forecasting. Expert Systems with Applications. 42, 2 (Feb. 2015), 855-863. DOI= https://doi.org/10.1016/j.eswa.2014.08.018.

[28] Varoquaux, G., Buitinck, L., Louppe, G., Grisel, O., Pedregosa, F. and Mueller, A. 2015. Scikit-learn: Machine learning without learning the machinery. GetMobile: Mobile Computing and Communications Review. 19, 1 (2015), 29-33.

[29] Gabralla L.A. and A., A. 2014. Prediction of Oil Prices Using Bagging and Random Subspace. In Proceedings of the Fifth International Conference on Innovations in Bio-Inspired Computing and Applications IBICA 2014. (Ostrava, Czech Republic). Springer, Cham, New York, NY, 343-354. DOI= https://doi.org/10.1007/978-3-319-08156-4_34.

[30] Macías-García, L., Luna-Romera, J. M., García-Gutiérrez, J., Martínez-Ballesteros, M., Riquelme-Santos, J. C. and González-Cámpora, R. 2017. A study of the suitability of autoencoders for preprocessing data in breast cancer experimentation. Journal of Biomedical Informatics. 72 (Aug.

2017), 33-44. DOI= https://doi.org/10.1016/j.jbi.2017.06.020.

[31] Choubin, B., Khalighi-Sigaroodi, S., Malekian, A. and Kişi, Ö. 2016. Multiple linear regression, multi-layer perceptron network and adaptive neuro-fuzzy inference system for forecasting precipitation based on large-scale climate signals. Hydrological Sciences Journal. 61, 6 (Apr. 2016), 1001-1009. DOI= https://doi.org/10.1080/02626667.2014.966721.

[32] Christensen, L., Krell, M. and Kirchner, F. 2017. Learning magnetic field distortion compensation for robotic systems. In 2017 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS). (Vancouver, BC, Canada, Sept. 24-28, 2017). IEEE, Vancouver, BC, 3516-3521. DOI= https://doi.org/10.1109/IROS.2017.8206194.