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Potential application areas of artificial intelligence in dairy industry

Yapay zekanın süt endüstrisinde potansiyel kullanım alanları

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Abstract

Food manufacturers are taking a proactive approach to food safety and quality issues through predictive modeling. This situation necessitates reaching the most accurate result with high speed and repeatability. Therefore, food manufacturers aim to integrate artificial intelligence systems into their routine production by utilising machine learning (ML), the Internet of Things (IoT), and deep learning (DL) through big data analysis. The fact that milk is easily spoilt due to its nature, that the quality of raw milk directly affects the quality of the final product and that raw milk production is predominantly carried out by both dispersed and small producers makes it mandatory for the dairy industry to focus on quality and food safety issues in a disciplined manner from raw materials to the end product. This review discusses the possibilities of utilising artificial intelligence models in the dairy industry to maintain quality and ensure food safety.

Keywords: Artificial intelligence, Milk quality, Dairy products, Food safety, Big data

Öz

Gıda üreticileri, tahmine dayalı modelleme yoluyla gıda güvenliği ve kalitesi konularında proaktif bir yaklaşım benimsemektedir. Bu durum, yüksek hız ve tekrarlanabilirlik ile en doğru sonuca ulaşmayı gerektirmektedir. Bu nedenle gıda üreticileri büyük veri analizleri ile makine öğrenmesi (ML), nesnelerin interneti (IoT) ve derin öğrenme (DL) gibi modelleri kullanarak yapay zeka sistemlerini rutin üretimlerinin bir parçası haline getirmeyi hedeflemektedir. Sütün doğası gereği kolay bozulabilir olması, çiğ sütün kalitesinin nihai ürünün kalitesini doğrudan etkilemesi ve çiğ süt üretiminin ağırlıklı olarak hem dağınık hem de küçük üreticiler tarafından gerçekleştirilmesi, süt endüstrisinin hammaddeden nihai ürüne kadar disiplinli bir şekilde kalite ve gıda güvenliği konularına odaklanmasını zorunlu kılmaktadır. Bu derlemede, süt endüstrisinde kaliteyi korumak ve gıda güvenliğini sağlamak için yapay zeka modellerinden yararlanma olanakları tartışılmaktadır.

Anahtar Kelimeler: Yapay Zeka, Süt kalitesi, Süt ürünleri, Gıda güvenliği, Büyük veri

1. Introduction

Milk and dairy products have a distinct place in the food industry with their high nutritional value and wide consumer base. Milk is not only nutritious for humans due to the nutrients it contains, but also provides a favourable environment for the growth of microorganisms. Raw milk can harbour a wide variety of pathogenic or non-pathogenic microorganisms depending on the production conditions [1]. Although processes such as pasteurisation and thermal sterilisation are applied, pathogenic microorganisms, especially *Listeria monocytogenes*, may contaminate the product and threaten public health through inadequate heat treatment or biofilms formed on plant equipment. Ensuring food safety in the dairy industry is not only a common problem in underdeveloped or developing countries but also is encountered in developed countries. For example, it has been reported that 1-6% of food poisoning cases reported in developed countries are related to milk and dairy products [2]. In addition, adulteration and quality fluctuations in dairy products are also an important problem. In particular, fraudulent practices such as adding water, vegetable oil or nitrogen sources such as melamine to milk or milk products put consumer health at risk. The melamine scandal in China in 2008 raised the concerns of millions of people worldwide about dairy products and emphasised the importance of food safety inspections [3]. Therefore, in the dairy industry, food safety (*i.e.*, production of pathogen-free and healthy dairy products) and quality control (*i.e.,* maintenance of desired nutritional and sensory properties, prevention of fraud) are important for brand prestige, public health and regulatory compliance. Although traditional methods (*e.g.*, microbiological culture tests, chemical analyses, sensory evaluations) have been used to achieve these objectives, these methods have limitations such as being time-consuming, labour-intensive and reproducibility problems. In recent years, Artificial Intelligence (AI) supported approaches promise significant innovations in this field. AI includes algorithms and technologies that can solve complex problems by learning from large data sets.

Thanks to AI applications in the dairy industry, more effective prediction of risks, fast and automatic quality

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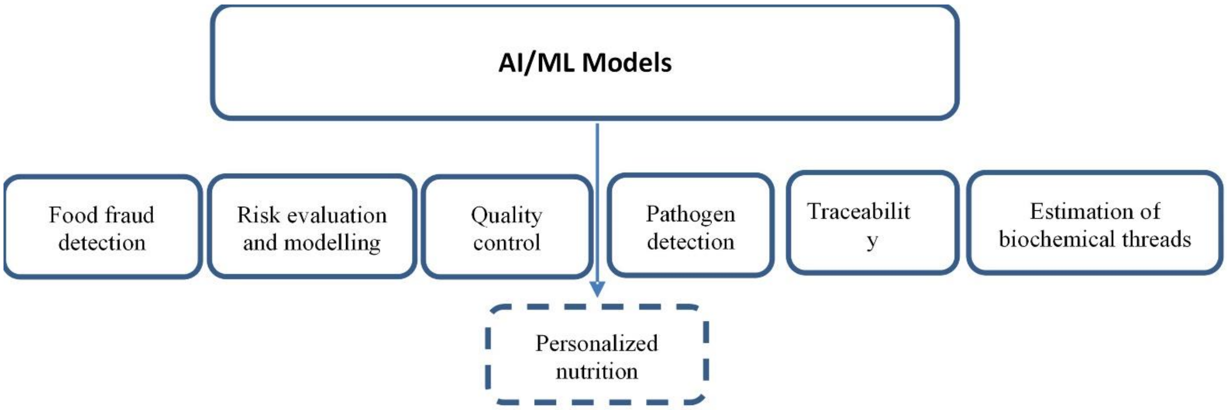

Figure 1. Potential applications of AI and machine learning models in the food industry. Adapted from [5]

control, optimisation in production processes and real-time decision support systems become possible. Liu et al. [4]. stated that scientific studies on 15 different AI-supported models have become visible since 2012, but the real leap has been seen since 2018. The same researchers showed that among 15 different research disciplines, food technology is the scientific field where the most research on AI/ML-supported models is conducted.

AI and Machine Learning (ML) applications in food systems can be utilised for a number of different purposes (Figure 1). The use of AI and ML in the food industry is increasing. Food businesses utilise AI/ML supported systems for the rapid detection of pathogens, chemical residues, physical hazards and allergens. Chettri [5] states that AI/ML-assisted prediction models provide over 90% success, especially in the detection of pathogens and prediction of occurrence/contamination pathway.Although prediction models based on big data analysis are primarily used for fraud detection in milk and dairy products, risk prediction, quality control and quality monitoring at the farm level, pathogen/virulence detection and (bio)-chemical risk identification, this innovative approach is expected to gain an important place in the field of personalised nutrition shortly as well [5]. In this article, the use of artificial intelligence in food safety and quality protection in the dairy industry, its key technologies and sectoral impacts are discusse

2. Artificial intelligence-based applications to the dairy industry

There are many potential applications of AI technologies in the dairy industry. In this section, the three most prominent areas will be detailed: Microbial Analysis, Quality Classification by Image Processing and Automation, and Optimisation of the Production Process. These areas are critical for food safety and quality assurance and are where AI offers tangible contributions.

2.1. Microbial analysis and food safety in dairy products

Control of microbial load and the presence of pathogens in dairy products is a top priority for food safety. Traditionally, microbial analysis is performed by culture inoculations in petri dishes or molecular methods such as Polymerase Chain Reactions (PCR) and it takes a long time to get results. New approaches supported by AI are coming into play to speed up this process and increase sensitivity. It has been shown that AI can perform bacterial identification much faster than traditional methods with an accuracy of *ca*. 97% [6]. AI has the potential to be applied in analysing test results, patient symptoms, and other data associated with possible infection and predicting the conditions of disease occurrence [7]. An AI-based automated plate reading mobile application called Rumi has been developed to detect mastitis-causing pathogens in milking cows. Similarly, microorganism identification can be performed based on 3D identification (by optical image formation) and image analysis of micro- and nano-organisms (with Gabor digital holographic microscopy) [8-11]. On the one hand, ML models integrated with advanced sensor systems increase the speed and precision of sample analysis. For example, researchers from the University of Connecticut have developed a system that uses 12 different chemical sensors on a 96-well plate and interprets the data generated by these sensors with ML [12]. This new technology can detect eight different types of pathogenic and spoilage bacteria in milk samples in as little as two hours with over 98% accuracy. Each of the sensors interacts with the metabolites of the bacteria in the milk and generates a unique signal pattern, which is fed to an ML algorithm to detect the bacteria species with high accuracy. Thus, the time cost of traditional culture methods is greatly reduced and real-time microbial monitoring close to the production process becomes possible.

The combination of metagenomic data analysis and AI has made comprehensive analysis of the milk microbiome a new food safety tool. In a study where microbial DNA sequences of raw milk samples (shotgun metagenomic data) were analysed using AI, abnormal conditions in milk production (*e.g.*, milk containing antibiotic residues or milk mixed from different farms) were detected [13]. In this study, researchers extracted microbiome profiles of tank milk samples collected from 58 different farms and then identified deviations in these profiles with AI algorithms. The results showed that differences in microbial composition that traditional statistical methods (such as principal component analysis, PCA) cannot distinguish, can be detected with high accuracy by AI [13]. Indeed, while classical analysis techniques were unable to clearly distinguish between samples in different classes, the AI model was able to both successfully classify samples and identify the microbial species (the '*driver'* species in the milk microbiome) that distinguish these classes. Thanks to this '*microbial signature*' approach, the conditions under which raw milk has passed (*e.g*., before *vs*. after pasteurisation, whether the cold chain has been broken, or whether it has come from an antibiotic-treated cow) can be understood simply by looking at the microorganisms in the milk.

AI-supported microbial analysis methods offer two critical advantages for the dairy industry: Rapid response capability and comprehensive data analysis. The speed factor significantly reduces food safety risks by enabling the detection of potential contamination before the product reaches the consumer, especially in products with a short shelf-life or products with a risk of rapid spoilage, such as fresh milk [14]. On the other hand, thanks to the big data processing capacity of AI, thousands of microbial species information or sensor patterns from a single sample can be evaluated holistically. This reveals subtle relationships that classical methods may miss. For example, nuances such as the presence of very low levels of a particular pathogen or the presence of a second bacterial metabolite correlated with a pathogen can be captured by AI models. As a result, AI-enhanced microbial analysis is becoming an innovative tool that acts as an early warning system in dairy products, protecting both producers and consumers.

2.2. Quality classification by image processing

Quality in milk and dairy products is often closely related to visual and physical characteristics. Factors such as product colour, texture, homogeneity, whether it contains foreign matter or not, and packaging integrity affect both consumer perception and safety criteria. Artificial intelligence automates the evaluation of these visual and physical quality parameters with computer vision techniques, minimising human error and providing standardisation.

Classification and sorting: Visuals collected by cameras and sensors on the production line can be instantly processed by AI algorithms to classify products in terms of quality. For example, in bottled milk production, the filling level and cap control of each bottle can be inspected with computer vision; missing filling or bottles with poorly fitting caps are automatically sorted on the line. Similarly, in a yoghurt filling line, tears in the cap foil or printing defects can be detected instantly and faulty products rejected. Such applications are already in use in many industrial plants and can make decisions in milliseconds with the help of deep neural networks that learn from product photographs. Since computer vision systems can scan far more products *per* minute than can be examined by the human eye, continuous quality control is possible without interrupting the production speed [15]. In one study, for example, an image processing-based sorting system detected faulty caps on a fruit juice bottling line about 70 *percent* faster than human inspection and significantly reduced maintenance costs. In the dairy industry, similar technologies are of great benefit, especially in the final inspection of packaged products and in the grading of products whose appearance is an indicator of quality, such as cheese.

Hyperspectral and spectral imaging: The human eye is sensitive to visible wavelengths between 380-700 nm, whereas many indicators associated with food quality (*e.g*., chemical composition changes, contaminants, spoilage products) may appear in spectra other than visible light. Therefore, techniques such as hyperspectral imaging have gained importance in food quality control. Hyperspectral cameras record the image of food by separating it into hundreds of wavelengths in very narrow bands. The resulting 'hyperspectral signature' contains detailed information about the chemical and physical composition of the product. By processing this high-dimensional data, artificial intelligence models can detect, for example, the presence of a foreign chemical in milk or the moisture distribution of cheese. Indeed, recent research has developed models that can detect adulteration in dairy products (*e.g*., water, carbonate, melamine adulteration) with high accuracy using hyperspectral imaging and demonstrated that they have significant practical applicability in milk quality assessment [16]. Aqeel et al. [16] used a near-infrared hyperspectral camera and ML to detect the type of adulteration (water adulteration, starch adulteration, detergent adulteration, *etc*.) in a milk sample with up to 100% accuracy. The multiclass model developed in this study evaluated the spectral reflectance signatures of the milk samples with various algorithms such as logistic regression, decision tree, support vector machines and linear discriminant analysis; the most successful result was obtained with the LDA algorithm and error-free classification was achieved in all validation samples. Thus, milk adulteration detection, which requires complex chemical tests in the laboratory environment, has become possible in a short time and with a non-destructive method. Table 1 summarizes the findings of some recent researche using AI applications in detecting milk adulteration.

Measurement of product characteristics: Image processing can be used for quantitative measurement of certain quality parameters as well as quality classification. For example, the colour measurement of whey powder is an indication of whether the product is subject to overheating due to the Maillard reaction.

By continuously measuring the colour of milk powder particles flowing through the production line, a system integrated with computer vision can send an alert to the control system when it detects an abnormal darkening. This allows operators to adjust the drying temperature or airflow immediately, ensuring that the product remains within the targeted quality range. Another example is systems in raw milk collection centres that analyse the turbidity or

Table 1. Key findings of recent studies using AI to detect adulteration in milk

Adulteration	Tools used	Output	References
Mixing cow milk with buffalo milk	FTIR spectroscopy with article swarm optimization	90.38% accuracy in the Ensemble Bagged Tree algorithm	[17]
Intentionaly added Urea, Starch, Sodium Bicarbonate, Maltodextrin, and Formaldehyde to milk	AI enabled IoT based multi-sensor system	96% accuracy rate based on SHAP (SHapley Additive exPlanations) analysis	[18]
Intentionally added starch, sucrose, formaldehyde to milk	FTIR data processed by a novel edge device (Jetson Nano) vs. Convolutional Neural Network (CNN)	94.8% accuracy in classifying the adulterants in milk	[19]
Modification of pH and electrical conductivity of farm milk by chemical adulterants	Fuzzy logic system combined with arduino mega microcontroller	Continuous data collection and storage in cloud system (Thing Speed web platform)	[20]
Melamin addition to milk	AI backed by spectral data analysis	Review of effectiveness of various spectral data analysis model in milk adulteration	[21]

colour of milk with optical sensors to detect milk with high somatic cell counts (a sign of mastitis) or contaminated with blood. Such rapid sorting practices ensure that problematic milk is sorted early and not mixed with healthy milk, thus maintaining overall quality.

Cheese maturity analysis by computer vision: A special and interesting example of quality classification is found in products that increase in value with maturity, such as cheese. In traditional productions, experts assess the degree of maturation by visually inspecting or tasting cheese at regular intervals. This method is both time-consuming and subjective. AI also comes into play in this field, making it possible to determine cheese maturity through photographs. For example, a recently developed AI model can automatically classify the maturity level of cheese by learning from images of cheese blocks matured at different stages [22]. For large-scale cheese producers, such a system offers significant labour savings and standardisation by eliminating the need to check each cheese wheel/block individually. Moreover, the ripening process becomes more traceable, as characteristics such as colour distribution on the surface of a cheese, rind thickness, and crack or mould formation can be objectively quantified and recorded. Subtle quality defects that would not be recognised by conventional methods (*e.g.*, microscopic cracks or abnormal moisture accumulation) can also be detected early using the data captured by computer vision.

In conclusion, quality classification by image processing is a comprehensive application area in the dairy industry that directly affects both food safety and product value. The AI-based systems are integrated into production processes by sustaining and accelerating in-line quality control, while also providing a powerful control tool against food fraud. Thus, the protection of brand reputation for manufacturers and access to reliable and consistent quality products for consumers are ensured.

2.3. Automation and optimisation of the production process

Dairy production is a complex process that involves many stages from raw milk intake to pasteurisation, fermentation to packaging and requires the control of many variables. AI is playing an increasing role in the automation and optimisation of these processes. The aim is to speed up decision-making processes, increase process consistency and improve resource utilisation by minimising human intervention.

Modern milk processing plants are equipped with a large number of sensors and measuring devices (meters measuring temperature, pH, flow rate, viscosity, moisture, etc.). Conventional automation systems control these sensor data according to predetermined thresholds. However, AI offers smarter control strategies by analysing sensor data not only according to instantaneous values, but also in the light of historical trends and multivariate relationships. For example, heating/cooling control in fermentation tanks in yoghurt production is usually based on a fixed time-temperature profile. However, an AI-enabled control system can optimise fermentation time in real- time by evaluating information such as the current live bacterial load of milk, ambient temperature and desired final acidity. If the target pH is approached faster than normal (e.g. if the milk contains more bacteria than initially expected), the system can terminate the fermentation slightly earlier, preventing the development of excess acidity in the yoghurt. Conversely, if fermentation is going slowly, the system can make it possible to reach the desired acidity by slightly increasing the temperature or extending the time [23].

AI not only controls production processes but is also used for optimisation. In milk pasteurisation, for example, the goal is to destroy pathogens while maintaining nutritional and sensory quality, which requires a balance between time and temperature. By analysing past pasteurisation data and end-product quality measurements, AI can learn the optimal time-temperature combinations. If there is a risk of overheating (leading to nutrient loss) or underheating (safety risk), it can recommend adjustments to optimise the system [24].

Another dimension in production automation is the development of decision support systems for operators. AI provides plant managers with a forecast of the likelihood of quality degradation in the raw product input, enabling them to take proactive action. An AI model that analysed production data of nine different product types in a dairy plant in real time was able to optimise processes to increase productivity in the plant by 20-40% [25].

When the cognitive capabilities of AI are combined with physical robotic systems, fully automated production lines emerge. Although the classic example of the use of robotics in the dairy industry is milking robots on farms, robots are also becoming increasingly common in the processing phase. For example, robotic arms that carry or turn cheese moulds can act like human eyes by gaining visual perception capability when integrated with AI. With computer vision support, a robot can determine the optimal gripping point when picking up a wheel of cheese, or if it detects unwanted mould in a block of cheese, it can direct it to a separate belt. In the packaging process, robots can also correct misplaced products with camera data. Such intelligent automation systems bring flexibility and adaptability beyond conventional automation. Even if there is a change in product size or type, AI-powered robots can quickly learn and adapt to the new situation. Thus, a high automation rate can be maintained even in enterprises with frequent product changes in flexible production lines.

The issue of predictive maintenance mentioned above should be emphasised again in terms of the continuity of automation. The unexpected failure of milk processing equipment (pasteurisers, steam boilers, pumps and valves, coolers, etc.) can lead to product losses and safety risks. A plant equipped with artificial intelligence continuously monitors machine data and applies anomaly detection algorithms to monitor the 'health status' of each machine. For example, an AI model that detects a millisecond increase in the motor vibration of a yoghurt filling machine can predict that this could be an impending mechanical problem and alert the maintenance team. Such proactive approaches significantly reduce maintenance expenditures and downtime.

3. Applications of artificial intelligence in the dairy industry

3.1. AI in raw milk acceptance

Raw milk quality: Raw milk is the basic input of all dairy products and its quality is decisive for the safety and standard of the final product. If the raw milk quality is insufficient, problems may occur between milking and transportation periods.. Therefore, quality and safety monitoring for raw milk starting from the farm is very critical and important. Artificial intelligence is used in various ways in control of raw milk quality and ensuring safety in transport. Milk quality is not routinely controlled in the farm level due to time and technical limitations. Contamination of milk at the farm environment can lead to serious financial losses. A 2017 EU report emphasises the lack of an effective monitoring and evaluation model for raw milk at farm level and the inadequacy of data collection and evaluation for milk yield, quality and animal welfare [26]. In the last 10 years, the integration of on-line and at-line measurement systems at farm level has started [27, 28]. Nowadays, technologies such as artificial neural networks (ANN), deep learning (DL), Internet of Things (IoT) and blockchain (BC) have been widely used in areas such as real-time quality monitoring, decision-making process optimisation and traceability in the milk supply chain [29].

Artificial intelligence systems are also used to improve fertilisation efficiency in dairy farms. It has been shown that the Pregnancy Probability Diagnosis Model developed from image analyses of cervical openings of dairy cows can detect the time of artificial insemination with an accuracy of 76% [30]. In addition, an AI-assisted Multiple Regression Model developed using logistic regression data is successfully used in the accurate prediction of the oestrus cycle in dairy cows with an accuracy of 83.2% [31].

Antibiotic and fraud detection: Antibiotic residues that should not be present in raw milk or substances such as water and melamine added for fraudulent purposes are serious problems in terms of milk quality and food safety. Artificial intelligence increases the sensitivity in the detection of these undesirable elements. Microbiome-based AI analyses can detect milk with antibiotics exogenously mixed into raw milk. Beyond traditional chemical tests, this approach can infer information about the history of milk by looking at the 'signature' of the microbial community in milk. Another AI-enabled method is adulteration detection by analysing the chemical profile or spectroscopic data of raw milk samples [16]. Similarly, artificial neural network-based models have been shown to successfully predict milk spoilage tendency or shelf stability by interpreting milk volatile profiles obtained by gas chromatography [32]. All these developments facilitate on-site and rapid assessment and classification of raw milk quality.

Transport and cold-chain monitoring: Milk is usually transported from the farm to the factory in insulated tankers, where the cold chain must not be broken. Tankers equipped with IoT sensors can continuously transmit temperature and location information, while AI algorithms can monitor this data and detect anomalies. For example, if the AI detects that a tanker is off route or the temperature inside is above 4°C, the system sends an alarm to the relevant units. This reduces the risk of spoilage, especially in long-distance milk transports or in hot climates. Furthermore, by analysing historical transport data, the AI can learn 'risk points' (e.g. if there are delays due to traffic on a certain route or if the temperature rises during certain hours), thus making it possible to optimise logistics planning [29]. However, there is still insufficient data to analyse the long-term impacts of AI-enabled raw milk transport logistics and the willingness of stakeholders (producers, milk collectors and collection centres, *etc*.). Today, dairy companies are widely use AI-assisted route optimization programs for raw mik collection. This allows dairy companines to reduce their carbon footprints as well. One food company in Türkiye has achieved to reduce its transportation costs by 12% by AI-assisted route optimization.

Quality classification in raw milk acceptance: Raw milk arriving at the factory can be classified and priced according to its quality (such as premium payment for high-quality milk). An AI-supported classification system can classify milk into different quality classes by looking at many characteristics (fat, protein, somatic cell count, bacterial load, presence of antibiotics, etc.) of a small sample taken from a milk truck at the same time. While this multi-parameter evaluation by humans in traditional methods can cause errors, AI provides a more accurate and precise classification by applying standard criteria consistently. For example, one model processed 11 different milk parameters and detected deviations from standard quality levels and was able to accurately determine the quality class of raw milk [33].

As mentioned above, technologies such as big data analysis, Internet of Things and blockchain offer very functional solutions in issues such as milk supply chain management, animal welfare and efficiency in milk production. Recently, within the scope of an EU project carried out by the Union of Dairy, Meat and Food Industrialists and Producers of Turkey (SETBİR), a model for big data analysis and instant data sharing has been created (https://www.setbir.org.tr/sut-degerlidir-tek-ihiyacimiz-kaliteli-sut/). For example, dairy companies should be able to see which individual producer has applied antibiotics through the system. It is thought that this application will lead to a decrease in the routine antibiotic follow-up expenses of dairy companies over time and encourage companies to switch to risk-based antibiotic follow-up procedures instead of routine. The model in Figure 2 is proposed for big data collection and analysis. For this model to be effective, the existence of a tracking system with a chip instead of an ear tag is a prerequisite. The registration information of the dairy animal whose treatment process is initiated through the e-prescription system will be transferred instantly and without intervention to the portal of the ministry, the relevant dairy company and the producer organisation to which the farm is affiliated through the data collaboration interface. This information will also be shared with the milk collection centre through the on-line warning system and the milk producer farm with antibiotics will be monitored. If the farm delivers the milk to the collection centre, the milk will be rejected and the antibiotic milk destruction procedure will be activated. If the farm has not delivered the milk with antibiotics to the collection centre, the producer organisation will check whether the milk with antibiotics is included in the destruction protocol. The collection centre will inform the producer organisation that the antibiotic destruction process has been completed. This model allows all the partners of mik supply chain (*e.g.*, Ministry of Agriculture, dairy company, cooperatives etc..) monitor the milk's journey from farm to dairies in a transparent manner. Thanks to this model, dairy farms will have the capacity to create risk maps for milk by analysing a large number of data. For example, they will be able to follow seasonal changes in the bacterial count or chemical composition of milk in advance and make in-house planning before the milk arrives at the dairy. The Ministry of Agriculture will use this model to optimise incentive premiums and subsidies for milk production.

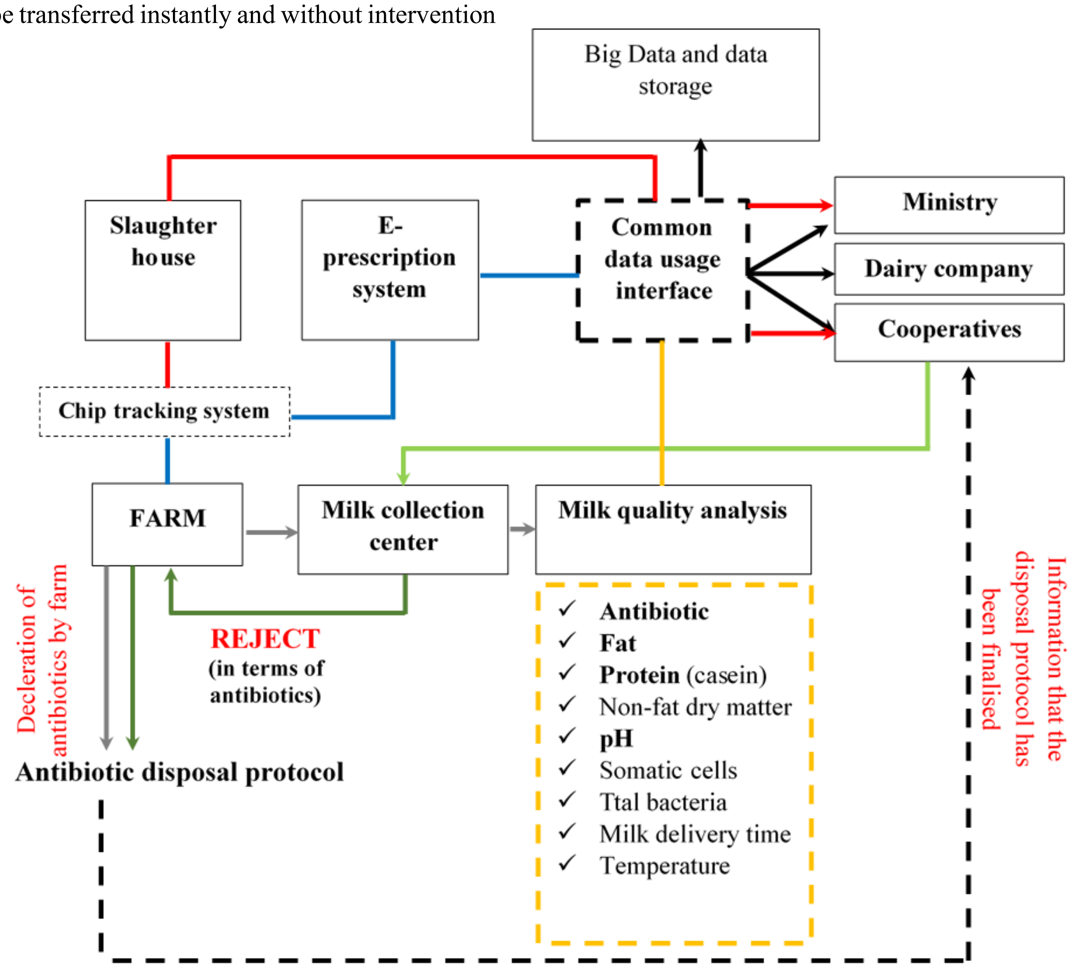

Figure 2. Proposed mik quality-tracking system from farm gate to the dairy company.

In summary, artificial intelligence helps in monitoring the quality and ensuring the safety of raw milk throughout the entire supply chain from the farm to the factory. AI applications in areas such as early detection of microbial and chemical risks, protection of the cold chain and identification of frauds make it possible to start production with safer raw materials and therefore to obtain more reliable final products.

3.2. AI in the production processes of dairy products

Yoghurt and similar fermented milk products

Yoghurt production is based on a controlled fermentation process. When milk is inoculated with specific starter culture bacteria (*e.g. Lactobacillus delbrueckii* ssp. *bulgaricus* and *Streptococcus thermophilus*) and kept at the appropriate temperature, lactic acid bacteria ferment the lactose in the milk to produce lactic acid and lower the pH of the milk. The success of fermentation and the quality of yoghurt depends on the correct determination of the incubation termination time, incubation temperature control, the microbiological and chemical quality of milk and starter culture activity [34]. Artificial intelligence enables the fermentation process to be monitored and controlled more closely and intelligently, resulting in consistency in yoghurt quality and increased efficiency in production. In traditional productions, yoghurt fermentation is monitored by pH measurement of samples taken at certain intervals or time tracking based on experience. However, continuous and real-time monitoring of each tank in an industrial environment is difficult. Nowadays, thanks to the developing sensor technologies (*e.g.* in-line pH sensors, optical sensors), pH, temperature and sometimes microbial activity indicators can be monitored instantaneously during fermentation. AI algorithms are used to make sense of the data from these sensors. For example, near-infrared (NIR) spectroscopy can monitor chemical changes in milk without adding any chemicals to the yoghurt mixture, simply by looking at the spectral characteristics of the light passing through the milk. In one study, yoghurt fermentation was monitored in real-time using NIR-based aquafotonomic spectroscopy, and the water release observed in the spectrum was correlated with features reflecting critical stages of fermentation such as protein denaturation and gelation [23]. By analysing the light absorption characteristics of the milk sample at specific wavelengths, the pH drop curve and gel formation were determined and the end point of fermentation (pH ~4.6) could be accurately predicted [23]. Such non-invasive monitoring technologies, coupled with AI, allow autonomous control of each fermentation tank.

Fermentation dynamics can vary depending on the initial conditions. For example, fermentation can proceed quickly or slowly depending on the protein content of the milk, initial bacterial concentration, or ambient temperature [34]. Machine learning models can predict the course of a new batch at an early stage by learning pH-time data from hundreds of past fermentation batches. In this way, it is possible to adjust the duration or optimize the temperature profile to achieve the desired goal. Research using domain adaptation techniques is trying to develop generalizable control algorithms by incorporating data from different yogurt production facilities into a common model [35]. For example, a model trained with data from one facility can be adapted to different conditions in another facility (transfer learning) so that it can make accurate predictions for completely different equipment and milk compositions.

Stopping the yogurt fermentation at the right time is important so that it remains neither too acidic (over-fermented) nor too sweet (insufficiently fermented). AI can provide much more consistent results than human intervention in determining the fermentation endpoint. Machine learning algorithms that evaluate this multivariate data obtained with sensor fusion offer more reliable control compared to looking at a single parameter (*i.e.*, pH). As a result, yogurt can be produced with the targeted acidity and textural properties every time; inconsistencies between production batches are minimized [23].

AI can not only monitor the process but also provide proactive suggestions when necessary. For example, if a fermentation batch is progressing slower than usual, the AI model can notice this and suggest additional time for the fermentation to finish. If fermentation is progressing quickly, a fast cooling process can be brought forward to limit the drop in pH. These proactive approaches can prevent unwanted variations in the quality of tons of product, especially in high-volume production in large fermenters. AI-supported models can also be used to predict interactions between yogurt starter cultures, leading to forming customer-oriented culture combinations. Yang et al. [36] analyzed the genomic data of 362 yogurt bacterial isolates according to the semi-supervised learning network model and applied fermentation tests to selected combinations for validation purposes. Based on the results of fermentation tests it was demonstrated that AI-backed bacterial combinations were paired with a high accuracy of 85%.

AI can also be used to assess the quality of yogurt after fermentation. For example, a quality control unit equipped with sensors can analyze the image to detect abnormalities, such as the smoothness of the surface of yogurts that have been cooled in containers or whey separation (water release). If there is more whey separation than expected in a batch, the model can relate this to the fermentation parameters and suggest a different setting for similar milk composition in the future. In this way, AI not only classifies the current batch but also learns for future productions, continuously improving the process.

Bioactive peptides are defined as protein fragments with a wide range of bioactivities such as antimicrobial, antiinflammatory, antimutagenic, antioxidant and antihypertensive effects. The stability and bioavailability of these components formed as a result of bacterial activity during the production of fermented dairy products may vary. With the help of tools such as AI/ML-supported data mining, sequence analysis and predictive modeling, it is possible to find and identify new bioactive peptides and optimize fermentation conditions [37-39].

In summary, AI applications in yogurt production have made the fermentation process transparent, traceable and controllable. Thanks to real-time data tracking and intelligent control, it has become easier to produce each batch of yogurt at target quality values. This means reducing waste (for example, preventing product destruction due to excessive acidity) and providing a more consistent product to the consumer.

Bi et al. [40] developed an AI-supported intelligent hybrid genetic algorithm (GA)-particle swarm optimization (PSO)-tabu search (TS) algorithm model for the optimization of consumer-oriented sensory properties of yogurt. This model has revealed satisfactory data on the effects of brand and storage conditions on consumer preferences.

Applications of AI in cheese production.

Cheese production includes the maturation phase for most varieties. Cheeses are aged for weeks or even months under certain conditions to reach the desired aroma and texture. During this process, controlling environmental conditions such as temperature, humidity, and airflow, and monitoring the condition of the cheeses require expertise. AI can offer innovative solutions in monitoring the cheese maturation process and quality control, as well as being used in cheese classification [41]. Maturity determination is done traditionally by experts periodically tasting or visually inspecting the cheeses. AI can both speed up and objectively evaluate this task. An AI system developed in Italy has been trained on a large dataset consisting of photographs of cheeses at different stages of maturity. This model can classify the degree of maturity of a new wheel of cheese with high accuracy by simply looking at its image [22]. With such an AI tool, it would be possible to determine which of the hundreds of cheese wheels in the warehouses are ready for sale in a few minutes. This improves the manufacturer's stock management and time-to-market delivery.

During the ripening of cheeses without a rind such as white cheese and fresh Kashar cheese, unwanted yeast and mold growth on the surface of the cheese may cause quality losses. With AI-based image processing, high-resolution photographs of cheeses in the maturation room can be analyzed to detect unwanted stains or color changes on their surfaces. For example, if an AI application detects mold colonies that are out of tolerance on the surface of the cheese, this cheese can be reported to the operator or automatically taken for cleaning. Similarly, cracks that may occur in Kashar cheese or color yellowing due to drying can be detected with computer vision [42].

In hard and large-size cheeses (*e.g.*, Gruyere, Emmental), the distribution of eyes (holes) in the internal structure or the presence of unwanted cracks are quality criteria. In traditional production, it is not possible to see the internal structure without cutting the cheese wheel in half. However, the inside of the cheese can be scanned with techniques such as X-ray imaging or magnetic resonance imaging (MRI), and meaningful data can be extracted from these scans with the help of AI. Loddo et al. [33] developed an AI-supported model using 195 cheese surface images, which successfully classified Pecorino cheeses according to their maturity levels. This model has also been validated with conventional methods. Correct adjustment of temperature, humidity and air circulation in ripening rooms directly affects cheese quality. AI is also used in the optimization of these parameters. Climate data of each shelf and each point can be collected with IoT sensors; the AI model can compare this data with ideal values and dynamically control the HVAC (heating, ventilation and air conditioning) system. In addition, the ripening speed of different cheeses can be modeled with this data, predicting which batches need a little more moisture or extra time. This saves energy and ensures problem-free ripening. For example, if it is determined that the lower shelves in a ripening room are cooler than the upper shelves, the AI can turn on the fans to compensate for this difference or suggest changes to the cheese stack.

In summary, artificial intelligence applications in cheese production make the invisible aspects of the ripening process visible and place quality control on an objective basis. In points such as automatic ripeness determination, surface defect analysis and provision of ideal environmental conditions, AI offers speed and precision advantages compared to traditional methods. This reduces the variability in cheese at different production times, helping each cheese block reach the consumer with the targeted features.

AI in the production of milk powder and other milk-based powder products

Industrial dairy-based powdered products such as milk powder, whey powder and cream powder are produced by spray drying or freeze drying methods, being the latter less pronounced. In the spray drying process, optimization of parameters such as temperature, airflow, and feed rate is important in terms of product quality (solubility, color) and energy efficiency. In addition, these products usually have a long shelf life, but there is a risk of spoilage if they get wet or are stored improperly. Spray drying is a complex process in which liquid milk is brought into contact with hot air in the form of fine droplets and turned into powder. The aim is to have the powder at the desired moisture content and quality characteristics, while also consuming minimum energy. AI can learn the most suitable operating conditions by analyzing the data collected from the drying system (inlet-outlet humidity, temperatures, air flow, particle size, *etc.*). An artificial neural network model can suggest balance points that provide both energy savings and target moisture values by considering the quality and yield of milk powder obtained under different conditions. For example, in a multi-objective optimization study, the conditions to simultaneously improve the environmental performance and economic performance of the milk powder drying system were calculated [44].

In addition, AI models can adjust drying parameters in real-time according to current input milk characteristics (dry matter, fat content). In this way, constant product quality is maintained, while the dryer operates at its most efficient level even when conditions change. For example, when milk with lower dry matter arrives, the system can automatically increase the temperature slightly and reduce the airflow to maintain target moisture. This flexibility ensures continuous optimum production without the need for operator intervention.

Since drying towers and auxiliary equipment operate at high temperatures, problems such as clogging and burning may occur. By monitoring sensor data, AI can detect a clogging or abnormal pressure increase at an early stage and notify maintenance teams. For example, an ML model that analyzes data from the pressure difference sensors of bag filters can optimize the planned cleaning interval by predicting that a filter that is normally cleaned every 8 hours will fill up in 6 hours in this batch. This prevents both product loss and equipment damage.

Milk powder and similar powdered products are hygroscopic. Depending on storage conditions, clumping, color change or oxidation may develop over time. AI creates shelf-life prediction models by learning from environmental data (temperature, humidity) collected during storage and periodic quality measurements of the product (color indices, peroxide value, *etc*.). In addition, factors that shorten the shelf life of the powdered product after the package is opened can be analyzed with AI. IoT-based smart packaging can continuously measure the oxygen and humidity levels inside and transfer them to the AI model; based on this data, the model can give a warning as “product can be used or not” [45].

4. Conclusion

The advantages of AI systems in food production, such as reducing production costs, ensuring food safety at a high level, traceability and preventing food fraud, are obvious. The food companines are increasingly using AI-supported tracking and monitoring systems. Despite its advantages, AI-supported models can well be used for non-ethical purpses such as manipulating consumers preferences, misreflecting the outputs of scientific studies so on. In addition, some risks including cyber security (AI system adapted to food systems can be hacked), environmetanl impacts (AI may not understand context and damage sensitive ecosystem), data personalization (who owns the data and hot will it be shared and privacy protected?) and bias and fairness (The data and information fed into AI may be inherently biased, so the output will also be biased) are strognly visible. Therefore, a legal basis for the application of AI systems is required. In 2019, OECD Council on AI principles was adopted by G20 countries. In 2020, 27 AI laws and statutes were passed by 14 US states. Following year, WHO guidance on Ethics and Governance of AI for health was launched and FDA introduced AI/ML based software as a medical device (SaMD) action plan. Finally, in 2023, European Parliement Artificial Intelligence Act was launched [46]. The latter Law was based on the risk assessment. A safe, transparent, traceable, non-discriminant and environmentally friendly AI system was at the core of Parliament’s expectation from the proposed Law [47]. The EU’s AI Law will be fully in effect after 24 months. It is expected that the use of AI-supported systems will come to the fore shortly to understand/direct consumer behavior.

Conflict of interest

Authors declared that there is no conflict of interest

Similarity rate (iThenticate): 3%

References

[1] S. P. Oliver, B. Jayarao, M. and R. A. Almeida, Foodborne pathogens in milk and the dairy farm environment: food safety and public health implications. Foodborne Pathogens and Diseases, 2(2), 115-29, 2005. https://doi.org/10.1089/fpd.2005.2.115.

[2] D. Grace, F. Wu and A. H. Havelaar, Foodborne diseases from milk and milk products in developing countries-Review of causes and health and economic implications. Journal of Dairy Science, 103(11), 9715-9729, 2020. https://doi.org/10.3168/jds.2020-18323.

[3] C. Xiu and K.K. Klein, Melamine in milk products in China: Examining the factors that led to deliberate use of the contaminant. Food Policy, 35(5), 463-470, 2010. https://doi.org/10.1016/j.foodpol.2010.05.001.

[4] Z. Liu, S. Wang, Y. Zhang, Y. Feng, J. Liu, and H. Zhu, Artificial intelligence in food safety: a decade review and bibliometric analysis. Foods, 12, 1242, 2023. https://doi.org/10.3390/foods12061242.

[5] K. B. Chhetri, Application of artificial intelligence and machine learning in food quality control and safety assessment. Food Engineering Reviews, 16(1), 1-21, 2024. https://doi.org/10.1007/s12393-023-09363-1.

[6] X. Han, Q. Liu, Y. Li, M. Zhang, K. Liu, , L.-Y. Kwok, H. Zhang and W. Zhang, Synergizing artificial intelligence and probiotics: A comprehensive review of emerging applications in health promotion and industrial innovation. Trends in Food Science and Technology, 159, 104938, 2025. https://doi.org/10.1016/j.tifs.2025.104938.

[7] P. Devi, K. Subburamu,V. A. Giridhari, B. Dananjeyan and T. Maruthamuthu, Integration of AI based tools in dairy quality control: Enhancing pathogen detection efficiency. Journal of Food Measurement and Characterization, (published on-line on May 17, 2025), 2025. https://doi.org/10.1007/s11694-025-03269-8.

[8] I. Moon, F. Yi and B. Javidi, Automated three-dimensional microbial sensing and recognition using digital holography and statistical sampling. Sensors 10(9), 8437–8451, 2010. https://doi.org/10.3390/s100908437.

[9] T. Fukuda and O. Hasegawa, Expert system driven image processing for recognition and identifcation of microorganisms. Proceedings of International Workshop on Industrial Applications of Machine Intelligence and Vision, IEEE Japan, sayfa 33-38,

Tokyo, April 1989. https://doi.org/10.1109/MIV.1989.40518.

[10] S. Yeom and B. Javidi, Automatic identifcation of biological microorganisms using three-dimensional complex morphology. Journal of Biomedical Optics, 11(2), 024017, 2006. https://doi.org/10.1117/1.2187017.

[11] P. M. Iftikhar, M. V. Kuijpers, A. Khayyat, A. Iftikhar, and Sa. M. deGouvia de, Artificial intelligence: a new paradigm. Cureus, 12(2), e7124, 2020. https://doi.org/10.7759/cureus.7124.

[12] Y. Wang, Y. Feng, Z. Xiao and Y. Luo, Machine learning supported single-stranded DNA sensor array for multiple foodborne pathogenic and spoilage bacteria identification in milk. Food Chemsitry, 463, Part 2, 141115, 2025. https://doi.org/10.1016/j.foodchem.2024.141115.

[13] K. L. Beck, N. Haiminen, A. Agarwal, A. P. Carrieri, M. Madgwick, J. Kelly, V. Pylro, B. Kawas, M. Wiedmann and E. Ganda, Development and evaluation of statistical and artificial intelligence approaches with microbial shotgun metagenomics data as an untargeted screening tool for use in food production. mSystems, 9(11), e-00840-24, 2024. https://doi.org/10.1128/msystems.00840-24.

[14] T. Abass, E. O. Itua, T. Bature and M. A. Eruaga, Innovative approaches to food quality control: AI and machine learning for predictive analysis. World Journal of Advanced Research and Reviews, 21(3), 823–828, 2024. https://doi.org/10.30574/wjarr.2024.21.3.0719.

[15] X. Song, X. Zhang, G. Dong, H. Ding, X. Cui, Y. Han, H. Huang and L. Wang, AI in food industry automation: applications and challenges, Frontiers in Sustainable Food Systems. 9, 1575430, 2025. https://doi.org/10.3389/fsufs.2025.1575430.

[16] M. Aqeel, A. Sohaib, M. Iqbal S.S. and Ullah, Milk adulteration identification using hyperspectral imaging and machine learning. Journal of Dairy Science, 108(2), 1301-1314, 2025. https://doi.org/10.3168/jds.2024-25635.

[17] S. Colak, I. Uzunsoy, A. Narin and U. Duran, Adulteration detection of cow milk in buffalo milk using Fourier-transform infrared spectroscopy and artificial intelligence-based techniques. Journal of Food Composition and Analysis, 140, 107203, 2025. https://doi.org/10.1016/j.jfca.2025.107203.

[18] K. Goyal, P. Kumar and K. Verma, XAI-empowered IoT multi-sensor system for real-time milk adulteration detection. Food Control, 164, 110495, 2024. https://doi.org/10.1016/j.foodcont.2024.110495.

[19] R. U. Mhapsekar, L. Abraham, N. O'Shea and S. Davy, Edge-AI implementation for milk adulteration detection. IEEE Global Conference on Artificial Intelligence and Internet of Things (GCAIOT), 108-113, virtual, 2022. https://doi.org/10.1109/GCAIoT57150.2022.10019173.

[20] P. P. Lal, A. A. Prakash, A. A. Chand, K. A. Prasad, U. Mehta, M. H. Assaf, S. F. Mani and K. A. Mamun, IoT integrated fuzzy classification analysis for detecting adulterants in cow milk. Sensing and Biosensing Research, 36, 100486, 2022. https://doi.org/10.1016/j.sbsr.2022.100486.

[21] R. L . Lü, H. Y. He, Z. Jia, S. Y. Wang, N. B. Cai and X. B. Wang, Application progress of spectral detection technology of melamine in food. Spectroscopy and Spectral Analysis, 42(7), 1999-2006, 2022. https://doi.org/10.3964/j.issn.1000-0593(2022)07-1999-08.

[22] A. Perniciano, L. Zedda, C. Di Ruberto, B. Pes and A. Loddo, CRDet: An artificial intelligence-based framework for automated cheese ripeness assessment from digital images. IEEE/CAA Journal of Automatica Sinica, (in press), 2025. https://doi.org/10.1109/JAS.2024.125061.

[23] J. Muncan, K. Tei and R. Tsenkova, Real-time monitoring of yogurt fermentation process by aquaphotomics near-ınfrared spectroscopy. Sensors, 21(1), 177, 2021. https://doi.org/10.3390/s21010177.

[24] M. S. Hadi, B. S. R. Sugiono, M. A. Mizar, A. Witjoro and M. Irvan, Enhancing low-temperature long-time milk pasteurization process with a C4.5 algorithm-driven AIoT system for real-time decision-making. Journal of Food Process Engineering, 47, e14606, 2024. https://doi.org/10.1111/jfpe.14606.

[25] O. Oztuna Taner and A. B. Colak, Dairy factory milk product processing and sustainable of the shelf-life extension with artificial intelligence: a model study. Frontiers in Sustainable Food Systems, 8, 1344370, 2024. https://doi.org/10.3389/fsufs.2024.1344370.

[26] European Union, (EU). 2017. Welfare of cattle on dairy farms, (2025). https://op.europa.eu/en/publication-detail/-/publication/8950fa88-d651-11e7-a506-01aa75ed71a1/language-en Accessed 3 June 2025.

[27] C. Frazzoli, A. Mantovani and R. Dragone, Local role of food producers' communities for a global one-health framework: the experience of translational research in an Italian dairy chain. JACEN, 3, 14-19, 2014. https://doi.org/10.4236/jacen.2014.32B003

[28] C. Frazzoli, B. Bocca and A. Mantovani, The one health perspective in trace elements biomonitoring. Journal of Toxicology and Environmental Health Part B, 18, 344-370, 2015. https://doi.org/10.1080/10937404.2015.108573.

[29] G. J. Serrano-Torres, A. L. López-Naranjo, P. L. Larrea-Cuadrado and G. Mazón-Ferro, Transformation of the Dairy supply chain through artificial intelligence: A systematic review. Sustainability, 17(3), 982, 2025. https://doi.org/10.3390/su17030982.

[30] M. Nagahara, S. Tatemoto, T. Ito, O. Fujimoto, T. Ono, M. Taniguchi, M. Takagi and T. Otoi, Designing

a diagnostic method to predict the optimal artificial insemination timing in cows using artificial intelligence. Frontiers in Animal Sciences, 5, 1399434, 2024. https://doi.org/10.3389/fanim.2024.1399434.

[31] R. A. Romadhonny, A. B. Gumelar, T. M. Fahrudin, W. P. A. Setiawan, F. D. C. Putra, D. R. Nughoro, Estrous cycle prediction of dairy cows for planned artificial insemination (AI) using multiple logistic regression. International Seminar on Application for Technology of Information and Communication (iSemantic), 157-162, Semarang, 2019. https://doi.org/10.1109/ISEMANTIC.2019.884272.

[32] B. Vallejo-Cordoba, Predicting milk shelf-life based on artificial neural networks and headspace gas chromatographic data. Journal of Food Science, 60(5), 885-888, 2006. https://doi.org/10.1111/J.1365-2621.1995.tb06253.x

[33] R. Dragone, G. Grasso, G. Licciardi, D. Di Stefano and C. Frazzoli, Sensors driven system coupled with artificial intelligence for quality monitoring and HACCP in dairy production. Sensing and Bio-Sensing Research, 45, 100683, 2024. https://doi.org/10.1016/j.sbsr.2024.100683.

[34] B. Özer, Yogurt Science and Technology. Sidas Press. Izmir, 2006.

[35] A. Bowler, M. Pound and N. Watson, Convolutional feature extraction for process monitoring using ultrasonic sensors. Computers & Chemical Engineering, 155, 107508, 2021. https://doi.org/10.1016/j.compchemeng.2021.107508.

[36] S. J.Yang, M. Bai, W. C. Liu, W. C. Li, Z. Zhong, L. Y. Kwo, G. F. Dong and Z. H. Sun, Predicting *Lactobacillus delbrueckii* subsp. *bulgaricus-Streptococcus thermophilus* interactions based on a highly accurate semi-supervised learning method. Science China-Life Sciences, 68(2), 558-574, 2025. https://doi.org/10.1007/s11427-023-2569-7.

[37] H. M. Habib, R. Ismail, M. Agami A. F. and El-Yazbi, Exploring the impact of bioactive peptides from fermented milk proteins: a revew with emphasis on health implications and artificial intelligence integration. Food Chemistry, 481, 144047, 2025. https://doi.org/10.1016/j.foodchem.2025.144047.

[38] K. R. Choi and S. Y. Lee, Systems metabolic engineering of microorganisms for food and cosmetics production. Nature Reviews Bioengineering, 1(11), 832–857, 2023. https://doi.org/10.1038/s44222-023-00076-y.

[39] A. Das, R. N. Behera, A. Kapoor and K. Ambatipudi, The potential of metaproteomics and artificial intelligence to establish the next generation of probiotics for personalized healthcare. Journal of Agricultural and Food Chemistry, 71(46), 17528-17542 2023. https://doi.org/10.1021/acs.jafc.3c03834.

[40] K. X. Bi, S. Y. Zhang, C. Zhang and T. Qui, Consumer-oriented sensory optimization of yogurt: And artificial intelligence approach. Food Control, 138, 108995, 2022. https://doi.org/10.1016/j.foodcont.2022.108995.

[41] L. Zedda, A. Perniciano, A. Loddo and C. Di Ruberto, Understanding cheese ripeness:An artificial intelligen ce-based approach for hierarchical classification. Knowledge-Based Systems, 295, 111833, 2024. https://doi.org/10.1016/j.knosys.2024.111833.

[42] A. Bosakova-Ardenska, Recent trends in computer vision for cheese quality evaluation. Engineering Proceedings, 60(1), 12, 2024. https://doi.org/10.3390/engproc2024060012.

[43] A. Loddo, C. DiRuberto, G. Armano and A. Manconi, Automatic monitoring cheese ripeness using computer vision and artificial intelligence. IEEE Access, 10, 122612, 2022. https://doi.org/10.1109/ACCESS.2022.3223710.

[44] Z. Zhang, J. Zhang, W. Tian, Y. Li, Y. Song and P. Zhang, Multi-objective optimization of milk powder spray drying system considering environmental impact, economy and product quality. Journal of Cleaner Production, 369, 133353, 2022. https://doi.org/10.1016/j.jclepro.2022.133353.

[45] M. Mamat, F. Wong, H. T. Yew and J. A. Dargham, Estimating shelf life of packed fresh milk using odor and machine learning: A feasibility study. in: Internet of Things and Artificial Intelligence for Smart Environments. H.T. Yew, M. Mamat, J. A. Dargham, C. Seng Kheau and E. G. Moung, Eds., Springer, Singapore, pp. 143-165. 2024. https://doi.org/10.1007/978-981-97-1432-2_9.

[46] P. Detopoulou, G. Voulgaridou, P. Moschos, D. Levidi, T. Anastasiou, V. Dedes, E. M. Diplari, N. Fourfouri, C. Giaginis, G. I. Panautsopoulos, S. K. Papadopoulou, 2023. Artificial intelligence, nutrition and ethical issues: a mini review. Clinical Nutrition Open Science, 50, 46-56, 2023. https://doi.org/10.1016/j.nutos.2023.07.001.

[47] European Union Official Journal, Artificial Intelligence Act (Regulation (EU) 2024/1689). Published on 13 June 2024.