An automated on-line clinical mastitis detection system using measurement of electrical parameters and milk production efficiency

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Abstract: This study aims to assess a novel method for automatic on-line detection of clinical mastitis in an automatic milking system using the measurement of electrical parameters, data of milk production efficiency and neural network from the novel mastitis detection sensor. The sensors were used to measure following 9 parameters: the quarter-level milk yield (MY; kg), average electrical conductivity in milking session (AEC; mS/cm), pH of milk (pH), temperatures of milk (TP; ℃), milk production efficiency (MPE; kg/h) between successive milking sessions, milking time (MT; min), Milking efficiency (ME; kg/min), Milk production time (MPT; kg/h), cow number. The 9 measurements were inputted into a neural network to calculate the mastitis detection index. The network was trained with 44 healthy and 6 clinical mastitic cows. 42 of 44 healthy and 5 of 6 mastitic cows were classified correctly after training. The trained neural network predicted 164 of 176 healthy quarters correctly in different evaluation data sets. These results were better than the results obtained with the model usually used on the farm.

1. INTRODUCTION
Early detection of anomalies is an important issue in the management of group-housed livestock\textsuperscript{[1-7]}. Cow mastitis refers to the inflammatory reaction caused by pathogenic microorganism infection in the breast, which is one of the most common cow diseases\textsuperscript{[8]}. It is the disease with the highest incidence and the most serious harm among all cow diseases. Mastitis to cause a decline in the production and quality of milk, dairy cows, use fixed number of year to reduce, cause huge economic losses, at present, the world each year about 220 million milk cow mastitis caused by the loss of up to $35 billion, the United States has lost about $2 billion in the UK 3% of dairy cows were eliminated because of suffering from mastitis. Depending on whether symptoms of clinical mastitis can be divided into two types of clinical mastitis...
and recessive mastitis[9]. Clinical mastitis has obvious clinical symptoms. Cow milk has visible changes, such as clumping and darkening of color, and the appearance of lump and redness outside the breast. It is easy to be found and treated by taking immediate measures. However, due to the lack of any visible clinical symptoms, the diagnosis of invisible mastitis is relatively difficult. There is no obvious change in the appearance of the breast and milk, but the chemical composition of milk changes quantitatively. The specific manifestation is increased pH, increased electrical conductivity, and the number of somatic cells is more than 500,000 /mL. Detection of hidden mastitis can control its diffusion and improve the treatment condition[9].

Somatic cell count (SCC) is the trait most commonly used in breeding programmes for the analysis of mastitis resistance[10]. For the monitoring of SCC, DHI (dairy herd improvement) sampling analysis is mainly adopted, but the analysis cycle is long, the implementation process is cumbersome, the equipment is expensive, and the monitoring needs to be corrected frequently. Foss company of Denmark designed the FossMatic 5000 detector for somatic count, which is too expensive and difficult for general milk farms to afford, and requires professional personnel to operate. Compared with the former, PORTASCC Digital Reader milk somatic cell detector in the United States is more convenient. This system is suitable for outdoor field detection, but the detection time is long, the storage requirements of test paper, activator and color card are relatively high, and the testing environment requires appropriate temperature and avoiding direct sunlight.

Many studies showed that EC of milk from cows affected by both clinically and subclinically mastitis is higher than EC of milk from healthy cows[11]. But previous studies have shown that the use of only EC in different detection algorithms was unable to achieve the ISO (2007) standard Se (>70%) and Sp (>99%) for CM detection[12].

The method of milk pH value is intuitive, easy to operate, and its cost is low, and it is not affected by the external environment temperature. Exploiting multisensor information could lead to sustainable improvements in the detection of mastitis.

Infrared thermograph technology (IRT) can sense the energy radiated by the thermal motion of the object itself, convert the Infrared signal into the processed electrical signal, to form the thermal Infrared image reflecting the surface temperature information of the object. By exploring the difference between eye surface temperature and breast surface temperature, IRT is used to detect mastitis of cows. Generally, the thermal imager is used to detect the eye surface temperature and breast skin surface temperature of dairy cows[13]. Due to the partial deformation of dairy cow breasts with the movement of dairy cows, it is impossible to achieve accurate positioning. Previous researches mainly focus on manual marking.

The purpose of this article is to establish the cow milk production, milk production efficiency, average electrical conductivity, high electrical conductivity, the milk (5 minutes), the highest average flow velocity of average flow velocity, pH, pH high temperature, milk, milk early days, whether suffering from mastitis, cow number 12 parameters and the cow estrus LVQ neural network model of probability and used the model to validate the actual detection of milk.

2. MATERIALS AND METHODS
After infection with mastitis, chloride and sodium ions in milk increase significantly, which leads to the increase of milk conductivity and pH value. At the same time, the range of the milk conductivity of cows infected with mastitis was larger than the corresponding value without infection. So we through many experiments and based on analyzing the test results, find out the cow infected and uninfected mastitis milk electrical conductivity and pH value of the critical value and the change range of upper and lower critical point, and the critical value stored in the permanent memory of single-chip computer system as a future mastitis diagnosed benchmark, when the measurement of conductivity and pH value exceeds the specified benchmark, thought that the cow mastitis or suspected infection; On the contrary, it was considered not infected.
2.1. Data Source
From January to March 2019, data from 60 cows on a cattle farm in Tai’an, Shandong province, among them 50 holstein lactation cows were randomly selected and 10 mastitis disease cows. Data of 43,200 groups were collected from 4 lactation areas and 200 sampling sites for each cow. Milk data samples were collected twice a day before entering the milking shed in the morning and evening. During the test period, 47 lactation cows were being healthy and 3 cows suffered mastitis disease.

2.2. Measurements
This detection sensor is mainly composed of electrical conductivity measurement system, pH measurement system, temperature measurement system, clock system, communication system, signal detection and control system (pH electrode, conductivity electrode, temperature sensors and corresponding modulation circuit), storage system, keyboard display system, dairy cattle identification system, expert system, and CPU, etc.

Because the conductivity and pH value vary with the temperature, a temperature measuring system is designed to compensate the conductivity and pH value of milk at different temperatures.

Since the conductivity and pH value of milk of the same cow change with different fetal times, age, milking time, milking times and lactation period, the critical points of conductivity, pH value and range of conductivity for mastitis diagnosis should also be timely changed.

2.3. Data processing
The original dataset had nine measurements (features), the cow milk production, milk production efficiency, average electrical conductivity, high electrical conductivity, the milk (5 minutes), the highest average flow velocity of average flow velocity, pH, pH high temperature, milk, milk early days, whether suffering from mastitis, cow number.

As the dataset used for prediction of sub-clinical mastitis was collected from only a single farm, to provide a reliable base for generalization of the findings of this study, the dataset was transformed by Z-Standardization (for each feature, subtracting the mean and dividing by the standard deviation).

2.4. LQV Neural Network
Learning vector quantization (LVQ) neural network is a three-layer network structure[14]. Figure 3 is a typical LVQ neural network structure. The first layer is the input layer, the second layer is the competition layer, and the third layer is the linear layer. The competition layer is used to classify the input vectors. The linear layer converts the classification information passed from the competition layer into the expected category defined by the user. Classes that are learned from the competition layer are usually called subclasses, and classes that are learned from the linear layer are called expected classes. LVQ algorithm is a kind of learning algorithm that trains the competitive layer with teachers. It is evolved from Kohonen competitive algorithm. LVQ neural network has been widely used in pattern recognition [8].
Fig.2 Architecture of LVQ neural network

Specific calculation steps are as follows:

(1) initialize the direct weight $\omega_{ij}$ and learning rate $\eta$ ($\eta > 0$) of input layer and competition layer, and $\eta = 0.001$ in this algorithm;

(2) input vector $x = (x_1, x_2, x_3, \ldots, x_{12})^T$ is sent to the input layer, and the distance between content-layer neuron and input vector is calculated according to formula (1):

$$d_i = \sqrt{\sum_{j=1}^{12} (x_j - \omega_{ij})^2}, \quad i = 1, 2, \ldots, 12$$

where $x_1$, quarter-level milk yield (kg); $x_2$, average electrical conductivity (mS/cm); $x_3$, peak electrical conductivity (mS/cm); $x_4$, peak milk flow rate (kg/min); $x_5$, average milk flow rate (kg/min); $x_6$, average pH value; $x_7$, peak pH value; $x_8$, temperatures of milk ($^\circ$C); $x_9$, milk production efficiency (kg/h) between successive milking sessions; $x_{10}$, days in milk (d); $x_{11}$, had mastitis ever (is or not); $x_{12}$, cow number. $\omega_{ij}$, weight between input layer j and competitive layer neuron i.

(3) select the two competing layer neurons i and j with the smallest distance from the input vector.

(4) if neuron i and neuron j meet the following two conditions: ① neuron i and neuron j correspond to different types; ② distance between neuron i and neuron j and the current input vector $d_i$ and $d_j$ meet:

$$\min \frac{d_i}{d_j} > \rho$$

where $\rho$, the input vector may fall into the window width close to the middle plane of the two vectors, generally taking about two-thirds.

Therefore, ① if the category $C_i$ corresponding to neuron i is consistent with the category $C_x$ corresponding to the input vector, the weight correction formula of neuron i and neuron j is:

$$\begin{align*}
\omega_{in} &= \omega_{io} + \eta (x - \omega_{io}) \\
\omega_{jn} &= \omega_{jo} - \eta (x - \omega_{jo})
\end{align*}$$

where $\omega_{in}$, the weight of neuron i after modified; $\omega_{io}$, the weight of neuron i before correction; $\omega_{jn}$, the weight of neuron j after correction; $\omega_{jo}$, the weight of neuron j before correction;

② if the category $C_j$ corresponding to neuron j is consistent with the category $C_x$ corresponding to the input vector, then the weight correction formula of neuron i and neuron j is as follows:

$$\begin{align*}
\omega_{in} &= \omega_{io} - \eta (x - \omega_{io}) \\
\omega_{jn} &= \omega_{jo} + \eta (x - \omega_{jo})
\end{align*}$$

(5) If the termination condition is met, it ends; otherwise, return to step (2).
3. RESULTS AND DISCUSSION

Table 1 shows the data of healthy lactating cows numbered 16109 without mastitis, and table 2 shows
the data of healthy lactating cows numbered 16109 without mastitis. As can be seen from the data in the
two tables, milk conductivity, pH value and milk-producing efficiency of cows have significant changes
after mastitis. Figure 3 shows the data curves of lactating cows numbered 16109 before and after mastitis.
Due to the diversity of experimental data features, data with different features have different dimensions.
In order to eliminate the differences in different data dimensions, experimental data need to be normalized.
The dataset was transformed by Z - Standardization (for each feature, subtracting the mean and dividing
by the standard deviation). Figure 4 shows the data curves of Z - Standardization processing various
characteristics of the data after the offset.

Table 1 Part data of No. 16109 healthy cow

| COW NUM | Conductivity | Milk yield | pH | Temperature | Milking time | Milking efficiency | Milk production duration | Milk production efficiency |
|---------|--------------|------------|----|-------------|--------------|--------------------|--------------------------|--------------------------|
| 16116   | 8.87         | 7.3        | 5.9 | 37.59       | 6.8          | 1.559              | 12.02                    | 0.774                    |
| 16116   | 9.12         | 10.6       | 6.18| 37.69       | 6.2          | 1.5                | 12.02                    | 0.774                    |
| 16116   | 9.04         | 9.3        | 6.35| 38.07       | 6.6          | 1.576              | 12.152                   | 0.856                    |
| 16116   | 8.91         | 10.4       | 6.25| 37.89       | 6.5          | 1.4                | 12.197                   | 0.746                    |
| 16116   | 9.16         | 9.1        | 5.92| 37.82       | 6.4          | 1.531              | 11.536                   | 0.85                     |
| 16116   | 7.66         | 9.8        | 6.02| 37.55       | 6.3          | 1.54               | 12.349                   | 0.786                    |
| 16116   | 9.01         | 9.7        | 6.26| 38.07       | 5.9          | 1.508              | 11.612                   | 0.76                     |
| 16116   | 8.72         | 8.9        | 6.25| 37.5        | 6.9          | 1.362              | 12.071                   | 0.779                    |
| 16116   | 9.03         | 9.4        | 5.85| 38.01       | 6.8          | 1.426              | 12.039                   | 0.806                    |
| 16116   | 9.02         | 9.7        | 6.19| 37.99       | 6.5          | 1.4                | 11.973                   | 0.76                     |
| K_a     | 9.0565       | 7.7807     | 6.110/6 | 37.6721       | 5.7265     | 1.3582              | 12.0014                   | 0.6484                   |
| K_b     | 0.4277       | 1.3765     | 0.168/3 | 0.2581       | 0.7238     | 0.1455              | 0.2010                    | 0.1126                   |
| K_c     | 0.0344       | 0.1106     | 0.013/5 | 0.0207       | 0.0581     | 0.0117              | 0.0162                    | 0.0090                   |
| K_d     | 0.1829       | 1.8948     | 0.028/3 | 0.0666       | 0.5239     | 0.0212              | 0.0404                    | 0.0127                   |
| K_e     | -2.1926      | 0.0598     | 0.089/9 | -0.1043      | 0.1169     | -0.4433             | 0.2164                    | -0.0035                  |
| K_f     | 0.0472       | 0.1769     | 0.027/6 | 0.0069       | 0.1264     | 0.1071              | 0.0168                    | 0.1736                   |

K_a - Mean; K_b - standard deviation; K_c - mean SE; K_d - variance; K_e - skewness; K_f - coefficient of variation;

Table 2 part data of No. 16109 dairy cows with mastitis

| COW NUM | Conductivity | Milk yield | pH | Temperature | Milking time | Milking efficiency | Milk production duration | Milk production efficiency |
|---------|--------------|------------|----|-------------|--------------|--------------------|--------------------------|--------------------------|
| 16116   | 9.43         | 6.8        | 6.04| 37.93       | 4            | 1.275              | 12.031                   | 0.424                    |
| 16116   | 10.2         | 5.1        | 6.18| 38.28       | 5.4          | 1.148              | 12.127                   | 0.511                    |
| 16116   | 9.99         | 6.2        | 6.22| 37.82       | 5            | 1.02               | 11.844                   | 0.431                    |
| 16116   | 9.95         | 5.1        | 6.29| 37.71       | 5.2          | 1.192              | 12.036                   | 0.515                    |
| 16116   | 10.01        | 6.2        | 6.1 | 38.07       | 4.5          | 0.867              | 11.802                   | 0.33                     |
| 16116   | 9.91         | 3.9        | 6.04| 38.26       | 6.6          | 1.152              | 12.323                   | 0.617                    |
According to the simulation results in figure 5, the accuracy rate, recall rate and precision rate of detection of cow mastitis based on LVQ neural network in the existing samples were 93.5%, 94.8% and 91.5%, respectively. In order to illustrate the effect of lvq-based cow mastitis diagnosis scheme, this paper also compares the diagnosis methods based on random forest, support vector machine and BP neural network algorithm, and the results are shown in figure 5.

![Fig.3 Dataset of the No. 16109 dairy cows](image1)

![Fig.4 Dataset of the No. 16109 dairy cows after Z - Standardization](image2)
4. CONCLUSIONS
In this paper, the LVQ neural network model was used to diagnose dairy cow clinical mastitis, and the traditional support vector machine (SVM), BP neural network and random forest model were compared. It can be seen from the test results that the new LVQ neural network based auxiliary diagnosis method for dairy cow clinical mastitis has a high accuracy rate. LVQ neural network is expected to be an effective and practical auxiliary diagnosis tool for cow mastitis, reducing subjective misdiagnosis by computer and improving the diagnostic accuracy.

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