Taylor & Francis
Taylor & Francis Group

World's Poultry Science Journal

ISSN: 0043-9339 (Print) 1743-4777 (Online) Journal homepage: www.tandfonline.com/journals/twps20

Machine learning application in growth and health prediction of broiler chickens

B. Milosevic, S. Ciric, N. Lalic, V. Milanovic, Z. Savic, I. Omerovic, V. Doskovic, S. Djordjevic & L. Andjusic

To cite this article: B. Milosevic, S. Ciric, N. Lalic, V. Milanovic, Z. Savic, I. Omerovic, V. Doskovic, S. Djordjevic & L. Andjusic (2019) Machine learning application in growth and health prediction of broiler chickens, World's Poultry Science Journal, 75:3, 401-410, DOI: 10.1017/S0043933919000254

To link to this article: https://doi.org/10.1017/S0043933919000254

Published online: 02 Dec 2019.

doi:10.1017/S0043933919000254

Machine learning application in growth and health prediction of broiler chickens

B. MILOSEVIC[1]*, S. CIRIC[1], N. LALIC[1], V. MILANOVIC[1], Z. SAVIC[1], I. OMEROVIC[2], V. DOSKOVIC[3], S. DJORDJEVIC[1] and L. ANDJUSIC[1]

[1]University of Pristina, Faculty of Agriculture Kosovska Mitrovica, Serbia; [2]State University of Novi Pazar, Serbia; [3]University of Kragujevac, Faculty of Agronomy, Cacak, Serbia
***Corresponding author: bozidar.milosevic@pr.ac.rs**

Artificial intelligence (AI) already represents a factor for increasing efficiency and productivity in many sectors, and there is a need for expanding its implementation in animal science. There is a growing demand for the development and use of smart devices at the farm level, which would generate enough data, which increases the potential for AI using machine learning algorithms and real-time analysis. Machine learning (ML) is a category of algorithm that allows software to become accurate in predicting outcomes without being explicitly programmed. The essential principle of machine learning is to construct algorithms that can receive input data and use statistical analysis to predict an output. Exploitation of machine learning approaches, by using different training inputs, derived the prediction accuracy of growth and body weight in broiler chickens that ranged from 98 to 99%. Furthermore, a neural network with an accuracy of 100% identified the presence or absence of ascites in broiler chickens, while the support vector machine (SVM) model obtained an accuracy rate of 99.5% in combination with machine vision for the recognition of healthy and bird flu-challenged chickens. Consequently, machine learning algorithms, besides accurate growth prediction of broiler chickens, can successfully contribute to health disorders prediction. It is obvious that machine learning has a great potential for application in the future. This paper analyses machine learning applications in broiler growth and health prediction, and its ability to cope with high inputs of data and non-linearity can successfully replace common methodology.

Keywords: machine learning; broiler; growth; health

Introduction

The informatics revolution offered solutions in many areas of agricultural production worldwide. The decision-making process is supported by huge amounts of data collected by a variety of sensors and electronic devices, providing a better approach to

Received for publication October 26, 2018
Accepted for publication March 19, 2019

understanding processes within the production environment. As new opportunities arise a part of the research can essentially be done by machine learning. Machine learning is defined as the field of science that promotes machines' ability to learn without exact programming through learning past behaviours and rules from old data (Cihan, 2017). Machine learning is already part of many scientific interests, such as medicine (Kang *et al.*, 2015; Zhang *et al.*, 2017; Maksimović *et al.*, 2016), meteorology (Cramer *et al.*, 2017; Rhee and Im, 2017; Aybar *et al.*, 2016), economics (Barboza *et al.*, 2017; Zhao *et al.*, 2017; Jović *et al.*, 2016; Maksimović *et al.*, 2017) and aquaculture (López *et al.*, 2017; Zhou *et al.*, 2018). This review aims to introduce machine learning methods used in poultry management systems, and to underline potential improvements in broiler productivity, health and welfare.

An overview on machine learning

Machine learning process can be explained as a computer code where a performance standard is optimised using past data or knowledge. Model needs to be defined with some variables and, through providing data, a computer program is trained to optimise the parameters of the model which could be designed to predict or to describe. *Figure 1* contains the machine learning pipeline.

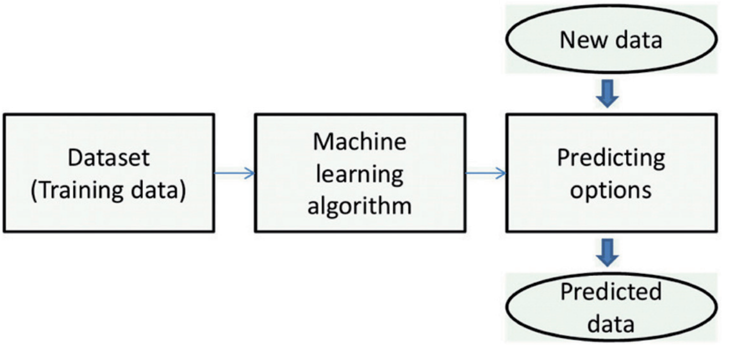

Figure 1 General pipeline of machine learning.

Machine learning, depending on the learning type, can be supervised and unsupervised, with many learning models (*Table 1*) and learning algorithms (*Table 2*), which are validated by different statistical measures (*Table 3*).

Vapnik (1995) was first to describe support vector machines (SVMs) as a binary classifier that creates a linear separating hyper-plane to classify data instances. This model has been used for classification, regression, and clustering, which were the most frequently used algorithms that support vector regression (Smola, 1996), and least squares that support the vector machine (Suykens *et al.*, 2002). Artificial neural networks are supervised models that are used for regression and classification problems, where the radial basis function networks, back-propagation, perceptron algorithms, and resilient back-propagation, are mostly present in the literature. Deep learning (DL) or deep neural networks belong to artificial neural networks, but contains several hidden layers between the input and output layers. The convolutional neural network (CNN) is typical representative of deep learning (Goodfellow *et al.*, 2016), together with deep Boltzmann machines and deep belief networks (Salakhutdinov, 2009).

Table 1 Machine learning models.

Model
Support vector machines (SVMs)
Deep learning (DL)
Dimensionality reduction (DR)
Decision trees (DT)
Artificial neural networks (ANN)
Ensemble learning (EL)
Instance based models (IBM)
Bayesian models (BM)

Table 2 Machine learning algorithms.

Model
Adaptive-neuro fuzzy inference systems (ANFIS)
Bayesian belief network (BBN)
Bootstrap aggregating (Bagging)
Bayesian network (BN)
Back-propagation network (BPN)
Classification and regression trees (CART)
Convolutional neural networks (cnns)
Deep boltzmann machine (DBM)
Deep belief network (DBN)
Deep neural networks (DNN)
Extreme learning machines (elms)
Ensemble neural networks (enns)
Generalized regression neural network (GRNN)
K-nearest neighbour (KNN)
Least squares-support vector machine (LS-SVM)
Multivariate adaptive regression splines (MARS)
Multi-layer perceptron (MLP)
Multiple linear regression (MLR)
Ordinary least squares regression (OLSR)
Principal component analysis (PCA)
Partial least squares regression (PLSR)
Radial basis function networks (RBFN)
Random forest (RF)
Supervised kohonen networks (skns)
Self-organising maps (soms)
Group method of data handling (GMDH)
Support vector regression (SVR)

Table 3 Statistical measures for the validation of machine learning algorithms.

Model
Coefficient of determination (R2)
Root mean squared error (RMSE)
Root mean square error of prediction (RMSEP)
Average relative root mean square error (RRMSE)
Mean absolute error (MAE)
Mean absolute percentage error (MAPE)
Mean percentage error (MPE)

Regression aims to provide the prediction of an output variable according to known input variables. Present algorithms include linear regression and logistic regression, as well as stepwise regression. More complex regression algorithms have been developed, such as ordinary least squares regression, multivariate adaptive regression splines and multiple linear regression. (Friedman, 1991; Quinlan, 1992; Craven and Islam, 2011).

Decision trees are the primary learner in ensemble models, at first random forest (Breiman, 2001), with additional boosting and bagging implementations, such as boosting technique (Schapire, 1999) and bootstrap aggregating or bagging algorithms are used (Breiman, 1996). Bayesian inference is used for solving either classification or regression problems and is a base for probabilistic graphical models under the Bayesian model (Pearl, 1988).

Broiler growth and machine learning

Growth of any living being is a complex, nonlinear dynamic and is not easy to model. Commonly used system identification approaches use linear model structures, which are not able to deal with the nonlinearity present during the entire growth process of broilers. A promising alternative is the soft computing approach and machine learning models and algorithms with the ability to approximate nonlinear functions (Johansen *et al.*, 2017). Poultry growth is usually modelled using the Gompertz model, using average body weight data over a period of time for a given breed under specific farm management conditions. Regularly implemented selection and genetic changes, nutritional factors and environmental concerns, however, make such models limited in their effectiveness because of the difficulty of fitting the growth curve across time, bird strains and other variables. Furthermore, generating data for every strain of birds under continually changing variables is difficult, time consuming, and expensive (Ahmad, 2009).

Neural networks offer an alternative to regression analysis for biological growth modelling, which have been experimentally confirmed (Roush *et al.*, 2006). This research included twenty-five male chicks (Ross × Ross 308) raised in an environmental chamber. Body weights were determined daily and feed and water were provided *ad libitum*. Average body weights of 18 birds were used as the data points for the growth curve to be modelled. Comparison was made between the modelling by the Gompertz nonlinear regression equation and neural network modelling. Accuracy of the models was determined by mean square error (MSE), mean absolute deviation (MAD), mean absolute percentage error (MAPE), and bias, which showed that the Gompertz equation underestimated the values whereas the neural networks produced little or no overestimation of the observed body weight responses Dynamic control of the growth of broiler chickens has potential benefits for farmers in terms of improved production effectiveness, as well as for animal welfare, *e.g.* in terms of improved leg health.

Demmers *et al.* (2010) introduced a differential recurrent neural network (DRNN) identified from experimental data to represent broiler chicken growth using a nonlinear system identification algorithm. The DRNN model was used as the internal model for nonlinear model predictive control (NMPC) to achieve a group of desired growth curves. The experimental results demonstrated that the DRNN explained dynamics of the broiler growth process convincingly well. The DRNN based NMPC was able to specify feed intakes in real time so that the broiler weights accurately followed the desired growth curves ranging from −12% to +12% of the standard curve. The overall mean relative error between the desired and achieved broiler weight was 1.8% for the period from day 12 to day 51. Similarly Demmers *et al.*

(2018) identified a differential recurrent neural network (DRNN) from experimental data to represent animal growth using a nonlinear system identification algorithm. The DRNN model was then used as the internal model for nonlinear model predictive control (NMPC) to achieve a group of desired growth curves. The experimental results demonstrated that the DRNN model captured the underlying dynamics of the broiler and pig growth process reasonably well. The DRNN based model was able to specify feed intakes in real time, so that the weights accurately followed the desired growth curves ranging from −12% to +12% and −20% to +20% of the standard curve for broiler chickens and pigs, respectively. The overall mean relative error between the desired and achieved broiler or pig weight was 1.8% for the period from day 12 to day 51 and 10.5% for the period from week five to week 21, respectively.

Another study by Johansen *et al.* (2017) investigated neural network forecasting models trained on farm-scale broiler batch production data from 12 batches from the same house. The model forecasted future broiler weight and used environmental conditions such as heating, ventilation, and temperature along with behaviour, such as feed and water consumption. Results indicated that the dynamic interconnection between environmental conditions and broiler growth could be captured by the model. Additionally, neural network model with a back-propagation algorithm successfully found the relationship between the inputs and outputs of feed intake, weight gain and feed conversion ratio variables (Ghazanfari, 2014). High coefficient of determination (R^2) and T values for the ANN model in comparison to linear regression showed that the artificial neural network (ANN) was an efficient method for growth performance prediction in the starter period for broiler chickens.

Three neural networks were used in the research conducted by Ahmad (2009), where actual growth data were used to predict broiler growth over the next 50 days. The Back-Propagation-3 neural network gave the best fitting line, with predictions fitting closely to the actual data points. The R^2 was 0.998, which clearly supported machine learning models and algorithms for modelling broiler growth in the future and decision-making process at the farm level. This conclusion was supported by a study where 190 artificial intelligencebased models were developed and compared for predicting the body mass of chicks from 2 to 21 d of age subjected to different duration and intensities of thermal challenge (Ferraz *et al.*, 2014). The neural networks were most accurate in predicting the body mass of chicks from 2 to 21 d of age after they were subjected to the input variables, and showed an R^2 of 0.9993 and a standard error of 4.62 g. The used machine learning model in this study enabled the simulation of different scenarios by changing the level of different inputs, which can be embedded into the heating control systems.

Similar conclusions were given in another study (Moharrery *et al.*, 2007), where a three-layer feed forward artificial neural network was used to predict body weight, plasma hormones and liver enzymes in broiler chickens. Six diet parameters were selected (ME: metabolisable energy in the diet; CHO: carbohydrate, CP: crude protein; MCHO: metabolisable carbohydrate; OM: organic matter; gram intake during growing period) as inputs (predictor) and parameters for the output (*Figure 2*, *Table 4*). Birds were fed diets containing different concentration of energy and protein.

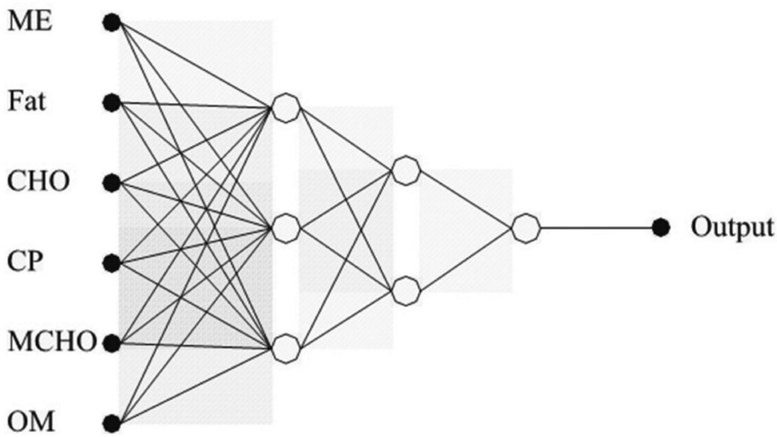

Figure 2 Structure of proposed artificial neural network (Moharrery *et al.*, 2007)

The network provided the simulation of the final results with the contribution percentage of each dietary component to the production trait under study. This method allowed the simulation of enzyme patterns in the liver, providing the contribution of plasma hormones from each diet to the broiler physiology variables under study. The network performance obtained in this study was very high (99%), which was acceptable.

Table 4 Comparison of results for observed and ANNs predicted values (Moharrery *et al.*, 2007).

Parameter	BW	FI	FE	IVL	MDH	ICD	AAT	IGF	GH	T3	T4
Mean											
Observed	1009	1782	49.1	28.36	15.17	25.52	49.33	3.318	1.146	4.302	13.03
Predicted	1010	1783	49.1	28.37	15.13	25.29	49.13	3.311	1.046	4.301	13.05
P value[1]	0.9972	0.9587	0.9382	0.9133	0.9719	0.9238	0.9161	0.8845	0.9969	0.9945	0.7926
Error, %[2]	0.084	0.058	-0.017	0.017	-0.248	-0.911	-0.403	-0.218	0.019	-0.022	-0.033
SD	1.095	0.261	1.450	1.220	1.328	3.777	4.334	2.082	0.284	0.711	2.425
Bias	1.005	1.005	0.9996	0.9989	0.9979	0.9880	0.9946	0.9981	1.000	0.9998	0.9993
Accuracy	1.0032	1.0007	1.0075	1.089	1.0057	1.0187	1.0146	1.0062	1.0023	1.0037	1.0071
MSE	0.947	4.705	0.698	0.344	0.203	0.980	2.124	0.064	0.003	0.030	0.314

BW: body weight; FI: feed intake; FE: feed efficiency; IVL: in vitro lipogenesis; MDH: malate dehydrogenase; ICD: isocitrate dehydrogenase; AAT: aspartate aminotransferase; IGF: insulin-like growth factor-I; GH: growth hormone; T3: triiodothyronine; T4: thyroxine. [1] this value showed a statistically significant difference between observed and predicted values. [2] error percentage = (((predicted - observed)/observed)*100). SD: standard deviation of the mean (error). MSE: mean square of the error.

Advances in technology currently provide new interesting combinations of machine learning and electronic equipment in determination of broiler body weight as the main growth indices in production. This combination may replace manual weight measuring, which decreases animal's welfare and increases human involvement and labour costs. Specific combinations of the machine vision and artificial neural networks were used to estimate live body weight of broiler chickens reared for 42 days (Amraei *et al.*, 2016). Imaging was performed two times daily and strong correlations between the body weight and five physical extracted features were found. Different ANN techniques, including

Bayesian regulation, Levenberg–Marquardt, scaled conjugate gradient and gradient descent were used. Bayesian regulation with an R^2 value of 0.98 was the best for prediction of broiler weight. Wang *et al.* (2017) introduced a three-dimensional camera, which can measure phenotypic features in order to determine broiler weight. Their procedure of image pre-processing consists of image cropping, median filtering, OTSU threshold segmentation and binarisation. During this process, nine features were extracted with a mathematical geometry method, including area, uniformity, width, length, radius, perimeter, volume, back width and age. These nine features were used to construct a back propagation neural network with body weight as an output. Based on these data, the body weight estimation model was established to realise the population weight estimations. The root mean square error (RMSE) was 0.048 kg, mean relative error (MRE) was 3.3%, optimal fitness was 0.994, minimum relative error was 0.5% and the maximum relative error was about 11%. These results showed that the proposed method was feasible and effective for constructing broiler weight estimation models, providing a theoretical basis for estimating broiler growth by using machine vision technology.

Broiler health and machine learning

Poultry diseases are a major source of economic losses to farmers and pose a serious threat for the human population health. Consequently, monitoring and early warning of disease outbreaks are essential in poultry breeding. As previously elaborated, machine learning possesses the ability to cope with nonlinear connection between different variables, which makes its use in broiler health prediction possible. Kirby *et al.* (1997), tried to identify broilers with ascites using multiple linear regression and logistic regression. They found that a linear regression model was complex and did not show normally distributed errors, which increased chances of false predictions. On the other hand, a logistic regression model was found to be simple, biologically meaningful and statistically powerful.

Ascites is one of the main sources of economic problems in the broiler industry (Wideman, 1988; Wideman and Bottje, 1993). Defining physiological factors that categorise broilers with a predisposition to ascites could be helpful in order to eliminate these individuals from the flock. Artificial neural networks were found to effectively identify broilers with and without ascites (Roush *et al.*, 1996). The model was a three-layer back-propagation neural network with an input layer of 15 physiological variables with an output layer of two factors (the presence or absence of ascites). A comparison was made between laboratory diagnostic results and the neural network predicted ascites incidence, and the neural network accurately (100%) identified the presence or absence of ascites in the training set. Furthermore, probabilistic neural networks based on non-invasive inputs showed acceptable results (Roush *et al.*, 1997). Inputs were oxygen concentration in the blood, body weight, electrocardiogram, haematocrit, S wave, and heart rate of individual birds. As in the previous study, output was presence or absence of ascites. The conclusion was that the use of models developed with artificial neural networks may enhance the diagnosis of ascites in broilers, and may help developing broiler strains without a propensity for ascites.

If thermal conditions inside a poultry house are beyond the comfort limits, the bird physiologically adapts to maintain normal temperature and focuses only on survival (Medeiros *et al.*, 2005), which leads to lower productivity. The best indicator of heat stress in broiler is their rectal temperature (Campos *et al.*, 2004; Spiers *et al.*, 2004). Hence, research was done with the objective of developing and evaluating artificial neural networks for the prediction of broilers' rectal temperature in function of thermal conditions air temperature, relative humidity, and air velocity. The selected multilayer perceptron (MLP), achieved excellent results, providing estimates with an average error of 0.78% for the training set and 1.02% for the validation set (Lopes *et al.*, 2014).

Another technique that may have future applications is support vector machines (SVM), a type of machine learning algorithm, used by Hepworth *et al.* (2012), to identify risk factors for hock burn incidence, using recorded data relative to farm management conditions (stocking density, number and age of parent flocks, sex, and rearing system) together with daily water consumption, average weekly weight, mortality, and slaughterhouse outcomes (rejections, downgrades, and hock burns). Results were compared to manually build logistic regression models in order to test SVM. Conclusions were that this technique had great potential to improve poultry health and welfare as it proved robust for a broad range of complex data sets.

Machine vision and learning algorithm applications for broiler disease detection is an effective method to prevent large-scale outbreaks of disease (Zhuang *et al.*, 2018). In this study broilers infected with bird flu virus were placed in isolator cages for obtaining images and extracting features of healthy and sick chickens. These features were analysed by machine learning algorithms and the effect of each feature on the recognition accuracy was obtained. The SVM model obtained an accuracy rate of 99.469% for the test samples, which was superior to those of the other machine learning algorithms. The experimental results showed that the machine learning algorithms could effectively differentiate broilers from the image background, extract the posture information of broilers, and precisely and quickly identify the health status of broilers, which can be used for the smart identification of broiler health status in the future.

Conclusions

This review analysed machine learning application in broiler industry, at particular its' use in growth and health prediction. It was observed that recent developments in computer science have effectively addressed the problems in broiler industry. Some results are very promising and give an excellent basis for future research, especially in the field of growth modelling, disease detection, and finally, animal welfare improvement.

References

AHMAD, H.A. (2009) Poultry growth modelling using neural networks and simulated data Poultry growth modelling using neural networks and simulated data. *The Journal of Applied Poultry Research* **18 (3)**: 440-446.

AMRAEI, S., MEHDIZADEH, S. and SALARI, S. (2016) Broiler weight estimation based on machine vision and artificial neural network. *British Poultry Science* **58 (2)**: 200-205.

AYBAR, R.A., JIMÉNEZ, F.S., CORNEJO, B.L., CASANOVA, M.C., SANZ, J.J., SALVADOR, G.P. and SALCEDO, S.S. (2016) A novel Grouping Genetic Algorithm-Extreme Learning Machine approach for global solar radiation prediction from numerical weather models inputs. *Solar Energy* **132**: 129-142.

BARBOZA, F., KIMURA, H. and ALTMAN, E. (2017) Machine learning models and bankruptcy prediction. *Expert Systems With Applications* **83**: 405-417.

BREIMAN, L. (1996) Bagging Predictors. *Machine Learning* **24**: 123-140.

BREIMAN, L. (2001) Random Forests. *Machine Learning* **45**: 5-32.

CAMPOS, O.F., CUNHA, D.N.F.V., PEREIRA, J.C., JUNQUEIRA, M.M., MARTUSTELLO, J.A., PIRES, M.F.A. and LIZIEIRE, R.S. (2004) Utilização de diferentes abrigos para bezerros de rebanhos leiteiros em condições tropicais durante a época das águas: temperatura retal, frequência respiratória e consumo de água. Proceedings of the XLI Reunião Anual da Sociedade Brasileira de Zootecnia, Brazil, pp. 1-5.

CIHAN, P., GÖKÇE, E. and KALIPSIZ, O. (2017) A review of machine learning applications in veterinary field. *Kafkas Üniversitesi Veteriner Fakültesi Dergisi* **23 (4)**: 673-680.

CRAMER, S., KAMPOURIDIS, M., FREITAS, A.A. and ALEXANDRIDIS, A.K. (2017) An extensive evaluation of seven machine learning methods for rainfall prediction in weather derivatives. *Expert Systems With Applications* **85**: 169-181.

CRAVEN, B.D. and ISLAM, S.M.N. (2011) Ordinary least-squares regression, in: MOUTINHO, L. & HUTCHESON, G.D. (Eds) *The SAGE Dictionary of Quantitative Management Research*, pp. 224-228 (SAGE Publications).

DEMMERS, G.M., CAO, Y., GAUSS, S., LOWE, C.J., PARSONS, D.J. and WATHES, M.C. (2018) Neural predictive control of broiler chicken and pig growth. *Biosystems Engineering* **173**: 134-142.

DEMMERS, T.G.M., CAO, Y., GAUSS, S., LOWE, J.C., PARSONS, D.J. and WATHES, C.M. (2010) Neural Predictive Control of Broiler Chicken Growth. IFAC Proceedings Volumes, Volume 43, Issue 6, Pages 311-316.

FERRAZ, P.F.P., JUNIOR, T.Y., JULIO, Y.F.H., CASTRO, J.O., GATES, R.S., REIS, G.M. and CAMPOS, A.T. (2014) Predicting chick body mass by artificial intelligence-based models. *Pesquisa Agropecuária Brasileira* **49 (7)**: 559-568.

FRIEDMAN, J.H. (1991) Multivariate Adaptive Regression Splines. *The Annals of Statistics* **19**: 1-67.

GHAZANFARI, S. (2014) Application of Linear Regression and Artificial Neural Network for Broiler Chicken Growth Performance Prediction. *Iranian Journal of Applied Animal Science* **4 (2)**: 411-416.

GOODFELLOW, I., BENGIO, Y. and COURVILLE, A. (2016) Deep Learning, MIT Press: Cambridge, MA, USA, pp. 216-261.

HEPWORTH, P.J., NEFEDOV, A.V., MUCHNICK, I.B. and MORGAN, K.L. (2012) Broiler chickens can benefit from machine learning: Support vector machine analysis of observational epidemiological data. *Journal of The Royal Society Interface* **9**: 1934-1942.

JOHANSEN, V., BENDTSEN, S.D., JENSEN, R.J. and JESPER, M.M. (2017) Data Driven Broiler Weight Forecasting using Dynamic Neural Network Models. *IFAC-PapersOnLine* **50**: 5398-5403.

JOVIĆ, S., MAKSIMOVIĆ, G. and JOVOVIĆ, D. (2016) Appraisal of natural resources rents and economic development. *Resources Policy* **50**: 289-291.

KANG, J., SCHWARTZ, R., FLICKINGER, J. and BERIWAL, S. (2015) Machine learning approaches for predicting radiation therapy outcomes: A clinician's perspective. *International Journal of Radiation Oncology, Biology, Physics* **93**: 1127-1135.

KIRBY, Y.K., MCNEW, R.W., KIRBY, J.D. and WIDEMAN, R.F. (1997) Evaluation of logistic versus linear regression models for predicting pulmonary hypertension syndrome (ascites) using cold exposure or pulmonary artery clamp models in broilers. *Poultry Science* **76**: 392-399.

LOPES, A.Z., JUNIOR, T.Y., LACERDA, W.S. and RABELO, D. (2014) Predicting Rectal Temperature of Broiler Chickens with Artificial Neural Network. *International Journal of Engineering & Technology IJET-IJENS* **14 (05)**: 29-34.

LÓPEZ, C.X.A., NACHTIGALL, F.M., OLATE, V.R., ARAYA, M., OYANEDEL, S., DIAZ, V., JAKOB, E., RÍOS, M.M. and SANTOS, L.S. (2017) Fast detection of pathogens in salmon farming industry. *Aquaculture* **470**: 17-24.

MAKSIMOVIĆ, G., JOVIĆ, S., JOVANOVIĆ, R. and ANICIC, O. (2016) Management of health care expenditure by soft computing methodology. *Physica A: Statistical Mechanics and its Applications* **465**: 370-373.

MAKSIMOVIĆ, G., JOVIĆ, S., JOVOVIĆ, D. and JOVOVIĆ, M. (2017) Analyses of Economic Development Based on Different Factors. *Computational Economics*: 10.1007/s10614-017-9786-1.

MEDEIROS, C.M., BAÊTA, F.C., OLIVEIRA, F.M., TINÔCO, I.F.F., ALBINO, L.F.T. and CECON, P. R. (2005) Efeitos da temperatura, umidade relativa e velocidade do ar em frangos de corte. *Engenharia Agrícola* **13 (4)**: 277-286.

MOHARRERY, A. and KARGAR, A. (2007) Artificial Neural Network for prediction of plasma hormones, liver enzymes and performance in broilers. *Journal of Animal and Feed Sciences* **16**: 293-304.

PEARL, J. (1988) Probabilistic Reasoning in Intelligent Systems. *Morgan Kauffmann San Mateo* **88**: 552.

QUINLAN, J.R. (1992) Learning with continuous classes. *Machine Learning* **92**: 343-348.

RHEE, J. and IM, J. (2017) Meteorological drought forecasting for ungauged areas based on machine learning: Using long-range climate forecast and remote sensing data. *Agricultural and Forest Meteorology* **237-238**: 105-122.

ROUSH, W.B., CRAVENER, T.L., KIRBY, Y.K. and WIDEMAN, R.F., (1997) Probabilistic neural network prediction of ascites in broilers based on minimally invasive physiological factors. *Poultry Science* **76**: 1513-1516.

ROUSH, W.B., DOZIER, W.A. and BRANTON, S.L. (2006) Comparison of Gompertz and neural Network Models of Broiler Growth. *Poultry Science* **85 (4)**: 794-797.

ROUSH, W.B., KIRBY, Y.K., CRAVENER, T.L. and WIDEMAN, R.F. (1996) Artificial neural network predictions of ascites in broilers. *Poultry Science* **75**: 1479-1487.

SALAKHUTDINOV, R. and HINTON, G. (2009) Deep Boltzmann Machines. *AIStats* **1**: 448-455.

SCHAPIRE, R.E. (1999) A brief introduction to boosting. Proceedings of the IJCAI International Joint Conference on Artificial Intelligence, Volume 2, pp. 1401-1406.

SMOLA, A. (1996) Regression Estimation with Support Vector Learning Machines. Master's Thesis, The Technical University of Munich.

SPIERS, D.E., SPAIN, J.N., SAMPSON, J.D. and RHOADS, R.P. (2004) Use of physiological parameters to predict milk yield and feed intake in heatstressed dairy cows. *Journal of Thermal Biology* **29 (7-8)**: 759-764.

SUYKENS, J.A.K., VAN GESTEL, T., DE BRABANTER, J., DE MOOR, B. and VANDEWALLE, J. (2002) Least Squares Support Vector Machines, World Scientific: Singapore.

VAPNIK, V. (1995) Support vector machine. *Machine Learning* **20**: 273-297.

WANG, L., SUN, C., LI, W., JI, Z., ZHANG, X., WANG, Y., LEI, P. and YANG, X. (2017) Establishment of broiler quality estimation model based on depth image and BP neural network. *Transactions of the Chinese Society of Agricultural Engineering* **33 (13)**: 199-205.

WIDEMAN, R.F. (1988) Ascites in poultry. *Monsanto Nutrition Update* **6 (2)**: 1-7.

WIDEMAN, R.F. and BOTTJE, W.G. (1993) Current understanding of the ascites syndrome and future research directions. Nutrition and Technical Symposium Proceedings, pp. 1-20.

ZHANG, B., HE, X., OUYANG, F., GU, D., DONG, Y., ZHANG, L., MO, X., HUANG, W., TIAN, J. and ZHANG, S. (2017) Radiomic machine-learning classifiers for prognostic biomarkers of advanced nasopharyngeal carcinoma. *Cancer Letters* **403**: 21-27.

ZHAO, Y., LI, J. and YU, L. (2017) A deep learning ensemble approach for crude oil price forecasting. *Energy Economics* **66**: 9-16.

ZHOU, C., LIN, K., XU, D., CHEN, L., GUO, Q., SUN, C. and YANG, X. (2018) Near infrared computer vision and neuro-fuzzy model-based feeding decision system for fish in aquaculture. *Computers and Electronics in Agriculture* **146**: 114-124.

ZHUANG, X., BI, M., GUO, J., WU, S. and ZHANG, T. (2018) Development of an early warning algorithm to detect sick broilers. *Computers and Electronics in Agriculture* **144**: 102-113.