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Mathematical Model of Mastitis Detection Using Milk Data Obtained from Sensors

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Abstract: A lot of scientific and research work has been carried out on the detection of mastitis by means of milk data obtained from online sensors of automatic milking systems (AMS) and invasive/non-invasive sensors for animals in livestock farms. In most of these works, mathematical models and algorithms are proposed with different efficiency of mastitis detection as a result of combining certain types of sensor data. However, most farms cannot incorporate enough sensors into their operations due to limited resources and do not conduct laboratory testing activities, which require time, labor and money. This is especially related to animal diseases, which can lead to global problems if timely measures are not taken. In this article, a generalized mathematical model has been developed based on the capabilities of the farm, the effective use of the sensors used in practice, that is, the detection of animal diseases, in particular, mastitis, using sensor data. The originality of the proposed model is that it does not require strict sensor data or indicators related to mastitis. The reason is that, firstly, existing sensor data is processed by linking it to previous historical records, static data, golden rules, and external factors. Secondly, the results of the sensors are summarized by weight coefficients. The result of the model shows the presence of mastitis in the current dairy cow in the [0, 1] interval.

Keywords*: mastitis, incorporate, diseases, laboratory, coefficients*

Introduction

This article is a continuation of the scientific and practical research carried out within the innovative project IL-392103072-“Development of a mobile application for electronic management of livestock complexes” [3-5]. As part of the creation of the “National PLF – Smart livestock” platform, the main focus of tasks is the automation of veterinary services for cattle health [[7]]. In this direction, analysis of detection of cattle diseases by sensors was carried out in [21], as a result, a mathematical model is proposed for detection of cattle diseases with multiple parameters [20].

Nowadays, automatic milking systems (AMS) equipped with modern technology have proven to facilitate the daily activities of livestock farms, increase labor costs and improve production efficiency. However, the data obtained from AMS are usually used in a statistical manner. That is, in practice, some necessary indicators of animals (for example, milk) are used in the preparation of statistical reports based on previous historical records. Coordination to decision-making as a result of daily or periodic individual collection of indicator data related to the vital activity of livestock, combining different types of data with various influencing factors and existing rules is one of the important scientific-innovative and economic-social issues.

According to statistics [3], from 5 to 35% of culled cows are animals with mastitis, including atrophy of parts of the udder. The total incidence of milk mastitis in animals is 24-45% in all types of farms. Diagnosis of the disease requires direct veterinary examination, if possible, chemical analysis of milk and various parts of animal udder. Animals treated for mastitis have an average milk

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yield of 7-32% in the next lactation compared to the previous one. Thus, there is an acute problem of detecting cases of subclinical mastitis in animals in the early stages of the disease. Standard methods of mastitis detection include several types used in combination: clinical examination of animal udder and milk secretion; checking the taste of milk; chemical analysis and measurement of milk electrical conductivity.

This article presents the development of a new mathematical model for determining mastitis in dairy cows based on sensor data. During the research, the analysis of scientific sources showed that the diagnosis of mastitis is mainly based on milk parameters. Quantitative indicators of milk parameters are determined by visual observation, special sensors and laboratory tests. These indicators include lactation number (LN), days in milk (D), milk yield (MY), electrical conductivity (EC), somatic cell count (SCC), L-lactate dehydrogenase (LDH), and milk yield per hour (MYH). The remaining part of our paper is structured as follows: In Section 1, the basics of the process of sensor data used in the detection of diseases up to decision-making, the factors affecting the development of mastitis in cows and the process map of the treatment of detected mastitis are analyzed; Section 2 presents the exact ranges of sensor indicators such as EC, SCC and MY that are widely used for mastitis detection; Afterwards, the mathematical and algorithmic basis of the indexed sources for the detection of mastitis, which is the essence of the work, is analyzed in Section 3; Finally, Section 4 shows a proposed mathematical model for the detection of mastitis based on analytical data.

1. Basics of detection of mastitis in cows using sensors

In general, clinical/subclinical biological changes in animal health are carried out on the basis of real human visual observation, in-line and online sensors on the cow's body, data obtained through special laboratory-expert examinations and historical information, and a decision is made on the disease. The use of sensor data in dairy farm management is illustrated by the scheme in Figure 1 [[14]].

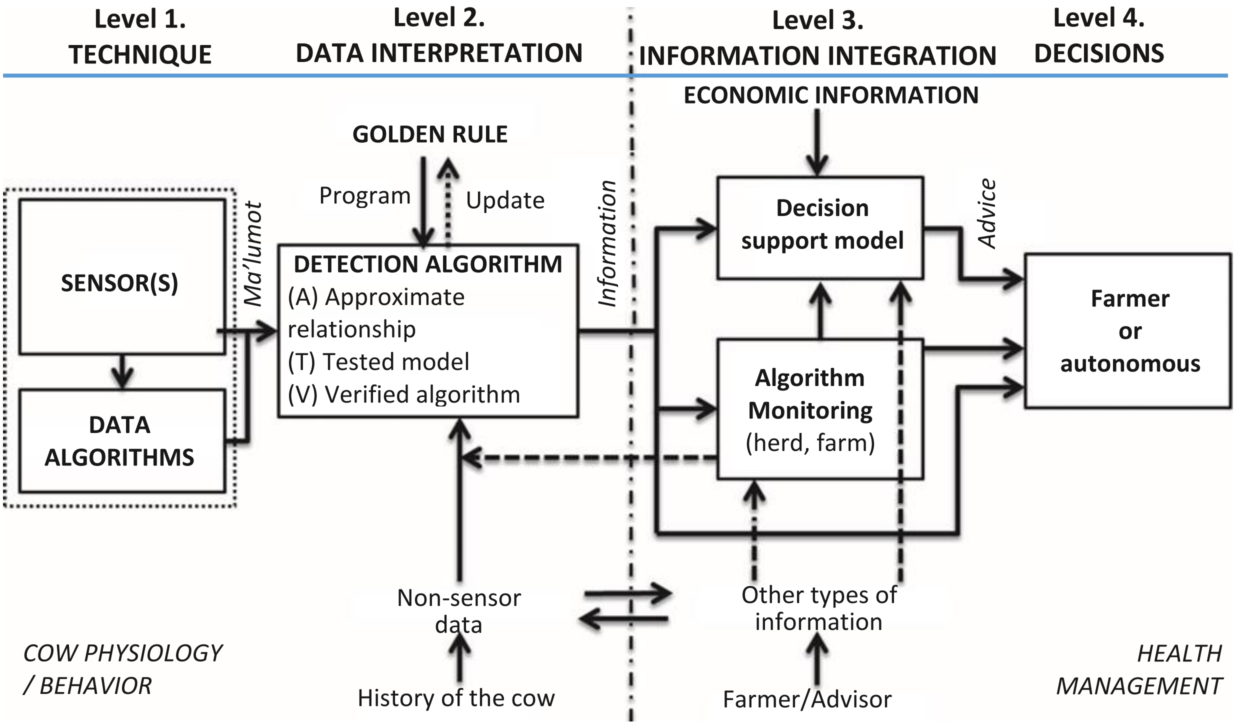

Figure 1. Scope of using sensor data in dairy farm management

The diagram shows the process describing the steps from sensors to decision-making. Sensors that measure the state or condition of cows are described in Level 1. The 2 categories defined at this level measure only the parameter and the approximate relationship. Some sensors directly transmit the data received from the object to the next level, while others process this data through algorithms (for example, a signal is detected in a pedometer and it is converted into data representing steps per unit of time using algorithms). In order to determine the status of cows (for example, estrus) in the Level 2, which is called data interpretation, the real data obtained from the previous level (sensors) are processed using special algorithms together with golden rules and static data (for example, cow disease records, visual observations). Level 3 integrates the information obtained from the previous level with other information (for example, economic information) and makes decisions or provides advice for the farmer. The last Level 4 is called decision-making, where decisions are made by the farmer or autonomously by the sensor system.

According to Zigo's research [[18]], the causes of mastitis in cattle can be divided into two groups. In the first group, inflammation of the udder and milk ducts is caused by microbes, and in the second group, incorrect technological methods are used during milking, metabolic disorders, udder injuries, and various stress factors during the development of mastitis.

It is important to influence the factors of the external environment in the interaction between the infectious agent and the cow's organism. The susceptibility of a dairy cow to mastitis is mainly related to the immunological and reactive state of the mammary gland and the following factors: age, lactation period, its stages, milk yield, anatomical features. Due to the many internal and external causes that cause mastitis, it is considered as a multifactorial disease (Fig. 2).

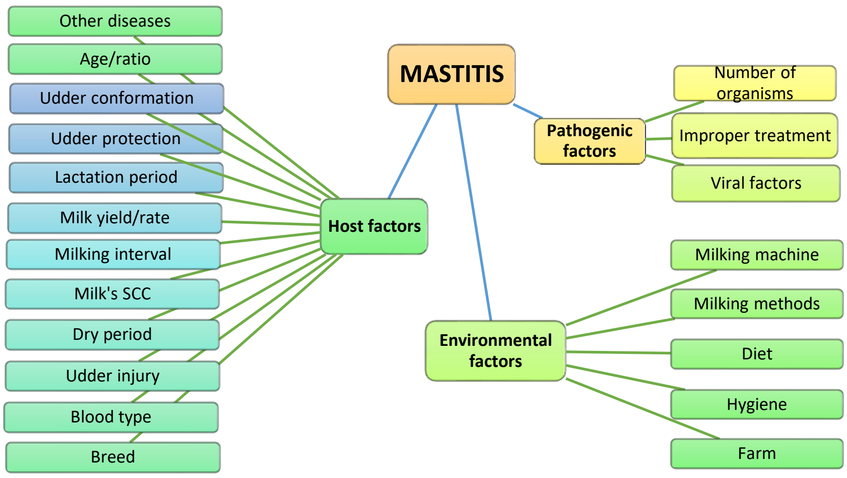

Figure 2. Factors influencing the development of mastitis in dairy cows [[1]]

Until now, more than 137 different organisms have been identified as causative agents of cow mastitis, including bacteria, viruses, mycoplasmas, yeasts and algae, but bacteria remain the main causative agent of this complex (95 percent of all milk infections) [18-24]. As a general rule, each case of mastitis is considered to be caused by a single primary pathogen, since usually only one type of bacteria is detected in milk samples taken from the affected glands. At the same time, simultaneous infection with two different types of pathogens is rare.

The clinical presentation of mastitis is characterized by sudden onset, changes in the composition and appearance of milk, decreased milk yield, and cardinal signs of inflammation in the infected quarters of the mammary gland. In contrast, low concentrations of pathogens with lower virulence lead to asymptomatic subclinical infections in udder or milk, resulting in reduced productivity and increased SCC.

Mastitis is an inflammation of part of the cow's udder (International Dairy Federation, 2011), often with pathogens entering through the teat, causing intramammary infection (IMI). There are two main types of mastitis: subclinical (hidden) and clinical (with obvious visual symptoms). The most dangerous of them is subclinical, and the udder and milk look normal from the outside. Latent mastitis occurs 5-10 times more often than clinical manifestations. If subclinical mastitis is not detected in time, after some time it will progress to the clinical stage.

Bonestroo conducted extensive analytical research on mastitis detection with modern methods in his dissertation work on "Sensor-based mastitis management in automatic milking system farms" [10]. When mastitis is detected, farmers perform six treatment options: (I) additional diagnosis to support a treatment decision, (II) antibiotic treatment, (III) alternative treatment (e.g., increased milking frequency or use of analgesics), (IV) do nothing, (V) weaning (premature termination of lactation) or (VI) destroying the infected animal. The selection of animals for treatment or no treatment is usually based on factors affecting the rate of treatment. Such factors may include parity, number and condition of infected udder quarters, SCC, history of mastitis, duration of infection, type of pathogen, and number of constitutive units.

Farmers can use sensor data to provide valuable information to improve mastitis decisions. Figure 3 illustrates the Data-Information-Decision framework for mastitis, i.e. how data leads to information and how information is used by farmers to make good decisions. In this case, data (left) consists of a set of rough indicators, and information (middle) is defined as information processed on the basis of decision-making. Decision (right) is a mastitis-related treatment decision (for example, treatment during lactation, culling, weaning, or herd separation) based on information from the cow. Data fit depends on data accuracy and information relevance (which can be assessed using variable importance measures in machine learning models). The value of information for a decision (for example, treatment of mastitis after detection of mastitis by a mastitis detection algorithm) depends on the accuracy and relevance of the information to the decision.

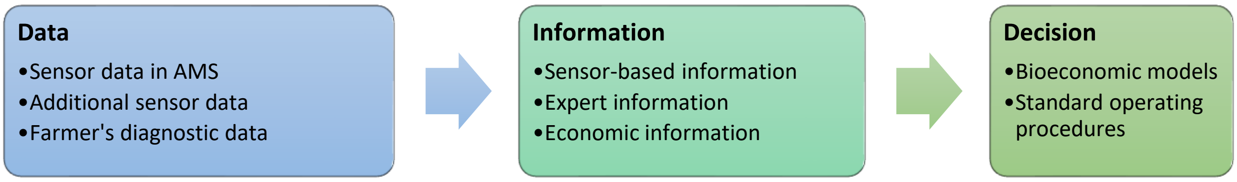

Figure 3. A “data-information-decision” system for mastitis decision-making.

2. Indicators of the main factors representing mastitis

Today, modern AMS includes sensors that track indicators to determine cow and milk condition. In AMS, sensors can continuously measure disease symptoms and milk composition to detect signs of abnormal milk and mastitis. AMS has the following inflammatory indicators for milk analysis: SCC, color, milk enzymes (eg. N-acetyl β-D-glucosaminidase or LDH) and EC, daily milk yield (DMY) and others. SCC is a traditional and widely used indicator for the diagnosis of mastitis. SCC is a measure of cells per milliliter of milk. Recently, several technologies have been used to evaluate SCC using AMS or AMS complementary tools. The accuracy of the sensors is tested with mixed results, where it is shown that cell counters can estimate SCC moderately to very well, depending on the technology used. The color sensor is mainly used to detect whiteness in milk (that is, to detect the presence of blood) and must be used in combination with other sensors. LDH has been shown to be capable of detecting IMI (milk infection) leading to mastitis, but less so than SCC. EC has long been used as an indicator of clinical and subclinical mastitis, but EC is inferior to SCC in detecting subclinical mastitis.

This article focuses on the important data for automatic detection of mastitis in cows, turning them into information and developing a mathematical tool that helps in decision-making. In this research, existing works on milk properties (EC, SCC) are analyzed, more importance was given to the analysis of milk yield. Models for sensor-based detection of mastitis are analyzed, and as a result, a new mathematical approach is proposed for mastitis detection.

Mastitis occurs mostly in cows during the first half of the lactation period (above 60%, when the mammary gland is working hard). Experiments have shown that the origin of the disease depends on the age of the animal. For example: 12.1% of cows under 5 years old, 63.6% between 5-10 years old, and 24.3% of cows aged 10 years and older were infected[1].

Somatic cell count (SCC) is the most common and mandatory method for mastitis diagnosis. Because the cow's innate immune system fights inflammation by increasing SCC. Mastitis alters milk by increasing SCC in the milk. Somatic cells consist of blood cells such as lymphocytes, macrophages, and epithelial cells of the inner umbilical wall. There is considerable evidence of a direct relationship between SCC and udder levels of inflammation. According to the recommendation of applied scientific studies of scientists, the level of SCC in normal milk should be less than 200,000 cells/ml. If the SCC in milk is more than 200,000

[1] Livestock diseases. Book No.71

cells/ml, it indicates that the animal may be suffering from subclinical mastitis [12].

Although other methods of mastitis detection are not mandatory, they are used to control the quality of milk and diagnose the degree of abnormality. These include the electrical conductivity (EC) method of milk. Milk has a normal EC of 4.0 to 6.0 mS/cm at 25 °C. However, milk from mastitis-affected cows conducts electricity better than milk from healthy cows due to increased Na+ and Cl- ions and reduced K+ ions and lactose content. In other studies, a milk EC increase of 15% compared to the previous 7 days, more precisely, a milk EC reading at the high extreme of 6.5-13.00 mS/cm at 18°C, is considered mastitis. Therefore, conductivity measurement helps in early detection of mastitis [[10]].

There is a close relationship between the EC of milk and the content of lactose and salt. Non-udder-related diseases, metabolic problems, nutrition, breed, stress and changes in lactation stage have a greater effect on EC and a lesser effect on SCC. Currently, there are several portable devices based on EC measurement, such as MASTITRON LF 3000, DRAMINSKY mastitis detector or Milk Checker N-4L.

Another factor in determining mastitis is udder temperature. In the experimental research work, 4 groups were separated from the dairy cows in the herd with the same number: 1- healthy cows with a negative kenotest test (-), 2nd group - cows with a suspicious sample according to the kenotest (+), 3 -group includes animals with subclinical mastitis (++) and group 4 with mastitis in a clinically clear stage (+++). In the thermographic method, the udder temperature was measured simultaneously in groups using a DT 9875 hand-held thermal imager, and the probability density of temperature distribution in all groups was described by the normal law Average maximum udder temperature during milking was 36.2°C for healthy cows, 38.5°C for subclinical mastitis and 39.6°C for severe clinical mastitis. As a result of this research, a linear regression equation was formed: y=1.14x+35.05; where y is the average maximum temperature of the udder of cows; x - health status according to kenotest (x=1,2,3,4); the approximate accuracy is high R^2=0,9997 [[11]].

Usually, milk yield and activity of infected dairy cows are reduced. For example, in mastitis, changes in cow gait (pedometer activity) or milk production compared to the average value of the previous 7 days have been determined. In D.J.Wilson's work (2004), when two of these conditions are fulfilled, the cow is called mastitis: 1) EC over 30%; 2) decrease in pedometer activity from 40%; 3) milk yield decreases by 7% for days 1-45, 20% for days 46-114, 17% for days 115-199, and 35% for days after 199 compared to the lactation period of cows [[17]].

The milking rate should be taken into account when predicting mastitis. Information on the MYH is obtained from a milk quantity measuring device and/or other device. Speed does not really require individuality The milking rate increases during the 1-4 lactation periods, and the average rate is 1.3-2.1 liters per minute. The milking rate increases from the beginning of lactation in line with productivity, and it is determined that its control can vary by 10-15% from the norm or from the previous day. In this case, it is necessary to record the maximum speed, milking duration and milk temperature during milking.

The milk yield of a dairy cow affected by mastitis is reduced. Therefore, the control of milk production is an important factor. Control of milk production should be in accordance with the lactation curve. A graphical representation of changes in milk yield during the lactation period (≈305 days) is called a lactation curve (LC). Typically, LC increases rapidly until reaching a peak and then slowly decreases until a resting (drying) period. In [14], various equations have been proposed for the construction of LC.

Previously fixed 5 (1, 3, 7, 14, 30) days are selected for the lactation period in relation to the mastitis disease. Because, in the veterinary field and scientific researches, the previous 7 and 14 days a taken into account for the latent period of mastitis. Now the calculation of productivity differences between fixed days and current day for mastitis is shown. In this case, the λ_i expert coefficient is introduced for the importance of fixed days: $\sum_{i=1}^{5}\lambda_i = 1$. For example, $\lambda = (0.1; 0.1; 0.3; 0.4; 0.2)$.

Calculations are made for selected milk days of the lactation period. d – current day, m – current milk yield, and current day prediction for LC:

$$\delta_0 = f_i(d) - m, \quad (1)$$

the prediction difference for the previously fixed 5 days:

$$\delta_j = \lambda_j \left\{ \frac{1}{j} f_{\hat{\kappa}}(d-j) - m_p \right\} \ (j < d). \quad (2)$$

The general correlation is as follows:

$$\left| \delta_0 - \frac{1}{\nu} \sum_{p=1}^{\nu} \delta_p \right| < \rho, \quad (3)$$

where $f_{\hat{\kappa}}$ – day-matching shift function for LC during lactation, ν - analysis intervals from 1 to 5. Usually $\nu = 5$, if $j > d$, i.e. there are no previous intervening days compared to the current d day, then ν decreases. ρ – the amount of milk given, if the difference is greater than ρ, then there is a change in milk productivity. That is, if $\rho > |0|$, it goes to the next step as a symptom of mastitis, and this is an important indicator.

SCC, LDH, EC, DMY parameters mentioned above in milk using the sensors are important in determining mastitis. Milk parameters can be conditionally divided into two groups depending on all cows and their individuality: relatively constant (SCC, LDH, EC) and individual (DMY). As an example, to be more specific, the deviation of SCC or EC indicators from the interval of a specified criterion can be considered as a symptom of a disease. However, estimating MY through the LC is not very accurate and precise. This can be caused by DMY loss in many cows in the herd, cows having or previously/recently treated for another disease, environmental factors, feeding problems, individual biological characteristics, breed, number of lactations and season. Also, in the milking parlors of most farms, there are not only sensors that analyze the composition of milk, but also individual electronic milk meters. From the economic point of view, it is necessary to develop a multi-factorial system that helps the farmer to make realistic decisions, to produce more information from a small number of sensor data, and to automate conventional milking parlors with low cost.

3. Analysis of mastitis detection models

In general, the state of the animal is determined by the values of random functions obtained from various sensors: $S(t) = (r_1(t), r_2(t), \dots, r_N(t))$, where $r_i(t)$ - value of the sensor at time t, N - number of sensors.

In Antonov's work [[19]], for the problem of determining mastitis, a linear regression equation was used in terms of milk flow and EC. It has three sets of parameters: $\mu_i(t)$ - daily milk flow value, $\eta_i(t)$ - daily value of milk's EC, $\nu_i(t) = \{0, 1\}$ - the presence of mastitis in the animal according to the expert's decision (t - the number of days in the lactation period (≈305), n - number of animals. A general mathematical regression model is as follows:

$$\nu_i(t) = k_1 \mu_i(t) + k_2 \eta_i(t) + b, (i = 0,1, \dots, n). \quad (4)$$

Here, it is necessary to find the relationship between the input and output parameters to estimate the regression coefficients k_1 and k_2. Regression analysis allows determining the influence of individual independent characteristics on the result. If the input parameters $\mu(t)$ and $\eta(t)$ are taken as a two-column matrix X, and the output parameter $\nu(t)$ is taken as a vector Y, then the least squares vector of regression coefficients is equal to r:

$$r = (X^T X)^{-1} X^T Y \quad (5)$$

But using the regression model and the least squares method requires the data to be of the same size. Therefore $|\mu_i(t) - \eta_i(t)|$ $(i = 1..n)$ the difference should not be large. In our cases, the milk production index is measured in thousands of mL per day, but the electrical conductivity of milk is measured in mS/cm. According to the definition of the Euclidean norm, this makes one parameter more important than the other, but in reality it is not. It should be noted that inputs have different distribution functionsIn order for the mathematical model to give correct results, the functions must be performed independently of time. Therefore, the necessary data is pre-processed. Normalization and centering of random functions should be performed.

Centering the function $\mu_i(t)$ is carried out according to (3) and (4).

$$T(t) = \frac{1}{n} \sum_{i=1}^{n} \mu_i(t) \quad (6)$$

$$R_i(t) = \mu_i(t) - T(t), \ i = 1..n \quad (7)$$

The expected value of the $R(t)$ function is 0, and after reflection (6) and (7) the data is evenly distributed around the OX axis. The distribution of the random function $R(t)$ is reflected so that it does not depend on time. Then the centered function $R(t)$ is normalized. Calculation of the standard deviation (SD) of the milk yield data of the whole herd is carried out according to (8) and (9):

$$\sigma = \sqrt{\frac{1}{n}\sum_{i=1}^{n} R(t)^2} \tag{8}$$

$$\hat{\mu}_i(t) = \frac{R_i(t)}{\sigma},\ \ i = 1..n \tag{9}$$

Then the regression coefficients and the free term of the equation are calculated using (5) (Table 1).

Table 1. Regression coefficients for (4)

Regression	Value coefficient
k1 (milk production coefficient)	-0,0493
k2 (conductivity coefficient)	0,1933
b (constant term)	0,1022

Thus, the real mastitis is represented as a set of points in the graph constructed on the input coordinates of the plane approximating the symptom space (Figure 1). The regression model provides the complexity needed to estimate the probability of mastitis in animals. A regression model to determine the presence of mastitis in animals is shown in (10). Coefficients are calculated using the method of least squares.

$$v_i\ (t) = -0.0493\hat{\mu}_i(t) + 0.1933\hat{\eta}_i(t) + 0.1022,\ i = 1..n. \tag{10}$$

In [[16]], Tian Fuyang evaluated a new method for automatic online detection of clinical mastitis using a neural network in AMS. 9 parameters are measured using sensors: milk quarter level (MO; kg), average milking electrical conductivity (AEC; mS/cm), milk pH (pH), milk temperature (TP; ℃), milk production efficiency between consecutive milking sessions (MPE; kg/h), milking time (MT; min), milking efficiency (MD; kg/min), milk production time (MDO; kg/h), number of cows. 9 measurements are entered into the neural network to calculate the mastitis detection index. In this study, the learning vector quantization (LVQ) neural network model is used to diagnose clinical mastitis in dairy cows, and the LVQ model is compared with conventional support vector machine (SVM), BP neural network, and random forest model. LVQ is a three-layer network structure of a neural network [14]. The first layer is input, the second layer is competition and the third layer is linear layer. A competition layer is used to classify the input vectors. The linear layer transforms the classification data passed from the competing layer into the user-defined expected category. The classes derived from the competition layer are usually called subclasses, while the classes derived from the linear layer are called expected classes.

The proposed calculation steps are as follows:

(1) Initialize weight ω_{ij} and learning rate $\eta(\eta > 0)$ of input layer and competition layer (in this algorithm, η=0,001);

(2) The input vector $x = (x_1, x_2, \ldots, x_{12})$ is sent to the input layer, the distance between the neural layer content and the input vector is calculated by (11):

$$d_i = \sqrt{\sum_{j=1}^{R}\left(x_j - \omega_{ij}\right)^2},\ i = 1,2,\ldots,12, \tag{11}$$

where x_1 - volume of milk per quarter (kg); x_2 - AEC (mS/sm); x_3 - highest EC (mS/sm); x_4 - highest and x_5 - average milk flow rate (kg/min); x_6 - average and x_7 - highest pH value; x_8 - milk temperature (℃); x_9 - milk yield between consecutive milkings (kg/h); x_{10} - days in milk (d); x_{11} - diseased with mastitis (yes or no); x_{12} - cow number; ω_{ij} - weight between j neuron input va i competition layer.

(3) Two competing layer neurons i and j with the smallest distance from the input vector are selected.

(4) if neuron i and neuron j fulfill these two conditions: ① neurons i and j are of different types; ② the distance between neurons i and j and the current input vectors d_i and d_j is the same:

$$\min\left\{\frac{d_i}{d_j}, \frac{d_j}{d_i}\right\} > \rho \tag{12}$$

where ρ - the input vector can be within a window width close to the median plane of the two vectors, usually occupies about two-thirds.

Therefore, ① if the category C_i corresponding to neuron i corresponds to the category C_x corresponding to the input vector, the weight correction formula for neuron i and neuron j is (13), ② if the category C_j corresponding to neuron j corresponds to the category C_x corresponding to the input vector, then the weight correction formula for neuron i and neuron j is (14):

$$\begin{cases} \omega_{in} = \omega_i + \eta(x - \omega_{i0}) \\ \omega_{jn} = \omega_{j0} - \eta(x - \omega_{j0}) \end{cases} \quad (13)$$

$$\begin{cases} \omega_{in} = \omega_{i0} - \eta(x - \omega_{i0}) \\ \omega_{jn} = \omega_{j0} + \eta(x - \omega_{j0}) \end{cases} \quad (14)$$

where ω_{in} – the weight of neuron i after correction; ω_{i0} - the weight of neuron i before correction; ω_{jn} - the weight of neuron j after correction; ω_{j0} - the weight of neuron j before correction.

(5) If the termination condition is met, it terminates; otherwise return to step (12).

The experimental results of the study show that the new method of diagnosing clinical mastitis for dairy cows based on the proposed LVQ neural network has high accuracy.

Chagunda's research has developed a dynamic deterministic biological model that estimates the risk of mastitis for a given cow on a given day [6]. The model combines the real-time mastitis index measured in milk with other known risk factors for mastitis. The model is primarily triggered when new lactate dehydrogenase (LDH), EC, and disease record values are recorded. Amount of LDH (mol/min) as input and smoothed using an extended Kalman filter before processing with the biological model. Key inputs in the model are calving date, LDH activity (mol/min/L) and milk yield (L) values. While LDH creates indicator-based risk (MIBR), others related to the animal and herd create additional risk factor (ARF). MIBR and ARF are used together to create a risk of mastitis. ARF factors do not affect LDH. The model distinguishes between acute and chronic mastitis. Acute mastitis has a rapid increase in LDH in a relatively short period of time, while chronic mastitis has a gradual increase in LDH over a long period of time.

The model outputs: 1) the overall risk of acute mastitis, 2) the relative rate of chronic mastitis, 3) when the next sample should be taken. The results are very good at detecting mastitis: using a mastitis risk cut-off of 0.7, the sensitivity for detecting clinical mastitis is 82% and the specificity is 99%.

Nazire Mikayil identified mastitis using fuzzy logic (FL) model in [4]. The input data and their value ranges for the prediction of subclinical mastitis using FL are as follows: LR (lactation ranks, 1-7 integer); MY (milk yield, 10-50 days/liter); EC (electrical conductivity, 3-6 mS/cm); AMD (average milking duration 3.7-19 minutes) and S (seasons, 1-4 integer). And the output is mastitis detection (MD, 0-1 binary). Verbal expressions and fuzzy set intervals for LR, MY, EC, AMD, and MD are defined as follows:

- *first* (1≤ x<2), *middle* (1 < x < 5) and *last* (4<x≤ 7) for LR;
- *low* (10≤x<20), *normal* (18<x<31), *high* (28<x<42) and *very high* (40<x≤50) for MY;
- *low* (3≤x<4), *normal* (3.5<x<4.5) and *high* (4<x≤6) for EC;
- *short* (3.7≤x<7), *normal* (6<x<12) and *long* (11<x≤19) for AMD;
- *winter* (0<x<2), *spring* (1<x<3), *summer* (2<x<4) and *autumn* (3<x<5) for S;
- *healthy* (0≤x<0.4) and *subclinical mastitis* (0.3<x≤1) for MD.

Relevance degrees are calculated using the Mamdani fuzzy model, average weight, min-max inference, and centroid defuzzification methods. Various functions are used to plot input and output data. Here, triangular (15) and trapezoidal (16) functions are used to calculate the degree of relevance of the generated input and output values.

$$\mu_A(x; a_1, a_2, a_3) = \begin{cases} a_1 \le x \le a_2, & (x - a_1)/(a_2 - a_1) \\ a_2 \le x \le a_3, & (a_3 - x)/(a_3 - a_2) \\ x > a_3 \mid x < a_1 & 0 \end{cases} \quad (15)$$

$$\mu_A(x; a_1, a_2, a_3, a_4) = \begin{cases} a_1 \le x \le a_2, & (x - a_1)/(a_2 - a_1) \\ a_2 \le x \le a_3, & 1 \\ a_3 \le x \le a_4, & (a_4 - x)/(a_4 - a_3) \\ x > a_4 \mid x < a_1 & 0 \end{cases} \quad (16)$$

Rules for the model are formulated based on data obtained from daily milking (MY, AMD, EC, S, LR) samples and laboratory-observed subclinical mastitis during a 15-month follow-up. Below are the common MD conditions for healthy cows shown in the MD model:

- Rule 1: if LR is last; MY is normal; EC is normal; AMD is short; S is autumn;

- Rule 24: if MY is very high, MD is healthy;
- Rule 25: if EC is low, MD is healthy;
- Rule 26: if AMD is short, MD is healthy;
- Rule 69: if LR is first; MY is low; EC is low; AMD is short; S is a spring;
- Rule 74: if LR is middle; MY is low; EC is normal; AMD is short; S is spring.

Some subclinical cases of mastitis infection in the MD model are given below:

- Rule 13: if LR is last; MY is high; EC is high; AMD is normal; S is autumn;
- Rule 35: if LR is middle; MY is normal; EC is normal; AMD is normal; S is winter, MD is subclinical mastitis.
- Rule 41: if LR is middle; MY is high; EC is high; AMD is long; S is winter;
- Rule 42: if MY is low; EC is high; AMD is long;
- Rule 47: if LR is last; MY is high; EC is high; AMD is normal; S is winter;
- Rule 48: if LR is first; MY is normal; EC is normal; AMD is short; S is spring;
- Rule 68: if LR is last; MY is high; EC is normal; AMD is normal; S is spring.

The analysis of the results obtained in the study showed that lactation ranks (LR) and daily MY of 4 seasons (S) of Holstein-Friesian cows ranged from 14.29±1.680 to 34.20±2.430 kg/min; EC from 3.99±0.097 to 4.50±0.322 mS/cm; AMD from 4.38±0.317 to 9.04±1430 min/cow; SCC ranged from 29488 to 228026 cells/mL. The FL model showed 82% sensitivity, 74% specificity, and 60% error. Fuzzy logic can be a useful tool for developing a mastitis detection model, and the error rate can be reduced with more data parameters.

4. The result. A new model of mastitis detection

Suppose that there are m sensors for mastitis detection in practice, and at least one type of information needs to be obtained from each sensor. Also, let there be some mathematical functions/algorithms (Y) that process m sensor data individually and/or some of them together. It is known that all sensors have their share (α) in the diagnosis of the disease. Here, the sum of the results of the algorithms applied to the data of all sensors in relation to the given share is taken as an indicator of the disease. In general, the model of detection of cattle diseases using sensors can be given as follows:

$$F = \prod_{i=1}^{R} \overline{\Theta}^{i} \left\{ \frac{1}{m} \sum_{k=1}^{m} \alpha_k \Phi\left(Y^k\left(x_{k,p_i}\right) + b_k - \varepsilon_k\right) \right\},$$
$$0 \le \alpha_k \le 1, \Sigma\alpha_k = 1, 0 < \overline{\Theta}^{i} \le 1, \qquad (17)$$

where m – number of sensor, $\overline{\Theta}$ – vector, where the constant units affecting the disease (for example, the age of the cow, the number of lactations and the percentage values for milk months), Y^k – data processing function for sensor k, x_{k,p_i} – data received from sensor k, b_k and ε_k – are the factor affecting the function Y^k and the amount of deviation, respectively, Φ – function to put a value in the range [0,1], α_k – share of sensor k in disease detection.

In order to calculate the above-mentioned factors using (17), the following constants, Y^k functional specification and criteria are introduced:

- Constant data: DMY - days in milk, LO - number of lactation, MYM - month of lactation period, D - number of days in milk, Age - age of the cow.
- $\overline{\Theta}^1$ – having mastitis in milk months: $\overline{\Theta}^1 = \begin{cases} \text{MYM} < 4 \rightarrow 0.5 \\ \text{MYM} \ge 4 \rightarrow 1.0 \end{cases}$.
- $\overline{\Theta}^2$ – having mastitis for the age of the cow: $\overline{\Theta}^2 = \begin{cases} \text{Age} \le 5 \rightarrow 0.2 \\ 5 < \text{Age} \le 10 \rightarrow 1.0. \\ \text{Age} > 10 \rightarrow 0.3 \end{cases}$
- $Y^1(MY)$ – determination of milk yield in one milking. The standard deviation is 15-20% reduction in liters of milk. It is checked based on the comparison with the previous milk days (2) and the deviation condition (3).
- $Y^2(MYH)$ – determination of milking rate (kg/minute). Standard deviation is 20% rate reduction. The current rate is compared to the previous 7 days. Here, if number of lactation is LO=[1; 4], rate is >1.3;>1.4; >1.5; >1.6 respectively and if LO >4, then rate is >1.7. ~
- $Y^3(EC)$ – determination of electrical conductivity in milk. Invariant norm is EC>6.0 mS/cm at ~25°C and 15% increase compared to the previous 7 days.
- $Y^4(SCC)$ – somatic cell count function. Invariant norm is SCC>500,000. The previous period is not taken into account.

Now, if the above invariants, criteria and determining functions are put into (17), it will be possible to determine the risk of mastitis:

$$F = \overline{\Theta}^1 \cdot \overline{\Theta}^2 \frac{1}{4}\Big(\alpha_1 \underset{0<x\le1}{Y^1(MY)} + \alpha_2 \underset{0<x\le1}{Y^2(MYH)} + \alpha_3 \underset{0<x\le1}{Y^3(EC)} + \alpha_4 \underset{0<x\le1}{Y^4(SCC)}\Big) \qquad (18)$$

In (18), the data of 4 sensors are taken into account. When the number of sensors changes, the arithmetic mean distribution will also change. In addition, other algorithms or models can be used to calculate Y^i.

Conclusion

In this article, mastitis detection models based on various mastitis factors have been studied and the model expressed in (17) is proposed. That is, a universal mathematical model of mastitis detection is developed by combining the data obtained from existing sensor types in livestock farms with invariable information and rules. The uniqueness of the model is that it does not require specific types of sensor data. The diversity of the number of data received from sensors in each farm does not affect the principles of calculation, it can only reduce the accuracy of the result. The universality of this model is that data on possible mastitis have their own weight in the model, invariable data have a uniform effect on all factors, and separate mathematical-algorithmic functions are developed for each sensor data. These functions can be organized in any way, and the calculations in the model are simple and understandable. Experimental tests on the reliability and accuracy of the model are being conducted at the livestock farm located in the Aral Sea region, which is the object of the innovative project called "Development of a mobile application for electronic management of livestock complexes" - No. IL-392103072. The analysis of the results will be given in full in the further research works.

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