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APPLICATION OF BACK-PROPAGATION NEURAL NETWORK TO EVALUATE ELIMINATION CRITERIA OF LIVESTOCK BREEDING SOWS

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Abstract. *Pork is the most consumed meat and has the highest self-sufficiency rate among the livestock products. In Taiwan, it accounts for approximately 90% of the self-sufficiency rate of the livestock products. Thus, the pig industry is essential in food supply in Taiwan. The results of this study can aid pig farmers in evaluating sows. Back-propagation neural networks were used to select the breeding season, parity, primary breeding age, weaning-to-rebreeding duration, and number of live piglets in the first birth to enhance the sows' breeding performance and screening of sows with prolific genes. The road method, which predicts the number of piglets that may survive in a sow's second delivery, was used as a criterion for eliminating sows. The data source is Taiwan Livestock Farm. The data includes 1,512 matching records, and the parameters are divided into different groups. The results indicated that the learning rate was set to 1.0, the number of hidden nodes is set to 18 (3.5 times), and the highest prediction accuracy of this model is 84.62%. The study evaluated whether sows have a better reproductive performance and provides a basis for the screening of sows.*
Keywords: Data mining, Back-propagation neural network, Sow elimination criteria

1. **Introduction.** In Taiwan, pork is the most important source of meat for daily consumption. Livestock farms are essential cost indicators of production efficiency. In particular, the efficiency of piglet production directly affects the operating costs of livestock farms. The reproductive performance of the sow is related to the operational effectiveness of the livestock farm and an indicator for assessing the reproductive performance of the sow is the number of pigs per litter [1]. The reproductive efficiency of sows from Denmark is the highest among all pork-producing countries. The number of piglets in the sows from Denmark can reach more than 30 pigs per year, thus, ranking first in the world [2]; whereas a sow from Taiwan can produce approximately 22 piglets per year. Compared with Denmark, the breeding techniques of Taiwanese pig farms require further improvement. Therefore, improving the efficiency of piglet production and cow screening process is essential to the effectiveness of livestock farms. This study collected the screening variables of sows through literature and data collection. The data of a pig farm in Taiwan were converted into clusters according to the grouping rules in literature, and data mining techniques were used to analyze and reverse the neural network. The number of live piglets delivered by sows was predicted and could provide a reference for pig farmers in screening sows. We choose the back-propagation neural network because through the data mining technology, the inverted transmission neural network was used to predict the number of live sows, and the accuracy of the prediction of the inverse transmission neural network model was verified. In this study, the relevant variables affecting the number

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of live piglets in the sows corroborated those in literature, and the data were grouped according to the grouping rules compiled in this study. The model obtained in this study could help pig farmers to provide future sows before the second birth.

2. Literature Review.

2.1. Comparison of reproductive performance of pigs. Taiwanese hog breeds are produced by hybridizing different varieties, usually the three varieties of Yorkshire (Y), Landrace (L), and Duroc (D), among which Blueris and Yorkshire breeds are crossed. The sows (LY) and the three breed-hybrid pigs (LY-D) produced by mating with Duroc boars are the most common, as shown in Table 1, compared with other varieties. The average number of nipples was the highest among the three breeds of pigs, and litter number was even better than that in purebred pigs.

Table 1. Comparison of reproductive performance of different pig breeds

Variety combination	Number of litters	Average litter size	Average live litters	Average dead litter	Average number of nipples	Breeding rate 1 (%)	Breeding rate 2 (%)
L-L	185	9.92	9.02	0.89	7.82	88.5	81.0
D-D	86	9.72	8.16	1.53	6.86	85.5	73.2
B-B	66	11.36	9.26	*2.11	7.45	80.6	66.9
L-Y	440	10.80	9.44	1.35	7.70	83.5	73.9
L-D	2377	10.41	9.50	0.93	8.28	88.4	81.1
L-B	60	10.53	8.88	1.65	7.47	85.3	73.1
Y-L	43	*12.26	9.79	*2.47	8.22	83.1	71.2
B-D	27	9.81	8.63	1.19	7.74	90.6	77.8
LY-D	954	10.65	9.62	1.03	*8.50	*89.6	*82.0
LD-Y	99	*11.17	9.93	1.24	7.30	74.9	67.1
YL-D	61	10.61	9.33	1.28	*8.46	*90.1	80.3
LYL-D	31	10.77	9.84	0.94	*8.47	*87.1	80.2
Average	5722	10.49	9.43	1.07	8.10	85.9	77.2

Note: Breeding rate 1 = number of nipples/average live litter size; breeding rate 2 = number of nipples/average litter size

2.2. Parameters to improve reproductive performance. The reproductive performance of sows can be influenced using several methods. The method for evaluating the reproductive performance of sows includes the following indices.

1) Sow productive index (SPI): This index is used to calculate the reproductive capacity of sows in each birth. The required parameters include the number of births per piglet and the 21-day-old corrected litter weight, as shown in the following formula:

$$\mathrm{SPI} = 100 + 6.5(\mathrm{L} - \mathrm{L}_{\mathrm{avg}}) + 2.2(\mathrm{W} - \mathrm{W}_{\mathrm{avg}})$$

L: the number of births per piglet
W: 21-day-old corrected litter weight (kg) = age-old multiplier × (measured nest weight)
avg: Average

2) Most probable sow productivity: This index is used to predict the breeding index of sows in future production. The formula is based on the SPI for the next estimation, as the following formula shows:

$$\mathrm{MPSP} = 100 + b(\mathrm{SPI}_{\mathrm{avg}} - 100)$$

$$b = \frac{n * r}{1 + (n - 1) * r}$$

$$r = 0.25$$

n = cumulative production
SPI_{avg}: Average SPI for sows

3) Breeding value for sow productivity: This index is used to predict the breeding value of a sow, that is, the pros and cons of the sow offspring. This index can be used as a breeding method for later breeding with boars. The decision reference is as shown in the following formula:

$$\text{BVSP} = 100 + c(\text{SPI}_{\text{avg}} - 100)$$
$$c = \frac{n * 0.2}{1 + (n-1) * r}$$
$$r = 0.25$$

Based on the calculation of the aforementioned index, the factors affecting the reproductive performance of the sow are as follows.

A. Sow parity: The first production of sows.

B. The number of piglets in the litter: The number of piglets produced by the sow.

C. The number of litter is from the milk nest on the 21st: The weight of the piglets on the first day of the sow.

In addition, other factors affecting the reproductive performance of sows include breed of the sow [3], parity [4,5], duration from lactation to rebreeding [4,5], number of live births [5,6], age of first mating [5,7], season [5,8], and pig farm size [5].

3. **Research Structure and Method.**

3.1. **Research structure.** According to previous literature, this study summarized the parameters affecting the number of sows that gave birth to piglets. The farm record data provided by the cooperative livestock farms were screened and grouped. The pigs in a case farm in Taiwan were collected. Through the data mining technology, the inverted transmission neural network was used to predict the number of live sows, and the accuracy of the prediction of the inverse transmission neural network model was verified.

3.2. **Operational variables.** The farm records contained necessary information about sows, pig breeding records, and pig birth records. The primary data of the sow included the breed of the pig, number of live births, age of the first breeding, and number of sows; the breeding record of the pig included the date of breeding, number of boars, number of sows, and duration from lactation to rebreeding. The delivery record included the date of delivery, number of births, number of litter, and number of live piglets.

The screening rules included the variety, parity, age of the sow, age from weaning to rebreeding, and number of piglets delivered by a sow. In the absence of the birth record of the first child, the number of live births and age of the first breeding were unknown; the sows were prioritized after the seventh birth of the commercial pasture sows [9]. Therefore, the sow delivery records for the first and sixth births were not used. A sow record with an initial age fewer than 160 days or more than 400 days was not used. Data on sows with more than 19 births, number of weaned piglets, and duration from lactation to rebreeding for more than 61 days were considered of no value [5].

Based on the weather and climate in Taiwan, the breeding season was divided into two groups, namely summer (1 May to 30 September) and nonsummer (1 October to 30 April). The sow parity was divided into five groups: second, third, fourth, fifth, and sixth births; the first breeding age of the sows was divided into three groups: 160-229, 230-277, and 278-400 days. The sows were rebreeded after weaning. The spacing is divided into three groups: 0-6, 7-12, and 13 days. The number of live births was divided into four groups: 1-7, 8-11, 12-14, and more than 15 heads [5].

3.3. **Research methods.** Data grouping refers to the division of data into several clusters according to characteristics or similarity in the database, such that a high degree of similarity exists within the same cluster. This grouping is also known as data segmentation. The grouping method is a method of unsupervised learning because it does not need to rely on specific rules to train data. Common algorithms include k-means [9], self-organizing maps [10], and other algorithms. Artificial neural networks originate from the neural structure which mimics the human brain, and the design concept attempts to mimic the characteristics of biological neurons. The reverse-transitive neural network transforms the input and output problems of a set of samples into nonlinear optimization. The principle is calculated using the steepest slope method in calculus and successively adjusted. The network links the weight value to minimize the error between the predicted value and the actual target value [11]. The network learning process of the inverse neural network algorithm, including the forward and reverse transfer directions, is continuously calculated through the forward and reverse transfer, thereby achieving the predicted effect.

The neural network architecture comprises input, hidden, and output layers. The hidden layer may have three or four layers. In general, the hidden layer affects the final prediction effect, which is higher than if the layer is not secure to converge and cause significant errors. The back-propagation neural network is a supervised learning network. The primary purpose of supervised learning is to reduce the difference between the network output value and the actual data. When the forward transfer causes considerable difference between the estimated output value obtained by the network calculation and the learned target output value, the network automatically reverses the transfer to correct the weighted value and the bias value. The difference between the estimated output value and the target output value is usually compared using an error function (referred to as the sum of squared error) to represent the difference between the calculated data and the actual output data. The formula is calculated as follows:

$$E = \frac{1}{2}\sum_{j}^{m}(T_j - Y_j)^2$$

Here,
T_j = target output value of the jth output layer.
Y_j = the estimated output value of the jth output layer.
m = one of the neurons.

Half of the aforementioned formula is used to derive the energy function differential. When the E value is higher than the error tolerance value specified by the experimenter, the reverse transfer, that is, the back-transfer neural network calculus starts and calculates the weight correction amount so that the error function drops to the maximum gradient direction, and the calculation method is as follows:

η = learning rate. This learning rate is the magnitude of the correction amount which controls the weight of the knot so that the correction error function is minimized. Generally, the learning rate is too large or too small, which leads to poor network convergence. Generally, the learning rate is 0.5, or a value between 0.1 and 1.0 can be obtained as the learning rate.

The inverted transfer neural network can construct nonlinear models, effectively solve complex nonlinear problems, and exhibit adaptability. The neural network can input different types of variables, and the prediction accuracy is high. It has fuzzy inference ability and affects the number of live births of sows. Many variables and the complexity of the problem are not a general linear problem, which is consistent with the problem domain of this study. Therefore, this study used the inverse transfer neural network algorithm as a method to predict the number of live piglets delivered by a sow.

A livestock farm in Taiwan provided the research data, consisting of 1,512 breeding records, including the parental line of the parent family Landrace. Duroc said that the LD variety combination is 918. Although the farm has records of other varieties, the data are small. Therefore, this study only used the LD breeding combination.

4. **Results.**

4.1. **Experimental environment.** The operating system used in this study was C#'s AForge Neuro kit. This study used the inverse transfer neural network for prediction. Using the double bending function as the conversion function error, the square of the error was used. The convergence threshold was set when the training sample training accuracy rate was more than 90%, and the output value reached 0.7 or above, and the threshold value below 0.3 was predicted to be correct.

The input variables included the breeding season, parity, age and number of live births of the sow, and duration from lactation to rebreeding. The number of live births of the sow is the output variable. The appropriate number of hidden layer nodes was discovered through the trial and error method. The number of input layer variables was 1, 2, 2.5, 3, 3.5, and 4. Because the numbers of hidden layers of 2.5 and 3.5 have a decimal point, the number of hidden layer nodes has unconditional carry for a decimal point; the learning rate of 0.5 was based on the suggestions provided in the past. The recommended minimum value of 0.1 and the maximum value of 1.0 were used for testing.

4.2. **Data screening and data group conversion.** First, the history data of all the sows collected in the past is compiled in Table 2. Through the grouping rules, the data is grouped into Table 3. The training data sheet was added to the data to complete the training of the sows' dataset.

The combination of the original data and the screening rules resulted in 86 training samples, and the training sample was 70% of the original data (a total of 60). The remaining 30% of the data were used as test samples (a total of 26 pens).

Table 2. Training classification model data set (before processing)

Data No.	Breeding date	Sow	First breeding age	First birth	Number of live births after weaning to re-breeding	Live number
0000001	5/1	2	229	7	6	7
0000002	9/30	3	230	8	7	11
0000003	10/1	4	277	12	12	12
0000004	4/30	6	278	15	13	15

Table 3. Training classification model data set (after processing)

Data No.	Breeding date	Sow	First breeding age	First birth	Number of live births after weaning to re-breeding	Live number
0000001	1	2	1	1	1	1
0000002	1	3	2	2	2	2
0000003	2	4	2	3	2	3
0000004	2	6	3	4	3	4

4.3. **Back-propagation neural network assessment.** The results indicated that when the learning rate was 1.0, and the hidden node was set to 18 nodes, the highest test accuracy rate was 84.62%. When 20 hidden layers were used, the test accuracy decreased as shown in Table 4.

TABLE 4. Back-propagation neural network test and training results

Learning rate 0.1						
Hidden layer node	5	10	13	15	18	20
Training accuracy	96.67%	95%	91.67%	96.67%	Unconverge	Unconverge
Test accuracy rate	53.85%	61.54%	65.38%	80.77%		
Sum of squared errs	1.3	1.57	2.54	1.57		
Learning rate 0.5						
Hidden layer node	5	10	13	15	18	20
Training accuracy	93.33%	98.33%	98.33%	91.67%	95%	88.33%
Test accuracy rate	53.85%	76.92%	80.77%	76.92%	73%	61.54%
Sum of squared errs	2.48	1	0.5	2.5	2	3.5
Learning rate 1.0						
Hidden layer node	5	10	13	15	18	20
Training accuracy	95%	96.66%	93.33%	98.33%	90%	93.33%
Test accuracy rate	65.38%	69.23%	65.38%	80.77%	84.62%	61.54%
Sum of squared errs	2.47	1	3	0.5	3	2

5. Conclusion.

In this study, the relevant variables affecting the number of live piglets in the sows corroborated those in literature, and the data were grouped according to the grouping rules compiled in this study. The inverted transmission-like neural network was used to predict the number of live births of the sows. The results demonstrated a test success rate of up to 84.62, verifying the correlation between the parameters used in this study and the number of live piglets delivered by the sow.

In the past, pig farmers could only determine the number of live piglets after delivery. The model obtained in this study could help pig farmers to provide future sows before the second birth. The number of live piglets is given, and after the second child is delivered, it is evaluated whether the sow has a better reproductive performance than the previous sow.

Because of lack of data, the study was limited to the combination of LD pig breeds. In future, combinations of different breeds and other parameters affecting the number of litter for sows are expected to be collected, and the number of live births can be predicted for different breeds. To improve the prediction accuracy rate. Because the neural network has black box characteristics in the learning process, the prediction model can only be constructed through historical data, but cannot be explained. Pig weight record is expected to be collected in the future. The formula can be used to enhance the breeding of pigs. Moreover, performance methods can be cross-validated with this study to assist pig farmers in assessing the reproductive performance of pigs.

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