Application of soft computing models for prediction of subclinical mastitis in indigenous breed of dairy cattle in India

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Received: 11 November 2019 / Accepted: 10 December 2019 / Published online: 27 February 2020
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Abstract: Mastitis is an important problem in dairy cattle. Soft computing models i.e. Adaptive Neuro Fuzzy Inference System (ANFIS) can be possible way out for detecting this disease. Therefore, the present study was undertaken for predicting the subclinical mastitis in indigenous breed such as Sahiwal cows and Murrah buffaloes. The selected eight parameters for study were Milk pH, electrical conductivity, temperature (udder, milk and skin), milk yield, dielectric constant and milk somatic cell counts. Animals were judged healthy and infected as per milk somatic cell counts. Accordingly, animals were classified into three categories, i.e., healthy, subclinical and clinical mastitis animals. Data generated were utilized for developing ANFIS models to identify healthy versus mastitis animals. Also, Multiple Linear Regression (MLR) models were developed for comparing classification accuracy of proposed models using Root Mean Square Error (RMSE) technique. ANFIS models were found to be superior as compared to MLR models for both the breed with RMSE 0.23 (Shahiwal cows) and 0.20 (Murrah buffaloes) as compare to MLR model 4.88 (Shahiwal cows) and 4.08 (Murrah buffaloes). Hence, it is deduced that ANFIS can be used as a suitable technique for detecting mastitis in indigenous breed of dairy cattle.

Keywords: Adaptive Neuro Fuzzy Inference System, Mastitis; Murrah buffaloes; Sahiwal cows; Soft computing models; Subclinical mastitis

Introduction

With an increasing trend in milk production the incidence of mastitis in dairy cattle and buffaloes has also increased, incurring great loss in terms of economic loss and future productivity of dairy animals (Barth, et al. 2000). It is evident from the studies conducted in the United States of America that economic loss associated with mastitis on dairy farms are approximately US $200 per cow/year leading to annual loss of US $2 billion for dairy industry (Bogni, et al. 2011). In India, annual economic loss incurred by dairy industry on account of udder infections has been estimated to be Rs 6264.18 crores and out of which loss of Rs 4515.54 (70-80%) has been attributed to subclinical mastitis (Dang, et al. 2010). In another report from India (De Mol and Woldt, 2001; Dua, 2001; Gaddi, et al. 2016, Srivastava, et al. 2015) the annual economic loss due to mastitis has been calculated as Rs7165.51 crores, Losses being almost same for cows (Rs 3775.58) and buffaloes (Rs 3637.78). Subclinical mastitis has been estimated to account for 57.93% (Rs 4293.69) of the total economic loss due to mastitis. Hence, there is an urgent need to identify certain diagnostic tools to detect mastitis at its earliest stage. The changes in the ion concentration of mastitis milk induce some variations in the electrochemical properties of milk and have the potential to be used as an effective technique for early prediction of mastitis (Jacceh, 2003; Mammadova and Keskin, 2013). The present study was therefore designed to study the mastitis induced variation in electro chemical properties in conjunction with other milk quality parameters in indigenous breed of dairy cattle by application of Adaptive Neuro Fuzzy Inference System (ANFIS).

Evidently, there was no study to identify mastitis in indigenous dairy cattle i.e. Sahiwal cows and Murrah buffaloes using ANFIS models. Moreover, the ANFIS models developed for exotic cattle were based on individual parameter. Hence, in this paper, these models have been developed on the basis of Milk pH, electrical conductivity, temperature (udder, milk and skin), milk yield, dielectric constant and milk somatic cell counts for detection of mastitis in the dairy cattle. These models would not only help in rapid detection of raw milk quality but also facilitate timely isolation of animals susceptible to subclinical mastitis, for proper treatment to avoid the economic losses. The classifying ability
of above proposed models has been evaluated in comparison with that of conventional Multiple Linear Regression (MLR) models, which have also been developed in this study.

**Materials and Methods**

A total no of 670 milk samples were collected from hundred lactating Sahiwal cows. Simultaneously 517 milk samples were collected from Murrah buffaloes for the investigations purpose. The breeds were maintained by Livestock Research Centre at ICAR – National Dairy Research Institute, Karnal, India for a period of one year, i.e., March, 2013 - February, 2014. Milk samples were collected twice a day, i.e., in the forenoon (11.30 AM) and in the evening (4.30 PM). Milk samples were tested for mastitis by analyzing the milk somatic cell counts using microscopic method (Mammadova and Keskin, 2015). Animals having milk SCC below 200000 per ml were categorized as healthy animals, whereas, SCC in the range of 200000 - 500000 per ml were considered to be subclinical mastitis animals (Alhussien and Dang, 2018). The remaining animals with milk SCC more than 500000 per ml were positioned in clinical mastitis category. Further, other parameters like pH and Electrical conductivity and Dielectric Constant were determined by precision handheld pH meter (Haana instrument, range 0-14), EC meter (Oriental Instrument Ltd. Japan range 0-13 mS/cm) and dielectric constant meter (PSAW454 frequency range 9-10 MHz) respectively. The temperature of milk was measured by regular thermometer (glass thermometer range 0-100 ºC) whereas, temperature of skin and udder of animals were measured with infrared thermometer. Milk yield was recorded at the time of sampling collection using weighing balance. Further, SCC were determined by microscopic method (Mammadova and Keskin, 2015) in which milk was heated to 40°C in a water-bath, and set aside at that temperature for 15 minutes before cooling it to 20°C by stirring gently. About 0.01 ml of milk was spread on a 1cm² (0.5 cm × 2 cm) area of a microscopic slide and was dried in a horizontal position. Furthermore, The data generated above were utilized for models development (ANFIS and MLR) using Milk pH, electrical conductivity, temperature (udder, milk and skin), milk yield and dielectric constant as a input variables whereas milk

![Figure 1 Schematic diagram of ANFIS model](image-url)
somatic cell counts is used as output variable in dairy cattle i.e. Sahiwal cows and Murrah buffaloes.

**Adaptive neuro fuzzy inference system model**

ANFIS is fusion of neural network and Fuzzy Inference System (FIS). The connectionist networks are used to determine the parameter of the FIS. It combines both the fuzzy logic (FL) and neural network (Seegers, et al. 2003; Skrzypek, et al. 2004). FL was an exodus from classical Boolean logic as it implements soft linguistic variables on a continuous range of truth values, which allows transitional values to be defined between conventional binary. FL application solves the problem with three steps: first it convert numerical values to a set of fuzzy values, an inference system based on fuzzy if-then rules and defuzzification (Sharma, et al. 2014) as shown in Figure1.

ANFIS model can be of two types, *i.e.*, Mamdani and Sugeno. The Sugeno-type system was used in this study. The architecture of ANFIS has following five layers to accomplish the tuning process of the fuzzy modelling system (Veleva, et al. 2010).

Layer 1: Every node in this layer is an adaptive node with a node function which is called Membership Function (MF). Parameters of membership functions are known as premise or antecedent parameters.

Layer 2: Every node in this layer is a fixed node, which multiplies the incoming signals and sends the product out. Each node represents the firing strength of a fuzzy rule.

Layer 3: In this layer every node calculates the ratio of the one firing strength to the sum of all rules’ firing strengths. The outputs of this layer are called normalized firing strengths.

Layer 4: In this layer every node is an adaptive node (*i.e.*, linear combination of input variables). Parameters in this layer are referred to as subsequent parameters.

Layer 5: The single node in this layer is a fixed node that computes the overall output as the summation of all incoming signals.

This five-layer network architecture, ANFIS being a hybrid model puts the fuzzy model into the framework of adaptive networks that computes gradient vectors systematically. The Fuzzy Toolbox under MATLAB software was used for all simulation experiments. The ‘trial and error’ method using error back propagation with three data partitioning schemes i.e. 70:30, 80:20 and 90:10 (training set : testing set) were explored for model development. The network was best trained with 10, 50 and 100 epochs; learning rate as 0.01 and error goal as 0.001, which was determined empirically. Each training experiment was conducted ten times with different combinations of the parameters such as, data partitioning scheme, epochs, range of influence, Squash Factor, accept ratio and reject ratio. For the model selection, the architecture of connectionist model was decided by ‘trial and error’ procedure. The MATLAB programming environment has been used for training and simulation experiments. SAS 9.3 was used for developing MLR models.

**Model performance analysis**

The performance of neural network models, ANFIS and MLR models was evaluated in terms of Root Mean Square percent error (%RMSE) at 70:30, 80:20 and 90:10 partitioning schemes. The RMSE, calculated using formula as given below.

\[
\text{RMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^{N} \left(\text{Prediction Error} \right)^2} \quad (3)
\]

**Results and Discussion**
The Mean ± SE values of milk pH, electrical conductivity, dielectric constant, temperature of skin, udder and milk of animal in normal, subclinical and clinical mastitis cases in Sahiwal cows and Murrah buffaloes have been presented in Table 1. There is a considerable variation in all the quality characteristics or the traits among the healthy, subclinical and clinical mastitis cases in both the group of animals. A difference has been noticed in the values of all the traits in the Sahiwal cows and the Murrah buffaloes, which could be attributed to the differences in compositional aspects and the salt balance of cow and buffalo milk, which has resulted in the variation in the electrochemical properties and other quality parameters of milk in both the species as shown in Table 1.

The data above generated were used for proposed model development. For the ANFIS models development, the MATLAB Toolbox ANFIS interface was used. A total of 7 inputs i.e. milk pH, electrical conductivity, milk yield, dielectric constant, temperature (milk, udder and skin) were used for training (70%, 80%, and 90% of all data) and milk SCC as a output data were entered into the system for model training and testing. Inputs were fuzzified using the FL technique. Rules and an inference system were prepared by the system using the artificial neural networks technique. Each training experiment was conducted ten times with different combinations of the parameters such as epochs, range of influence, Squash Factor, accept ratio and reject ratio. The Sugeno inference method was used here as a mining method. The Sugeno inference method is similar to the Mamdani inference method used in the fuzzy expert systems, except that the output data membership functions can be either constant or linear in the Sugeno method. The membership function of the outputs in the established model was defined as constant.

Performance results of ANFIS models developed with different data partitioning schemes (i.e., 70:30, 80:20 and 90:10) to detect mastitis milk in Sahiwal cows and Murrah buffaloes, are presented in Table 2. The model performance was selected based on minimum average testing error. The least value of testing error, i.e., 0.23 was found with data partitioning scheme as 90:10 with 0.5 range of influence, 1.25 squash factor 0.9 accept ratio, 0.15 reject ratio and 50 epochs in Sahiwal cows whereas in Murrah buffaloes, the least value of testing error was found 0.20 with data partitioning scheme as 90:10 with 0.5 range of influence, 2 squash factor 0.5 accept ratio, 0.15 reject ratio and 50 epochs. Mammadova and Keskin (2015) evaluated two mastitis detection models and reported that ANN model yielded a sensitivity rate of 80%, a specificity rate of 91%, and an error rate of 64%. These values were 55%, 91%, and 35% for the ANFIS model. It showed that error rate in ANN model is higher than the ANFIS. Similar study was done by Cavero et al. (2006) and concluded that Fuzzy logic is a useful tool to develop a detection model for mastitis. A noticeable decrease in the error rate can be made possible by means of more informative parameters. Comparable results were obtained by Krieter et al (2007) but with lower values than reported by Mammadova and Keskin (2015).

Multiple linear regression model performance

The Multiple linear regression models were also developed with the same data partitioning schemes as used for constructing the ANFIS models described in previous section, i.e., 70:30, 80:20 and 90:10. The MLR equations thus developed for Sahiwal cows and Murrah buffaloes are shown in Table 3.

The accuracy of fit was checked by calculating the RMSE between experimental and predicted values of SCC. The lower the value of RMSE the better was the goodness of fit. Generally, a good description of data is considered, on average, with RMSE to be smaller than 7%. The mastitis detection accuracy of MLR models varied between 4.08% and 22.90%.

**ANFIS vis-a-vis conventional regression models**

There are different models available for detecting the mastitis like Conventional Regression Models (MLR, Logistic regression...
Table 2  ANFIS model based on error back propagation to classify healthy and infected Sahiwal cows and Murrah buffaloes with different data partitioning scheme

| Epochs of Influence | Range of Squash Factor | Accept Ratio | Reject Ratio | RMSE % | Range of Influence | Squash Factor | Accept Ratio | Reject Ratio | RMSE % | Range of Influence | Squash Factor | Accept Ratio | Reject Ratio | RMSE % | Range of Influence | Squash Factor | Accept Ratio | Reject Ratio | RMSE % |
|---------------------|------------------------|--------------|--------------|--------|-------------------|--------------|--------------|--------------|--------|-------------------|--------------|--------------|--------------|--------|-------------------|--------------|--------------|--------------|--------|
| 10                  | 0.80                   | 1.00         | 0.50         | 0.15   | 0.84              | 0.90         | 1.00         | 0.10         | 0.15   | 0.83              | 0.50         | 1.25         | 0.50         | 0.15   | 0.51              |
|                     | 0.80                   | 0.90         | 0.50         | 0.10   | 0.25              | 0.50         | 2.00         | 0.50         | 0.15   | 0.42              | 0.90         | 2.00         | 0.50         | 0.15   | 0.35              |
|                     | 0.90                   | 0.20         | 0.50         | 0.15   | 0.36              | 0.50         | 2.50         | 0.50         | 0.15   | 0.37              | 0.50         | 2.00         | 0.10         | 0.15   | 0.47              |
| 50                  | 0.90                   | 0.20         | 0.50         | 0.15   | 0.34              | 0.90         | 2.00         | 0.50         | 0.15   | 0.34              | 0.50         | 1.25         | 0.90         | 0.15   | 0.23              |
|                     | 0.80                   | 0.90         | 0.50         | 0.10   | 0.70              | 0.90         | 1.00         | 0.10         | 0.15   | 0.74              | 0.90         | 2.00         | 0.50         | 0.15   | 0.32              |
|                     | 0.50                   | 0.50         | 0.50         | 0.15   | 0.48              | 0.50         | 2.50         | 0.50         | 0.15   | 0.35              | 0.90         | 2.50         | 0.10         | 0.01   | 0.31              |
| 100                 | 0.90                   | 2.00         | 0.50         | 0.15   | 0.35              | 0.50         | 1.25         | 0.50         | 0.15   | 0.60              | 0.50         | 1.25         | 0.50         | 0.15   | 0.41              |
|                     | 0.90                   | 1.50         | 0.80         | 0.01   | 0.43              | 0.90         | 1.00         | 0.10         | 0.15   | 0.64              | 0.90         | 1.00         | 0.10         | 0.15   | 0.26              |
|                     | 0.80                   | 0.90         | 0.50         | 0.10   | 0.80              | 0.50         | 2.00         | 0.50         | 0.15   | 0.32              | 0.50         | 2.00         | 0.50         | 0.15   | 0.26              |

| Epochs of Influence | Range of Squash Factor | Accept Ratio | Reject Ratio | RMSE % | Range of Influence | Squash Factor | Accept Ratio | Reject Ratio | RMSE % | Range of Influence | Squash Factor | Accept Ratio | Reject Ratio | RMSE % | Range of Influence | Squash Factor | Accept Ratio | Reject Ratio | RMSE % |
|---------------------|------------------------|--------------|--------------|--------|-------------------|--------------|--------------|--------------|--------|-------------------|--------------|--------------|--------------|--------|-------------------|--------------|--------------|--------------|--------|
| 10                  | 0.50                   | 1.25         | 0.50         | 0.15   | 0.28              | 0.50         | 1.25         | 0.50         | 0.15   | 0.25              | 0.50         | 1.25         | 0.50         | 0.15   | 0.24              |
|                     | 0.90                   | 1.25         | 0.50         | 0.15   | 0.23              | 0.90         | 1.25         | 0.50         | 0.15   | 0.24              | 0.70         | 1.25         | 0.50         | 0.15   | 0.23              |
|                     | 0.50                   | 2.00         | 0.50         | 0.15   | 0.28              | 0.70         | 1.25         | 0.50         | 0.15   | 0.22              | 0.50         | 1.25         | 0.80         | 0.15   | 0.24              |
| 50                  | 0.50                   | 1.25         | 0.50         | 0.15   | 0.26              | 0.50         | 1.25         | 0.50         | 0.15   | 0.27              | 0.50         | 1.25         | 0.50         | 0.15   | 0.27              |
|                     | 0.90                   | 1.25         | 0.50         | 0.15   | 0.26              | 0.50         | 1.25         | 0.10         | 0.15   | 0.24              | 0.50         | 1.25         | 0.10         | 0.15   | 0.26              |
|                     | 0.50                   | 2.00         | 0.50         | 0.15   | 0.20              | 0.50         | 1.25         | 0.10         | 0.1   | 0.24              | 0.50         | 2.00         | 0.50         | 0.15   | 0.20              |
| 100                 | 0.50                   | 1.25         | 0.50         | 0.15   | 0.28              | 0.50         | 1.25         | 0.50         | 0.15   | 0.28              | 0.90         | 1.25         | 0.50         | 0.15   | 0.27              |
|                     | 0.90                   | 1.25         | 0.50         | 0.15   | 0.27              | 0.90         | 1.25         | 0.50         | 0.15   | 0.27              | 0.70         | 1.25         | 0.50         | 0.15   | 0.25              |
|                     | 0.50                   | 2.00         | 0.50         | 0.15   | 0.26              | 0.50         | 1.25         | 0.10         | 0.1   | 0.30              | 0.50         | 1.00         | 0.90         | 0.15   | 0.25              |

Table 3  Multiple linear regression equations for Sahiwal cows and Murrah buffaloes

| Data partitioning scheme | MLR Equation | Sahiwal cows |
|--------------------------|--------------|--------------|
| 70:30                    | SCC=0.147pH+3.36EC+0.60UT+0.27MT+0.71ST+0.08MY+0.786DC-129.99 |
| 80:20                    | SCC=1.29pH+3.24EC+1.39UT+0.50MT+1.96ST+0.134MY+0.91DC-118.33 |
| 90:10                    | SCC=2.11pH+4.37EC+1.61UT+0.61MT+2.71ST+0.29MY+0.76DC-139.89 |
| Murrah buffaloes         |              |
| 70:30                    | SCC=0.059pH+5.53EC+0.034UT+0.179MT+0.063ST+0.29MY+0.65DC-73.46 |
| 80:20                    | SCC=0.126pH+5.50EC+0.04UT+0.21MT+0.025ST+0.25MY+0.53DC-61.15 |
| 90:10                    | SCC=0.198pH+5.41EC+0.079UT+0.263MT+0.035ST+0.20MY+0.4433DC-60.25 |

EC= Electrical conductivity, UT= Udder temperature, MT= Milk temperature, ST= skin temperature, MY= Milk yield, DC= Dielectric constant
Table 4 Comparison of developed ANFIS vis-à-vis MLR model for different data partitioning schemes of Sahiwal cows and Murrah buffaloes

| Data Partitioning Scheme | RMSE %  |
|--------------------------|---------|
|                          | ANFIS model | MLR model |
| **Sahiwal cows**        |          |          |
| 70:30                    | 0.34     | 4.88     |
| 80:20                    | 0.32     | 11.39    |
| 90:10                    | 0.23     | 8.38     |
| **Murrah buffaloes**    |          |          |
| 70:30                    | 0.20     | 22.90    |
| 80:20                    | 0.22     | 4.72     |
| 90:10                    | 0.23     | 4.08     |

*The values of RMSE% in ANFIS model are from table 2 etc., ANN, ANFIS, Support Vector Machine (SVM) and others. The comparative performance of ANFIS models vis-à-vis MLR models developed in this paper was made in terms of RMSE on test set and results are presented in (Table 4). The percent root mean square error of ANFIS models in Sahiwal cows varied between 0.23 to 0.84 whereas that of MLR models ranged between 4.88 and 11.39. In case of Murrah buffaloes, percent root mean square error varied between 0.20 to 0.28 whereas that of MLR models ranged between 4.08 and 22.90. Mammadova and Keskin (2013) have also used binary logistic regression model and found that the error rate of logistic regression model was 57% and finally concluded that SVM technique has the potential to perform better than such traditional statistical methods as logistic regression. The above presented results indicate that ANFIS is far better than Conventional Regression Model (MLR).

Conclusions

In this paper, several soft computing models (ANFIS) have been developed and validated to identify healthy vs. mastitis Sahiwal cows and Murrah buffaloes on the basis of Milk pH, electrical conductivity, temperature (udder, milk and skin), milk yield, dielectric constant and milk Somatic cell counts of normal and mastitis milk. The error back propagation training algorithm with Bayesian regularization scheme and several combinations of different values of network parameters was empirically investigated. The performance of ANFIS models was compared to that of classical multiple linear regression models. The comparative analysis of the results thus obtained revealed that ANFIS models was more superior than multiple linear regression models.

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