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Artificial Neural Networks- An Introduction and Application in Animal Breeding and Production: A Review

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ABSTRACT

With the advent of newer methods and tools for accurate analysis, the outcomes of researches have become increasingly precise. This increase in reliability of research findings and forecasting is well demanded in various fields of science including those under animal breeding as well as its allied aspects such as production. One such recent breakthrough is an artificial neural network (ANN), which is a system of hardware and/or software programmed to function like the operation of neurons in the human brain. ANNs are a variety of deep learning technology, which also falls under the umbrella of artificial intelligence. The determination of milk yield, quality of meat animals, predicting breeding values, inferring demography and recombination, genome-enabled prediction are few of the sectors where ANN has proved to be a valuable asset. The correlation coefficient between the experimental values and those predicted with the help of ANN was found to be close to 1. These studies were a significant indication of the impactful ability of ANN. The early selection of superior bulls, culling of low performing ones, frequent prediction of breeding values and taking into account the non linearity encountered in biological research are few of the many benefits of using ANN in researches of animal genetics and production. Hence, considering its prodigious role, this current review has been written to highlight the role and impact of ANN in livestock studies.

Key words: Artificial neural network, Correlation coefficient, Input, Layers, Linear regression, Neuron, Output, Weights.

The complexities of the human nervous system can be described as boundless. Brain quality is mirrored within the quality of its structural makeup (Koch and Laurent, 1999). Its abilities and the mechanism of function in order to process new information or recall previously gathered knowledge is a work of machinery in itself. The attempt to replicate the same intricacies of a biological nervous system onto machines is the blueprint of Artificial Intelligence. Since, the inception of machines, there has been endless efforts to achieve precision by improving their way of functioning. At the very beginning, machines mainly functioned with the help of specifically designed programmes aimed to give specific results. The programmes determine the set of actions that is to be accomplished automatically by the machine or system in order to accomplish the desired result. Alan Turing in 1935 proposed 'learning machine' that could learn and become artificially intelligent. Machine learning is a branch of artificial intelligence (AI) and computer science which revolves around the use of data and algorithms to imitate the learning process of humans *and* thereby improving its accuracy over time. Another term 'deep learning' was introduced to the machine learning community by Rina Dechter in 1986. Deep learning can be called as a sub category of machine learning that arranges algorithms in layers to form associate degree "artificial neural network" that may learn and make intelligent choices on its own (Parrish, 2018). The terms machine learning and deep learning are sometimes used interchangeable. However, both have different capabilities and functioning methodologies. Basic machine learning models usually require guidance to improve its performance. However, with a deep learning model, an algorithm has the ability to determine on its own if a prediction is accurate or not, through its own neural network.

The forecasting of livestock productivity, closer to the actual production is acrucial step for better management of financial system of livestock holders. Therefore, a brand new paradigm is utilized in genetic breeding for choice functions supported principles of learning in a very machine intelligence approach. In this context, Artificial Neural Networks (ANN) are described as a future tool within the deciding process in various fields of science with great potential in both animal and plant genetics (Gianola *et al.,* 2011; Ventura *et al.,* 2012 and Nascimento *et al.,* 2013). ANN provides a powerful learning technique on complex features

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by predicting future results based on training data (Shaneh and Butler, 2006). It uses semi-parametric and non-parametric methods for the genomic-enable prediction of quantitative traits by accounting for non-additive and non-linear effects as well as genotype-environment interactions (Gianola *et al.,* 2006 and de Campos *et al.,* 2010). In animal breeding, ANNs affirm to have better performance ability than frequently used standard linear regression models in predicting phenotypic values (Gianola *et al.,* 2011).

Introduction to artificial neural network

Biological neurons

The fundamental unit of biological nervous system is the neuron. The biological neurons consist of three main parts: dendrites, a cell body or soma and an axon. The neurons are connected with the use of axons and dendrites. The connecting regions are referred to as synapses. Dendrites possess several thin extensions that form the dendritic tree. The fundamental purpose of which is to receive continuous signals from several other pre-synaptic neurons or the external environment and transfer the information to the cell body. In the cell body, all signals received by the dendrites are combined and processed, producing an activation potential. This action potential determines if the neuron can trigger an electric impulse along its axon (da Silva *et al*., 2016). If this action potential is above the excitation threshold of the neuron, an electric impulse is produced and propagated. When the impulse reaches the end of an axon, neurotransmitters are released into the synapses and the process continues into the next neurons. The practicality of a neuron is reliable on its synaptic weighting capability, which is additionally effectual and deep seated into the cerebral chemistry (Hodkin and Huxley, 1952). This chain of reactions makes learning possible to living organisms.

Artifical neurons

The first model of an artificial neuron was developed in 1943 by Warren McCulloch, a neurophysiologist and Walter Pitts, a mathematician. They are the elementary units in an artificial neural network. These artificial neurons are interconnected into larger structures within an ANN. It is a function programmed on the basis of biological neurons. Since, ANN reflect the behaviour of the human brain, it allows the computer programs to recognize patterns and solve common problems in the fields of AI, machine learning and deep learning (IBM Cloud Education, 2020). The network's classification behaviour is determined by the weights of the links that interconnect the neurons. The task for machine learning is to provide algorithms capable of finding weights that result in good classification behaviour. This search is accomplished by a process commonly referred to as a neural network's training (Kubat, 2021).

Homology between biological neuron and artificial neuron

Artificial neural network (ANN) is machine learning concept. It was developed as a form of artificial intelligence to imitate a biological nervous system (neural network) and function as a mathematical information processing system (Pereira *et al.,* 2009). ANN as the name suggests, are interconnected artificial neurons. They are organized in different set of layers thus mimicking the structure of the human brain. It basically represents a nonlinear statistical modelling tool. With the information learned through repeated experience it can provide classification, pattern recognition, optimisation and the realisation of forward-looking forecasts (Atil and Akilli, 2016). Table 1 demonstrates the homology between biological neuron and an artificial neuron.

Concept of artificial neural network

The dendrites of a biological neuron are connected to several adjoining neurons. Each instance a neuron fires, of the dendrites receives positive or negative charge and the input is then passed to the soma (cell body). If the mixture input is bigger than the axon hillock's threshold value, then the neuron fires and an output is transmitted down the axon. The strength of the output remains constant throughout its passage through the soma and axon. It is regardless of whether the input was just above the threshold, or a several hundred higher. The output strength reaches each terminal button with an equivalent intensity which it had at the axon hillock. Each terminal button is connected to other neurons through a gap called synapse. Similar concept is used in ANN.

According to the illustration (Fig 1), this artificial neuron consists of 3 input signals, each receiving values (say) I_1, I_2 and I_3 which are further coupled to the weights W_1, W_2 and W_3 which can have positive or negative values. The weights are the adjustable parameters which change according to the training sets presented to the network. They also provide the strength of the input signals. The effect of a particular synapse in the postsynaptic neuron is given by I_jW_j, the sum of this combination (Σli Wi) decides whether or not the neuron will be triggered. This is known by comparing this sum at the threshold of the neuron. This processed input is then converted into an output and transmitted to the next neuron. Multilayer neural networks, commonly utilized in animal breeding contain multiple layers of computational units. They are usually interconnected in a feed forward way. These networks use different techniques of learning, the most popular being back propagation. Here, the output values of that cycle are then compared with the correct answer to compute the worth of some predefined error-function. The error is then fed back into the network. Using this information, the algorithm adjusts the weights of every connection to adjust the strength of error function to some extent. The network repeats this process (called as "epochs") for a sufficiently large number

Table 1: Homology between a biological neuron and an artificial neuron.

Biological	Artificial neuron	Explanation
Synapse	Weights	Communication between the neurons
Axons	Outputs	One-way relay of instructions
Dendrites	Inputs	Receiving the instructions

of training cycles. The sole aim of the network is usually to merge to some state where the error of the calculations is reduced (Chayjan, 2010). ANN models are supposed to be an equivalent principle in an effort to simulate the training process of the human brain by using complex algorithms.

Following are the steps in a learning algorithm of an ANN (Fig 2):

1. The process starts with the weights (w_{ij}) and biases (b_j) for the network parameters.
2. The artificial neuron then takes a set of examples of input data and passes them through the network to obtain their prediction.
3. The neural network compares these predictions and calculates the loss that was generated.
4. ANN performs the back propagation (back flow of information) in order to circulate this loss to each and every parameter in the input layer.
5. The weights apply this newly generated information to update the parameters in such a way that the total loss is minimized.
6. The network continues repeating the previous steps until the model can be considered good. In this way, artificial neural networks achieve accuracy.

Types of artificial neural networks

Feed forward ANN

This type of ANN is also referred to as bottom-up or top-down. This is because it allows signals to travel from input to output only.

Feed back ANN

These types of networks have signals travelling in both directions. This bidirectional flow of information is facilitated by the loops in the network. These ANN are called Feed Back ANN. Here, results derived from earlier input are fed back to the network (like memory). Until then, the whole network remains at the equilibrium point. Following which replacement equilibrium must be found. This type is highly relevant during the analyses performed in animal breeding (Fig 3).

Parts of an artificial neural network

An artificial neural network is often divided into three parts, called layers.

Input layer

This is the layer responsible for receiving input signals. The activation function produces limit values whose sole purpose is to keep the inputs normalized.

Hidden layers

This layer is consists of neurons which are responsible for extracting patterns associated with the data which is being analyzed.

Output layer

This layer is composed of neurons responsible for producing and presenting the final network output.

Classes of artificial neural network

They are classified according to their learning mechanism.

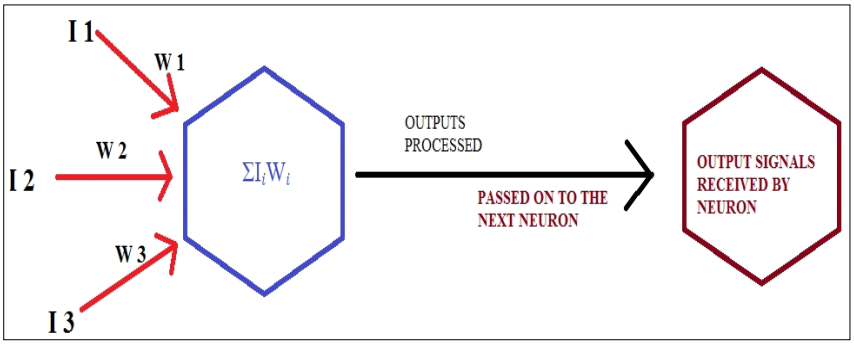


Fig 1: Illustration of information flow by an artificial neuron in an ANN.

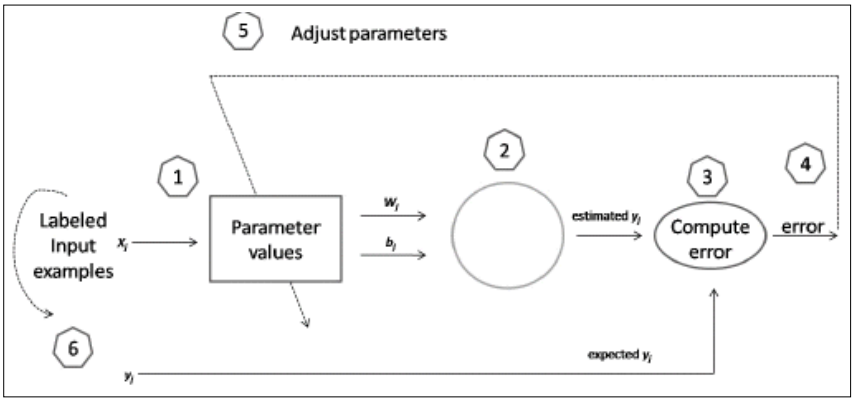


Fig 2: Steps of learning algorithm of artificial neural network. (Ribeiro, 2019).

Single layer feedforward network (SLFN)

The SLFN have just one input layer and a single neural layer, which is also the output layer. Thus, the information always flows in a single direction, from the input layer to the output layer. Therefore the number of outputs will always coincide with its amount of neurons (Ribeiro, 2019).

Multilayer feedforward network (MLFN)

The multiple layers are composed of one or more hidden layers of neuron. They mainly serve the purpose of solving problems those associated with function approximation, pattern classification, *etc.* (Ribeiro, 2019).

Back propagation network

The principle of back propagation is a way of propagating the entire loss back to the neural network to understand what proportion of the loss every node is liable for correction. It is the method of fine-tuning the weights of a neural network. It is based on the error rate obtained in the previous epoch (*i.e.* iteration). Thereby, reduction of error rates makes the model reliable by increasing its simplification. This is commonly used ANN in animal breeding and production studies (Al-Masri, 2019).

Applications of artificial neural network in animal breeding

Milk production prediction of dairy animals

The accuracy of milk production forecasts on dairy farm animals is very important for economic dairy farm management. Milk production in dairy animals is usually represented in the form of lactation curve representing a nonlinear pattern of production. Therefore, the non-linear function should be exercised for prediction of lactation milk yield (Dongre and Gandhi, 2016). The commonly used conventional methods 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 (Okkan *et al*., 2014). Therefore, for the first time Macrossan *et al.* (1999) used ANN to predict the daughter's milk production using, information of dam, sire, herd and environmental factors as inputs. Chaturvedi *et al.* (2013) reported that the prediction of life time milk production of a dairy cow is possible using artificial neural networks. Following are some of the studies and their findings regarding prediction of milk prediction of dairy cattle.

(i) Prediction of life time milk production in cattle using ANN in Sahiwal cattle (Gandhi *et al.,* 2009)

The traits considered as inputs were age at first calving, first lactation milk yield, first lactation length, first service period and first dry period. The accuracy of prediction of lifetime production from multiple regression analysis was found to be 25.92% from the training set when all the 5 traits were incorporated in the equation. It was 28.09% forthe test data set where 2 or 3 traits were incorporated. The accuracy of prediction the lifetime production by ANN from training and test set data were 29.81% and 28.88%, respectively. The root mean square errors of prediction were also lower from ANN prediction. Higher estimates of accuracy from ANN revealed that this technique can be used as an alternate approach to predict lifetime milk production in Sahiwal cattle.

(ii) A comparative evaluation of ANN and MLA was done to predict the first lactation 305 days milk yield (FL305DMY) of Karan Fries cattle at NDRI (Sharma *et al.,* 2006)

The accuracy of prediction was slightly higher in case of ANN model than the conventional regression model (57.61 versus 52.80%). The mean error sum of squares (MSE) estimated from ANN method were lower than that estimated from multiple linear regression (MLR) for FL305 DMY.

(iii) The prediction of life time milk production of a dairy cow artificial neural networks (Karan Fries cows maintained at National Dairy Research Institute, Karnal Haryana, India) (Chaturvedi *et al.,* 2013)

In this study the output performance of the ANN model in simulating cow's performance was compared with the experimental data. The output results of ANN were found to be close to the actual results of the experiment. Thus, ANN can be used to predict the total milk amount with minimum error. The maximum correlation coefficient found was close to 1, thus indicating accuracy. The study concluded that ANN

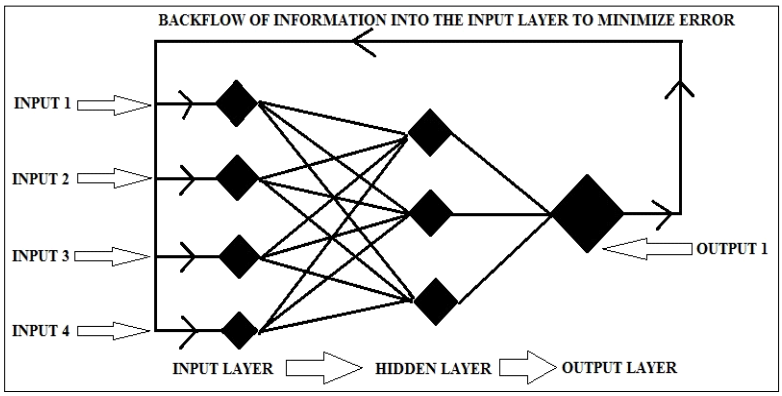


Fig 3: Illustration of a feed back ANN.

models used in this study have the potential of predicting future performance of cows on the basis of early expression traits.

(iv) Prediction of daughter's first lactation milk yield based on recorded genetic traits of their parents was performed by Njubi *et al.,* 2009

In this study, the performance of the ANN model in simulating daughter performance was compared with the industry default technique rectilinear regression (LR) model. The correlation coefficients between the observed and the estimated daughter milk yield for the ANN was found to be high, more than 0.80. Including sire information resulted in more accurate predictions by a neural network which was justified by reduced root mean square error. The results are an indication that ANN models have the potential of predicting daughter first lactation milk yield by using parent performance variables.

ANN application in case of meat animals

The morphometric assessment and early prediction of body weights are important aspects of breeding of meat animals. ANN can be applied for predicting the performance of the meat animal. Precise early prediction tends to be economically feasible since early detection of superior qualities helps in the selection of elite animals. Some of the studies where ANN has been used for analysis are as follows.

(i) Goyache *et al.* (2001) conducted a study on using AI to style and implement a morphological assessment system in beef

Morphological assessment in beef cattle includes body condition scoring and reproductive tract scoring. Experts are usually assigned to judge the beef cattle by the method of scoring. In this study, ANN model was also used for morphological assessment for body condition scoring and reproductive tract scoring for selection of elite animal for breeding. All of the correlations between the scoring of experts and ANN obtained were significant, starting from 0·57 to 0·90. The differences between ANN and human experts were not significant according to Lopez *et al.* (2020). All the average expected errors were found to be below 1 point.

(ii) Prediction of carcass meat percentage in young pigs using linear regression models and artificial neural networks (Nedza *et al.,* 2016)

In this study, accuracy was increased using backfat thickness and loin eye height measurements as well as daily gains and age on test day as input variables. The study concluded with the finding that based on the fattening and slaughter performance test results of live pigs, ANN is significantly more accurate compared to the three-variable linear regression model.

(iii)Improving genomic prediction accuracy for meat tenderness in nellore cattle using artificial neural networks (Lopes *et al.*, 2020)

Pedigree based analyses indicated that meat tenderness is moderately heritable (0.35). This indicates that it can be improved by direct selection. In the study, comparison between prediction by Bayesian regression models and ANN was done. Prediction accuracies were found to be very similar across the Bayesian regression models. It ranged from 0.20 (Bayes A) to 0.22 (Bayes B) and 0.14 (Bayes Cπ) to 0.19 (Bayes A) for the additive and dominance effects, respectively. On the other hand, ANN achieved the highest accuracy (0.33) of genomic prediction of genetic merit.

Neural networks for predicting breeding values

In a breeding program, genetic progress or response can be maximized through accurate selection of superior animals which will be selected as parents of next generation. For this the key component is fast and reliable prediction of breeding value for selection of candidates. However, prediction of breeding value is challenging and time consuming so it is done periodically. In that case, fast and low cost alternative that can provide rapid prediction of breeding value with acceptable accuracy shall allow timely selection and culling decisions. The prompt identification of superior males can lead to earlier collection and distribution of semen and thereby allow more genetic progress (Shahinfar *et al.,* 2012). Since, in case of machine-intelligence approach every information is requisite, it is obligatory that relevant inputs are to be considered in the training process of the ANN. de Silva *et al.* (2016) reported that selection efficiency was evaluated by means of the power of the ANN to discard a genotype that might eventually have a comparatively low genetic value and/or select a genotype that might have a high genetic value. The estimation of the genetic value as performed by the ANN was found to be simpler than that of the mean genotypic value, estimated by maximum likelihood (MLE) in both simulated scenarios.

Following are few examples where ANN was used for prediction of breeding values.

(i) Prediction of breeding values of body weight using feed-forward back propagation multilayer perceptron ANN (Ghotbaldini *et al.*, 2019)

The study reported that predicting breeding values by ANN had higher R^2 and Pearson's correlation coefficients with the experimental breeding values. It also had lower standard deviation and mean square error. The two networks applied in this study have correlation coefficient of 0.703 and 0.864. Therefore, ANN can replace the MLR models.

(ii) Prediction of breeding values for dairy cattle using artificial neural networks (Shahinfar *et al.*, 2012)

The inputs used in the study are age at first calving, days in milk, ambient temperature, ambient humidity, length of

photoperiod, milk and fat production of each cow and average of contemporaries along with Expected Breeding Value (EBV) for milk and fat of parents. When ANN was used, correlation between actual and predicted EBV increased and the error component decreased. For milk yield EBV had correlations of 0.917 and for fat yield EBV that had correlations of 0.926, with reference EBV. In case of 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. Increasing number of input variables led to predictions of EBV with greater accuracy in case of ANN prediction.

Inferring demography and recombination using ANN

Another emerging use of ANN in population genetics is the deduction of demographic history and recombination rates. Deducing the genome-wide landscape of recombination rates in populations is a central aim in genomics. The reason being, the influence patterns of linkage from genetic mapping to understanding evolutionary history (Schrider *et al.* 2015). A feed-forward ANN has the capability to learn the mapping of summary statistics onto parameters with excellent results. Adrion *et al.* (2020) stated that the estimation of accurate genome-wide recombination map even with small numbers of pooled or individually sequenced genomes can be done using "Recombination Landscape Estimation using Recurrent Neural Networks" (ReLERNN). It maintains high accuracy with regards to demographic model and has the potential to fill a much-needed role within the analysis of low-quality or sparse genomic data (Schrider *et al.,* 2020).

Genome-enabled prediction using ANN

ANN has proved itself as an efficient tool for marker-based genomic predictions of complex traits in animal and plant breeding (Ehret *et al*., 2015). ANN can capture cryptic relationships between SNPs and phenotypic values without the specific need of defining a genetic model. Ehret *et al.* (2015) conducted a study on the application of neural networks with back-propagation to genome-enabled prediction of complex traits in Holstein-Friesian and German Fleckvieh cattle. In order to assess the ability to predict milk traits using large-scale Single Nucleotide Polymorphism (SNP) data, examination of different non-linear network architectures and several genomic covariate structures in the form of network inputs was done in this study. The study concluded with the findings that ANN maybe more useful for complex trait *e.g.* protein yield, fat yield. This proved that a back-propagation learning algorithm maintains good predictive performance at low computational cost.

Predicting the culling reasons in cows based on routinely collected first-lactation records using ANN

ANN may be an effective method of classifying cows culled due to old age based on routinely collected first-lactation data. In a study conducted on Holstein-Friesian cows culled in Poland between 2017 and 2018 it was found that ANN were the most effective in predicting the culling of cows due to old age (99.76-99.88% of correctly classified cases) and 99.24-99.98% due to reproductive problems. It is significant because infertility is one of the conditions that are the most difficult to eliminate in dairy herds (Adamczyk *et al.,* 2021).

Monitoring the rumen fermentation pattern and prediction of pH, ammonia and volatile fatty acid concentrations in the rumen of dairy cattle using ANN

ANN can be an efficient tool to improve rumen volatile fatty acids (VFA) predictive models based on milk fatty acids (MFA). This is based on the notion that ANN has the potential of handling non-linear and complex data, even if these data are noisy and imprecise (Lek and Guégan, 1999).

(i) Craninx *et al.* (2007) conducted a study to predict the rumen fermentation pattern from milk fatty acids using ANN

The evaluation of the model performance showed a root mean square prediction error of 2.65%, 7.67% and 7.61% of the observed mean for acetate, propionate and butyrate, respectively. The results of ANN confirm that milk fatty acids have great potential to predict molar proportions of individual volatile fatty acids in the rumen.

(ii) Li *et al.* (2019) conducted a study to predict ruminal pH and ruminal ammonia and volatile fatty acid (VFA) concentrations by developing ANN using dietary nutrient compositions, dry matter intake *and* body weight as input variables

Evaluation of the ANN model exhibited prediction errors, with 4.19, 39.63, 19.57, 21.11, 31.32 and 28.15% of observed means for pH, ammonia, total VFA, acetate, propionate *and* butyrate, respectively. Therefore, we can assure from the observations that ANN model precision was acceptable for predicting ruminal metabolites.

Use of ANN to model reproductive performance and mortality

Yakubu and Nimyak (2020), conducted an experiment on non-descript rabbits in Plateau State, Nigeria to predict the average number of kits per birth and mortality number using ANN. The reliability on the ANN model was proved by fairly high coefficient of determination (R^2) (55.7%) and low root mean square error (RMSE) value of 1.22. The R^2 value obtained in the prediction of mortality using ANN implies that 61.1% of the variation in the number of mortality could largely be explained by variables such as flock size, age of farmers, experience in rabbit keeping and average number of kits per birth. Taking into consideration, the moderate to high variation explained by ANN model it could be used in the prediction of reproductive and mortality rate in non-descript rabbits.

CONCLUSION

From the above studies we can conclude that, ANN is comparatively superior to the presently used linear models of regression as it takes into consideration non linearity and uses parametric models unlike linear regression models. It has higher accuracy with low error root mean square due to its self learning ability. In case of linear models the error correction is manually done by standardization of data and by repetition of calculation. However, the error estimation and reduction is automatic in case of ANN by the help of back propagation. In this way, data spanning several decades can be analysed and predicted with the risk of error at a higher speed than regression models. The predicted data shows accuracy close to 1 as against linear models which have accuracy 0.5 to 0.8. With such advantages, it helps in analysis at a lower computational cost and high accuracy as compared to linear models. The mathematical modelling with the help of ANN for various parameters through entire livestock production chain is providing significant advantages in terms of increased process efficiency and quality control that result in economic benefits to livestock industry. Another important conclusion which we can draw is the prediction of breeding value can also be arrived from an ANN output. Hence, ANN with its brilliant flexible input and output structure is an important area for future research. Therefore, it's of great importance that more studies should be conducted to allow the event and application of ANN in the field of animal breeding and allied production studies.

Conflict of interest

All authors declare that they have no conflict of interest.

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