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Fuzzy logic is a powerful tool for the automation of milk classification

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ABSTRACT. The demand for the consumption of milk and dairy products by the consumer market is very high. This makes it difficult to analyze the large number of milk samples for quality. In addition to the requirement to consider many quality attributes, there are usually large number of producers, who need daily milk evaluations. The aim of the study was to evaluate the efficiency of fuzzy logic in decision making for the classification of milk. In the fuzzification stage, physical and chemical characteristics of the milk were considered as input linguistic variables. For each linguistic variable, pertinence functions were created, and these were made considering the trapezoidal forms. In the inference stage, rules were established for the association of linguistic variables and output variables (adulterated, inadequate and adequate). To verify the efficiency of the modeled system, 1,000 adulterated, inadequate and adequate milk samples were computationally simulated. Precision was verified when automating decision making in the classification of milk by the fuzzy logic, totaling 100% of correctness. Therefore, the fuzzy system is an efficient tool for the classification of milk and can be used advantageously by professionals in the field in order to reduce human and financial resources.

Keywords: adulteration; computational intelligence; diffuse logic; lactea drink.

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Introduction

Milk is one of the most consumed foods in the world (Altomonte, Salari, Licitra, & Martini, 2018), consequently, it is a constant target of adulteration. Such adulteration typically involves diluting and/or, adding cheap, low-quality and sometimes dangerous products. These adulterations aim to increase volume, mask inferior quality or replace natural substances in milk for economic gain (Nascimento, Santos, Pereira-Filho, & Rocha, 2017).

The high demand for consumption of milk and dairy products has made the consumer market more demanding when it comes to monitoring its quality. Therefore, there is great difficulty for technical professionals to analyze the large number of milk samples as to their quality. In addition to many quality attributes having to be considered, there is usually large number of assisted producers, who need daily milk evaluations.

The possibility of automating the classification of milk according to its quality can facilitate the work of professionals in this area, allowing the reduction of human, financial resources and time for analysis. In this context, it is important to use fuzzy logic in the automation of decision-making, since it translates verbal expressions, usually inaccurate, into numerical values, allowing the computational automation of a specialist's experience (Papadopoulos, Kalivas, & Hatzichristos, 2011; Mardani, Jusoh, & Zavadskas, 2015). In addition, this method allows the expert to infer whether a statement is partially true or partially false (Zadeh, 1965). It produces response systems that are as close as possible to human language and reasoning (Brandao, Gouvea Neto, Anjos, & Bell, 2017).

Computational intelligence techniques like this can contribute to the identification of possible contamination or fraud in milk, as it allows working with both qualitative and quantitative characteristics. It is reported in literature the use of fuzzy logic as a support mechanism for agriculture and other forms for decision making and for more precise actions that assist in the advancement of research in the area of animal production (Alavi, 2013). Therefore, the objective of the study was to evaluate the efficiency of fuzzy logic in decision making for the classification of milk.

Material and methods

The research was conducted at Montes Claros-MG (16° 44′ 13″ S, 43° 51′ 53″ W, 661 m). The logical system for structuring the fuzzy controller was based on three distinct steps: 'Fuzzyfication step', 'Inference step' and 'Defuzzyfication step' (Kaur & Kaur, 2012). In the fuzzyfication stage, linguistic variables were pre-established, using trapezoidal pertinence functions. Thus, the μA(x) pertinence function is defined as a trapezoidal fuzzy number, as shown in the equation below. The values of a, b, c and d were assigned according to the standards recommended by current legislation for milk quality.

$$trapmf(x; a, b, c, d) = max\left(min\left(\frac{x-a}{b-a}, 1, \frac{d-x}{d-c}\right), 0\right) \quad (1)$$

For the configuration of the fuzzy system, the following characteristics were used as input linguistic variables: Fat with low (a = 0, b = 0, c = 2.9, d = 3.0), medium (a = 2, b = 3.0, c = 4.0, d = 4.5) and high (a = 4.0, b = 4.5, c = 7.0, d = 7.0) pertinence functions; Protein with low (a = 0, b = 0, c = 2.8, d = 2.9), medium (a = 2.8, b = 2.9, c = 3.1, d = 3.3) and high (a = 3.1, b = 3.3, c = 5.0, d = 5.0) pertinence functions; Lactose with low (a = 0, b = 0, c = 4.0, d = 4.3), medium (a = 4.0, b = 4.3, c = 4.5, d = 5.0) and high (a = 4.5, b = 5.0, c = 7.0, d = 7.0) pertinence functions; non-fat solids (ESD) with low (a = 0, b = 0, c = 8.0, d = 8.4) and ideal (a = 8.0, b = 8.4, c = 15.0, d = 15.0) pertinence functions; Total solids (EST) with low (a = 0, b = 0, c = 11.0, d = 11.4) and ideal (a = 11.0, b = 11.4, c = 20 , d = 20.0) pertinence functions; Titratable acidity with low (a = 0, b = 0, c = 13.0, d = 13.5), medium (a = 13.5, b = 14.0, c = 18, d = 18.5) and high (a = 18, b = 18.5, c = 30.0, d = 30.0) pertinence functions; Relative density at 15 °C with low (a = 0, b = 0, c = 1.020, d = 1.028), medium (a = 1.020, b = 1.028, c = 1.034, d = 1.040) and high (a = 1.034, b = 1.040, c = 2.000, d = 2.000) pertinence functions; Cryoscopic index with low (a = -1.00, b = -1.00, c = -0.565, d = -0.555), medium (a = -0.565, b = -0.555, c = -0.530 , d = -0.520) and high (a = -0.530, b = -0.520, c = 1.00, d = 1.00) pertinence functions; and alizarol test (binary). As output variables, the following classes were considered: adulterated (a = 0.000, b = 0.000, c = 0.333, d = 0.366), inadequate (a = 0.300, b = 0.333, c = 0.666, d = 0.699) and adequate (a = 0.633, b = 0.666, c = 1,000, d = 1,000). All pertinence functions are shown in Figure 1.

In the inference stage, rules for the association of linguistic variables and subsequent classification were established. The connective 'E' was used in the rules, totaling 5,832 rules (3^6x2^3 combinations). These rules were established based on the classification that each possible combination (rule) would have, taking Brasil into consideration (2011). To perform the Fuzzy inference, the 'Mamdani min' method was used (Mamdani & Assilian, 1975).

For defuzzification, the centroid method was used. All statistical modeling was performed using the FuzzyToolkitUoN package of the R software. To verify the efficiency of the modeled system, 1,000 samples of adulterated milk, 1,000 samples of inadequate milk and 1,000 samples of adequate milk were simulated considering a uniform probability distribution. For this, the runif function of software R was used. In this simulation process, for the appropriate samples, values varying within the ranges recommended by Brasil (2011) (G: 3.01 to 5 g 100 mL; PT: 2.91 to 4.00 g 100 mL; 4.31 to 13.00 g 100 mL; ESD 8.41 to 13.00 g 100 mL, 11.4 to 13.00 g 100 mL; 14.00 at 18.00 g of lactic acid 100 mL; DR: 1.028 to 1.034 g mL; Cryoscopic Index: - 0.530 to - 0.555 °H; Alizarol test: brick red color). For inadequate samples, values were simulated with at least one characteristic outside the limits recommended by Brasil (2011). For all adulterated samples, the absence of brick red color was considered for the alizarol test. Half of the adulterated samples were simulated with the characteristics within the limits recommended by Brasil (2011) and half with at least one characteristic outside these limits. From these 3,000 simulated samples, a confusion table was made to demonstrate the efficiency of the method (percentage of correctness in the classifications). For the best discussion of the results, 25 samples from each class (adulterated, inadequate and adequate) were selected at random for presentation in this article.

Results and discussion

For the 3,000 simulated samples, 100% accuracy was verified in the classification by the Fuzzy system (Table 1).

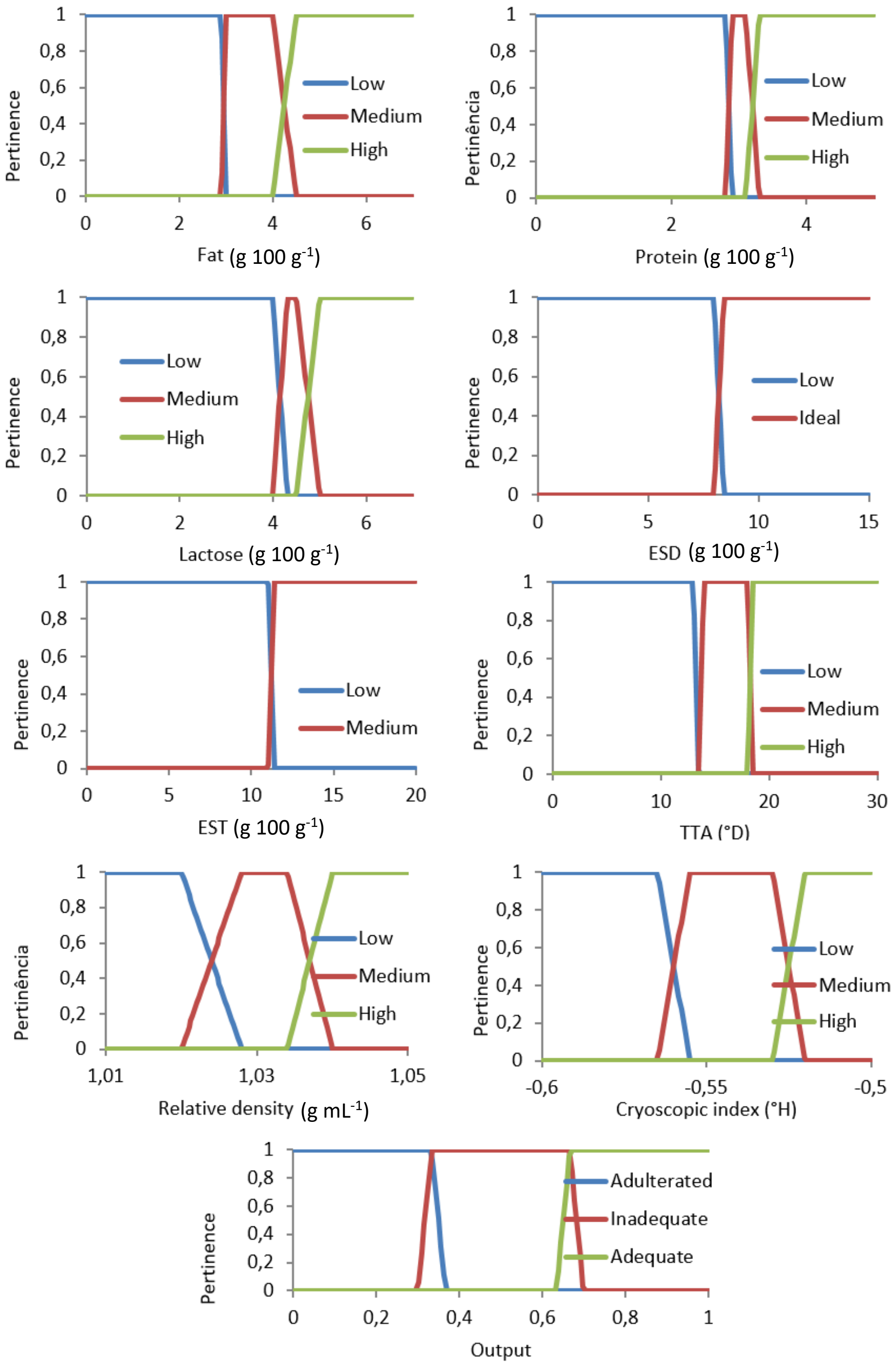

Figure 1. Pertinence functions assumed for linguistic variables using trapezoidal forms. Note: Non-fat solids (ESD); Total solids (EST); Titratable acidity (TTA).

Table 1. Confusion table for the classification of simulated milk samples by the Fuzzy system.

Simulation	Classification		
	Adulterated	Inadequate	Adequate
Adulterated	1000	0	0
Inadequate	0	1000	0
Adequate	0	0	1000
Hit rate	100%		

For the samples of inadequate milk presented in Table 2, it appears that the analyzes of fat, protein, lactose, non-fat solids (ESD), total solids (EST), density, acidity and cryoscopic index were within the standard established by current legislation. However, all samples (n = 25 100%) showed adulterations in the Alizarol test. In this test it is important that the result is the brick red color of the sample (negative test result), which was identified with a value of 2. The value 1 indicates that the milk is inadequate. Thus, even with milk showing ideal values for the other characteristics, it was classified as inadequate due to the Alizarol test, confirming the evidence of the decision making made by the appropriate classification of the Fuzzy logic.

As for the model tested for the analysis of adulterated milk, it was found that only the fat content showed permitted values. By the analysis of non-fat solids (ESD), four samples (2, 4, 10 and 20), or 16% of the total, were not in the standard established by current legislation (Table 3). For protein content, samples 1, 3, 5, 19 and 23 showed inadequate values. For the concentration of lactose (1, 6, 7, 14 and 24) and total solids (EST; 11, 17, 18, 21 and 25), five samples (20%) of each, respectively, presented unsatisfactory values. As for density (9, 13 and 16) and acidity (4, 12 and 21), three samples (12%) from each analysis showed values outside of what is allowed by the legislation in force. For the cryoscopic index, samples 5, 8, 14, 15 and 22 do not meet the established standards (Table 3). All 25 samples, shown in Table 3, were classified as adulterated by the fuzzy logic.

As for the system modeled with the appropriate milk samples, all showed adequate values of protein, lactose, fat, non-fat solids (ESD), total solids (EST), acidity, density, cryoscopic index and Alizarol test (Table 4). All samples were classified as adequate by the fuzzy logic.

The relevance shown in Table 4 of the first samples (1 to 8) is less than that of the last ones for the group of adequate milk. This happened possibly due to the poorer quality of the first milk samples compared to the others. In this context, there is an association between the relevance value of the analyzed samples and the quality of milk, which suggests the use of this criterion as a bonus for producers.

Many types of fraud in fluid milk are reported in literature, with the addition of water and whey as the most frequent, with the main objective of increasing the produced volume (Zocche et al., 2002). But other types of fraud are also reported, such as the addition of acidity neutralizers, density replenishers, antimicrobial substances, as well as unusual substances such as physiological serum and glucose serum (Carvalho et al., 2015).

For the class of inadequate milk samples (Table 2), it was observed that all 25 samples had different values for the Alizarol test than the required by Brasil (2011), that is, they had positive results. In this case, instability to Alizarol could be associated with microbiological acidity due to incorrect handling from milking to storage or because it is a non-acid unstable milk (Sezer et al., 2018).

Table 2. Efficiency of the Fuzzy system for 25 simulated milk samples with 'inadequate' classification.

Sample	Simulated variables									Pertinences		
	Fat	Protein	Lactose	ESD	EST	TTA	Density	CI	Alizarol	Inadequate	Adulterated	Adequate
1	4.992	3.197	5.869	10.868	11.933	14.598	1.032	-0.534	1	51,257	0	0
2	4.37	3.769	4.736	10.211	12.83	15.617	1.029	-0.534	1	52,628	0	0
3	3.626	3.194	5.054	9.928	11.799	15.794	1.03	-0.532	1	52,637	0	0
4	3.534	3.92	4.809	12.939	11.719	17.306	1.03	-0.534	1	61,866	0	0
5	4.313	3.79	4.482	11.121	12.761	15.975	1.03	-0.534	1	62,753	0	0
6	3.915	3.817	4.814	12.224	12.645	15.159	1.032	-0.545	1	62,972	0	0
7	4.724	2.932	4.668	11.539	12.924	14.193	1.033	-0.543	1	66,283	0	0
8	3.368	3.238	5.418	9.172	11.952	17.356	1.031	-0.546	1	69,207	0	0
9	3.929	3.306	4.857	12.202	12.834	16.384	1.033	-0.54	1	71,545	0	0
10	3.585	3.246	4.561	12.818	11.796	17.048	1.032	-0.55	1	73,180	0	0
11	3.739	3.737	4.876	11.664	12.42	16.206	1.033	-0.55	1	75,379	0	0
12	4.007	3.407	4.593	11.478	12.882	14.361	1.03	-0.547	1	81,324	0	0
13	4.738	3.768	4.586	8.793	12.516	14.002	1.03	-0.542	1	82,713	0	0
14	4.067	3.977	5.188	10.911	12.705	14.284	1.03	-0.539	1	86,475	0	0
15	4.061	3.953	5.155	10.885	12.123	15.068	1.029	-0.546	1	87,774	0	0
16	4.449	3.961	4.332	12.265	11.57	16.764	1.033	-0.545	1	89,805	0	0
17	4.573	3.461	4.542	8.5	11.668	17.455	1.028	-0.535	1	91,481	0	0
18	3.265	3.781	5.422	10.775	12.44	16.798	1.033	-0.554	1	100	0	0
19	3.232	3.344	5.649	9.748	12.799	14.717	1.028	-0.535	1	100	0	0
20	3.432	3.363	5.052	12.691	12.823	17.789	1.033	-0.545	1	100	0	0
21	3.159	3.832	4.369	8.782	11.807	14.814	1.031	-0.543	1	100	0	0
22	3.497	3.739	5.314	12.024	12.429	15.753	1.028	-0.545	1	100	0	0
23	3.034	3.056	5.714	9.991	12.871	15.713	1.029	-0.549	1	100	0	0
24	4.634	3.08	5.386	9.443	12.529	14.208	1.031	-0.535	1	100	0	0
25	3.565	2.929	5.281	12.764	11.625	17.404	1.033	-0.532	1	100	0	0

Note: Non-fat solids (ESD); Total solids (EST); Titratable acidity (TTA); Cryoscopic index (IC).

Table 3. Efficiency of the Fuzzy system for 25 simulated milk samples with 'adulterated' classification.

Sample	Simulated variables									Pertinences		
	Fat	Protein	Lactose	ESD	EST	TTA	Density	CI	Alizarol	Inadequate	Adulterated	Adequate
1	4.231	2.453	4.222	12.408	12.447	15.063	1.031	-0.544	2	0	53.764	0
2	3.134	3.121	4.73	3.183	12.502	15.135	1.028	-0.554	2	0	53.886	0
3	4.318	1.99	5.498	12.395	12.466	16.097	1.029	-0.538	2	0	63.67	0
4	4.592	3.808	5.33	3.667	11.834	13.82	1.033	-0.536	2	0	64.144	0
5	4.626	2.186	5.459	10.232	11.56	17.756	1.029	-0.526	2	0	64.172	0
6	4.174	3.503	3.639	9.049	12.056	16.262	1.028	-0.545	2	0	65.011	0
7	4.143	3.64	3.004	12.747	12.505	16.266	1.028	-0.55	2	0	71.301	0
8	4.369	3.151	5.548	10.001	12.391	16.389	1.033	-0.566	2	0	73.928	0
9	4.123	2.984	5.037	9.944	11.927	14.192	1.041	-0.553	2	0	75.342	0
10	4.508	3.038	4.907	4.001	11.538	17.145	1.033	-0.542	2	0	81.403	0
11	3.633	3.136	5.83	11.794	9.468	16.46	1.034	-0.54	2	0	81.542	0
12	4.426	3.376	5.856	8.67	12.555	12.657	1.029	-0.538	2	0	85.375	0
13	4.596	3.545	4.94	11.999	11.955	14.397	1.013	-0.545	2	0	88.042	0
14	3.425	3.098	3.42	11.296	11.036	14.265	1.029	-0.571	2	0	100	0
15	3.445	3.402	5.685	11.407	12.785	14.16	1.031	-0.518	2	0	100	0
16	3.457	2.979	5.894	9.041	12.567	14.4	1.015	-0.534	2	0	100	0
17	3.158	3.483	5.53	10.644	10.522	16.833	1.033	-0.533	2	0	100	0
18	3.749	3.85	5.693	12.224	9.614	15.039	1.031	-0.552	2	0	100	0
19	4.85	2.319	5.024	11.776	12.324	17.794	1.029	-0.531	2	0	100	0
20	4.624	2.96	4.463	3.797	12.962	15.632	1.031	-0.543	2	0	100	0
21	3.657	2.955	5.322	9.381	10.756	11.446	1.032	-0.532	2	0	100	0
22	3.09	3.452	5.783	8.721	12.735	15.124	1.03	-0.592	2	0	100	0
23	4.619	2.386	4.346	12.498	11.683	16.704	1.031	-0.538	2	0	100	0
24	4.685	3.354	3.128	9816	11.852	17.403	1.03	-0.541	2	0	100	0
25	4.538	3.693	5.646	8.865	9.615	15.969	1.031	-0.53	2	0	100	0

Note: Non-fat solids (ESD); Total solids (EST); Titratable acidity (TTA); Cryoscopic index (CI).

Table 4. Efficiency of the Fuzzy system for 25 simulated milk samples with 'adequate' classification.

Sample	Simulated variables									Pertinences		
	Fat	Protein	Lactose	ESD	EST	TTA	Density	CI	Alizarol	Adulterated	Inadequate	Adequate
1	4.082	3.952	5.845	12.327	11.637	14.546	1.030	-0.534	2	0	0	50.201
2	4.248	3.101	5.318	11.650	12.161	16.258	1.030	-0.553	2	0	0	50.261
3	4.252	3.291	5.123	10.447	12.692	17.422	1.033	-0.532	2	0	0	50.552
4	4.263	3.169	4.857	12.667	12.413	14.408	1.028	-0.530	2	0	0	52.722
5	4.265	3.886	4.727	10.724	12.998	15.384	1.030	-0.532	2	0	0	53.141
6	4.511	3.191	5.597	10.608	12.156	17.353	1.032	-0.539	2	0	0	54.417
7	4.227	3.273	4.650	12.506	12.945	16.931	1.029	-0.547	2	0	0	54.430
8	3.321	3.062	4.724	8.613	11.626	15.614	1.030	-0.552	2	0	0	55.073
9	4.838	2.934	4.615	12.373	11.546	16.964	1.033	-0.539	2	0	0	76.989
10	4.065	3.033	4.614	12.826	12.025	16.179	1.030	-0.536	2	0	0	77.118
11	3.091	3.143	4.904	11.669	11.610	17.665	1.032	-0.539	2	0	0	78.434
12	4.102	3.656	5.577	12.352	11.495	14.828	1.031	-0.545	2	0	0	79.525
13	4.671	3.579	4.914	11.857	11.541	15.210	1.030	-0.538	2	0	0	82.965
14	3.619	3.298	4.578	10.469	11.670	17.167	1.030	-0.541	2	0	0	84.258
15	3.217	3.269	4.995	10.663	12.479	15.520	1.031	-0.530	2	0	0	84.853
16	4.070	3.363	4.334	11.412	11.709	15.418	1.029	-0.543	2	0	0	85.882
17	4.060	2.976	5.241	11.466	12.869	17.250	1.030	-0.536	2	0	0	87.844
18	3.436	3.276	4.939	12.086	11.538	14.142	1.032	-0.544	2	0	0	87.874
19	3.298	3.949	5.922	10.890	12.315	17.861	1.030	-0.539	2	0	0	100.000
20	3.452	3.765	5.524	10.359	11.743	17.462	1.029	-0.547	2	0	0	100.000
21	4.819	3.452	5.272	10.989	12.014	16.220	1.033	-0.539	2	0	0	100.000
22	4.516	3.790	5.211	8.515	12.310	17.180	1.033	-0.554	2	0	0	100.000
23	4.724	3.672	4.427	12.196	12.624	15.103	1.028	-0.554	2	0	0	100.000
24	4.573	3.029	5.677	12.484	12.368	16.105	1.028	-0.531	2	0	0	100.000
25	3.500	3.788	4.436	12.294	11.947	16.850	1.031	-0.544	2	0	0	100.000

Note: Non-fat solids (ESD); Total solids (EST); Titratable acidity (TTA); Cryoscopic index (CI).

When analyzing the samples of adulterated milk (Table 3), it was noted that sample 4 had an ESD value lower than recommended, a fact that would associate it with the most common fraud in the dairy market, the addition of water. In this sample, the observed TTA values are also below the minimum recommended by the legislation, which leads to infer that this milk could have suffered the addition of neutralizers such as sodium hydroxide and, or, bicarbonate, in order to mask bacterial proliferation or even inadequate milk management.

In sample 9, the density value is higher than that recommended by the legislation in force, suggesting that this milk could have been the subject of fraud by skimming or adding constituents (Lu et al., 2017). Regarding the change in density, it appears that, if milk is fraudulently added to water, there will be a reduction in the value of this variable. However, this is not a conclusive test to detect watering, as a double fraud, such as skimming and water addition, for example, can keep the density of milk within the values recommended by law (Souza, Silva, Leotério, Paim, & Lavorante, 2014).

Milk can present changes in the lactose content, and this factor represents a reduction in the specific weight and the freezing point of the milk, producing effects that are like the fraud by adding water (Rodrigues Júnior et al., 2016). In sample 14, lactose and CI values were lower than the reference values. One way to rule out suspected fraud is to determine non-fat solids (ESD) and total solids (EST). If these parameters are within the standard established by the legislation, it is confirmed, then, that it is only a milk with low nutritional value. However, when analyzing the EST of the sample, it was noted that it was below the recommended value, confirming that this milk could have been the object of fraud by watering.

Regarding the samples of the adequate group (Table 4), it was observed that all of them had values within the reference range for milk considered to be of good quality, and samples with defuzzyfication values, whose pertinence was equal to 100. It would represent those that contained all the characteristics simultaneously closer to what is considered good quality milk.

The high fat content in milk is considered as a bonus parameter for the producer, since it is a milk of greater nutritional value and a reference for the industry in the manufacture of butter (Rani, Sharma, Arora, Lal, & Kumar, 2015).

It is important to have strategies that detect and thus curb fraud in the dairy sector and improve agricultural performance. In the literature, uses of fuzzy logic are cited as a support mechanism for agriculture. In the studies by Djekic, Smigic, Glavan, Miocinovic, and Tomasevic (2018), Ma, Fan, Li, and Tanga (2018) and Oliveira, Amendola, and Nääs (2005), the authors proved the effectiveness of Fuzzy logic when used to improve the ambience, animal and milk production.

In recent years, fuzzy logic has been one of the artificial intelligence methods used to solve problems that are eliminated from quality assessment situations that consist of cases of uncertainty. The fuzzy logic theory has a more flexible structure than the classic logic theory, as it describes the events with a degree of precision that is between '0' and '1' pointed to the object. The decision support system is based on fuzzy logic, which offers people a more realistic and objective perspective in decision making (Akilli, Atil, & Kesenkaş, 2014).

Mol and Woldt (2001) used a fuzzy logic model to classify mastitis alerts in a set of cows milked in an automatic milking system. The authors observed that the number of detected cases decreased slightly after classification with the Fuzzy logic and the number of false-positive alerts decreased considerably. Based on the findings, the classification by a diffuse logical model proved to be very useful to increase the applicability of automated monitoring in the status of cows.

It appears that fuzzy logic has also been used in the development of products and systems, in addition to the control of industrial processes, electronic entertainment, diagnostic systems, domestic applications and other specialized systems. In the study by Sami, Shiekhdavoodi, Almassi, and Marzban (2013), the authors assessed sustainability on agricultural farms; accordingly, a model based on the fuzzy inference system was developed. The results of the analysis of the developed model proved that it is satisfactory in terms of complexity for sustainability in the agricultural sector, since the model based on fuzzy logic has the advantage of working with linguistics and uncertain data (Carneiro et al., 2019).

Akgül, Akgül, and Doğan (2014) used the Mamdani method, with the affiliation function values determined by the average weight, using three trapezoidal areas of affiliation functions created to evaluate the completion of fermentation with a pH of 4.6 in the industrial production of kefir. In conventional control systems, the pH value can be found by the experimental method. However, when using fuzzy logic, one can obtain an optimization of the system found, comparing the numerical values obtained with pH values that should be. Eventually, to reach the desired pH value of 4.6 in the production of kefir, with the use of fuzzy logic, people's workload will decrease, and business productivity may be increased. In this case, both cost and time can be saved.

Xie, Ni, and Su (2017), studying feedlot systems, temperature, humidity and air quality for pig breeding, found that these factors are important for the health and productivity of animals. In this context, the fuzzy comprehensive evaluation (FCE) theory was adopted for the multifactorial assessment of environmental quality in two systems of commercial pig feedlots using real measurement data. The authors found that the FCE method can significantly increase sensitivity and perform an effective and integrative assessment. It can be used as part of environmental control and alert systems for managing the pig building environment to improve livestock production and welfare.

Perrot et al. (2006) carried out a review and observed that fuzzy logic is used in food applications to capture and formalize the descriptive sensory evaluation performed by a quality team in studies that developed an indirect measure of the properties of a food product, in addition to controlling food processes.

Akilli et al. (2014) developed a decision support system based on fuzzy logic that aimed to classify the quality of raw milk samples. The input variables of the system were the bacterial count, somatic cell count and the values for the amount of protein in the milk samples. The output variables of the fuzzy logic were designed by measuring the quality value of raw milk and calculating the success of the analysis. The authors realized that the results were compared with the experts' decisions and, due to the comparison, it was found that the system had an 80% success rate.

Thus, it appears that fuzzy logic has good efficacy in different studies aimed at improving the agricultural, food and dairy systems. In the dairy system, the number of samples, the number of variables to be analyzed, the frequency of carrying out the analysis, and the interpretation of the results are factors that can make it difficult for the analyst to make decisions regarding each batch of milk. The fuzzy logic proved to be efficient for decision making in this work, allowing simultaneous qualitative analysis of the physical-chemical characteristics in the classification of milk. In this context, it allows a fast and efficient classification of milk, optimizing the process in the entire dairy market.

Conclusion

There is precision in the automation of decision making regarding the classification of milk through fuzzy logic, enabling the optimization of time, financial and human resources in dairy, farms and cooperatives.

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