International Journal of Chemical and Biochemical Sciences
(ISSN 2226-9614)
Journal Home page: www.iscientific.org/Journal.html

Neural Network Analysis of Hematological Parameters in Cows and Assessment of Their Potential Milk Productivity

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Abstract

The study aimed to develop a technology for computing the cognitive value index of blood values obtained from a cow blood test based on the EuclidNN neural network. By comparing the potential and actual milk production of a cow, it is possible to determine the necessary amount of feed and reduce the risk of disease to livestock due to pathogens. Ten black-and-white cows were selected for the experiment, with a milk yield of more than 8,000 kg in 305 days. The EuclidNN computing neural network was used to assess the biochemical intensity of animal blood processes. According to the results of the study, a new information technology was developed and tested, which can process the blood values of cows and calculate the potential milk productivity of each individual, depending on the lactation age and blood values of the cow.

Keywords: Milk production, neural network, biochemical analysis

Full length article **Corresponding Author*, e-mail: *selina.marinav@gmail.com*

1. Introduction

Cow health and milk productivity are ensured by complex biochemical processes occurring in the blood [1-3]. In this regard, the study of the hematological parameters of cows makes it possible to control the age-related weakening of the intensity of internal metabolic processes in the animal body and a decrease in the resistance of animals to pathogenic infections [4-6]. The inclusion of biologically active supplements in animal diets has a positive effect on metabolic biochemical processes in their body and increases their milk productivity [7, 8]. With an increase in the age of cows (from the lactation sequence number), milk productivity initially increases to the maximum value and then decreases [9, 10]. Young cows have a lower fat content in milk compared to older animals. This indicator improves to the fourth or fifth lactation. After the sixth calving, it decreases annually by almost 0.02 [11-13]. The purpose of this study is to create an information technology based on the use of the computational neural network EuclidNN, which determines the index of cognitive significance of blood indicators based on cow blood indicators at the output, reflecting indirectly the potential milk productivity of cows. Comparing the potential milk productivity with the actual milk productivity of cows makes it possible to assess the necessary and sufficient amounts of animal feed and reduce the risks of animal diseases from pathogenic infections.

2. Materials and methods

The experiment was conducted at the collective farm named after the 50th anniversary of the USSR in the Vologda region, Russia. Ten black-and-white cows with a milk yield of more than 8,000 kg of milk in 305 days were selected for the experiment. For 90 days, a humic preparation was included in animal diets (administered individually at a dose of 30 g per day). The cows were fed according to the norms of a balanced and differentiated diet with multicomponent silage and concentrated feed mixture and hay [14]. When processing animal blood counts, it was assumed that blood counts reflected the intensity of biochemical metabolic processes occurring during the digestion of feed in animal rumens. We associate an increase in milk productivity with an increase in the intensity of biochemical processes.

Therefore, the computational neural network EuclidNN (Fig. 1) [15, 16] was used to assess the intensity of biochemical processes based on animal blood parameters. It calculates the index of cognitive significance of cow blood parameters (Cognitive Salience Index, CSI) [17], reflecting in dimensionless form the intensity of biochemical processes in the animal body.

2.1. EuclidNN neural network calculation algorithm

The first problem that had to be solved when building the EulidNN neural network (Fig. 1) was the choice of the number and types of animal blood parameters [14] sufficient to predict the milk productivity of cows and the physiological parameters of animals. The solution to this problem had to be found at the stage of training and validation of the EuclidNN neural network [18, 19], which provided the opportunity to change not only the values of the coefficients of mathematical models but also the network structure of the computational neural network EuclidNN. The conducted recurrent search for the minimum number of informative blood indicators ended with the selection of nine cow blood indicators presented in Table 1.

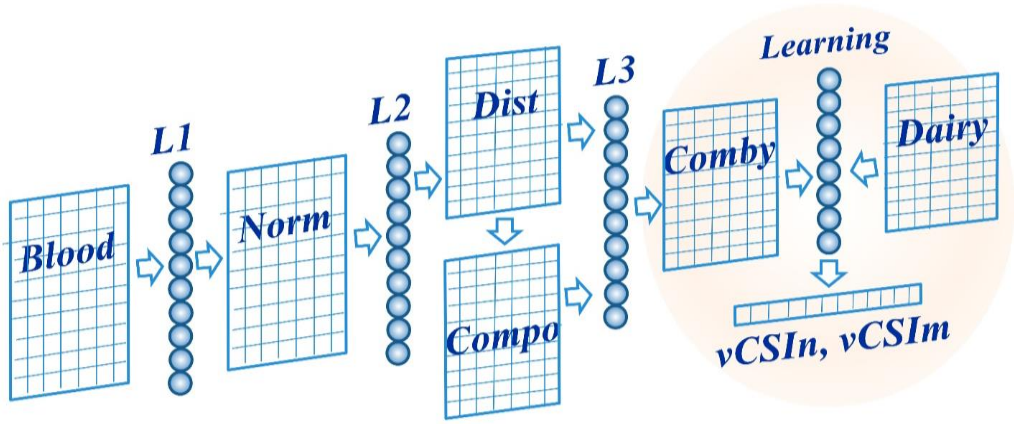

Figure 1. The computational neural network EuclidNN which allows calculating the vectors vCSIn (cognitive vector of lactation age of cows) and vCSIm (cognitive vector of milk productivity of cows) based on cow blood parameters. Blood is a matrix of cow blood indicators. Norm is a matrix containing normalized data of the Blood matrix. Dairy is a matrix of the milk productivity of cows. Dist is a matrix of distances between cow blood counts. Compo is a matrix of orthogonal coordinate components in the space of cow blood parameters. Comby is a matrix containing the results of nonlinear combinational transformations of these Dist and Compo matrices. L1, L2, and L3 are layers of artificial neurons performing matrix transformations of numerical data. Learning is a layer of artificial neurons that provide training and validation of the EuclidNN neural network based on correlation analysis of data from the Comby and Dairy matrices.

The L1 neuron layer normalized the data of the Blood matrix (Fig. 1) [20], which contained cows' blood parameters (Table 1). The normalization results according to formula (1) are stored in the Norm matrix.

$$Norm_{jk} = \frac{Blood_{jk} - \frac{1}{10} \cdot \sum_{k=1}^{k=10} Blood_{jk}}{\sqrt{\sum_{k=1}^{k=10} \left[Blood_{jk} - \frac{1}{10} \cdot \sum_{k=1}^{k=10} Blood_{jk}\right]^2}} \tag{1}$$

where $Blood_{jk}$ are the values of the Blood matrix; j=1,2,...,9 are the ordinal numbers of cow blood indices; k=1,2,...,10 are the ordinal numbers of cows (Table 1).

The L2 neuron layer calculates the Dist matrix (the matrix of Euclidean distances between cow blood parameters in the 9-dimensional normalized space of the blood parameters) using formula (2) [21].

$$Dist_{mn} = \sqrt{\frac{1}{9} \sum_{j=1}^{j=9} \left(Norm_{jn} - Norm_{jm}\right)^2} \tag{2}$$

where m, n=1,2,...,10 are the ordinal numbers of cows; j=1,2,...,9 are the ordinal numbers of cow blood parameters (Table 1).

The L2 neuron layer calculates the Compo matrix, the matrix of the main coordinate components (proper orthogonal vectors, EigenVectors) in the normalized space of cow blood parameters using the data of the Dist matrix and the standard computational procedure [22].

$$Compo = EigenVectors(Dist) \tag{3}$$

The L3 neuron layer calculates the Comby matrix, the numerical data of which is obtained by linear and nonlinear combinational transformations of the data contained in the Dist and Compo matrices. The data of the Comby matrix is necessary at the training stage of the EuclidNN neural network.

The Learning neuron layer is used for training and validation of the EuclidNN neural network based on correlation analysis of data from the Comby and Dairy matrices [23, 24]. After performing the training procedure and validation of the EuclidNN neural network, it was found that the vCSIn vector (the cognitive vector of the lactation age of cows) correlated with Compo10 (the 10th orthogonal component of the normalized space of cow blood parameters), and the vCSIm vector (the cognitive vector of cow milk productivity) correlated with Compo2X3, the resulting combination product of the 2nd and 3rd components of the normalized space of blood parameters of cows. As a result, the values of the vCSIn and vCSIm vectors were calculated using formulas (4) and (5).

$$vCSIn_k = -Compo10_k \cdot 3.65 + 5 \tag{4}$$

$$vCSIm_k = -Compo2X3_k \cdot 4.71 + 5 \tag{5}$$

where k=1,2,...,4 are the ordinal numbers of the experiment variants (Tables 3 and 4).

In addition to cow blood counts, Table 1 shows the correlation coefficients of the vCSIn, vCSIm vectors, and the vCSIm/vCSIn ratio with cow blood counts and with the ordinal numbers of cow lactation.

The vCSIm/vCSIn ratio served as a classification measure in the presentation by scaling [25] indicators of t milk productivity of cows (Table 2, Fig. 2).

3. Results and discussion

1. The neural network can determine the potential cow milk production capabilities based on blood parameters, which prolongs their life.

2. Cows No. 10096, 10825, 11277, and 10870 yield milk above the norm. This will lead to their withdrawal from dairy production due to early diseases.

A new information technology based on the use of artificial intelligence in the form of the EuclidNN neural network was developed. This information technology was able to process cow blood counts and calculate the potential milk productivity of each animal, depending on the lactation age and cow blood counts. The final product of neural network calculations was the vCSIm/vCSIn index ratio. This ratio characterizes the potential milk productivity, which is described by a domed dependence (Fig. 3, [11-13]), since the potential milk productivity of cows increases at the initial lactations, and then gradually decreases.

If a cow is overfed to maintain high milk yields above potential milk productivity, then additional energy for milk secretion in the mammary gland will be taken away from the cow's immune system, which means that the protective barriers of the animal body will decrease and the risks of animal diseases from pathogenic infections will increase. Among the studied cows, the risks of diseases are highest in cows 10096 (4th lactation), 10825 (3rd lactation), 11277 (3rd lactation), and 10870 (3rd lactation) (Fig. 3, Table 3). For these cows, it is necessary to reduce the volume of feed. In this case, they will yield less milk, but they will produce milk in subsequent lactations. The cost of bringing one cow to a production state is much higher than the continuation of the life of a cow with a reduced milk yield.

Table 1. The average blood and milk productivity of cows and the ordinal numbers of lactation of cows and the correlation coefficients of the vCSIn, vCSIm, and vCSIm/vCSIn vectors with blood indicators and milk productivity

Cow inventory number	125	595	10096	10825	10870	11277	11570	12180	12517	13765	vCSIn	vCSIm	vCSIm/ vCSIn
Cow reference number	1	2	3	4	5	6	7	8	9	10			
1. Triglycerides, mmol/l	0.11	0.1	0.05	0.09	0.13	0.07	0.17	0.06	0.06	0.12	-0.02	-0.23	-0.10
2. Lymphocytes, %	41.7	57.7	25.9	28.6	75.1	55.8	25	30.6	50	33.1	0.02	0.77	0.49
3. Uric acid, mmol/l	51.9	68.8	108.6	51	56.2	38.7	39.1	35.5	58.8	57.7	-0.01	-0.35	-0.24
4. Total cholesterol, mmol/l	4.29	6.24	5.05	6.56	4.06	7.2	3.9	2.83	5.3	4.97	-0.02	0.31	0.19
5. Red blood cells, 1012/l	4.51	4.43	6.9	5.44	7.29	6.48	3.63	5.28	5	5.3	-0.06	0.44	0.30
6. Hematocrit, %	20.1	19.5	25.8	22.4	31.5	27.3	15.2	22.5	20.8	19.3	0.10	0.59	0.29
7. Potassium, mmol/l	5.8	5.7	5.6	6	1.8	4.7	5.8	6.5	6.5	5.6	-0.02	-0.47	-0.28
8. Average platelet volume, fl	5.5	6.5	5.7	5.7	6	6.4	6.1	5.6	5.4	5.3	0.06	0.15	-0.10
9. Average hemoglobin concentration in the red blood cells, g/l	343	343	372	348	342	318	368	342	346	341	0.04	-0.85	-0.67
vCSIn	7.7	4.6	5.2	5.7	5.0	5.1	4.9	4.6	4.4	2.8	1	-	-0.67
vCSIm	4.4	5.3	2.7	5.3	7.1	6.8	2.2	5.3	5.8	5.0	-	1	0.76
vCSIm/vCSIn	0.58	1.15	0.51	0.94	1.42	1.33	0.45	1.16	1.31	1.79	-	-	1
Lactation reference number	7	3	4	3	3	3	3	2	2	1	0.94	-	-0.68
Milk productivity, kg/lactation	7,799	9m503	9,237	9,997	11,355	12,374	4,201	9,915	10,432	9,444	-	0.85	0.67

Table 2. Classification scale of cow milk productivity indicators arranged in ascending order by the ratio of vCSIm/vCSIn indices

Reference number on the classification scale	1	2	3	4	5	6	7	8	9	10
Cow inventory number	11570	10096	125	10825	595	12180	12517	11277	10870	13765
vSCIn	4.9	5.2	7.7	5.7	4.6	4.6	4.4	5.1	5.0	2.8
vCSIm	2.2	2.7	4.4	5.3	5.3	5.3	5.8	6.8	7.1	5.0
Lactation reference number	3	4	7	3	3	2	2	3	3	1
Actual milk productivity, kg/lactation	4,201	9,237	7,799	9,997	9,503	9,915	10,432	12,374	11,355	9,444
Potential milk productivity, kg/lactation	4,321	6,071	7,525	8,683	9,545	10,111	10,380	10,354	10,031	9,412
vCSIm/vCSIn	0.45	0.51	0.58	0.94	1.15	1.16	1.31	1.33	1.42	1.79

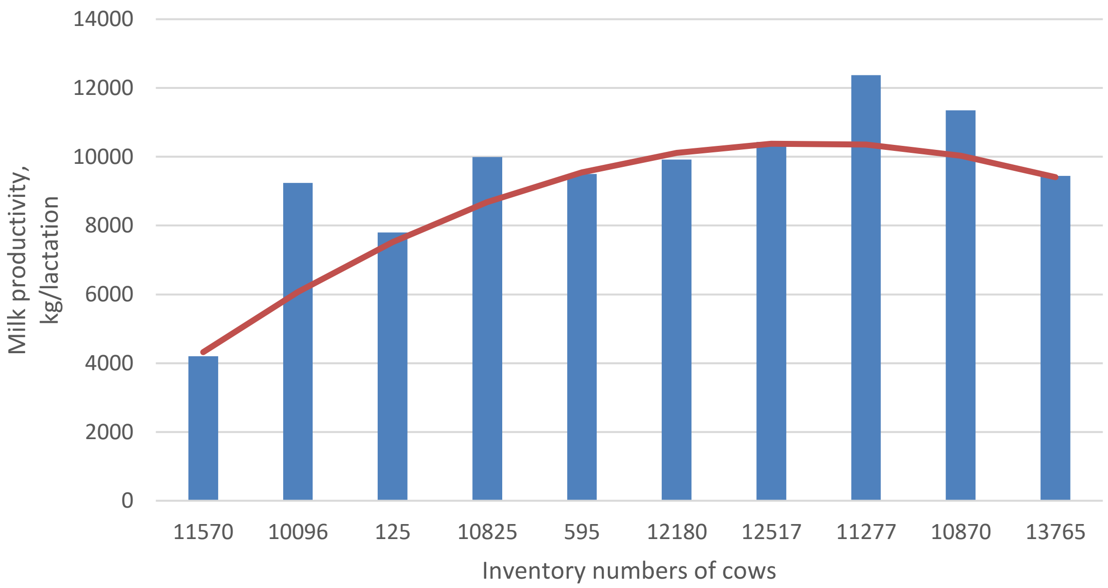

Figure 2. Comparison of potential (red line) and actual (bars) cow milk productivity based on the results of mathematical processing of cow blood parameters by the EuclidNN neural network and the use of the scale method for the ordered arrangement of milk productivity data in ascending vCSIm/vCSIn ratio (Table 2)

4. Conclusions

A blood test is a safe procedure for animals. Based on the blood indicators, one can calculate the current potential milk productivity, which allows for responding promptly to changes in the state of animal health and providing nutrition with a balance of energy resources aimed at milk synthesis and protection from pathogenic infections, as well as taking measures for emergency treatment of cows.

Acknowledgments

The study was funded with grant No. 23-26-00234 of the Russian Science Foundation, https://rscf.ru/project/23-26-00234

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