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Neural Network Ranking of Feed Additives According to the Index of Milk Productivity and Biochemical Parameters of Cow Blood

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Cows' potential milk productivity, their health, conditional lactation age, and the intensity of internal biochemical processes in their bodies require constant monitoring to respond in time to age-related and infectious changes. It is proposed to use computational neural networks to control biochemical processes in cows' bodies. Processing blood counts using computational neural networks allows one to determine the potential milk productivity of cows and draw reasonable conclusions regarding the effect of feed and feed additives on their milk productivity. Based on these findings, there is a unique opportunity to form a daily diet that has a positive effect on cows' health and productive longevity. The study introduces a new information technology based on the GeorgyNN neural network, which calculates the LactCSI and MilkCSIp indices representing conditional lactation age and potential milk productivity, respectively. Using the values of the MilkCSIp vs LactCSI indices for each cow, one can conduct a two-dimensional ranking of cows and present the ranking results in the form of a Scale1 matrix; using the values of the MilkCSIf vs MilkCSIp indices, one can present the results in the form of a Scale2 matrix. The analysis showed that brewer's spent grain (BSG) reduced the intensity of internal biochemical processes, while the Cellobacterin probiotic increased it. These findings suggest that the impact of these feed additives is primarily influenced by the cows' genetic and microbiome specificity. This approach enables the formulation of daily diets that improve cows' health, longevity, and productivity. The priority in the impact of these external biotic and abiotic factors on biochemical processes is likely determined primarily by the genetic specificity of cows and the specificity of the intestinal microbiome for the digestion of feed and probiotic supplements.

Keywords: Blood counts and milk productivity indicators of cows, feed additives with brewer's spent grain, Cellobacterin probiotic, index ranking of diets, computational neural network GeorgyNN.

INTRODUCTION

Cows' health and milk productivity depend on the intensity and direction of biochemical processes occurring in their bodies (Mkrtchyan *et al*., 2023; Bo-fei, 2020; Yefimova, 2019). The constant monitoring of cow indicators provides a unique opportunity to observe the course of internal metabolic processes in real time and assess the intensity of the immune system's response to external pathogenic infections (Romanov *et al*., 2015; Sudarev *et al*., 2009; Vinogradova *et al*., 2015). Based on blood counts, it is possible to study the effect of biologically active feed additives on internal biochemical and immune processes (Wang *et al.*, 2008; Fedosova *et al*., 2022; Volgin *et al*., 2018). However, traditional methods primarily rely on average daily milk yield to optimize nutritional diets, which may not be sufficient in cases of sudden health deterioration, age-related changes, or in-depth studies on the effects of feed additives and probiotics. Milk productivity changes non-monotonously with an increase in the lactation number. In the first lactation, milk productivity increases, and then gradually decreases (Sudarev, 2009; Volgin *et al*., 2018). To simulate the extreme dependence of milk productivity on lactation age, we used the GeorgyNN computational neural network (Fig. 1) (Zaikina *et al*., 2022) designed to process cow blood counts and calculate the MilkCSIp and LactCSI indices (Sutrop, 2001). Here, the

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MilkCSIp and LactCSI indices are delegated the rights to quantify the level of potential milk productivity and conditional lactation age of cows in comparative scientific studies. GeorgyNN is additionally equipped with a learning service (Schmidhuber, 2015; Kruglov, 2002; Pogodaev *et al*., 2021), which allows for a reverse cyclic search for the correct CSI procedure that converts blood counts into the MilkCSIp and LactCSI indices. The exit from these cycles is possible only after a scientific and theoretical examination of the simulated dependence of milk productivity on conditional lactation age and biologically active additives to nutritional diets. The application of neural networks in digital agriculture is without bounds. Countless studies have demonstrated its effect in optimizing animal health and feed management. Kamilaris and Prenafeta-Boldú (2018) reviewed various applications of deep learning in agriculture; they highlighted the application in weed identification, plant recognition, fruit counting, soil moisture content prediction, and crop yield prediction. Kujawa and Niedbała (2021) highlighted the application of neural networks in identifying pests and diseases, decision-making, and studying the effect of weather conditions. In their study, Zeng *et al*. (2022) also supported the use of neural networks in decision-making and highlighted the integration of a geographical information system. Dragojlovic *et al*. (2019) highlighted the application of artificial neural networks for predictive purposes and analyzing the application of liquid in animal feed production. A study by Chumakova *et al*. (2023) demonstrated that artificial neural networks can predict the production rate and percentage of dust for a particular mill, thereby reducing production costs and increasing efficiency. A different study by Imanbayeva *et al*. (2024) displayed the application of a neural network based on near-infrared spectroscopy of milk to optimize cow feed management. The application of neural networks in animal feed management is a significant step in improving animal health and the quality of farm animal byproducts. Other applications include real-time feed additives, diet adjustments, and nutrient deficiency prediction. The predictive and analytical nature of neural networks in agriculture leads to targeted and efficient diet and feed additives management, cost reduction, and overall improvement of animal health. The application of neural network ranking in the context of dairy farming represents significant progress in resource management and operational efficiency. Using neural networks to rank feed additives based on their impact on cows' milk productivity and health indicators, this technology allows farmers to optimize feed formulations with high accuracy. This approach reduces resource losses by preventing overfeeding or underfeeding and ensures that each cow receives a diet tailored to its specific health and productivity needs. It maximizes the economic return on feed investments while supporting sustainable farming practices and improving the overall welfare of animals. The purpose of this study was to visualize the non-formalized extreme dependence of milk productivity on conditional lactation age and feed additives to the main diet using Scale ranking matrices. To achieve this goal, the following tasks were performed.

1. The development of GeorgyNN with CSI training and assessment procedure service that converts cow blood counts into the MilkCSIp and LactCSI index values.
2. The training of GeorgyNN and the scientific and theoretical examination of the CSI procedure based on the analysis of correlations of the MilkCSIp and LactCSI indices with indicators of milk productivity, the MilkCSIf index, and the ordianl lactation number.
3. The ranking of feed additives according to the MilkCSIp and LactCSI indices and the MilkCSIf and MilkCSIp indices and filling out of the corresponding Scale ranking matrices.
4. The analysis of the effect of conditional lactation age and feed additives to the basic diet on milk productivity based on the obtained Scale matrices.

MATERIALS AND METHODS

To study the effectiveness of feeding brewer's spent grain (BSG) and the Cellobacterin probiotic to dairy cows in the Kobralovsky Socio-Entrepreneurial Corporation (Leningrad region, Russia), from November 21, 2007, to January 31, 2008, a scientific and production experiment was conducted on black-and-white dairy cows (Bolshakov *et al*., 2009a; Bolshakov *et al*., 2009b). The diets covered the animals' needs for energy, nutrients, and mineral elements following existing norms and with a productivity level of 18.0 kg of milk/day from each cow. The control group (CG) was fed a basic diet without additives and probiotics. The first experimental group (EG1) received BSG without a probiotic as an additive to the basic diet. The second experimental group (EG2) received BSG enriched with Cellobacterin as an additive to the basic diet (Bolshakov, 2009). Based on the study results, we determined the average milk productivity of each cow and the fat and protein content in milk (Table 1). At the end of the experiment, we also determined the protein, carotene, reserve alkalinity, calcium, and phosphorus content in the cows' blood (Table 1).

RESULTS

***GeorgyNN calculation and training algorithm*:** When processing blood counts, we assumed that they carried the imprint of biochemical metabolic processes in the animals' bodies. Therefore, it was proposed to use GeorgyNN to decipher blood counts and represent the desired non-formalized extreme dependence of milk productivity on the conditional lactation age (Fig. 1). GeorgyNN was used to determine the MilkCSIp and LactCSI indices by mathematically converting blood counts (Table 1). In

Table 1. Milk productivity indicators, blood counts, the MilkCSIp, MilkCSIf, and LactCSI indices, and correlation coefficients of the MilkCSIp, MilkCSIf, and LactCSI indices with blood counts and milk productivity.

Indicators	Herd No.	No.	1. Calcium, Mmol/l	2. Phosph-orus, Mmol/l	3. Total protein, g/l	4. Carotene, mg/%	5. Reserve alkalinity, vol.% CO_2	Lact CSI, b/r	Milk CSIp, b/r	Milk CSIf, b/r	6. Lactation number	7. Avg. daily milk yield, Milk, kg	8. Avg. fat content, %	9. Avg. protein, %
CG	574	1	2.64	1.83	90	0.61	47.5	6.4	4.2	1.9	3	16.3	3.53	2.92
	725	2	2.96	1.63	91	0.53	51.9	3.1	2.8	2.0	2	16.4	3.42	2.93
	8836	3	2.56	1.98	87	0.63	50.2	5.1	5.2	5.2	2	19.6	3.54	3.05
	8917	4	2.70	1.97	78	0.57	45.7	4.1	4.1	2.5	2	16.9	3.57	3.02
	8925	5	2.57	1.87	82	0.38	46.6	4.1	5.3	6.7	2	21.1	3.22	2.95
EG1	44	6	2.57	1.70	80	0.64	61.8	7.4	4.8	4.2	3	18.6	3.66	3.05
	190	7	2.62	1.58	79	0.48	50.0	5.6	4.9	5.9	3	20.3	3.67	3.00
	386	8	2.90	1.70	89	0.31	55.6	5.8	6.2	6.0	2	20.4	3.84	3.13
	445	9	2.14	2.22	75	0.35	52.0	2.9	4.8	5.9	2	20.3	3.66	3.07
	477	10	2.88	2.03	91	0.56	46.6	5.6	5.1	5.9	2	20.3	3.65	3.02
EG2	515	11	2.48	1.95	90	0.62	45.7	5.4	6.3	5.8	3	20.2	3.62	3.00
	590	12	2.63	1.75	91	0.74	48.4	6.0	4.0	4.9	3	19.3	3.63	2.99
	855	13	2.51	1.75	101	0.81	52.9	4.6	5.1	7.0	2	21.4	3.61	3.04
	8952	14	2.90	1.62	86	0.76	49.9	3.8	7.3	4.5	2	18.9	3.91	3.26
	641	15	2.75	1.99	84	0.73	52.9	5.1	5.1	6.3	2	20.7	4.09	2.94
Correlation	LactCSI		0.084	-0.245	0.151	0.210	0.298	1	-	0.01	0.68	0.01	0.17	-0.14
coefficient	MilkCSIp		0.019	-0.014	0.020	0.044	0.004	-	1	0.55	-0.12	0.55	0.45	0.71
	MilkCSIf		-0.34	0.22	0.11	-0.08	0.06	-	-	1	-0.19	1	0.23	0.19

*Formula for calculating the index MilkCSIf = Milk $\cdot$ 0.99 $kg^{-1} - 14.2$, where Milk is the average daily milk yield, kg

conditions of incomplete initial knowledge, to find the correct formulas for the CSI procedure, GeorgyNN had to be equipped with the Learning service, which performs training and reviewing of the CSI procedure in a reversible cyclic mode of varying formulas and coefficients of the CSI procedure.

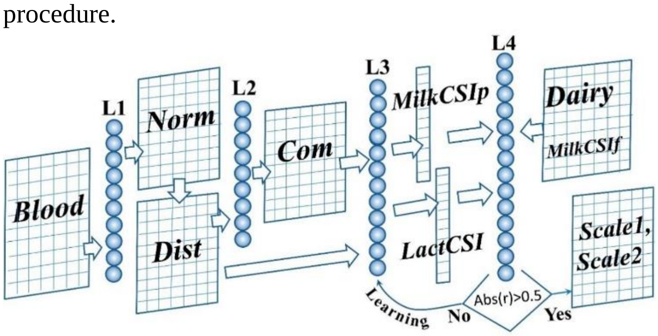

Figure 1. GeorgyNN converts cow blood counts into MilkCSIp and LactCSI indices in Learning cycles. Explanations of the algorithm for GeorgyNN computing and training are given in the text.

1. The L1 neuron layer performs line-by-line normalization (Mascarenhas, 2018) of the Blood matrix data containing cow blood counts (Fig. 1, Table 1) and records the normalization results in the Norm matrix.

$$Norm_{jk} = \frac{1}{V_j} \cdot \left(Blood_{jk} - M_j\right) \qquad (1)$$

$$M_j = \frac{1}{15} \cdot \sum_{k=1}^{15} Blood_{jk} \qquad (2)$$

$$V_j = \sqrt{\sum_{k=1}^{15} \left(Blood_{jk} - M_j\right)^2} \qquad (3)$$

where $Blood_{jk}$ is the individual blood counts; j=1,...,5 are the ordinal numbers of blood counts (Table 1); k=1,...,15 are the ordinal numbers (Table 1).

2. The L1 neuron layer calculates the Dist matrix using the column data of the Norm matrix and the standard computational procedure *EuclidDistance()* (Everitt *et al*, 2011).

$$Dist_{kl} = Euclid\ Distance\ (Norm_{1k}, \ldots, Norm_{5k};)\ Norm_{1l}, \ldots, Norm_{5l} \qquad (4)$$

where k, l = 1,...,15 are the ordinal numbers of cows (Table 1); *Euclid Distance ()* is the standard procedure for calculating Euclidean distances from data in the columns of the Norm matrix.

3. The L2 neuron layer calculates the Com matrix using the Dist matrix data and the standard computational procedure *Eigen Vectors ()* for calculating the eigenvectors of the Dist matrix.

$$Com = EigenVectors(Dist) \qquad (5)$$

4. The L3 neuron layer in Learning cycles (Widrow *et al.*, 2013) calculates the CSI index in the mode of varying the formulas of the CSI procedure (Fig. 1). The formulas of the CSI procedure in Learning cycles vary by combining the operands of addition, subtraction, multiplication, and division of the digital data of the Dist and Com matrices. The Learning cycles were completed by selecting formulas (6) and (7) for the CSI procedure to calculate the MilkCSIp and LactCSI indices.

$$MilkCSIp_k = Com13_k \cdot 4{,}0 + 5 \quad (6)$$

$$LactCSI_k = Com2x3_k \cdot 4{,}6 + 5 \quad (7)$$

where $Com13_k$ is the normalized data of the 13th row of the Com matrix; $Com2x3_k$ is the normalized data of the product of the 2nd and 3rd rows of the Com matrix; k=1,...,15 are the ordinal numbers of cows (Table 1).
The values of the MilkCSIp and LactCSI indices calculated by the CSI procedure of GeorgyNN are shown in Table 1.

5. The L4 neuron layer in Learning cycles (Fig. 1) calculates the correlation coefficients (Table 1) for the MilkCSIp, MilkCSIf, and LactCSI indices with blood counts, milk productivity indicators, the MilkCSIf index, and the ordinal lactation numbers, represented by data from the Dairy matrix and Table 1. The Learning cycles were completed when the correlation coefficients of the MilkCSIp index with milk productivity indicators reached r=0.55, 0.45, 0.71, and the correlation coefficient of the LactCSI index with the ordinal lactation numbers reached r=0.68 (Table 1).
6. After exiting the Learning cycles, two matrices were formed: Scale1 represented a two-dimensional ranking of cows according to the MilkCSIp vs LactCSI indices (Fig. 2), and Scale2 represented a two-dimensional ranking of cows according to the MilkCSIf vs MilkCSIp indices (Fig. 3). The filled Scale matrices visualize the dependence of milk productivity on the conditional lactation age and biological additives to the basic nutritional diet (Tolstova, 2006).

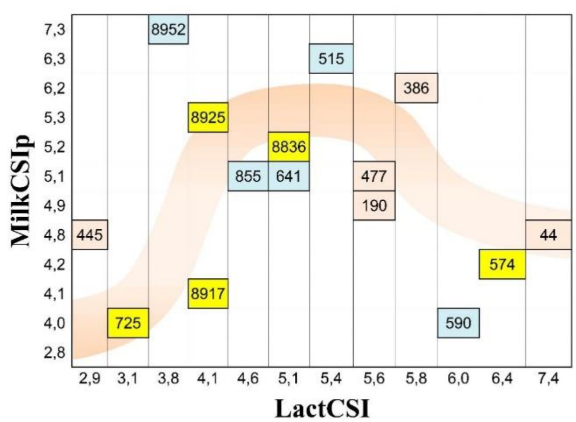

Figure 2. The Scale1 matrix represents the results of a two-dimensional ranking of milk productivity according to the MilkCSIp vs LactCSI indices, which demonstrate the dependence of potential milk productivity on the conditional lactation age and feed additives to the basic diet. Cows No. 725, 8917, 8825, 8936, and 574 are included in the CG. Cows No. 445, 477, 190, 386, and 44 are included in the EG1. Cows No. 8952, 855, 641, 515, and 590 are included in the EG2.

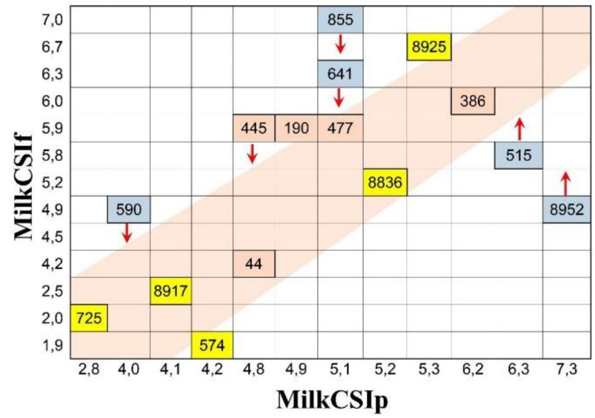

Figure 3. The Scale2 matrix represents the results of a two-dimensional ranking of milk productivity according to the MilkCSIf vs MilkCSIp indices, which demonstrate the actual and potential milk productivity ratio depending on feed additives to the basic diet. Cows No. 725, 8917, 8825, 8936, and 574 are included in the CG. Cows No. 445, 477, 190, 386, and 44 are included in the EG1. Cows No. 8952, 855, 641, 515, and 590 are included in the EG2.

DISCUSSION

Cows' potential milk productivity, their health, conditional lactation age, and the intensity of internal biochemical processes in their bodies require constant monitoring to respond in time to age-related and infectious changes. Usually, only during cow milking, the average daily milk yield is monitored to achieve an optimal nutritional diet and milk productivity. This method of feed optimization is not applicable in the case of a sudden deterioration in animal health, a decrease in the intensity of biochemical processes due to age-related changes, and scientific studies of the effect of feed additives and probiotics on milk productivity, this claim is supported by the results of these authors (Vorobyov *et al*., 2023) who developed a technology using the EuclidNN neural network to assess the cognitive value of cow blood parameters and predict their potential milk productivity. The results of their research showed that the EuclidNN could effectively predict milk productivity and help manage feed to prolong cow health and productivity. It has become relevant to extract operational information about biochemical processes from blood counts, using computational neural networks. Processing blood counts using computational neural networks allows us to determine potential milk productivity and draw reasonable conclusions regarding the effect of feed and feed additives on milk productivity. Based on these findings, there is a unique opportunity to form a daily diet that has a positive effect on cows' health and productive longevity. A new information technology based on the use of artificial intelligence in the form of GeorgyNN allows calculating the LactCSI index=0...10 b/r, representing quantitative changes in conditional lactation age, and the MilkCSIp index=0...10 b/r, representing quantitatively potential milk productivity. Using the values of the MilkCSIp vs LactCSI indices for each cow, one can conduct a two-dimensional ranking of cows and present the ranking results in the form of a Scale1 matrix (Fig. 2). The relationship between LactCSI and MilkCSIp shows a decrease in milk productivity after the peak. This movement is consistent with the work of (Różańska-Zawieja *et al.*, 2021) who studies the effect of feeding management on lactation curve and milk production. Using the values of the MilkCSIf vs MilkCSIp indices for each cow, one can conduct a two-dimensional ranking of cows and present the ranking results in the form of a Scale2 matrix (Fig. 3). The CG cows had different conditional lactation ages but were located within the corridor of potential milk productivity (matrix Scale1, winding strip in Fig. 2) and the linear corridor of actual milk productivity (matrix Scale2, strip in Fig. 3). This means that CG cows' diets had been optimized before conducting this experiment with a feed additive containing BSG. After BSG without a probiotic was added to the diet (EG1), there was some deviation from optimal diets, especially evident in cow No. 445. That is, the actual milk productivity of that cow exceeded the potential milk productivity (Fig. 3). This is consistent with the authors (Getu *et al*. 2020) who confirmed that intake of BSG even at a supplementary level increased daily milk yield and milk production efficiency. This also agrees with the authors (Lisci et al., 2022) who concluded that integration of BSG intake leads to an increase in current milk yield, milk total solids content, and milk fat yield. Adding BSG without a probiotic reduced the intensity of internal biochemical processes that determine milk productivity in cow No. 445. Therefore, the feed volume for this cow should be reduced so that the actual and potential milk productivity are equal. When BSG and Cellobacterin (EG2) were added to the diet, diverse deviations from the optimal nutrition were observed (Fig. 3). In cows No. 590, 641, and 855, it is necessary to reduce feed volumes to equalize the actual and potential milk productivity, and in cows No. 515, and 8952, on the contrary, the feed volumes should be increased. The addition of BSG and Cellobacterin as additives in cow diet is a novel idea as previous research works proved difficult to obtain and further studies is required to optimize its effectiveness in dairy cow feed. Perhaps BSG reduces the intensity of internal biochemical processes, while Cellobacterin increases it. This hypothesis is supported by the results of the author (Yildirim *et al*., 2020) who concluded that the metabolic pathways of cows which were fed with Cellobacterin were increased. The priority in the influence of external biotic and abiotic factors on biochemical processes is probably determined primarily by cows' genetic specificity and the intestinal microbiome for the digestion of feed and additives with probiotics. Aside from these factors, epigenetics and external biotic and abiotic factors such as diet composition, stress, pathogen, and environmental temperature possess the ability to enhance or inhibit biochemical processes. The scalability of the GeorgyNN model is a crucial consideration for its practical application in the dairy industry. The model's architecture is designed to handle large datasets, making it suitable for application in larger dairy operations. Additionally, its adaptability to different regions with varying environmental conditions and dairy practices is facilitated by its learning capabilities, which allow it to be retrained with new data as needed. Future work will focus on optimizing the model for scalability and assessing its performance across diverse agricultural contexts.

Conclusion**:** The study demonstrates the effectiveness of using computational neural networks, specifically GeorgyNN, to monitor and enhance the milk productivity and health of dairy cows. By analyzing cow blood counts, the neural network can determine the potential and actual milk productivity, thus aiding in the optimization of dietary regimens. The findings indicate that brewer's spent grain (BSG) alone tends to reduce the intensity of internal biochemical processes, whereas the addition of Cellobacterin probiotic counteracts this effect, suggesting a synergistic relationship between diet and probiotic supplementation. This technological approach not only enhances productivity but also promotes sustainable farming practices and improves animal welfare by tailoring diets to individual cow needs. Despite the promising results, several limitations need to be recognized. Firstly, the study involved a relatively small sample size, which may affect the generalizability of the findings. Secondly, the short duration of the experiment could impact the long-term applicability and reliability of the results. Thirdly, the study was confined to a specific region, and unique environmental factors in this area may have influenced the outcomes, thereby limiting the relevance of the findings to other geographic locations. Additionally, genetic variability among cows and differences in their intestinal microbiomes could significantly affect the results, indicating that outcomes might vary across different breeds. Lastly, implementing and maintaining advanced neural network systems in a farming context might require substantial technical expertise and resources. Future research should aim to address these limitations and investigate several key areas. Firstly, conducting studies on larger and more genetically diverse populations of cows across various regions would improve the generalizability of the findings. Secondly, extending the duration of experiments would allow for the observation of long-term effects of dietary changes and neural network optimizations on cow health and productivity. Thirdly, developing more user-friendly and cost-effective neural network systems would facilitate broader adoption in the dairy industry. Additionally, incorporating a range of variables such as environmental conditions, cow behavior, and health status would help create a more comprehensive model for dairy farm management. Lastly, evaluating the environmental and economic impacts of optimized feeding practices is essential to ensure both sustainable and economically viable farming operations. The use of neural networks in animal agriculture raises several ethical considerations. Ensuring the welfare of animals is paramount, and the deployment of AI technologies should not compromise this. Additionally, data privacy and the transparency of AI decision-making processes are critical to maintaining trust in these technologies. Ethical guidelines must be established to govern the use of AI in agricultural settings, ensuring that the technology is used responsibly and for the benefit of both animals and farmers.

***Authors' contributions*:** All authors equally contributed to this study.

***Conflict of Interest*:** Authors have no conflicts of interest to declare.

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***Ethical statement*:** This study was conducted in accordance with the ethical standards of the institution and the national research committee. All applicable guidelines for the care and use of animals were followed, and the study protocol was approved by the appropriate ethics review board.

Availability of data and material: The datasets generated and/or analyzed during the current study are available from the corresponding author upon reasonable request

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***Code Availability*:** The code used for the neural network analysis in this study (GeorgyNN) is available from the corresponding author upon reasonable request

***Consent to participate*:** The study did not involve human participants. All procedures involving animals were conducted in compliance with ethical standards.

***Consent for publication*:** All authors have reviewed and approved the final version of the manuscript for publication

***SDG's addressed*:** The study aligns with goals related to sustainable agriculture, such as:
- SDG 2: Zero Hunger (by improving food production efficiency).
- SDG 12: Responsible Consumption and Production (through optimized resource use in dairy farming).

REFERENCES

Bolshakov, V.N., E.A. Lapitskaya, L.A. Kryazhevskikh, I.N. Nikonov, V.V. Soldatova, T.N.Grudinina, V.I. Prokopeva, and G.Yu. Laptev. 2009a. Creation of technological foundations for the process of recycling waste from the brewing industry through microbiological processing for the needs of livestock breeding. Agrarnyi vestnik Urala 10:37-40.

Bolshakov, V.N., I.N. Nikonov, V.V. Soldatova, G.Yu. Laptev. 2009b. Brewer's spent grains in dairy cattle diets. Molochnoe i myasnoe skotovodstvo 8:22-23.

Chumakova, E.V., D.G. Korneev, T.A. Chernova, M.S. Gasparian, and A.A. Ponomarev. 2023. Comparison of the application of FNN and LSTM based on the use of modules of artificial neural networks in generating an individual knowledge testing trajectory. Journal Européen des Systèmes Automatisés 56:213-220.

Dragojlovic, M.D., L.L. Pezo, S.D. Colovic, Z.S. Vidosavljevic, L.M. Pezo, R.R. Colovic, M.B. Kokic, M.O. Djuragic. 2019. Application of soybean oil and glycerol in animal feed production, ANN model. Acta Periodica Technologica 50:51-58.

Everitt, B.S., S. Landau, M. Leese and D. Stahl. 2011. Cluster analysis. john wiley & sons pp. 348.

Fedosova, O.A., V.V. Kulakov, O.A. Karelina and G.V. Ulivanova. 2022. The level of basic morphological and biochemical indicators of the cows' blood depending on productivity, quantity, and stage of lactation. Vestnik RGATU 14:73-82.

Getu, K., A. Getachew, T. Berhan and A. Getnet. 2020. Supplementary value of ensiled brewers spent grain used as replacement to cotton seed cake in the concentrate diet of lactating crossbred dairy cows. Tropical Animal Health and Production 52:3675-3683.

Imanbayeva, Z., G. Mussirov, A. Nurgaliyeva, T. Rakhimov, G. Akhmetova, D. Kaldybayeva and A. Petrov. 2024. Enhancing agricultural efficiency and land resource management through information systems. Qubahan Academic Journal 4:342-354.

Kamilaris, A. and F.X. Prenafeta-Boldú. 2018. Deep learning in agriculture: a survey. computers and electronics in agriculture 147:70-90.

Kruglov, V.V. and V.V. Borisov. 2002. Artificial neural networks. Theory and practice. Moscow: Goryachaya liniya Telkom 216:01128.

Kujawa, S. and G. Niedbała. 2021. Artificial neural networks in agriculture. Agriculture 11:497.

Lisci, S., M. Grosso, H. Karring, R. Hajrizaj and M. Errico. 2022. Brewer's spent grain: its value as renewable biomass and its possible applications. Zenodo (CERN European Organization for Nuclear Research) vol. 92.

Mascarenhas, W.F. 2018. Fast and accurate normalization of vectors and quaternions. Computers & Applied

Mathematics 37:4649-4660.
Mkrtchyan, G.V. and M.D. Boiko. 2023. The relationship between cows' biochemical blood counts and milk production parameters in groups with different productivity levels. International Research Journal 8:1-6.
Pogodaev, A.K., E.L. Khabibullina and D.M. Inyutin. 2021. Application of neural network models for constructing production rules of expert systems. Applied Mathematics and Control Issues 2:73-92.
Romanov, V.N., N.V. Bogolyubova, V.A. Devyatkin, V.N. Grishin and L.A. Ilina. 2015. Features of digestive and metabolic processes in young cattle when a "protected" form of carnitine is included in the diet. Vestnik RUDN 1:35-42.
Różańska-Zawieja, J., S. Winnicki, J. Zyprych-Walczak, A. Szabelska-Beręsewicz, I. Siatkowski, W. Nowak, B. Stefańska, R. Kujawiak and Z. Sobek. 2021. The effect of feeding management and culling of cows on the lactation curves and milk production of primiparous dairy cows. Animals 11:1959.
Schmidhuber, J. 2015. Deep learning in neural networks: an overview. Neural Networks 61:85-117.
Sudarev, N.P., D. Abylkasymov and E.A. Voronina. 2009. Useful lifespan of dairy cows. Livestock Production of Russia 5:51-52.
Sun, B.F., Y.C. Cao, C.J. Cai, C. Yu, S.X. Li. and J.H. Yao. 2020. Temporal dynamics of nutrient balance, plasma biochemical and immune traits, and liver function in transition dairy cows. Journal of Integrative Agriculture 19:820-837.
Sutrop, U. 2001. List task and a cognitive salience index. Field Methods 13:263-276.
Tolstova, Yu.N. 2006. Basics of multidimensional scaling. Moscow: KDU pp. 48
Vinogradova, N.D. and R.V. Paderina. 2015. Duration of use of dairy cows depending on growth rate and productivity in the first lactation. Izvestiya Sankt-Peterburgskogo agrarnogo universiteta 40:82-86.
Volgin, V.I., L.V. Romanenko, P.N. Prokhorenko, Z.L. Fedorova and E.A. Korochkina. 2018. Adequate feeding of dairy cattle is the basis for realizing the genetic productivity potential. Moscow: RAN 282:04004.
Vorobyov, N.I., N.V. Bogolyubova, A.V. Platonov, I.N. Nikonov, M.V. Selina, A.A. Guselnikova. and N.Yu. Sidnev. 2023. Neural network analysis of hematological parameters in cows and assessment of their potential milk productivity. International Journal of Chemical and Biochemical Sciences 24:320-325.
Wang, Q., Y.J. Chen, J.S. Yoo, H.J. Kim, J.H. Cho and I.H. Kim. 2008. Effects of supplemental humic substances on growth performance, blood characteristics and meat quality in finishing pig. Livestock Science 117:270-274Sutrop, U. List Task and a Cognitive Salience Index. Field Methods13:263-276.
Widrow, B., A. Greenblatt, Y. Kim. D. Park. 2013. The no-prop algorithm: a new learning algorithm for multilayer neural networks. Neural Networks 37:182-188
Yefimova, L.V., T.V. Zaznobina, O.A. Frolova, O.V. Ivanova and E.A. Ivanov. 2019. The relationship between milk quality indicators and the biochemical composition of blood in red-and-white cows. Problems of Productive Animal Biology 3:48-57.
Yildirim, E.A., G.Yu. Laptev, L.A. Ilyina, T.P. Dunyashev, D.G. Tyurina, V.A. Filippova, E.A. Brazhnik, N.V. Tarlavin, A.V. Dubrovin, N.I. Novikova, V.V. Soldatova and S.Yu. Zaitsev. 2020. The influence of a dietary enterococcus faecium strain-based additive on the taxonomic and functional characteristics of the rumen microbiota of lactating cows. Sel Skokhozyaistvennaya Biologiya 55:1204-1219.
Zaikina, A.S., N.P. Buryakov, N.I. Vorobev. and I.N. Nikonov. 2022. Neural network analysis of the correspondence of the microbial and organismal biosystem of the poultry intestine to the fractal-stochastic model. Perm Agricultural Bulletin 4:98-106.
Zeng, C., F. Zhang. and M. Luo. 2022. A deep neural network-based decision support system for intelligent geospatial data analysis in intelligent agriculture system. Soft Computing 26:10813-10826.