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Mastitis detection in Dairy Cows

C. Henze, D. Cavero-Pintado and J. Krieter*

Christian-Albrechts-Universität Kiel
Faculty of Agricultural and Nutritional Science
Institute of Animal Breeding and Husbandry
Olshausenstraße 40, 24098 Kiel
Germany
*email: chenze@tierzucht.uni-kiel.de

1. Abstract

The aim of the present research was to investigate the usefulness of neural networks and fuzzy logic in the early detection and control of mastitis in cows as a decision support for farmers.A data set from the automatic milking system of the experimental farm "Karkendamm", containing 403,537 milkings of 478 different cows was used. Mastitis was determined according to three definitions: udder treatment (1) or somatic cell counts (SCC) over 100,000/ml (2) or SCC over 400,000/ml (3). Definitions 2 and 3 also in combination with udder treatment. Electrical conductivity, milk production rate, milk flow and days in milk were used as information for the study. With the fuzzy logic tool sensitivities from 83.2 % to 92.9 % and specifities from 75.8 % to 93.9 % (depending of the definition of mastitis) have been reached, but also high error rates from 41.9 % to 95.5 %. The results of the neural network were sensitivities from 78.6 % to 84.2 %, specifities from 51.1 % to 74.5 % and error rates from 51.3 to 80.5 %.

2. Introduction

Mastitis is the most costly disease in dairy cattle today and remains one of the major problems concerning the dairy industry (Heald et al., 2000; Seegers et al., 2003). Average economic losses due to mastitis are estimated to be around 150 Euro per cow and year (DVG, 2002). De Mol et al. (1997, 2001) indicated that early detection of mastitis is very important, not only because of the economic impact due to yield losses, but also because of the negative effects on the animals' welfare. In herds with an Automatic Milking System (AMS), identification of udder infections is no longer based on visual observation. In contrast, control programs managing the health status of the cows are introduced based on sensor measurements. Detection of mastitis can be automated by using an integrated system with sensor measurements of milk yield, milk temperature and the electrical conductivity of the milk (Frost et al., 1997). The suitability of electrical conductivity for mastitis detection has been analysed in previous research (Cavero et al., 2006). An improvement on the reported results was expected by multivariate analyses of the traits. Wendt et al. (1998) indicated the possibility of using the milk production rate as meaningful additional information to electrical conductivity to detect mastitis.

3. Materials and Methods

3.1 Data

Data were recorded at the University of Kiel's experimental farm Karkendamm between July 2000 and March 2004. During this period observations from 403,537 milkings were accumulated from 478 Holstein Friesian cows with a total of 645 lactations. The mean herd size was 124 cows on average per day. Milking took place in an AMS with 4 boxes. The average number of milkings per cow per day was 2.4 and the 305-day milk yield was approximately 9,200 kg on average.

3.2 Mastitis definitions

Udder health was classified on the basis of the cows' somatic cell count (SCC), which was measured weekly from pooled quarter milk samples taken from each cow, as well as information on udder treatments. A total of 52,535 SCC tests were carried out with 195,000 cells/ml on average. The Deutsche Veterinärmedizinische Gesellschaft e.V. (German Veterinary Medicine Association) has stated a value of 100,000 cells/ml as the threshold for mastitis (DVG, 2002). Such a low threshold ensures that most of the mastitis cows are recognised but also supplies a large list of cows classified as infected. The threshold of 100,000 cells/ml was used in the present study, as well as another less strict threshold of 400,000 cells/ml, which represents the European Union maximum bulk milk SCC legal limit for saleable milk. Two variants of mastitis definition were used in this investigation:

1) Treat+100: treatment performed and/or a SCC > 100,000 cells/ml,
2) Treat+400: treatment performed and/or a SCC > 400,000 cells/ml.

The milking days were classified as "days of health" or "days of mastitis". If two succeeding SCC measurements either both exceeded the threshold or both did not, all days between these measurements were also defined as "days of mastitis" or "days of health", respectively. In the other case, the day on which the SCC was recorded, and two days after and two days before, were defined according to this SCC value and the days in the middle were set to "uncertain days".

In addition, the day on which a treatment took place, plus two days before and two days after, were set to "days of mastitis" and up to ten days after the last treatment were considered "uncertain days". A mastitis block was defined as an uninterrupted sequence of "days of mastitis".

3.3 Fuzzy Logic

In this study, a multivariate model was used to improve the mastitis detection. The sensor data were the input for the fuzzy model. This system performs a combination of conditions with electrical conductivity, milk production rate, and milk flow rate using MATLAB software (Matlab, 2003). Preparation of data and the calculation of the classification parameters were performed by using SAS (2004).

Fuzzy logic translates natural language knowledge into formal mathematical modelling, so that it is suitable for computer processing (Biewer, 1997). The basic concept underlying fuzzy logic is that of a linguistic variable, a variable whose values are words rather than numbers. Although words are less precise than numbers, their use is closer to human intuition.

Unconventional modelling methods make better use of uncertain or imprecise data and vague knowledge about model components. The fuzzy set theory is based on an extension of the classical meaning of the term "set" and formulates specific logical and arithmetical operations for processing imprecise and uncertain information (Zadeh, 1965). In contrast to common sets, where each element belongs to a set or not, fuzzy sets have a range of membership between 0 and 1. The three steps of a fuzzy logic system are the fuzzification, fuzzy inference and the defuzzification (Zimmermann, 1991).

3.4 Neural Networks

The technique of neuronal networks was developed in the field of artificial intelligence to emulate a biological neural net in the human brain as an information processing system. It is a massively parallel distributed processor made up of simple processing units, called neurons (computation nodes).

There is a great variety of neural networks. They differ in the distribution and the interconnections between neurons. In this study, the multilayer feedforward network was used, where the neurons are organized in the form of layers. In these networks there is an input layer of source nodes that projects onto the next layer of neurons. In the input layer no computation is performed. The output layer generates a response to a given input. Between both the external input and the network output one or more intermediate layers of neurons exists. These layers are called hidden layers because they have not a direct representation in the reality, and most of the actual processing occurs there. The structure of the hidden layers can vary in terms of both the number of hidden layers and the number of neurons therein. In the feedforward networks, each layer has as its inputs only the output signals of the preceding layer. The neural network is fully connected, since every node in each layer is connected to every other node in the next layer. These connections are weighted, so that the signal propagates and it will be intensified or attenuated as in the nervous system. Each node of the hidden and output layers sums the weighted signals of the previous nodes and a bias, then the transmission of the outcoming signal to the following nodes is supplied by a non-linear function called the activation function. The activation limits the amplitude range of the output signal. Once the network weights and biases have been initialised, the network has to be trained. The learning process is called "supervised", because pairs of inputs and outputs that represent knowledge about the environment of interest are provided to the neural network in the training set. . During training, the weights and biases of the network are iteratively adjusted to minimize a given error function between the desired response and the actual response of the network. Preparation of data and also the calculation of the classification parameters in order to develop and test the neural network were performed by using MATLAB software (Matlab, 2004).

4. Results

4.1 Fuzzy Logic

Mastitis alerts were generated by a fuzzy logic model using electrical conductivity, milk production rate and milk flow rate as input data. To develop and verify the model, the dataset was randomly divided into training data (284,669 milkings from 319 cows) and test data (135,414 milkings from 159 cows). The evaluation of the model was carried out according to sensitivity, specificity and error rate. If the block-sensitivity was set to be at least 80%, the specificities ranged between 88.1% and 75.8% and the error rate varied between 75.7% and 41.9% depending on mastitis definition. Additionally, the average number of true positive cows per day ranged from 1.3 to 7.2, and the average number of false negative positive cows per day ranged from 4.1 to 5.2 in an average herd size for the test data of 39.7 cows per day. The results for the test data verified those for the training data, indicating that the model could be generalized.

Table 1: **Quality of mastitis detection with Fuzzy-Logic**

Training-data (84 cows/day)	**Block-sensitivity**	**Specifity**	**Error-rate**	**tp**[1)]	**fp**[2)]
Mastitis 1	80.1	77.5	46.7	12.9	11.2
Mastitis 2	81.2	89.1	77.2	2.4	8.0
Test-data (40 cows/day)	**Block-sensitivity**	**Specifity**	**Error-rate**	**tp**[1)]	**fp**[2)]
Mastitis 1	83.2	75.8	41.9	7.2	5.2
Mastitis 2	83.9	88.1	75,7	1.3	4.1

[1)] tp: True positive identified cows per day   [2)] fp: False positive identified cows per day

4.2 Neural Networks

Mastitis alerts were generated by a neural network model using electrical conductivity, milk production rate, milk flow rate and days in milk as input data. To develop and verify the model, the dataset was randomly divided into training and test data subsets. The evaluation of the model was carried out according to block-sensitivity, specificity and error rate. When the block-sensitivity was set to be at least 80%, the specificities were 51.1% and 74.9% and the error rates were 51.3% and 80.5% for mastitis definition 1 and 2, respectively. Additionally, the average number of true positive cows per day ranged from 1.2 to 6.4, and the average number of false negative positive cows per day ranged from 5.2 to 6.8 in an average herd size for the test data of 24 cows per day. The results for the test data verified those for the training data, indicating that the model could be generalized.

Table 2: **Quality of mastitis detection with a Neural Network**

Training-data (99 Cows/day)	**Block-sensitivity**	**Specify**	**Error-rate**	**tp**[1)]	**fp**[2)]
Mastitis 1	79.3	61.4	46.5	24.8	21.5
Mastitis 2	80.8	78.3	79.1	4.8	18.2
Test-data (24 cows/day)	**Block-sensitivity**	**Specify**	**Error-rate**	**tp**[1)]	**fp**[2)]
Mastitis 1	84.2	51.1	51.3	6.4	6.8
Mastitis 2	78.6	74.9	80.5	1.2	5.2

[1)] tp: True positive identified cows per day [2)] fp: False positive identified cows per day

5. Conclusions

An accurate mastitis detection system is urgently needed in farms with AMS and in conventional farms with a large herd size as an alternative to laborious visual observation. A model that detects mastitis early could be used in the future to support the management decision of the farmer.

Fuzzy logic was used to develop a detection model for mastitis that can be used in the future to support the management decision of the farmer. The application of fuzzy logic gives the model the advantage of being easy to interpret, easy to modify and adapt, by changing the membership functions and the bases of the rules. The main problem of developing the fuzzy logic models was the appropriate choice of suitable membership functions and set of rules. The optimal design has to be found by trial-and-error attempts. A noticeable decrease in the error rate is possible by means of more informative parameters. This could be achieved by improvement of sensor technology, and by the implementation of more explanatory traits. Fuzzy logic is a useful tool to develop a detection model for mastitis.

Also a neural network model was developed for mastitis detection using days in milk and pre-processed measurements of EC, milk yield and milk flow. The neural network model is easily implemented and automated using computer analysis. A limited number of mastitis indicators were analysed in the present study. Additional information related with mastitis would probably improve the performance of the model. For analysis of more complicated data, an neural network might be preferable, because of the non-linear relations between input and output and the fact that no assumption about the distribution of the different variables should be done. To sum up, neural networks are useful tools for computerised decision support systems.

6. Literature

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