Detection Of Estrus In Bovine Using Machine Learning

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Abstract— Estrus refers to the reproductive stage of cattle during which ovulation occurs. The day of estrus plays an important role in the reproductive life of a cow. Inseminating cow at perfect time of ovulation was a big deal for farmers. Bovines that undergo Silent Estrus will not show any mounting behaviors or physical signs. So detecting estrus in cows undergoing silent estrus is also a challenging task. The main aim of this study is to propose a simple method to detect the estrus in cow by classifying cows into estrus and non-estrus groups, using machine learning algorithm based on correlating the milk parameters such as fat, pH, SNF, specific gravity, density and the age, amount of milking, frequency of milking and breed of the cow. For estrus cows, milk parameters like pH and fat show high significant change whereas SNF and density shows moderate significant change. The selected parameters are fed into machine learning algorithms like Decision Tree Classifiers. The classification based on the selected parameters specifies higher performance for Decision Tree with accuracy 98%. Thus, Decision Tree classifier is defined as an effective classifier and a simple method to detect estrus in cow by utilizing milk parameters.

Keywords— Estrus, Bovine, fat, pH, Specific Gravity, SNF, Density, Machine learning algorithm.

I. INTRODUCTION

Estrus is said to be reproductive stage of cattle during which ovulation occurs which is also known as heat. The day of estrus plays an important role in the reproductive life of a cow since fertilization of the egg is possible only at this stage. The length of Bovine's estrus cycle is 21 days. The estrus cycle is divided into 4 stages. They are Proestrus (Day: 0-4), Estrus (Day: 4-5), metestrus (Day: 5-8 day) and diestrus (9-21 days). At the state of estrus, the cow ovulates and is ready for insemination. The fertile period of the ovulated egg is very short, only around 18 to 24 hours [11]. The egg will be at its most fertile state immediately following ovulation. So, it is very much necessary for an accurate heat detection.

If the heat detector does not show accurate result, then insemination will not occur at optimal time and failure of AI can occur. It takes more than 3 months to confirm the pregnancy of the inseminated cow. This is why it is so important to be able to identify estrus with maximum potential [12, 13]. The estrus for a normal healthy cow can be identified visually. The signs of estrus are standing to be mounted, mounting other cows, increased nervousness, swollen vulva and clear mucus discharge [26]. Farmers may miss out these signs if they do not notice these signs consciously [7, 8].

Effective heat detection is possible at farms where herd of cow is present. Since the number of herd mates can highly influence heat detection. While small number of cows can be very challenging. Even in herd some will show no interest in riding or being ridden and some cows will undergo silent estrus. Silent estrus is a state where estrus occurs without any physical signs [17, 27]. Farmers use Pressure Sensitive mount detector, tail paint and markers on the tail to detect whether any mounting is occurred or not. But this will not work for cows that undergo silent estrus in small group and cows that do not show interest on riding. Some techniques used to overcome this problem that are available today include ultrasound monitoring of ovary, detection of sex pheromone in excreta [23], P4 estimation in milk [15], measurement of vaginal conductivity using probes [16] and endometrial biopsy [24].

Ayodeji Folorunsho Ajayi et.al., (2020) defines the staging of the estrus cycle and induction of estrus in experimental rodents [24]. Methods like visual assessment of vaginal smear cytology, histological examination of reproductive organs which is invasive, vaginal wall impedance method where a probe is inserted into the vagina for 30 seconds and impedance is measured for which animals in estrus shows high impedance. Another method called urine biochemistry where the urine contains high concentration of fatty acids and high levels of protein and lipids in proestrus and estrus phase.

Mozūraitis et al., (2017), [23] analysed the fecal samples using solid phase micro extraction gas chromatography and found the presence of acetic acid and propionic acid in the headspaces of fecal samples of estrus cows. With low level of acid until a day before ovulation and peaking around 0.5 before ovulation.

Miura et al., (2017), [25] introduced a new method of detecting estrus by monitoring ventral tail base surface

temperature using a wearable wireless sensor. The sensor was attached to the ventral tail base at day 11 and temperature is measured for every 2 minutes throughout the day and highest value was analysed. A substantial change is seen around the time of behavioral estrus.

Nayan, V et al., (2020), [21] designed a dipstick using gold nanoparticles conjugated with a novel antipeptide antibodies against LH. This method is a lateral flow assay that detects the ovulation period by assaying a high level of LH in the urine of buffalo at the time of estrus.

Since these methods will be costlier, time consuming, less accurate and invasive, in this study a simple, noninvasive method for estrus detection using milk parameters utilizing machine learning algorithm is proposed based on correlating the milk parameters [2] such as fat [3], pH [1], SNF [3], specific gravity, density and the age, amount of milking, frequency of milking and breed of the cow. 15 estrus cows and 15 non-estrus cows were included in this study. Among the cows (n=50), 37 (74%) cows were HxF breed and 13 (26%) cows were Jersey breed. The mean age of cows were 9.4 ± 5.225 (mean \pm SD) and majority of cows were in the age group of 3 to 5 years. The milk parameters like fat and SNF were measured using digital milk analyser [9, 10]. pH and temperature of the milk were measured using commercial pH meter (ACETEQ Instruments India Inc.). Specific Gravity of the milk is measured using lactometer. Data like age, amount of milking, frequency of milking and breed of cow were known from the owners of the respective cow. The estrus state of cow is confirmed by a professional veterinary doctor. Machine learning algorithms like decision tree classifier and Naive Bayes classifier are applied for classifying estrus from non-estrus cow based on selected parameters. With the classifier results, Decision tree classifier is defined to be an efficient classifier for describing the estrus stage of cow with higher accuracy.

II. SAMPLES AND METHODS

A. Study design and population

Milk samples collected to determine the relationship of the estrus of cow to the milk properties was assessed on Holstein Friesian (n=37) breed and Jersey breed (n=13) cows reared in Dharmapuri, India. The samples were collected (approx. 50 ml) in a clean and dry container. Estrus cows (n=25) and non-estrus cows (n=25) were assessed. Milking was done in the morning between 5.00 AM to 7.00 AM. Samples were collected for 2 days (25samples/day). All the cows belong to different fields. The state of estrus or non-estrus was analyzed using veterinarian guide, information from cow owner, cow records, heat detector and rectal palpation. Milk parameters were measured within 2-3 hours of milking.

рН

The instrument used of measuring pH is a commercial pH meter that also indicates the temperature. The pH meter used was manufactured by ACETEQ Instruments India Inc. It is a pen type/ pocket model pH & temperature meter with accuracy ± 0.1 and resolution 0.01pH.

Specific Gravity and Density

The instrument used to measure the specific gravity (SG) of the sample is commercial lactometer. The Specific

Gravity was calculated from the lactometer reading. Density is calculated from specific gravity value.

Fat and Solid Non Fat

Fat and Solid Nonfat (SNF) was measured in a Milk Society. The equipment used is a Digital milk analyzer. Before analyzing the milk, it was homogenized using an Ultrasonic Processor, model FCO TU50. The Digital Milk Analyzer used is manufactured by EKOMILK ULTRA with DPS milk analyzer. It shows the value of fat as well as SNF [5].

Other parameters

Variables like age, amount of milking, frequency of milking and breed of cow were known from the information given by the owners. The means values of the parameters measured is given in table 1.

The study samples were divided into the following groups:

Group-I – Estrus cows (n=75)

Group-II – Non-Estrus Cows (n=75)

B. Feature Selection

An analysis was done between the mean and Standard Deviation values of all the listed parameters. From that analysis 5 features were observed showing significant variation during the time of estrus [14, 18]. They are fat [6], SNF, SG, Density and pH. For estrus cows, milk parameters like pH and fat show high significance whereas SNF and density shows moderate significance. pH is negatively correlated to fat (r = -0.4402), SNF (r = -0.2108) and Specific Gravity (r = -0.1238). pH value of estrus cow is significantly lesser then pH of non-estrus cow. SNF and fat value of estrus cow is significantly higher than the values of non-estrus cow. Temperature doesn't show any significant change towards estrus. TABLE LPARAMETERS AND THEIR MEAN AND SD VALUES

SI.NO	PARAMETER	MEAN±SD		
1.	Age (years)	9.4 ± 5.225		
2.	Fat (%)	3.76 ± 0.604		
3.	SNF (%)	9.62 ± 2.814		
4.	Specific Gravity	1.027 ± 0.001		
5.	pН	6.49 ± 0.234		
6.	Amount of milking	12.82 ± 2.154		
	(Litres/day)			
7.	Frequency of	2 ± 0		
	milking (per day)			
8.	Temperature (°C)	25.95 ± 2.468		
9.	Density (kg/m^3)	1027.66		
		±1.721		

C. Classification

Classification of the estrus and non-estrus cow is performed using ensemble tree methods and classifiers. Decision Tree Classifier is a simple and widely used classification technique. It applies a strait forward idea to solve the classification problem. Decision Tree Classifier poses a series of carefully crafted questions about the attributes of the test record. Each time it receive an answer, a follow-up question is asked until a conclusion about the class label of the record is reached [29, 30]. Naive Bayes classifier is based on the simplifying assumption that the attribute values are conditionally independent given target value. Among the various methods of supervised statistical pattern recognition, the Nearest Neighbour rule achieves consistently high performance, without a priori assumptions about the distributions from which the training examples are drawn. It involves a training set of both positive and negative cases. A new sample is classified by calculating the distance to the nearest training case; the sign of that point then determines the classification of the sample. The k-NN classifier extends this idea by taking the k nearest points and assigning the sign of the majority. Gradient boosting falls under the category of boosting methods, which iteratively learn from each of the weak learners to build a strong model. It can optimize classification, regression and ranking. Gradient boosting falls under the category of boosting methods, which iteratively learn from each of the weak learners to build a strong model [31]. The features that are selected are subjected to the classification process for analysis of estrus state. Classifier results are analyzed using the confusion matrix based on the performance parameters. Accuracy, specificity, sensitivity are determined with the true positive, true negative, false positive and false negative values of the confusion matrix. Decision tree classifier is defined to be more efficient for classification with accuracy of 98%.

III. RESULTS

There is a statistical significant correlation between the milk parameters like fat, SNF, SG, pH and Density in estrus and non-estrus groups. Fat shows significant positive correlation for SNF (r = 0.924). Fat is also positively correlated to SG (r = 0.219). pH shows significant negative correlation towards fat (r = -0.44), SNF (r = -0.21) and SG (r = -0.123).Different machine learning models were applied on this value to choose the effective learning model that detects estrus based on these variables. The level of fat in the milk increases during the estrus period. In the same way, SNF and SG also increases at the time of estrus. But the acidity of the milk increases during estrus and so the pH decreases and shows a negative correlation for estrus. The correlation between these parameters towards estrus is given in table 2.

SI.NO	Parameter	Correlation		
1.	Fat	r = 0.46102		
2.	SNF	r = 0.20028		
3.	SG	r = 0.03520		
4.	рН	r = -0.80999		
5.	Density	r = 0.03520		

TABLE II. CORRELATION BETWEEN MILK PARAMETERS AND ESTRUS

The features are trained with decision tree classifier, Logistic Regression, Naïve Bayes classifier, Random forest classifier and Linear SVM. The models are trained, tested and validated using MATLAB software (R2019B). The confusion matrix and ROC curve were obtained. The confusion matrix of Decision tree classifier shown in the figure1 and flowchart is given in figure 2.



Fig.1. Confusion Matrix of Decision tree classifier



Fig.2. Decision Tree Classifier Flowchart

The accuracy, specificity, F1 score, Precision and Recall were calculated from the confusion matrix. The comparison of evaluation metrics for all the 5 models is shown in table 3.

Si. no	Model	Accuracy	Precision	Recall	F1 Score	Specificity
1.	Decision Tree Classifier	0.98	1	0.96	0.98	1
2.	Logistic Regression	0.9	0.91	0.88	0.89	0.92
3.	Naïve Bayes Classifier	0.90	0.97	0.84	0.90	0.96
4.	Linear SVM	0.94	0.97	0.92	0.94	0.97
5.	Random Forest Classifier	0.5	1	0.5	0.66	0

TABLE III. COMPARISON OF EVALUATION PARAMETRIC AMONG MODELS

The accuracy curve is plotted and show in figure 3.



Fig.3 Accuracy of models

IV. DISCUSSION

In this study, we tried to correlate between the milk parameters like fat, SNF, SG, Density and pH and to detect the estrus by predicting using machine learning algorithms. Toledo-Alvarado et al, (2018) described changes in milk characteristics during estrous cycle. Milk composition, particularly fat, protein, and lactose, showed clear differences among the estrous cycle phases [2]. Fat increased by 0.14% from diestrus high-progesterone to estrous phase, whereas protein concomitantly decreased by 0.03%. Lactose appeared to remain relatively constant over diestrus high-progesterone, rising 1 day before the day of estrus followed by a gradual reduction over the subsequent phases. Varij Nayanab et al, (2020) discovered a lateral flow method for detection of LH in urine [21]. A qualitative ELISA for sensing LH was developed based on competitive binding of gold nanoparticles conjugated with epitope peptide and LH towards antipeptide antibodies against LH. They also further explored the detection of LH in buffalo urine using the gold nanoparticles LHP conjugate (AuNP-LHP) in dipstick format [19, 20]. These experiments provided a proof-of-concept towards applicability of LH based sensor for ovulation prediction in the buffaloes. Serap Göncü et.al., (2019) described about the sensor technology that monitors and increase the reproduction system of cattle [16]. Sensor technologies are newly used for cattle production management [22]. These innovative applications are leading to a more efficient cow management in terms of both physiology and sustainability. Efficiency of ultrasonography is 85-95%. Detection of estrus using sensor based fuzzy logic system gives 84.2% sensitivity. Use of nanotechnology for motion sensing in order to detect the restlessness of cow during heat gives accuracy of more than 82% [28].

In this study the proposed method have a simple method which is even non-invasive to detect estrus. The milk parameters that shows significant difference in estrus and non-estrus period are regularly monitored and classified using different machine learning techniques in which decision tree classifier is defined to be accurate and time consuming. This can also pave way for successful artificial insemination. It is also a cost efficient one. In current days, there is already an analyser available which can measure the fat and SNF values. Incorporating a pH and specific gravity measurer in that analyser itself will be quiet more easier. If all these 4 milk parameters are monitored and trained daily, there is a possible easier way of detecting estrus in that analyser itself.

V. CONCLUSION

Detecting estrus and successful impregnating of a cow is the single most important factor on the dairy farm. The Conception Rate of cow should be proportionate to that of being inseminated. This ratio shows the effectiveness of estrus detection in the farm. Till now there are multiple estrus like Visual observation. wavs to detect Computerized systems like Pedometry or Heat Watch which is a type of real time automated estrus detection system, Chin ball markers, Kamar Estrus Mount Detectors, Teaser animals, Progesterone tests, Videotaping [26]. These techniques will be useful while experiencing with herd of cows in dairy farms . The estrus detection in silent estrus and minimal cow dairy farms are quite difficult which may lead to decrease in livestock and farmers income. In order to introduce an effective, automated, no attention by owners, time consuming, non-invasive and general simple method, we are proposing the Decision Tree classifier as the efficient method for detecting estrus by utilizing milk parameters which gives 98% accuracy.

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