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Applications of artificial neural networks for enhanced livestock productivity: A review

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ABSTRACT

Artificial neural network models are machine-learning systems, a type of artificial intelligence. They have been inspired by and developed along the working principles of the human brain and its nerve cells. It is used in the modelling of non-linear systems. With the information learned through repeated experience, similar to human learning, artificial neural network can provide classification, pattern recognition, optimisation and the realisation of forward-looking forecasts. Artificial neural network has manifold applications in the field of livestock and allied sections for prediction of milk production, prediction of breeding values of bulls, estrous detection, mastitis prediction and lameness detection, detection of cows with artificial insemination difficulties, prediction of success rate of *in-vitro* fertilization, manure nutrient content, volatile fatty acids in the rumen of dairy animals. Artificial neural network models were determined to be more successful than cluster analysis. Most of the published works in data analysis use linear models for forecasting the production parameters; however, sufficient literature proved that by using artificial neural network better results obtained as compared to linear or classical methods. The present manuscript is an attempt to review the systematic information available in livestock and allied sector.

Key words: Artificial intelligence, Dairy animals, Estrous detection, Forecasting, Lameness, Mastitis, Milk production, Prediction

Livestock, an integral part of agricultural economy, plays a multifaceted role for providing livelihood support to the rural population from the developing countries. Livestock sector apart from contributing to national economy in general and to agricultural economy in particular, also provides employment generation opportunities (National Livestock Policy 2013). Forecasting livestock productivity is an essential step for better management of financial system of livestock holders provided that the forecasting should be closer to the actual production. An ANN, the information processing concept, is inspired from the human brain, and its use is a method of data analysis which emulates the brain's way of working. Neural networks exhibit the way in which arrays of neurons probably function in biological learning and memory (Zupan and Gasteiger 1991) . Artificial neural networks are computer systems that were designed as part of the research on artificial intelligence (AI). Most neural networks are software simulations run on conventional computers. The neural network is simply neurons (just like in the brain) joined together, with the output from one neuron becoming input to others until the final output is reached (Rosenblatt 1961). Different types of neural networks have been developed from time to time. Feed-forward neural network was the first type of ANN developed. In this network, the information moves only in one direction, forward from the input neurons through the hidden neurons (if any) to the output nodes. There are no cycles or loops in the network. Perceptron (a linear classifier) is the simplest kind of feed-forward ANN. Self-organizing maps (SOM) or Kohonen neural networks was initially developed to mimic human brain functioning. In human brain similar information is stored in certain regions (neighbouring neurons) of cortex. This is related to the mapping of inputs in the Kohonen map, which represents a type of unsupervised learning strategy and can be rationalised by the way how young children learn to recognize objects. Counter-propagation artificial neural networks (CP-ANN) is based on a two-step learning procedure, which is unsupervised in the first step. The first step corresponds to the mapping of objects in the input layer (Noviè 2008). The use of self-organising networks such as artificial neural networks is widely used in livestock industries for prediction in many fields of knowledge. Mathematical modelling for various parameters through the entire livestock production chain is providing significant advantages in terms of increased process efficiency and quality control, resulting in associated economic benefits to various livestock industry.

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Organisation of artificial neural network

The multilayer networks consist of multiple layers of computational units, usually interconnected in a feed

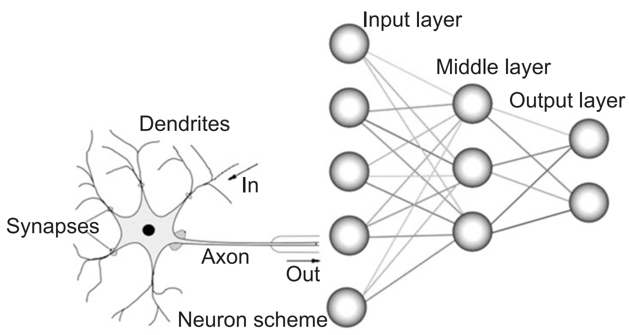

Fig. 1. Schematic diagram of a typical artificial neural network (Source: Kunzle 2015).

forward way. Multilayer networks use a variety of learning techniques, the most popular being back propagation and the output values are compared with the correct answer to compute the value of some predefined error-function. By various techniques, the error is then fed back through the network. Using this information, the algorithm adjusts the weights of each connection to reduce the value of error function by some small amount. After repeating this process (epochs) for a sufficiently large number of training cycles, the network usually converge to some state where the error of the calculations is small (Chayjan 2010). The input and output training pattern of the ANN is illustrated in Fig.1.

Application of ANN in milk production forecasting of dairy animals

Milk production in dairy animals which normally represented in the form of lactation curve follows the non-linear pattern of production; therefore, the non-linear function should be exercised for prediction of lactation milk yield. The prediction of life time milk production of a dairy cow is possible using artificial neural networks (Chaturvedi *et al.* 2013). The conventional methods of dairy animals milk yield forecasting like multiple linear regression method has limits for not addressing non-linearity and not considering the interdependency of independent variable used for forecasting the milk production. The accuracy of milk production forecasts on dairy farms animals is of paramount importance for dairy farm management. It will help them to know the milk production of their farm in advance, and formulate basis for culling of spent dairy animals and thus making profitable dairy business. The implication is that dairy cow farmers could make selection decisions of prospective productive cow earlier hence increasing genetic potential of dairy herds. Various reports suggested that dairy cow's milk production using artificial neural network could predict in an early stage of lactation with higher degree of accuracy than conventional methods of prediction. The daughter's milk production could be predicted from dairy dam, sire, herd and environmental factors using ANN tools (Macrossan 1999). In this regards, Njubi *et al.* (2009) investigated the use of back-propagation ANN to predict the performance of daughter's first lactation milk yield based on recorded genetic traits of their parents and found >0.80 correlation coefficients between the observed and the estimated milk yield from the ANN model and linear regression model methods. Sharma *et al*. (2006) compared ANN model and multiple linear regression model to predict the FL305DMY using partial lactation records of Karan Fries crossbred dairy cattle and reported that the accuracy of prediction from ANN model was slightly higher than that from conventional regression model (57.61 versus 52.80%). In accordance, Dongre *et al.* (2012); Gandhi *et al.* (2012) inferred that artificial neural network was better than the multiple linear regression analysis for prediction of first lactation 305 days milk yield with more than 80 % accuracy at an early stage of the lactation with lesser value of root mean square error. Similar results were observed in Brown Swiss cattle of Turkey (Gorgulu 2012). Njubi *et al* (2011) predicted second parity 305-day milk yield (SLMY305) in Kenyan Holstein-Friesian cows by comparing ANN with multiple linear regression (MLR) method based on first parity information and observed >0.80 correlation coefficients between the observed and the predicted SLMY305 from the two methods. However, Edriss *et al*. (2008) studied prediction of second parity milk yield and fat percentage based on first parity information to predict the performance of prospective productive cows and reported ANN was better predictor than multiple linear regression method. Grzesiak *et al.* (2006) found that the quality parameters of the designed neural networks were better than those of the regression model, for both the daily yields and test-day data (higher coefficients of determination and lower RAE and RMS). Murphy *et al*. (2014) assessed the suitability of three different modelling techniques i.e. non-linear auto-regressive model with exogenous input, a static artificial neural network and multiple linear regression model for the prediction of total daily herd milk yield of dairy cows. All three models predicted the daily production levels for standard lactation with root mean square error of 12.03%. It was revealed that the non-linear auto-regressive model with exogenous input was more accurate alternative to conventional regression modelling techniques, especially for short-term milk yield predictions. The potential of artificial neural networks and neuro-fuzzy systems for estimation of breeding values (EBV) of Iranian dairy cattle was done by Saleh *et al.* (2012) and revealed that the correlations between actual and predicted EBV for milk yield by the ANN and neuro-fuzzy system were 0.92 for both methods. Contrary to most of the finding, Sanzogni and Kerr (2011) reported that the standard feed forward ANN did not improve on the multiple regression technique for forecasting milk yield of dairy cattle. The uses of ANN have been extended to sheep and goat milk prediction too. Kominakis *et al.* (2002) used artificial neural networks for prediction of lactation as well as test-day milk yield(s) in Chios dairy sheep on the basis of input variables like county, herd, lactation, lambing month, litter size, milk yield recorder, test day and days in milk. An artificial neural network (ANN) model was developed to describe average daily gain in lambs from input parameters of GH, leptin, calpain, and calpastatin polymorphism, birth weight and birth type. The calculated statistical values corresponding to the ANN-model showed a high accuracy of prediction (Tahmoorespur and Ahmadi 2012). They observed the average difference between observed and predicted yields was statistically non-significant. Goyal and Goyal (2012) used ANN for predicting shelf life of dairy product and they concluded that ANN and statistical computerized methods, both can be employed for predicting shelf-life of dairy products.

Application of ANN in beef industry

The market of meat and meat products is growing continuously. Artificial neural networks are a well-known mathematical tool widely used and tested lately for the problem in meat production and technology. Its advantages are in the ability to handle non-linear data, highly correlated variables and the potential for identification of problems or classification. In particular, promising applications of ANN in relation to meat sector is in carcass classification, quality control of raw material, meat processing, meat spoilage or freshness and shelf-life evaluation, detecting off-flavours, authenticity assessment, etc. Artificial intelligence methods (ANN) were mainly investigated for the evaluation of meat sensory quality i.e. the properties that are subjectively evaluated or classified such as tenderness, colour or marbling score/level (Chandraratne *et al.* 2006, Qiao *et al.* 2007, Sheridan *et al.* 2007). There were also studies dealing with water-holding capacity of pork, quality of meat products and categorization to different pork or beef quality classes (Shiranita *et al.* 2000). A brief review has been made as per Table 1.

Table 1. The application of ANN in meat quality analysis

Parameter	Input data	Results	Reference
Marbling	Ultrasonography, pattern recognition	84% correctness	Brethour (1994)
Meat colour	pH, haem pigment, dielectric loss factor	70% correctness	Santé *et al.* (1996)
Cooked meat tenderness	Computer vision (digital colour image of meat)	R^2= 0.70	Li *et al.* (1999)
Meat tenderness (tough or tender)	Image texture analysis	83% correctness	Li *et al.* (2001)
Moisture content	Computer vision (colour features)	r =0.75	Zheng *et al.* (2007)

Application in animal reproduction

The ANN and multivariate adaptive regression spline (MARS) were more precise in detection of cows with artificial insemination difficulties in comparison to conventional statistical methods for the dairy cows using average calving interval, cow body condition index, lactation number, pregnancy length, sex of calf from previous calving and cow age input as variables (Grzesiak 2010). The ANN could be able to predict semen production in ram using phenotypic traits (Qotbi 2010) and fertilization potential of frozen spermatozoa of cattle and buffalo (Durairaj and Meena 2008.). Recently, attempt has been made in human patient undergoing fertility treatment for baby to forecast success rate of the treatment using IVF data which have opened a new vista in the livestock sector (Durairaj and Thamilselvan 2013).

Application in animal nutrition

Nutrients in animal manure are valuable inputs in agronomic crop production. Timely and reliable information on animal manure nutrient content will facilitate the utilization of manure as organic fertilizer and reduce any associated potential environmental problems. While the livestock population is increasing, the gap between the requirement and availability of feed and fodder is increasing primarily due to decreasing area under fodder cultivation and reduced availability of crop residues as fodder. Application of computer programing for better management of animal waste/manure and fodder is need of the hour. Artificial neural network can be used to determine nutrient content in dairy manure as well as proportions of individual volatile fatty acids in the rumen of dairy animals with higher coefficient of determination (R^2), modelling efficiency statistics and lower mean squared error of prediction (Chen 2008). Craninx *et al*. (2008) compared the prediction accuracy of the rumen fermentation pattern from milk fatty acids using artificial neural networks combined with statistical multi-linear regression model, based on odd and branched chain milk fatty acids in dairy cattle, in the study, ANN could not perform significantly better. However, the results confirm that milk fatty acids have great potential to predict molar proportions of individual volatile fatty acids in the rumen. Dong and Zhao (2014) studied the suitability and accuracy of modelling the rumen methane production of mixed rations for cattle using artificial neural network. The three layer back propagation neural network which indicated that the *in vitro* CH_4, CO_2 and total gas production of mixed rations for cattle could be reliably and accurately predicted based on the Cornell Net Carbohydrate and Protein System (CNCPS) carbohydrate fractions. The back propagation neural network models showed similar accuracy with the multiple regression model for predicting the CH_4 production and better accuracy for predicting the CO_2 and the total gas production than the multiple regression models.

Application of ANN in animal health

Lameness in dairy cow results in loss of milk yield, treatment costs, decrease in reproductive efficiency, and premature culling of animals. Lameness scoring is a routine procedure in dairy farm to screen in the progressive dairy farms. Subjective lameness scoring, which is the most popular lameness detection and screening method in dairy herds, has several limitations. It includes low intra-observer and inter-observer agreement and the discrete nature of the scores, which limits its usage in monitoring the lameness. Artificial neural networks could be use to develop an automated lameness scoring system comparable for detection of lameness in dairy cattle (Ghotoorlar *et al.* 2012, Mertens *et al.* 2012). Mastitis adversely affects the dairy industry around the world and it is probably the most important disease of dairy cattle. ANN could be used for early detection of pathogens in the quarters of dairy animals. The milk parameters associated with mastitis could be use to build robust ANN models and incorporation of such models in in-line milking systems may improve the efficiency and efficacy of detecting mastitis causing pathogens in milk before any clinical manifestations occur (Hassan 2007). This may form a reliable basis for managing and controlling mastitis at the farm level. Similarly, Ankinakatte *et al.* (2013) has attempted for early detection mastitis in cattle by comparing neural network models and generalized additive models with automated recorded data at the Danish Cattle Research Centre, Denmark. As indicators of mastitis, electrical conductivity, somatic cell scores, lactate dehydrogenase and milk yield were considered. Neural network appear to be marginally better for high specificities. More input variables could give better results. Wang and Samarasinghe (2005) studied two variations of ANN, the multilayer perceptron (MLP) and the self organizing map (SOM), and trained to detect the presence or absence of clinical mastitis. The MLP classified mastitis shows 84% accuracy whereas classification rate for discriminate classifier was 81% for sick cows. Both provided 100% accuracy for healthy cows. Contrary to this, Cavero *et al*. (2008) reported the performance of ANN was not satisfactory for mastitis detection in dairy cows. The ANN model could be used in herds with higher frequency of minor and contagious pathogens for diagnosing the bacteriologic status. The probabilities of diagnosing the bacteriologic status from three randomly selected cow groups and from new untested herds ranged from 57 to 71% when the artificial neural network used as compared to linear discriminant analysis from 42 to 57% (Heald 2000). A four balance system can be used for automatic lameness detection with probabilistic neural network (PNN) model developed. The model was able to detect all leg problems with only 1.1% of false alarm giving. The model developed by Pastell and Kujala (2007) has the potential to be used as an on-farm decision aid and can be used in a real time lameness monitoring system. Probabilistic neural network in the clinical diagnosis of cancers based on clinical chemistry data has been used by Shan *et al.* (2002).

Application of ANN in animal behaviour

Animal welfare is an issue of great importance in modern food production systems because animal behaviour provides reliable information about animal health and welfare. Various researches were designed for measuring behavioural parameters and transforming them into their corresponding behavioural modes (Kamo *et al.* 1998, Haykin 1999, Enquist and Ghirlanda 2008). In this context, Nadimi *et al.* (2012) studied 2.4-GHz ZigBee-based mobile ad hoc wireless sensor network (MANET) to study the animal behavioural pattern. The measured behavioural parameters were transformed into the corresponding behavioural modes using a multilayer perceptron based artificial neural network. The best performance of the ANN in terms of the mean squared error and the convergence speed was achieved when it was initialized and trained using two algorithms viz. *Nguyen–Widrow* and *Levenberg Marquardt* back-propagation, respectively. The average success rate of behaviour classification into five classes (i.e. grazing, lying down, walking, standing and others) was 76.2%. They found improvement regarding the performance of the designed MANET and behaviour classification compared to other studies.

Application of ANN in poultry industry

The ANN is an efficient method of predicting egg production for pullet and hen flocks. The ANN model could provide an effective means of recognizing the patterns in data and accurately predicting the egg production of laying hens based on investigating their age (Ghazanfari *et al*. 2011). Artificial neural network (ANN) was used to predict the final temperature of chicken carcasses in an industrial scale (Silveira and Belledeli 2013). It was also used to predict hormones and enzymes in broiler chicken (Moharrery and Kargar 2007). It can also be committed for breeder management, broiler breeder serological interpretation and hatchery management when sufficient data is available. The artificial neural network models could explain the production performance of poultry birds (Salle 2003).The method allows the decisions made by the technical staff to be based on objective, scientific criteria allows simulation of the consequences related to these decisions and reports the contribution of each variable to the variables under study.

The various applications of ANNs can be summarised into classification or pattern recognition, prediction and modeling. The ability of neural network learning by examples makes it more flexible and reliable. Various reports suggested artificial neural network is more accurate tool for forecasting the things related to livestock improvement, predominantly in dairy sector. However, use of number input variables could forecast the desired parameters with more precision. It also has potential applications in the pharmaceutical sciences ranging from interpretation of analytical data, drug and dosage form design through biopharmacy to clinical pharmacy. ANN can be regarded as a very powerful pattern recognition technique in analyses of environmental and climatic data in relation to livestock productivity. This could be used as a valuable performance assessment tool for dairy entrepreneur. Finally, ANN can be used quite accurately to study processes to improve livestock productivity.

REFERENCES

Ankinakattea S, Norberga E, Løvendahl P, Edwards D and Højsgaar S. 2013. Predicting mastitis in dairy cows using neural networks and generalized additive models: A comparison. *Computers and Electronics in Agriculture* **99**: 1–6.

Brethour J. 1994. Estimating marbling score in live cattle from ultrasoud images using pattern-recognition and neural-network procedures. *Journal of Animal Science* **72**(6): 1425– 32.

Cavero D, Tölle K H, Henze C, Buxadé C and Krieter J. 2008. Mastitis detection in dairy cows by application of neural networks. *Livestock Science* **114**: 280– 86.

Chandraratne M R, Samarasinghe S, Kulasiri D and Bickerstaffe R. 2006. Prediction of lamb tenderness using image surface texture features. *Journal of Food Engineering* **77**(3): 492– 99.

Chaturvedi S, Yadav R L, Gupta A K and Sharma A K. 2013. Life time milk amount prediction in dairy cows using artificial neural networks. *International Journal of Recent Research and Review* **5**: 1–6.

Chayjan R A. 2010. Modeling of sesame seed dehydration energy requirements by a soft- computing. *Australian Journal of Crop Science* **4**(3): 180–84.

Chen L J, Cui L Y, Xing L and Han L J. 2008. Prediction of the nutrient content in dairy manure using artificial neural network modeling. *Journal of Dairy Science* **91**(12): 4822–29.

Craninx M, Fievez V, Vlaeminck B and De Baets B. 2008. Artificial neural network models of the rumen fermentation pattern in dairy cattle. *Computers and Electronics in Agriculture* **60**(2): 226–38.

Dong R and Zhao G. 2014. The use of artificial neural network for modeling *in vitro* rumen methane production using the CNCPS carbohydrate fractions as dietary variables. *Livestock Science* **162**: 159– 67.

Dongre V B, Gandhi R S, Avtar Singh and Ruhil A P. 2012. Comparative efficiency of artificial neural networks and multiple linear regression analysis for prediction of first lactation 305–day milk yield in Sahiwal cattle. *Livestock Science* **147**: 192–97.

Durairaj M and Meena K. 2008. Application of artificial neural network for predicting fertilization potential of frozen spermatozoa of cattle and buffalo. *International Journal of Computer Science and System Analysis*, *Serials Publications* **2**(1): 1–10.

Durairaj M and Thamilselvan P. 2013. Applications of artificial neural network for IVF data analysis and prediction. *Journal of Engineering Computer and Applied Sciences* **2**(9): 11–15.

Edriss M A, Hosseinnia P, Edriss M, Rahmani H R and Nilforooshan A. 2008. Prediction of second parity milk performance of dairy cows from first parity information using artificial neural network and multiple linear regression methods. *Asian Journal of Animal Veterinary Advances* **3**: 222–29.

Enquist M and Ghirlanda S. 2008. *Neural Networks and Animal Behavior.* Princeton University Press. Princeton.

Gandhi R S, Monalisa D, Dongre V B, Ruhil A P, Avtar Singh and Sachdeva G K. 2012. Prediction of first lactation 305-day milk yield based on monthly test day records using artificial neural networks in Sahiwal cattle. *Indian Journal of Dairy Science* **65**(3): 229– 33.

Ghazanfari K N, Nobari K and Tahmoorespur M. 2011. Prediction of egg production using artificial neural network. *Iranian Journal of Applied Animal Science* **1**(1):10–16.

Ghotoorlar S M, Ghamsari S M, Nowrouzian I, Ghotoorlar S M and Ghidary S S. 2012. Lameness scoring system for dairy cows using force plates and artificial intelligence. *Veterinary Rececords* **170**:126– 30.

Gorgulu O. 2012. Prediction of 305-day milk yield in Brown Swiss cattle using artificial neural networks. *South African Journal of Animal Science* **42**(3): 31.

Goyal S and Goyal G K. 2012. Predicting shelf life of dairy product by using artificial neural networks (ANN) and statistical computerized methods. *International Journal of Computer Engineering Research* **3**(2): 20–24.

Grzesiak W, Blaszczyk P and Lacroixb R. 2006. Methods of predicting milk yield in dairy cows-Predictive capabilities of wood's lactation curve and artificial neural networks (ANNs). *Computers and Electronics in Agriculture* **54**: 69–83.

Grzesiak W, Zaborski D, Sablik P, ¯ukiewicz A, Dybus A and Szatkowska I. 2010. Detection of cows with insemination problems using selected classification models. *Computers and Electronics in Agriculture* **74**(2): 265–73.

Hassan K J. 2007. 'Application of artificial neural networks for understanding and diagnosing the state of mastitis in dairy cattle.' M.Sc. Thesis submitted to Lincoln University.

Haykin S. 1999. *Neural Networks - A Comprehensive Foundation*. New Jersey: Prentice-Hall.

Heald C W, Kim T, Sischo W M, Cooper J B and Wolfgang D R. 2000. A computerized mastitis decision aid using farm-based records: An artificial neural network approach. *Journal of Dairy Science* **83**(4): 711–20.

Kamo M, Kubo T and Iwasa Y. 1998. Neural network for female mate preference, trained by a genetic algorithm. *Philosophical Transactions of the Royal Society of London, Biol* **353**: 399–406.

Kominakis A P, Abas Z, Maltaris I and Rogdakis E. 2002. A preliminary study of the application of artificial neural networks to prediction of milk yield in dairy sheep. *Computers and Electronics in Agriculture* **35**(1): 35–48.

Kunzle Philippe. 2015. Vehicle Control with Neural Networks Game Dev.net. Accessed: April 22, 2015. http://www.gamedev.net/page/index.html

Li J, Tan J and Shatadal P. 2001. Classification of tough and tender beef by image texture analysis. *Meat Science* **57**(4): 341–46.

Li J, Tan J, Martz F A and Heymann H. 1999. Image texture features as indicators of beef tenderness. *Meat Science* (**53**)1: 17–22.

Macrossan P E, Hussein A A, Kerry M, Michael T and Gerard F. 1999. Bayesian neural network learning for prediction in the Australian dairy industry. *Advances in Intelligent Data Analysis Lecture Notes in Computer Science* **1642**: 395–406.

Mertens K C, Vangeyte J, Weyenberg S V, Campeneere S D and Vannuffe A. 2012. Automatic lameness detection in dairy cows using artificial neural networks. *International Conference of Agricultural Engineering*. http://cigr.ageng2012.org/images/fotosg/tabla_137_C1140.pdf

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.

Murphy M D, O'Mahony M J, Shalloo S, French P and Upton J. 2014. Comparison of modelling techniques for milk-production forecasting. *Journal of Dairy Science* **97**(6): 3352–63.

Nadimi E S, Jørgensen R N, Blanes-Vidal V and Christensen S. 2012. Monitoring and classifying animal behaviour using

ZigBee-based mobile ad hoc wireless sensor networks and artificial neural networks. *Computers and Electronics in Agriculture* **82**: 44–54.

National Livestock Policy. 2013. *Department of Animal Husbandry, Dairying & Fisheries.* Ministry of Agriculture, Government of India.

Njubi D M, Wakhungu J W and Badamana M S. 2009. Milk yield prediction in Kenyan Holstein-Friesian cattle using computer neural networks system. *Livestock Research for Rural Development*, Vol. 21; Retrieved June 24, 2014 *http://www.lrrd.org/lrrd21/4/njub21046.htm*

Njubi D M, Wakhungu J W and Badamana M S. 2011. Prediction of second parity milk yield of Kenyan Holstein-Friesian dairy cows on first parity information using neural network system and multiple linear regression methods. *Livestock Research for Rural Development*, **23**(3): Article# 64; http://www.lrrd.org/lrrd23/3/njub23064.htm

Noviè, M. 2008. Kohonen and counter-propagation neural networks applied for mapping and interpretation of IR spectra. *Artificial Neural Networks : Methods and Applications.* pp.45–60. (Ed.) Livingstone D. Humana Press, ISBN: 978–1–58829–718–1, New York.

Pastell M E and Kujala M. 2007. A probabilistic neural network model for lameness detection. *Journal of Dairy Science* **90**: 2283– 92.

Qiao J, Wang N, Ngadi M O, Gunenc A, Monroy M, Gariépy C and Prasher S O. 2007. Prediction of drip-loss, pH, and color for pork using a hyperspectral imaging technique. *Meat Science* **76**(1): 1–8.

Qotbi A A A, Nia P H, Seidavi A and Ghovvati S. 2010. Predictions of semen production in ram using phenotypic traits by artificial neural network. *African Journal of Biotechnology* **9**(30): 4822–25.

Rosenblatt F. 1961. *Principles of Neurodynamics: Perceptrons and the Theory of Brain Mechanisms*. Spartan Books, Washington D. C., Washington.

Saleh S, Hassan M Y, Caro L, Ahmad K, Majid K and Kent W. 2012. Prediction of breeding values for dairy cattle using artificial neural networks and Neuro-Fuzzy systems. *Computational and Mathematical Methods in Medicine* Article ID 127130.

Salle C T P, Guahyba A S, Wald V B, Silva A B, Salle F O and Nascimento V P. 2003. Use of artificial neural networks to estimate production variables of broilers breeders in the production phase. *British Poultry Science* **44**(2): 211–17.

Santé V S, Lebert A, Le Pottier G and Ouali A. 1996. Comparison between two statistical models for prediction of turkey breast meat colour. *Meat Science* **43**(3–4): 283– 90.

Sanzogni L and Kerr D. 2011. Milk production estimates using feed forward artificial neural network. *Computers and Electronics in Agriculture* **32**: 21–30.

Shan Y, Zhao R, Xua G, Liebich H M and Zhang Y. 2002. Application of probabilistic neural network in the clinical diagnosis of cancers based on clinical chemistry data. *Analytica Chimica Acta* **471**: 77–86.

Sharma A K, Sharma R K and Kasana H S. 2006. Empirical comparisons of feed-forward connectionist and conventional regression models for prediction of first lactation 305-day milk yield in Karan Fries dairy cows. *Neural Computer and Application* **15**: 359–65.

Sheridan C, O'Farrell M, Lewis E, Flanagan C, Kerry J and Jackman N. 2007. A comparison of CIE L and spectral methods for the analysis of fading in sliced cured ham. *Journal of Optics A-Pure and Applied Optics* **9**(6): 32–39.

Shiranita K, Hayashi K, Otsubo A, Miyajima T and Takiyama R. 2000. Grading meat quality by image processing. *Pattern Recognition* **33** (1): 97–104, ISSN: 0031–3203.

Silveira C L and Belledeli B D. 2013. Use of artificial neural network for industrial prediction of final temperature of chicken carcasses. *Journal of Food Process Engineering* **37**(1): 1–9.

Tahmoorespur M and Ahmadi H. 2012. A neural network model to describe weight gain of sheep from genes polymorphism, birth weight and birth type. *Livestock Science* **148**: 221–26.

Wang E and Samarasinghe S. 2005. On-line detection of mastitis in dairy herds using artificial neural networks. *International Congress on Modelling and Simulation.* Modelling and Simulation Society of Australia and New Zealand, December 2005, Pp. 273–278. ISBN: 0–9758400–2–9. http://www.mssanz.org.au/modsim05/papers/wang_e.pdf

Zheng C, Sun D W and Zheng L. 2007. Predicting shrinkage of ellipsoid beef joints as affected by water immersion cooking using image analysis and neural network. *Journal of Food Engineering* **79**(4):1243–49.

Zupan J and Gasteiger J. 1991. Neural networks: A new method for solving chemical problems or just a passing phase? *Anal Chim Acta* **248**: 1–30.