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RESEARCH ARTICLE

Evaluation of Microbiological Properties in Kefir Production with Fuzzy Logic-Based Decision Support System

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Abstract

Parallel to rising consumer interest in functional foods, attention to probiotic and natural-content products such as kefir has significantly expanded in recent years. As in all instruments related to food production, the aim in the kefir production process is to obtain a high-quality product, and to ensure the sustainability of production in a healthy manner. In this study, the aim is to develop a fuzzy logic-based decision support system for the quality evaluation of kefir samples categorized into somatic cell and fat (low/high) measurement groups. For this purpose, the system inputs were determined as incubation temperature, incubation time, storage time, total bacterial count, and pH. In the model output, kefir quality indices were calculated for each observation, and quality classes were obtained. In the comparative quality evaluations between the system and expert decisions, the fuzzy logic-based decision support system was found to have achieved a success rate of 93.75%. In addition, the Chi-square statistic ($\chi^2 = 110.667$) and Kappa statistic ($Kappa = 0.901, s_x = 0.048$) regarding the decisions made by both the expert and the system were found to be statistically significant (P<0.05). The results indicate that fuzzy logic can be effectively used as a decision support tool in the quality evaluation of kefir samples.

Keywords: Classification, Decision support system, Fuzzy logic, Kefir, Quality

INTRODUCTION

Kefir, a fermented milk beverage of Caucasian origin, has been gaining increasing importance in the food industry owing to its rich composition of probiotic microorganisms and its potential health benefits. It is known that various parameters are effective in the evaluation of kefir quality [1]. To obtain a high-quality kefir, the fermentation process must be carried out under optimal conditions, while maintaining the balance and diversity of microorganisms working in symbiosis [2].

In line with current technological advancements, literature show that in addition to classical methods, the use of artificial intelligence-based approaches in the quality evaluation of food products through various microbiological and physicochemical parameters has been increasingly adopted. The sole use of either subjective or objective methods in food quality evaluations may prove insufficient, particularly under conditions of uncertainty. In addition to measurable physical parameters, the integration of linguistic data based on expert opinion into the decision-making process provides a contribution to quality assessment procedures [3,4]. At this point, the fuzzy logic approach, which contributes to the processing of both quantitative and qualitative data, is regarded as an effective and powerful tool for dealing with uncertainty in measurements and the lack of precision in expert evaluations [5].

Scientific studies employing fuzzy logic-based methods in food quality assessment have demonstrated that it is possible to integrate numerical measurements and expert judgments within a common decision-making framework under conditions characterized by uncertainty and measurement errors. In the dairy industry, microbiological test outputs obtained from bulk tank milk have been transformed into linguistic variables through membership functions, and compound indicators related to milking practices and herd quality have been derived by means of inference using rule bases (e.g., Mamdani or Takagi-Sugeno-Kang) [6]. In sensory evaluation, panel scores have been integrated through fuzzification and rule-based/TSK modeling, allowing overall acceptability and product rankings to be calculated more consistently; this approach has been successfully applied to pistachio shell marmalade, various tea samples, and breads enriched with apple pomace [7-9]. In the context of packaging and storage, multi-criteria inputs such as modified atmospheric conditions, storage duration, and sensory descriptors have been synthesized within a fuzzy inference engine to perform suitability evaluations for various fruits [10]. In industrial quality control, product attributes that could not be precisely defined by sharp boundaries have been represented through knowledge-based fuzzy systems, enabling robust decision-making even in the absence of strict thresholds [11]. Furthermore, by means of hybrid designs that consider both subjective and objective criteria, the effects of different oil types and frying methods on the quality of potato slices have been evaluated through the integration of textual/sensory data and instrumental measurements within the same inference structure; similarly, the expression of expert cupping criteria for specialty coffee beans in fuzzy sets has provided consistent quality ratings [12,13].

The approaches and applied studies reported in the literature provide both a theoretical and practical foundation for the development of a fuzzy decision support system capable of performing holistic classification under uncertainty, specifically in the context of kefir. In the present study, measurable physical and microbiological indicators were integrated with expert opinions within a single inference architecture, and the suitability of the developed fuzzy logic-based system for reliably and consistently classifying kefir quality under uncertain conditions was examined. The hypothesis was tested that the classifications of the proposed fuzzy logic-based system after defuzzification would exhibit a statistically significant degree of agreement with expert evaluations. This study aimed to develop a fuzzy logic–based decision support system to evaluate the quality of kefir samples produced from raw milk with varying somatic cell counts and fat content. The analyses conducted within the scope of this research were structured into two main phases. Throughout the study, a methodological workflow was employed that integrated both experimental procedures and fuzzy logic modeling, ensuring a systematic and comprehensive approach to quality assessment. This article is organized into four main sections following the introduction. In the second section, the materials and methods of the research are explained in detail; the data collection process, the design of the fuzzy system, and the technical details related to fuzzy rules are presented. The third section includes the application findings and results of the developed system. In the fourth section, the aforementioned results are discussed in comparison with expert evaluations, and the performance and limitations of the system are assessed.

Material and Methods

Ethical Statement

As no procedures were carried out on animals in this study, approval from the Local Ethics Committee for Animal Experiments was not required.

Study Design

Milk samples used in kefir production were obtained from a private dairy farm in Kırşehir province. Within the scope of the research, analyses related to the determination of milk components and somatic cell counts were conducted in the laboratories of the Department of Animal Science, Faculty of Agriculture, Kırşehir Ahi Evran University. Kefir production and microbiological analyses of the kefir samples were carried out in the Agricultural Biotechnology laboratories of the same faculty.

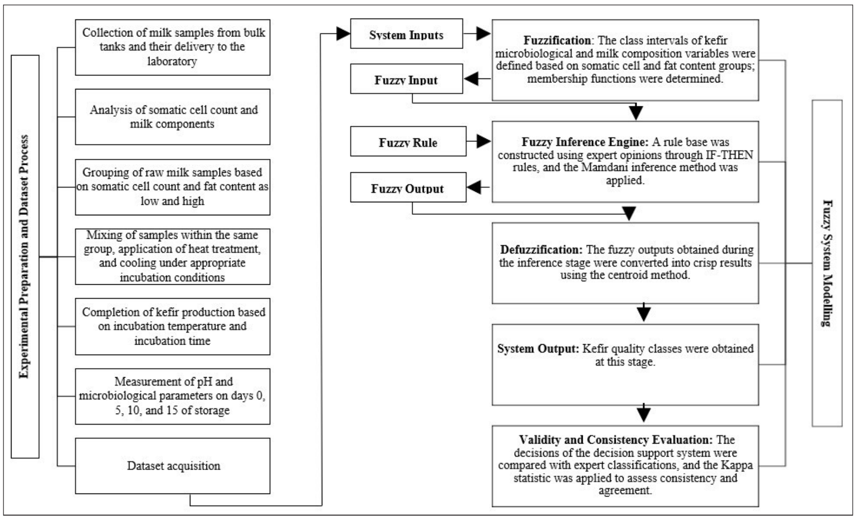

Fig 1. Flowchart of the research process and decision support system

The analyses conducted within the scope of this study were structured in two main phases. The methodological workflow applied throughout the research, including both experimental procedures and fuzzy logic modeling, is presented in *Fig. 1*. During the first phase, milk samples were obtained and transferred to the laboratory under strictly controlled hygienic conditions. Subsequently, analyses pertaining to milk components and somatic cell counts were performed, alongside microbiological examinations of the kefir samples. In the second phase, applications related to fuzzy system modeling were carried out, and the design of the decision support system was optimized to enhance analytical robustness.

In the operational process of the fuzzy logic-based decision support system, milk samples were initially classified into two groups, low and high, based on somatic cell count and milk fat content. In the subsequent stage, the milk samples within each group were separately coded and converted into kefir in accordance with the procedures outlined in the methodology section. The measurement values related to the input variables were obtained through chemical and microbiological analyses. In the functioning of the fuzzy system, five input variables were considered, particularly for the formulation of "if-then" rules to ensure successful application. During the process of converting the input variables representing the kefir samples into fuzzy numbers, class boundaries were established based on the Turkish Codex on Raw Milk and Heat-Treated Drinking Milk (Communiqué No: 2019/12), expert opinions, and a detailed literature review. The data were restructured through rule base connections created in accordance with fuzzy logic terminology and the architecture of the decision support system. In this way, a fuzzy system was developed by using the microbiological characteristics of the kefir samples included in the dataset. The system inputs were defined as "Incubation Time," "Incubation Temperature," "Storage Time," "pH," and "Total Aerobic Mesophilic Bacteria Count (TBC)." The system output was designated as "Kefir Quality Class."

Milk Sample Collection

Prior to sampling, milk in the bulk tanks was stirred to ensure homogeneity. Following this process, 1000 mL of milk was transferred into sterile tubes without the addition of any preservatives. Adhesive labels indicating the farm identification number and the sampling date were applied to each tube. The collected milk samples were placed between ice packs under hygienic conditions and transported in sealed containers to the laboratory of the Department of Animal Science, Faculty of Agriculture, Kırşehir Ahi Evran University. Upon arrival, the samples were stored at approximately +4°C, and all analyses were completed within five hours.

Milk Composition and Somatic Cell Count (SCC) Analyses

Within the scope of milk composition analysis, fat and solids-not-fat (SNF) contents were determined using a Funke Gerber LactoStar (3510) milk analyzer, which is located in the laboratory of the Department of Animal Science, Faculty of Agriculture, Kırşehir Ahi Evran University. For the determination of somatic cell count (SCC), milk samples were analyzed using a DeLaval brand cell counter in the same laboratory. Based on the results obtained, milk samples were classified into four groups according to somatic cell count (low/high) and fat content (low/high). The microbiological and chemical quality parameters of raw milk, as specified in the Turkish Food Codex Communiqué on Raw Milk and Heat-Treated Drinking Milk (Communiqué No: 2019/12), were used as a reference during the grouping of milk samples. The values used in the grouping stage are given in *Table 1* [14].

Table 1. *Class limits for somatic cell count and fat measurements*

Class Limits	Low	High
Somatic Cell Count (SCC) (cells/mL)	x<400.000	x≥400.000
Fat (%)	x<3.5	≥3.5

Kefir Production and Microbiological Analyses

Milk samples, previously grouped according to SCC and fat content levels (low/high), were homogenized within each group and subjected to heat treatment at 95°C for 3 min. After heat treatment, the milk samples were cooled to 25 degrees Celsius to be used for kefir production. Kefir production was carried out according to the traditional method, and each group was inoculated with 3% kefir grains. In accordance with the experimental design, two incubation temperatures "24°C and 28°C" were applied. For each temperature condition, two different incubation durations were implemented: the first group was incubated for 19 h, and the second group for 23 h. As a result of this grouping procedure, a total of 16 distinct kefir samples were obtained. PH values and total bacterial counts were measured on days 0, 5, 10, and 15 of storage. The enumeration of total aerobic mesophilic bacteria was performed using the pour plate method on Plate Count Agar (PCA; Darmstadt, Germany), followed by incubation at 30°C for 48 h. Colony-forming units were then counted [15]. pH measurements were conducted using a digital pH meter (Hanna HI 2211c pH/ORP Meter) with a sensitivity of 0.01 units [16].

Fuzzy Logic Based Decision Support System

The operation of fuzzy systems is based on interval mathematics and fuzzy logic, utilizing linguistic variables derived from membership functions as inputs in the decision-making process [17]. These input variables are matched through the antecedents of linguistic IF-THEN rules. The output of each rule is then converted into a numerical value by applying a defuzzification method based on the membership degrees of the relevant variables. The fuzzy inference system refers to the process of systematically mapping a comprehensive set of linguistic variables into output values through a rule-based framework. *Fig. 1* illustrates the operational structure of the fuzzy inference system. As shown in the diagram, the system architecture comprises four fundamental components: fuzzification, the fuzzy inference engine, the fuzzy rule base, and defuzzification.

In the fuzzification phase, converting crisp variables representing the quality evaluation of kefir samples into fuzzy inputs is carried out. During this process, the shape of the membership functions for the input variables, their positions on the x-axis, and the number of subsets is determined. By assigning a membership function ranging between 0 and 1 to each input variable, the transformation into linguistic variables is achieved [18]. A membership function essentially consists of five conceptual components: the core (elements with a membership degree of 1), the support (elements with membership degrees greater than 0), the boundary regions (elements with membership degrees between 0 and 1 surrounding the core), the crossover point (elements with a membership degree of 0.5), and the height (the maximum membership degree attained by any element of the set). In this study, triangular, trapezoidal, and S-shaped functions were used by considering the structure of the input variables and the variation in quality class intervals. The triangular membership function is represented by three parameters: the interval between parameters a and c constitutes the support, and parameter b represents the core of the membership function [17]. Its mathematical representation is given in Equation 1.

$$\mu_A(x;a,b,c)=\begin{cases} a\le x\le b, & (x-a)/(b-a)\\ b\le x\le c, & (c-x)/(c-b)\\ x>c \quad or \quad x<a, & 0\end{cases} \qquad [1]$$

The trapezoidal membership function is expressed by the function given in Equation 2, where the intervals between parameters $a-b$ and $c-d$ define the boundaries of the function, whereas the interval between parameters $b-c$ constitutes the core of the function [19].

$$\mu_A(x;a,b,c,d)=\begin{cases} a\le x\le b, & (x-a)/(b-c)\\ b\le x\le c, & 1\\ c\le x\le d, & (d-x)/(d-c)\\ x>d \text{ and } x<a, & 0\end{cases} \qquad [2]$$

The S-shaped membership function is represented by the mathematical expression given in Equation 3 for an increasing trend and in Equation 4 for a decreasing trend, through the parameters a_1, a_2, and a_3 [19].

$$\mu_A(x;a_1,a_2,a_3)=\begin{cases} -\infty < x < a_1 & 0\\ a_1\le x\le a_2 & 2[(x-a_1)/(a_3-a_1)]^2\\ [(a_2 < x\le a_3)] & 1-2[(x-a_2)/(a_3-a_1)]^2\\ a_3 < x < +\infty & 1\end{cases} \qquad [3]$$

$$\mu_A(x;a_1,a_2,a_3)=\begin{cases} -\infty < x < a_1 & 1\\ a_1\le x\le a_2 & 1-2[(x-a_1)/(a_3-a_1)]^2\\ (a_2 < x\le a_3) & 2[(x-a_2)/(a_3-a_1)]^2\\ a_3 < x < +\infty & 0\end{cases} \qquad [4]$$

In the inference phase, fuzzy information is expressed through IF-THEN rules using the logical connectors AND and OR. The process of deriving new information from the knowledge stored in the system's knowledge base is referred to as inference. In this process, the fuzzy sets in the knowledge base and the input and output variables in the model are defined, and the decision-making logic operates in conjunction. The rules were prepared based on expert knowledge and a detailed literature review, taking into account the number of subsets of the input

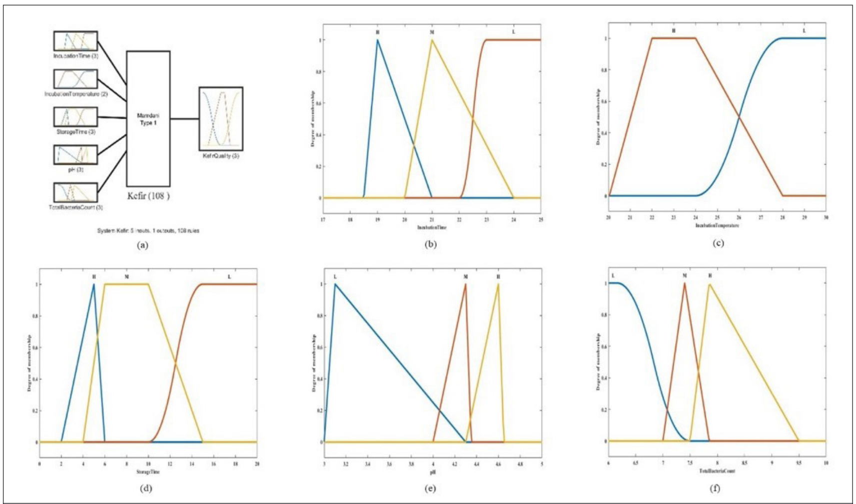

Fig 2. Designed fuzzy system (a), Incubation time membership function (b), Incubation temperature membership function (c), Storage time membership function (d), pH membership function (e) and Total bacteria count membership function (f)

variables. In this study, the 'Mamdani' inference method was used [20,21]. The rule structures of the Mamdani method are presented in Equation 5, where X_1 and X_2 represent input variables, and Z_1 and Z_2 represent output variables. A_1, B_1, A_2, and B_2 denote membership functions, while C_1 and C_2 indicate the fuzzy result sets at the end of each rule [22].

$$\begin{aligned} &If\ X_1 = A1\ and\ X_2 = B1\ then\ Z_1 = C_1 \\ &If\ X_1 = A2\ or\ X_2 = B2\ then\ Z_2 = C_2 \end{aligned} \quad [5]$$

In the defuzzification phase, converting the fuzzy information obtained during the inference phase into precise output values is carried out. In this study, the 'Centroid' defuzzification method was used [23]. The mathematical representation of the Centroid method is provided in Equation 6, where y_i represents the defined output variable, $\mu_c(y_i)$ represents the membership degree of the output variable, and y represents the defuzzified value.

$$y^* = \frac{\sum_{i=1}^{n} y_i \mu_c(y_i)}{\sum_{i=1}^{n} \mu_c(y_i)} \quad [6]$$

In the output of the system designed within the scope of the study, kefir quality indices were calculated for each observation, and quality classes were obtained. The applications related to the fuzzy logic-based decision support system were carried out in the R2024b (Matrix Laboratory) environment. The quality classes of the kefir samples were also obtained through expert opinion provided by a subject-matter specialist. The quality evaluations of the fuzzy logic-based decision support system and those of the expert were compared. In addition, Kappa statistics and agreement test results were included to assess the consistency of the decisions.

Results

In the design of the fuzzy system, the class intervals defined for the input variables are presented in *Table 2*. In this context, the classes were designed to be overlapping, in other words, to allow for partial intersection. According to the information provided in the table, in order to obtain high-quality kefir, the incubation time should be 19 h, and the incubation temperature must be maintained between 22-24°C. One of the significant indicators of high-quality kefir is the pH measurement, which is expected to be around 4.6. In the kefir production process, a total aerobic mesophilic bacteria count of 7.85 or a value close to it indicates that the kefir quality is high. Increases in the amount of total aerobic mesophilic bacteria within acceptable limits are interpreted as an indication that the kefir production has been carried out in a healthy manner and that the beneficial microorganisms within the structure of the kefir are functioning properly.

In the Matlab environment, to perform the fuzzification process, which is the first step of the fuzzy system design within the 'fuzzy logic designer', the membership functions of the selected parameters were defined. Additionally, the quality classes and class intervals were established based on the information presented in *Table 2*. The general structure of the fuzzy logic-based decision support system designed within the scope of this study is presented in *Fig. 2-a*. As can be seen in the toolbox, the system consists of five input variables and one output variable.

In the scope of this study, the membership functions of the input variables, are presented as follows: Incubation

Table 2. *Quality class ranges of input variables*

Class	Incubation Time (Hour)	Incubation Temperature (°C)	Storage Time (Days)	pH	Total Aerobic Mesophilic Bacteria Count (cfu/mL)
Low	$x \geq 22$	x<22 or 24>x	10>x	3<x<4.3	x<7.5
Medium	20<x<24	.	6<x<10	4<x<4.35	7<x<7.85
High	18.5<x<21	22<x<24	2<x<6	4.3<x<4.65	7.85≤ x ≤9.5

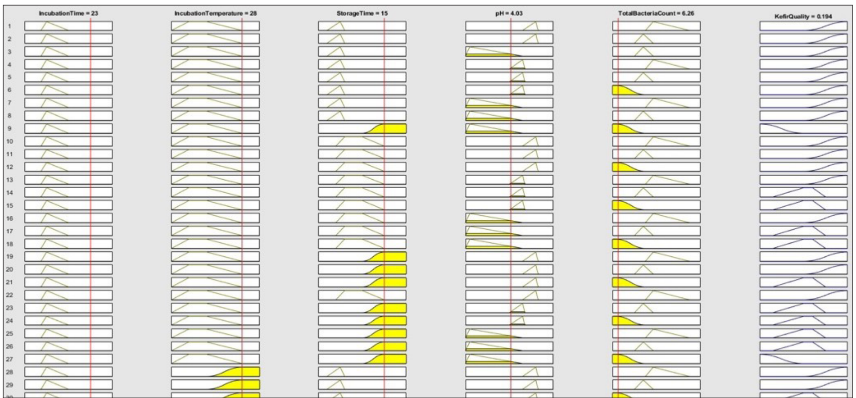

Fig 3. Fuzzy logic toolbox rule base

***Table 3.** Fuzzy rules*

Rule No		Input 1	Class		Input 2	Class		Input 3	Class		Input 4	Class		Input 5	Class		Kefir Quality
1	If	IncTime	H	AND	Inc.Temp.	H	AND	Stor. Time	H	AND	pH	H	AND	TBC	H	THEN	H
4	If	IncTime	H	AND	Inc.Temp.	H	AND	Stor. Time	H	AND	pH	M	AND	TBC	H	THEN	H
5	If	IncTime	H	AND	Inc.Temp.	H	AND	Stor. Time	H	AND	pH	M	AND	TBC	M	THEN	H
14	If	IncTime	H	AND	Inc.Temp.	H	AND	Stor. Time	M	AND	pH	M	AND	TBC	M	THEN	M
15	If	IncTime	H	AND	Inc.Temp.	H	AND	Stor. Time	M	AND	pH	M	AND	TBC	L	THEN	M
18	If	IncTime	H	AND	Inc.Temp.	H	AND	Stor. Time	M	AND	pH	L	AND	TBC	L	THEN	M
19	If	IncTime	H	AND	Inc.Temp.	H	AND	Stor. Time	L	AND	pH	H	AND	TBC	H	THEN	H
27	If	IncTime	H	AND	Inc.Temp.	H	AND	Stor. Time	L	AND	pH	L	AND	TBC	L	THEN	L
28	If	IncTime	H	AND	Inc.Temp.	L	AND	Stor. Time	H	AND	pH	H	AND	TBC	H	THEN	H
29	If	IncTime	H	AND	Inc.Temp.	L	AND	Stor. Time	H	AND	pH	H	AND	TBC	O	THEN	H
83	If	IncTime	L	AND	Inc.Temp.	L	AND	Stor. Time	H	AND	pH	H	AND	TBC	O	THEN	M
84	If	IncTime	L	AND	Inc.Temp.	L	AND	Stor. Time	H	AND	pH	H	AND	TBC	L	THEN	M
85	If	IncTime	L	AND	Inc.Temp.	L	AND	Stor. Time	H	AND	pH	M	AND	TBC	H	THEN	M
86	If	IncTime	L	AND	Inc.Temp.	L	AND	Stor. Time	H	AND	pH	M	AND	TBC	M	THEN	M
87	If	IncTime	L	AND	Inc.Temp.	L	AND	Stor. Time	H	AND	pH	M	AND	TBC	L	THEN	L
98	If	IncTime	L	AND	Inc.Temp.	L	AND	Stor. Time	M	AND	pH	L	AND	TBC	M	THEN	L
99	If	IncTime	L	AND	Inc.Temp.	L	AND	Stor. Time	M	AND	pH	L	AND	TBC	L	THEN	L
100	If	IncTime	L	AND	Inc.Temp.	L	AND	Stor. Time	L	AND	pH	H	AND	TBC	H	THEN	H
104	If	IncTime	L	AND	Inc.Temp.	L	AND	Stor. Time	L	AND	pH	M	AND	TBC	M	THEN	L
105	If	IncTime	L	AND	Inc.Temp.	L	AND	Stor. Time	L	AND	pH	M	AND	TBC	L	THEN	L
107	If	IncTime	L	AND	Inc.Temp.	L	AND	Stor. Time	L	AND	pH	L	AND	TBC	M	THEN	L
108	If	IncTime	L	AND	Inc.Temp.	L	AND	Stor. Time	L	AND	pH	L	AND	TBC	L	THEN	L

time in *Fig. 2-b*, incubation temperature in *Fig. 2-c*, storage time in *Fig. 2-d*, pH in *Fig. 2-e*, and total bacterial count in *Fig. 2-f*. The selection of membership functions was carried out by considering the variation and structural characteristics of the input variables. For instance, when the incubation time exceeds 23 h, declines in kefir quality and structural deficiencies are encountered. Therefore, the S-shaped membership function was preferred. However, for the classes defined as high and medium, the boundaries related to the incubation time could, using triangular membership functions, be represented, thereby enabling the transformation into fuzzy numbers. Similar interpretations are valid for incubation temperature and storage time. When evaluating the membership function of another input variable, pH, it was determined that the fuzzification of the continuous data obtained using triangular membership functions led to better system performance than other methods. Considering the conditions under which kefir bacteria are cultivated, S, and triangular membership functions were used to represent the total bacterial count variable based on the variation in the data structure. In the inference stage, a rule base was created for the representation of knowledge. A section of the rule table created for the input variables used is presented in *Table 3*. According to the fuzzy system structure, 108 "if-then" rules were formulated. The number of rules was obtained by the multiplication of the number of membership functions for each of the input variables. However, depending on the nature of the research, changes in the number of rules may occur in some cases. Here, "H" indicates high, "L" indicates low, and "M" indicates medium. The application of the rules indicates the decision's quality.

In *Fig. 3,* the general view of the fuzzy rules created with the help of the 'rule viewer' in the fuzzy logic toolbox of the Matlab Program is presented. The views in the first five columns represent the input variables, while the views in the rightmost column represent the kefir quality classes. As can be seen in *Fig. 3,* when the incubation time of the kefir sample is 23 h; the incubation temperature is 28°C; the storage period is 15 days; the pH value is 4.03; and the total bacterial count is 6.26 cfu/mL, the output value obtained using the defuzzification method is 0.194. The quality class decision of the fuzzy system for the kefir sample is interpreted as "low." When the figures were evaluated by an expert, it was confirmed that the fuzzy system produced realistic and accurate decisions.

As a result of the analyses conducted using the fuzzy logic-based decision support system, the changes in kefir

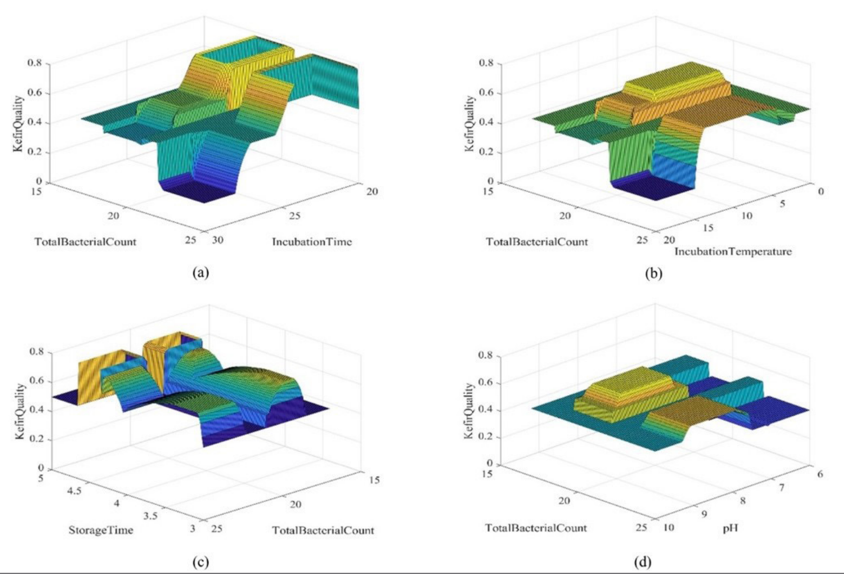

Fig 4. Surface view representations of the fuzzy logic-based decision support system: Total bacterial count- incubation time (a), Total bacterial count - incubation temperature (b), Total bacterial count - storage time (c), pH - total bacterial count - (d)

Table 4. *Fuzzy system and expert decision results for somatic cell groups*

Kefir Sample	SCC Group	Incubation Time (Hour)	Incubation Temperature (°C)	Storage Time (Days)	pH	TBC	System Decision	Expert Decision
1	Low	19	24	0	4.503	9.18	Medium	High
6	Low	19	28	0	4.480	9.22	Medium	High
18	Low	19	24	5	4.17	9.02	High	High
22	Low	19	28	5	4.14	9.18	High	High
28	High	23	24	5	4.13	8.95	High	High
35	Low	23	24	10	4.1	8.72	High	High
40	Low	23	28	10	4.09	8.38	Medium	Medium
48	High	23	28	10	4.11	8.76	Medium	Medium
57	High	19	24	15	4.077	6.37	Low	Low
64	High	23	28	15	4.009	6.49	Low	Low

quality were visualized in a three-dimensional graph. In *Fig. 4*, the surface view of the rules in the Matlab program is presented: total bacteria count-incubation time (a), total bacteria count-incubation temperature (b), total bacteria count-storage time (c), and pH-total bacteria count (d). As can be seen in *Fig. 4-a*, when the incubation time exceeds 20 h, significant decreases in kefir quality can be observed, especially under conditions of high bacterial load. The findings in *Fig. 4-a* indicate that exceeding a certain threshold of fermentation time negatively affects microbial viability and/or metabolic balance and leads to a decrease in product quality. In *Fig. 4-b*, when the incubation temperature exceeds 24°C, losses in kefir quality occur in parallel with decreases in bacterial count. At this point, it was determined that the increase in temperature negatively affected microbial activity and reduced fermentation efficiency. Similarly, *Fig. 4-c* shows that increases in storage time caused decreases in total bacterial count and kefir quality. *Fig. 4-d* also shows that decreases in pH and total bacterial count lead to decreases in kefir quality. The findings of the research demonstrate that reductions in the kefir quality index occur with decreasing pH values and low microbial density. It was concluded that the reflection of laboratory-prepared conditions on kefir quality could be interpreted successfully through fuzzy numbers and the fuzzy rule base within the fuzzy logic-based decision support system.

In *Table 4*, a portion of the quality evaluation results of kefir samples produced from milk samples categorized as having low or high levels according to somatic cell count is presented. Based on the evaluations conducted on the kefir samples, it was determined that the low somatic

Table 5. *Fuzzy system and expert decision results for milk fat groups*

Kefir Sample	Fat Group	Incubation Time (Hour)	Incubation Temperature (°C)	Storage Time (Days)	pH	TBC	System Decision	Expert Decision
1	Low	19	24	0	4.582	7.9	Orta	High
6	Low	19	28	0	4.514	8.99	Orta	High
18	Low	19	24	5	4.18	8.85	High	High
22	Low	19	28	5	4.13	9.03	High	High
28	Low	23	24	5	4.17	9.27	High	High
35	Low	23	24	10	4.12	8.38	High	High
40	Low	23	28	10	4.09	7.42	Medium	Medium
48	Low	23	28	10	4.09	8.14	Medium	Medium
57	High	19	24	15	4.116	5.86	Medium	Medium
64	High	23	28	15	4.029	6.26	Low	Low

cell group kefir was of better quality compared to those in the high somatic cell group. In the evaluation of kefir samples classified according to somatic cell count (SCC), an increase in SCC level was found to be associated with a decrease in kefir quality classifications. As presented in *Table 4*, kefir samples in the low SCC group were observed to be classified predominantly as medium or high quality, whereas samples in the high SCC group were more frequently determined to be of lower quality. In *Table 5* is presented a portion of the quality evaluation results, of kefir samples produced from milk samples categorized by milk fat content as low and high. Similar values were obtained regarding kefir quality across the milk fat profiles (Low/High). When the fuzzy logic-based decision support system and expert evaluations were compared within the scope of the SCC and fat groups, a correct classification rate of 93.75% and a high level of agreement were observed. Similarly, in the milk fat content groups, the system showed a 93.75% overlap with expert decisions, indicating consistent performance across different milk component groups. To evaluate the statistical agreement between the system and expert decisions, Cohen's Kappa coefficient and Chi-Square (χ^2) values were calculated. The results indicated that the Kappa statistic value reflected a very high level of agreement for both of somatic cell and fat groups (SCC group $Kappa = 0.901, s_x = 0.047$; Fat group $Kappa = 0.903, s_x = 0.048$). The designed fuzzy system could model expert decisions with high accuracy in accordance with multivariate quality parameters and demonstrated effective learning performance in samples characterized by uncertainty. The Chi-Square values (SCC group $\chi^2 = 110.667$; $Fat\ Group\ \chi^2 = 110.222$) calculated within the scope of the analyses proved statistically significant, demonstrating that the harmony between the fuzzy system and expert decisions was not coincidental but occurred through a strong relationship ($P<0.05$).

Discussion

A review of scientific studies in the literature addressing fuzzy logic-based decision support systems and quality classification problems has observed that features similar to those in the fuzzy system designed in this study are present. Moreover, the performance level of the findings is high. In the study conducted by Harris [24], the input variables were considered in terms of compositional (fat, dry matter) and hygienic aspects (SCC, total bacterial count). A system with a similar structure was designed, similar to our study. Kavdır and Guyer [25] designed a decision support system for apple quality grading using triangular and trapezoidal membership functions, along with the Centroid method, similar in structure to our study. Working with a much larger dataset than our research, the authors included input variables based on physical characteristics and reported a success rate of 89%. In the decision support system designed by Görgülü [19] for the quality classification of floral honey, triangular and trapezoidal membership functions and the Mamdani inference method were employed, similar to our study. A success rate of 94.28% was reported. Unlike our study, another study used a smaller number of samples and rules. In another study by the same author on fig fruit quality classification, a similar system operation and comparable success rate (94.26%) were observed [26]. Consistent with our study, a similar system operation was employed for agricultural product quality assessment by Baskar and Doraipandian [27]. Cha et al.[6] also designed a system incorporating triangular membership functions and the Mamdani inference method, similar to the structure of our study. In contrast to the current study, which used fewer samples, a different study used a larger number of samples, yet the system's success rate was reported as 77%. Akıllı et al.[28] developed a fuzzy logic-based decision support system aiming to classify raw milk samples into quality classes, utilizing the measured values of total bacterial count, somatic cell count, and protein content as input variables. Kefir production modeling was addressed similar to the present study, in the study conducted by Akgül et al.[29]. In that study, incubation temperature, incubation time, and culture inoculum ratio were used as input variables. Unlike our study, where pH was reported as the output variable to be achieved at the end of kefir production. Additionally, due to the use of fewer input variables than in our study, fewer rules were employed. Akgül et al [30] modeled a similar dairy product, yogurt, using the Mamdani inference method. The researchers, who employed a system structure similar to our study, defined pH as the output variable. In contrast to our study, a different number of membership subsets and rules were used in this study, and a total of 343 yogurt samples were analyzed. As in our study, a high system success rate of 90.27% was obtained for the system in question. In the study by Ertekin and Kaya [31], a similar structure was used with a fermented food product, and a comparable decision support system was designed. Similar to our study, microbiological analyses were used as input variables. As a result of their analysis, it was found that the decision support system which was established to determine the quality classes of samples showed a success rate of 85%. Unlike our research, the number of input variables in the study mentioned was three, and the number of rules was reported as 27. Upon reviewing fuzzy logic-based decision support systems designed for quality assessment of food and agricultural products in the literature, it has been determined that the number of input variables, membership functions, and subset counts vary depending on the nature of the product under investigation. System optimization is largely dependent on the accurate definition of the membership function. The subsequent stages of the system continue their operation through these functions. Therefore, a detailed literature review and system testing are of critical importance. Another crucial aspect is the accurate integration of expert knowledge into the system for the optimization of rules, as the performance of fuzzy systems largely depends on the knowledge-based consistency of the defined rules.

In this study, a decision support system was developed to assist in classifying the quality of kefir samples included in the dataset by evaluating their microbiological characteristics. By transforming numerical findings expressed as crisp values into fuzzy numbers, a large number of variables were simultaneously integrated into the system. Instead of binary definitions expressed only as "low-high," a more flexible perspective was introduced for addressing the quality problem. An objective approach was presented for the quality evaluation of kefir, one of the fermented dairy products. The experimental validation studies revealed that the system achieved a success rate of 93.75% in agreement with expert decisions. Furthermore, the statistical analyses of the system outputs indicated a highly significant level of consistency between the evaluations of human experts and the system results.

In conclusion, the developed fuzzy logic-based decision support system was able to classify kefir quality with high accuracy under conditions of uncertainty caused by measurements and environmental variables. In this regard, the fuzzy system contributed to the effective management of uncertainty in the quality control processes of dairy products and provided a flexible and reliable decision support approach. The study also examined the effects of grouping milk samples according to somatic cell count and milk fat content, on kefir quality. It was determined that increases in somatic cell count had a negative effect on kefir quality. It was also observed that increases in milk fat partially affected the kefir formation process. The total bacterial count was identified as the most important variable in kefir quality. The presence of probiotics, which enable the formation of kefir and are of great importance for human health, was identified as one of the most crucial factors determining kefir quality. When the effects of variations in the other input variables included in the system, on kefir quality were evaluated, it was observed that high-quality kefir was obtained with an incubation time of 19 h, an incubation temperature of 22-24°C, and a storage period of 5 days. In future studies, different perspectives may be developed by addressing different types of input variables, membership functions, inference, and defuzzification methods. It is also believed that the integration and optimization of different artificial intelligence methods will make a positive contribution to the quality assessment of fermented food products. The information presented in this study is expected to be beneficial to researchers working in the fields of food, agriculture, animal husbandry, and veterinary sciences in terms of decision-making, quality evaluation, and classification processes.

Declarations

Availability of Data and Materials: The datasets used and/or analyzed during the current study are available from the corresponding author (A. Akıllı) on reasonable request.

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