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Connectionist approach of predictive modelling in livestock management: A review

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Abstract
Connectionism is an approach to the study of human cognition that utilizes mathematical models, known as connectionist networks or Artificial Neural Networks (ANNs). Lack of connectionist model applications in dairying is quite paradoxical as data analyses are usually carried out in the field and connectionist models have shown to be more powerful than classical statistical methods to perform such tasks. Rapid, low-cost alternatives that can provide approximate prediction of breeding values with acceptable accuracy could allow more timely selection and culling decisions. Rapid identification of superior males can lead to earlier collection and distribution of semen and more rapid genetic progress. The conventional regression procedures can-not evaluate the Multicollinearity between independent factors; hence, it may result in biased outcomes. ANN has been proposed in alleviating the limitations of the traditional regression methods, and can be used to handle non-linear and complex data, even when the data are imprecise and noisy. A large number of ANN-based learning algorithms have been reported. The major studies reporting the application of connectionist models to animal production and management include the prediction of cow performance in terms of predicting total milk, fat and protein production of individual cow for early identification of superior animals; life time milk yield prediction; animal identification; mobility & weight estimation; body condition scoring; detection of mastitis and its stage of progression; oestrus detection *etc.* The studies show that the result obtained from the conventional methods and connectionist models are highly correlated and with least differences.

Keywords: Animal breeding model, artificial intelligence, artificial neural network, connectionist network, predictive modelling

Introduction

Connectionism is an approach to the study of human cognition that utilizes mathematical models, known as connectionist networks or Artificial Neural Networks (ANNs) (Rumelhart & McClelland 1986) [30]. The connectionist approach is very much inspired by biology and psychology. Connectionism theory is based on the principle of active learning given by the American psychologist Edward Thorndike (Donahoe, 1999) [8]. According to him, learning is achieved when an individual is able to form associations between a particular stimulus and a response. The prevailing connectionist approach today was originally known as parallel distributed processing (PDP) explained during '80s.The connectionist models have been used for engineering and economic predictions, and medical diagnoses. However, adoption of connectionist models to dairying is relatively slow, especially in India. This lack of connectionist model applications in dairying is quite paradoxical as data analyses are usually carried out in this field and connectionist models have shown to be more powerful than classical statistical methods to perform such tasks.

In a breeding program, genetic progress can be maximized through accurate identification of superior animals that will be selected as parents of the next generation and therefore breeding goals can be achieved (Salehi *et al.*, 1998) [31]. A key component of this process is fast and reliable prediction of breeding values for the animals under selection. But, prediction of breeding values is often a computationally challenging and time consuming task (Grzesiak *et al.*, 2003) [14]. Rapid, low-cost alternatives that can provide approximate prediction of breeding values with acceptable accuracy could allow more timely selection and culling decisions. Rapid identification of superior males can lead to earlier collection and distribution of semen and more rapid genetic progress (Salehi *et al.*, 1998) [31]. The conventional regression procedures can-not evaluate the multi-colinearity between independent factors; hence, it may result in biased outcomes.

When the correlation between variables is high, multi-collinearity takes place; therefore, it is difficult to obtain reliable estimates of the individual regression coefficients (Ruhil *et al.*, 2013) [29].
The use of connectionist models has undergone an exponential increase during the last few years due to their computational intelligence capabilities to solve different types of complex biological problems including those related to animal science and dairy research. These models have been successfully applied to classification, modelling and prediction problems. Their inherent characteristics vis-à-vis classical regression techniques make them especially suitable in regression analysis problems where some of the following conditions occur (Raja *et al.*, 2012; Sharma, 2006; Grzesiak & Zaborski, 2012) [12, 35, 36, 13]:

a) It is unclear or very hard to find out the rules that relate the target (dependent) variable to the other (independent) variables considered in the model.
b) Data are incomplete, imprecise or noisy. Noisy data are those data which introduce random fluctuations that make unclear or difficult to understand the real data or data with a large amount of additional meaningless information, lead to a false conclusion.
c) The problem requires a great number of dependant variables (problems with high dimensionality).
d) The model to be applied is non-linear.
e) There exists a great amount of data.
f) The environment of the variable or variables to model changes with time.

However, according to the literature reviewed, dairy and food science data fit these characteristics particularly well for several reasons:

a) Any dairy animal and its possible interactions with the different elements in its environment constitute a complex system with a large number of plausible relationships. In principle, it would be natural to assume these relationships as non-linear, due to the inherent complexity of living beings.
b) There are many variables that can be used to determine the state/behaviour of a dairy animal or to model one of the variables that characterises the animal. Thus, an excessive simplification of the problem may yield too many errors in the model. Accordingly, this is a non-linear and high dimensionality problem (Gorgulu, 2012) [11].
c) Incomplete data or errors in measures are quite likely.
d) These data are, generally, recorded on the basis of daily events, *i.e.*, feed intake, milk yield, *etc.*; and based on animal's growth over time. Hence, a system that can adapt to newly gathered data (generalisation) and can bring reliability to the new yielded results (validation) would be a desirable choice (Fernández *et al.*, 2006) [10].

The above discussion suggests not only the possibility of employing connectionist models in this field but also their suitability for problems of this kind. Thus, connectionist approach is suitable for prediction of output(s) for non-linear systems at various combinations. The process is based on learning of the network with the experimental values, thereby knowing the system behaviour; and then predicting the output values of the desired set of parametric combinations (Arbib, 2003) [3]. Dairy and Food Sciences represent a potential area for application of connectionist models. Connectionist models consist of layers of interconnected neurons, each neuron producing a nonlinear function of its input. Connectionist modelling approaches combine the complexity of some of the statistical techniques with the machine learning objective of imitating human intelligence. Connectionist models epitomise to a certain extent the behaviour of networks of neurons in the human brain so known as Artificial Neural Networks (ANN).

Relationship between AI, ML, DL, ANN and Data science

The terms Artificial Intelligence (AI), Machine Learning (ML), Deep Learning (DL) and Data Science, might sound confusing. Artificial intelligence refers to the simulation of human intelligence in machines that are programmed to think like humans and mimic their actions. Machine learning is an application of artificial intelligence that provides systems the ability to automatically learn and improve from experience without being explicitly programmed. Deep learning is a subset of machine learning in artificial intelligence that has networks capable of learning unsupervised from data that is unstructured or unlabelled. The differences between these terms are not clear-cut, but the diagram (Fig.1) will give a sense of the general uses of the terms, how they are related to one another and how all are threaded together by data science.

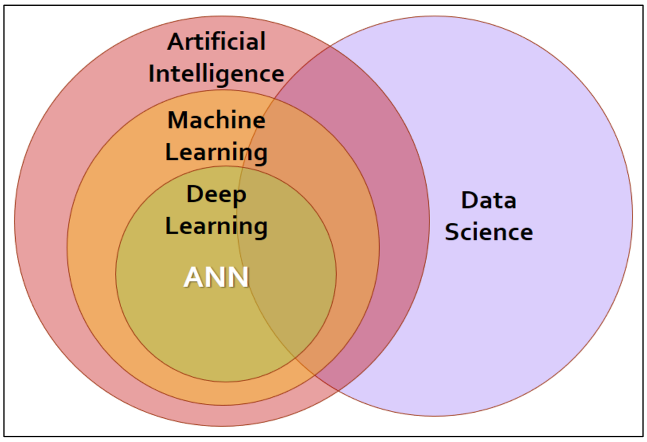

Fig 1: Relationship between AI, ML, DL, ANN and Data science

AI came in 1950's; Machine Learning came in the 80's; and Deep Learning came in recent years after 2010.

Artificial Neural Network (ANN)

Artificial neural network is a nonlinear statistical modelling tool that could perform intelligent tasks similar to those that are performed by the human brain. It obtains knowledge through learning by experience (Sharma & Sharma, 2004) [37]. It is one of the machine learning technique which is used increasingly in agriculture and allied sector as they are quick, powerful and flexible tools for classification and prediction applications for making various dairy farm decisions.
A neuron's dendritic tree is connected to thousands of adjoining neurons. A positive or negative charge is received by one of the dendrites as one of those neurons fires. The strengths of all the received charges are added together through the processes of spatial and temporal summation. Spatial summation occurs when several weak signals are converted into a single large one, while temporal summation converts a rapid series of weak pulses from one source into one large signal. The aggregate input is then passed to the soma (cell body). If the aggregate input is greater than the axon hillock's threshold value, then the neuron fires, and an output signal is transmitted down the axon. The strength of the output is constant, regardless of whether the input was just above the

threshold, or a hundred times as great. The output strength is unaffected by the many divisions in the axon; it reaches each terminal button with the same intensity it had at the axon hillock. Each terminal button is connected to other neurons across a small gap called a synapse (Singh, 2007) [38].
The action potential causes transmission of information from the axon of the first neuron (Pre-synaptic neuron) to the dendrites or cell body of the second neuron (Post-synaptic neuron) by secretion of chemical called neurotransmission. Process of learning occur at the synapse. Critical information are not transmitted directly, but stored in interconnections. The term 'connectionist model' initiated from this idea.
Though ANN is inspired by biological neural network of brain both can be correlate (Table.1). ANN is comprised of basic units, input paths and output paths (Fig.2). As information is stored in brain as strengths of synaptic gaps between neurons, similarly the knowledge is stored in ANN as weights associated with the interconnection between artificial neurons (Atil & Akilli, 2015) [4].

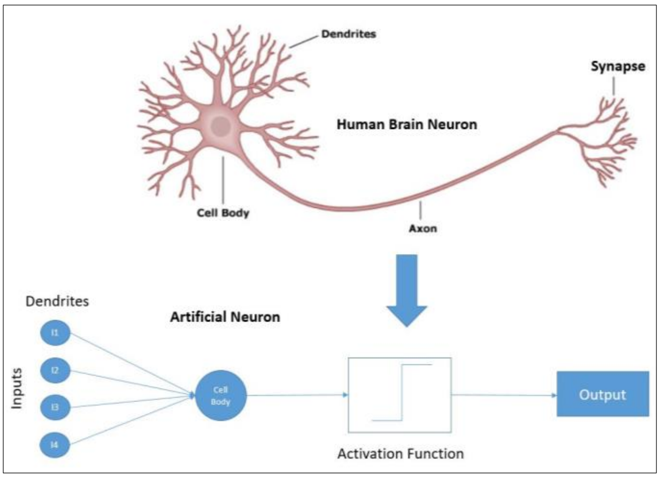

Fig 2: Anatomy of biological and artificial neurons.

Table 1: Functional similarity between components of biological and artificial neurons

Biological Neuron	Explanation	Artificial Neuron
Dendrite	Receiving the information	Inputs
Synapses	Communication between nerve cells	Weights
Axons	Transmission of information	Outputs

The input to a neuron may come from other neurons or directly from the input data. The complete network represents a complex set of interdependencies, which may incorporate any degree of nonlinearity, allowing very general functions to be modelled. Billions of neurons are connected together in the brain. They receive electrochemical signals from neighbouring neurons, they process it and forward it to the next neighbouring neurons in the network.
Artificial neural networks have been proposed in alleviating the limitation of the traditional regression methods, and can be used to handle non-linear and complex data, even when the data are imprecise and noisy (Raja *et al.*, 2012) [12]. These networks contain a set of processing components, also known as neurons or nodes whose functionality is based on biological neurons (Raja *et al.*, 2012) [12]. These units are formed in layers that process the input information and pass it to the next layers. Artificial and biological neurons, both have biases (predispositions) that affect the strength of their output. The neuron combines the inputs, incorporates effects of the predispositions and output signals. The capability of the network in processing is cumulated in the inter-unit connection strengths (or weights) that are acquired via a process of conformity to a collection of training pattern (Haykin, 1999) [16]. Training of ANN often facilitates discovery of previously unknown relationship between input and output variables, and these relationships have been used successfully in both classification and prediction problems (Sharma & Sharma, 2004) [37].
Neuron consists of three basic functional components (Fig.3). 1) Weighting Factors: The values $w_1, w_2, \ldots, w_n$ are weights to determine the strength of input vector $x=[x_1, x_2, \ldots x_n]T$. 2) Threshold: The node's internal threshold is the magnitude offset. 3) Activation Function: It performs a mathematical operation on the signal output. Most common action functions are linear threshold, S-shaped and tangent hyperbolic function. Choice of function depend on the problem solved by the neural network (Haykin, 2009) [17].

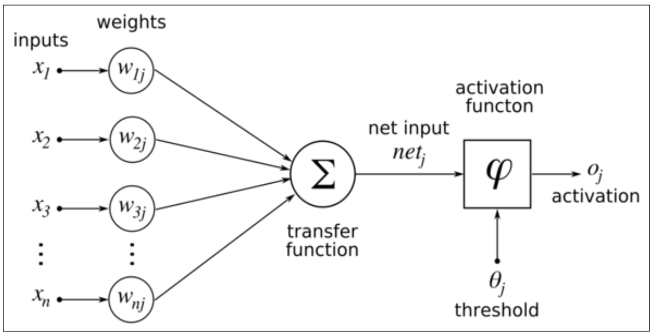

Fig 3: Components of artificial neural network

Connectionist models consist of the following three Principal elements (Goyal *et al.*, 2011) [12]:

a) Topology – the way a connectionist network is organised into layers and the manner in which these layers are interconnected;
b) Learning – the technique by which information is stored in the network; and
c) Recall – how the stored information is retrieved from the network.

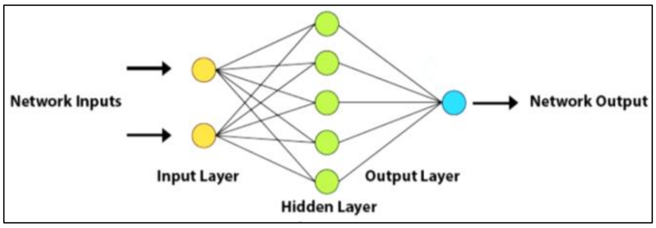

Fig 4: Network architecture

Network architecture or network topology

Connectionist network architecture refers to the types of interconnections between neurons (Fig.4, 5). Depending on the direction of information ANN are classified as feed forward networks and feedback networks (Sharma, 2013) [34]. A network is said to be fully connected if the output from a neuron is connected to every other neuron in the next layer. A network with connections that passes outputs in a single direction only to neurons on the next layer is called a feed-forward network. A feed-back network allows its outputs to be inputs to preceding layers. It forms closed loops so also known as recurrent networks. Feed-forward networks are faster than feed-back networks as they require a single pass only to obtain a solution (Jha, 2007) [18].

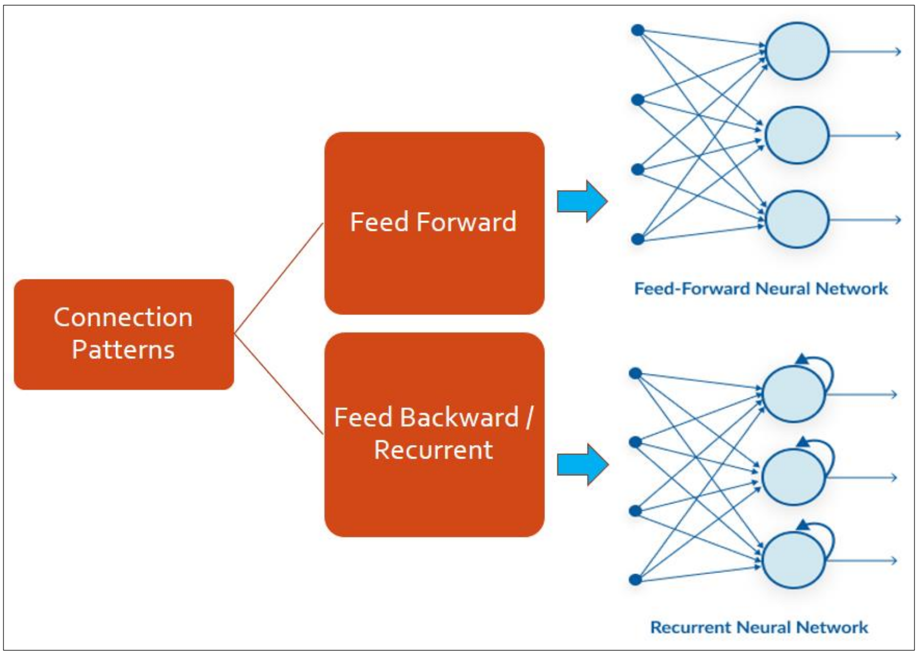

Fig 5: Types of neural networks

Connectionist learning

Learning in the present context may be defined as a change in connection weight values those results in the capture of information that can later be recalled. Generally, the initial weights for the network prior to training are set to random values within a predefined range. This technique is used extensively in error correction learning systems that are widely used in dairy production applications. The following learning methodologies are generally adopted for connectionist model training: a) Supervised learning; b) Unsupervised learning; and c) Reinforcement learning (Fig.6) (Chaturvedi *et al.*, 2013) [6].

a) Supervised learning, correct answer is provided for the network for every input pattern. Weights are adjusted regarding the correct answer. So, supervised learning is best for classification and regression problems.
b) Unsupervised learning, does not need the correct answer. The system itself recognize the correlation and organize patterns into categories accordingly.
c) Reinforcement learning, is quite similar to supervised learning but the algorithms are designed in such a way that the machine tries to find an optimal solution. It adopts the principle of reward and punishment, and by this approach it moves to the correct result.

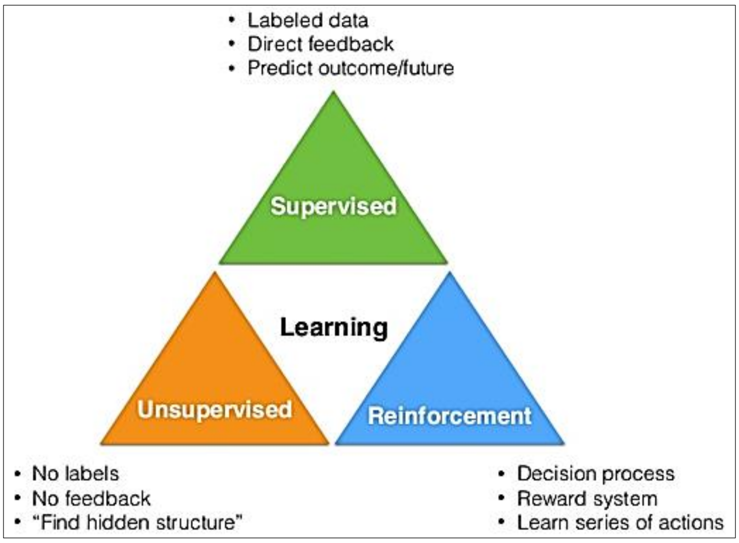

Fig 6: Types of connectionist learning

Network internal parameters

There are several network internal parameters related to network architecture and training process that are adjusted on *'trial and error'* basis so as to optimise the network performance. These parameters include: *i)* Hidden layers and hidden neurons, *ii)* Learning rate, *iii)* Training and testing tolerances, *iv)* Data pre-processing, *v)* Data partitioning, *vi)* Initial weights, and *vii)* Over-fitting and complexity regularisation (Jha, 2007) [18].

Constructing a connectionist model

The process to devise a connectionist model involves the following steps (Sharma, 2013) [34]:

a) The data to be used should be defined and presented to the neural network as a pattern of input data with the desired outcome or target.
b) The data are categorised to be either in the training set or test set. The connectionist model uses the training set in its learning process in developing the model. The test set is used to validate the model for its predictive ability and when to stop the training of the connectionist model.
c) The connectionist model structure is defined by selecting the number of hidden layers to be constructed and the number of neurons for each hidden layer.
d) The connectionist model internal parameters are set before starting the training process.
e) Now, the training process is started. It involves the computation of the output using the input data and the weights. A learning algorithm is used to 'train' the connectionist model by adjusting its weights to minimise the difference between the current connectionist model output and the desired output.
f) Finally, an evaluation process is carried out in order to determine if the connectionist model has 'learned' to solve the task. This will continue until an acceptable accuracy is achieved. When an acceptable level of accuracy is obtained, the connectionist model is then deemed to have been trained and ready to be utilised (Samarasinghe, 2016) [32].
g) As there are no fixed rules in determining the connectionist model structure or its parameter values, a large number of connectionist models may have to be constructed with different structures and parameters before determining an acceptable model. If a connectionist model is over trained, a curve-fitting problem may occur whereby the connectionist model starts to fit itself to the training set instead of creating a generalised model. This typically results in poor predictions of the test and validation dataset (Goyal *et al.*, 2011) [12].

Measure of performance evaluation for connectionist models

In order to establish the success and sufficiency of supervised training for the connectionist models, it is necessary to have some quantitative measure of learning. Root Mean Square Error (RMSE) is an adequate and commonly used error measure. RMSE is a useful measure of how close a network is getting its predictions to its target output values. For successful training, RMSE will decrease significantly in the initial stages of training and converge after a sufficient number of iterations have been completed. Generally, an RMSE value less than 0.1 (*i.e.*, with the prediction accuracy above 90 %) indicates that a network has sufficiently learned its training set (Sharma, 2013; Hamidi *et al.*, 2017) [34, 27].

Learning Algorithms

A prescribed set of well-defined rules for the solution of a learning problem is called as learning algorithm. It is a network with sufficient hidden layer neurons, can approximate any continuous function with arbitrary accuracy. The studies related to neural networks have led to the emergence of different network structures according to the different problem structure.

As per literature reviewed, learning algorithms commonly used in ANNs include back-propagation, Hopfield networks, counter propagation algorithms, radial basis function networks, self-organising maps, generalized regression neural network, single & multilayer perceptron algorithms, resilient back-propagation, adaptive-neuro fuzzy inference systems, Support Vector Machine, auto-encoder and supervised Kohonen networks, adaptive resonance theory and Convolutional Neural network (CNN) (Liakos *et al.*, 2018; Haykin, 2009) [21, 17].

Use of connectionist models

a) Classification: Pattern recognition, feature extraction, image matching
b) Noise Reduction: Recognize patterns in the inputs and produce noiseless outputs
c) Prediction: Extrapolation based on historical data (Hamidi *et al.*, 2017) [27]

Applications of Artificial Neural Networks in Animal Husbandry

The major studies reporting the application of connectionist models to animal production and management include the prediction of cow performance with regard to production in terms of predicting total milk, fat and protein production for individual cows for early identification of superior animals; life time milk yield prediction; animal identification; mobility & weight estimation; body condition scoring; detection of mastitis and its stage of progression; oestrus detection *etc.*

A) Application of ANN in Breeding Values Estimation

Different studies shows the application of ANN in Breeding Value (BV) prediction. Here two different studies has been discussed.

i) First study was conducted (Shahinfar *et al.*, 2012) [33] to investigate the potential of artificial neural networks and neuro-fuzzy systems, in order to Estimate Breeding Values (EBVs) of Iranian dairy cattle. In the study, initially, the breeding values of lactating Holstein cows for milk and fat yield were estimated using conventional best linear unbiased prediction (BLUP) with an animal model. Once that was established, a multilayer perceptron was used to build ANN to predict breeding values from the performance data of selection candidates. Then both BVs were correlated with BV obtained by BLUP method. Finally the result generated. Using ANN and NFS approaches, measured single trait predictions of milk yield EBV that had correlations of 0.917 and 0.926, respectively, and for fat yield EBV that had correlations of 0.926 and 0.932, respectively, with reference EBV. Furthermore, joint prediction of milk and fat yield EBV in multiple-trait implementations of ANN provided correlations of 0.925 and 0.930, respectively, with reference EBV for milk and fat production. The same prediction with NFS provided a correlation of 0.935 and 0.949 with reference EBV, respectively, for milk and fat. So, results obtained from both BLUP and connectionist models are highly correlated. For both methods, increasing the number of input variables led to predictions of EBV with greater accuracy.

ii) The second study was conducted (Kominakis *et al.*, 2002) [19] to test the usefulness of artificial neural networks (ANNs) for predicting lactation as well as test-day milk yield(s) in Chios dairy sheep on the basis of a few (2–4) available test-day records at the beginning of a lactation period. Input variables were the county, herd, lactation, lambing month, litter size, milk yield recorder, test day and days in milk (after lambing) when the first milk sample was obtained. They found that the average difference between observed and predicted yields was generally statistically non-significant ($p < 0.05$) while predicted standard deviations were underestimated. Values of Pearson and rank correlations between observed and predicted lactation yields ranged from 0.87 to 0.97. Better predictions were obtained as the number of records used for training increased from 500 to 1000, the number of test-day records increased from 2 to 4, and data pre-processing (*i.e.* encoding of data) was employed.

B) Application of ANN in other Tools Associated with Animal Breeding

Connectionist models have applications in many areas of animal breeding. Many studies shows its utility in various operations of animal breeding (Table 2).

Table 2: Studies related to other applications of ANN in animal breeding

Application	Key Points	Result	Reference
Milk Production Forecasting	• Can be done for long- and short- term period	• Three models used to predict the daily production levels for a full lactation of 305 day • RMSE = 0.12	Murphy *et al.*, 2014 [25]
Life Time Milk Yield Prediction		• 2972 lactation records of 977 cows used • Predicted & observed data differ non- significantly	Chaturvedi *et al.*, 2013 [6]
Animal Identification	• Automatic recording and analysis of animal behaviour through video data.	• Accuracy of 86.8 % for automatic cropping of cow's body region and 97.01% for cow's pattern identification	Zin *et al.*, 2018
Mobility & Weight Estimation	• Body weight of livestock is essential for different purposes. • Wither height, hip height, body length, hip width of cows can be determined	• 3D body condition assessment with photogrammetry • Correlation coefficient of estimated live weights and weights obtains from scale, R=0.995	Sakir & Ilker, 2018
Body Condition Scoring	• Images analysis techniques used • Extract characteristics like distance and areas between anatomical points, angles, depth pixels values; cow counter	• 3D cameras & thermal cameras used • Accuracy of automatic estimated scores to be within ±0.25	Singh, *et al.*, 2007 [38]
Oestrus Detection	• Model inputs: traits activity measured by pedometer, and the period (days) since last oestrus.	• Oestrus detections in 373 dairy cows • Averaged sensitivity, specificity and error rate were 77.5, 99.6 and 9.1% respectively	Krieter *et al.*, 2005 [20]

C) Application of ANN in other tools associated with livestock management practices

The connectionist models are useful tool to make various farm and livestock management activities easy (Table.3). They increase the accuracy and reliability of data recording. Thus, connectionist models can also be used for big data recording and analysis.

Table 3: Studies related to successful use of ANN in livestock management

Animal Species	Observed Features	Functionality	Models/ Algorithms	Reference
Calf	Data: chewing signals from dietary supplement, Tifton hay, ryegrass, rumination, and idleness.	Identification and classification of chewing patterns in calves	DT/C4.5	Pegorini *et al.*, 2015 [26]
Cattle	Features like grazing, ruminating, resting, and walking (Recorded using collar systems with three-axis accelerometer and magnetometer)	Classification of cattle behaviour	EL/ Bagging with tree learner	Dutta *et al.*, 2015 [9]
Cattle	Milk fatty acids	Prediction of rumen fermentation pattern from milk fatty acids	ANN/BPN	Craninx *et al.*, 2008 [7]
Cattle	Zoometric measurements of the animals, 2 to 222 days before the slaughter	Prediction of carcass weight for beef cattle 150 days before the slaughter day	SVM/SVR	Alonso *et al.*, 2013 [1]
Bovine	Geometrical relationships of the trajectories of weights along the time	Estimation of weight trajectories for future evolution with only one or a few weights.	SVM (Support Vector Machine)	Alonso *et al.*, 2015 [2]
Hens	6 features created from mathematical models related to farm's egg production line and collected for 7 years	Early detection and warning of problems in production curves of commercial hens eggs	SVM (Support Vector Machine)	Morales *et al.*, 2016 [24]
Pigs	3D motion data by using two depth cameras	Tracking and behaviour annotation of pigs to measure behavioural changes for welfare and health monitoring	Gaussian Mixture Models (GMMs)	Matthews *et al.*, 2017 [22]
Pigs	1553 colour images with pigs faces	Pigs face recognition	Convolutional Neural Network (CNN)	Hansen *et al.*, 2018 [15]

Statistical regression v/s Connectionist Model

In statistical regression, the parameters or constants of the equation are determined for a given mathematical equation, which relates the inputs to the output(s). In classical regression paradigm, the type and nature of the equation relating the inputs with the output has to be initially formulated clearly. However, connectionist models do not require such an explicit relationship between the inputs and the output (s), (Tasdemir & Ozkan, 2018) [39]. In statistics, the analysis is limited to a certain number of possible interactions. Whereas more terms can be

examined for interaction and included in connectionist models. By allowing more data to be analysed at the same time, more complex and subtle (*Not very noticeable*) interactions can be determined (Boniecki *et al.*, 2013) [5].
Fuzzy and not-so-clear datasets can also be analysed and their interaction can be studied with connectionist models, whereas statistical regression analysis will fail in such situation. Generally, connectionist models can perform better than statistical regression analysis for prediction, modelling and optimisation even if the data are noisy and incomplete. It is also ideally suited when the inputs are qualitative in nature; and the inputs or the output can't be represented in mathematical terms unlike other modelling techniques such as expert systems, a connectionist model can use more than two parameters to predict two or more parameters (Grzesiak *et al.*, 2003) [14]. In addition, connectionist models differ from traditional methods due to their ability to learn about the system to be modelled without a prior knowledge of the process parameter (McQueen *et al.*, 1995) [23].

Conclusion

Connectionist models produce results that are straightforward and don't need any transformations. The results are highly correlated with results obtained from conventional methods. Connectionist models are amongst various intelligent modelling methods, which are capable to solve a very important problem, *i.e.*, processing of unstructured and incomplete numerical information about non-linear and non-stationary systems. Connectionist models possess the capability for re-learning according to new data, and it is possible to add new observations at any time. This is difficult to realise with classical regression analysis techniques. Connectionist models give outputs with lower error rate without any advance computational facilities. So it may be used as an alternative technique for predicting the breeding values. Connectionist models need three data sets: training set (> 65 % data), testing set (> 15 % data), validating set (> 15 % data), to prevent over-fitting problem. By applying machine learning to sensor data, farm management systems are evolving into real time artificial intelligence enabled programs that provide rich recommendations and insights for farmer decision support and action with the ultimate scope of production improvement.

Future Prospects

Some limitations such as ANN require large data set (> 65 %) and longer time duration (days to months) for training of the algorithms, can be reduced by using more advanced machine learning tools and by further research in this field. The usage of connectionist models will be even more widespread, allowing for the possibility of integrated and applicable tools. This integration of automated data recording, data analysis, machine learning implementation, and decision-making or support will provide practical tools for modern animal husbandry to increase production levels and bio-products quality.

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