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The advent of artificial intelligence in dairy farming: A comprehensive overview

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Abstract
The dairy sector plays a crucial role in providing nutritious food, generating income, and creating employment opportunities worldwide. With a growing population, the demand for dairy products is expected to rise, but challenges such as limited arable land and climate change will impact livestock productivity. To enhance productivity and resource efficiency, dairy production systems require technological innovations to aid decision-making for better herd management. Artificial intelligence is transforming dairying by providing innovative solutions to optimize various dairy husbandry practices by employing technologies like machine learning, deep learning, computer vision, fuzzy logic systems, natural language processing and expert systems to support data-driven decisions and promote sustainability. However, AI adoption faces hurdles such as identifying farms, obtaining real-time data, high costs, technical complexity, data privacy issues, and a digital divide favoring larger farms. This review offers a comprehensive overview of AI applications in dairy farming, focusing on their transformative potential, challenges, and prospects.

Keywords: Artificial intelligence, machine learning, deep learning, computer vision, natural language processing, dairy farming

Introduction

The dairy sector, a cornerstone of our food system, is vital in fulfilling the triple benefits of providing nutritious food, generating income, and creating productive employment opportunities. As per an estimate by the United Nations, the global population is projected to reach around 10.28 billion by 2067 (United Nations 2024) [107]. Additionally, by the same year, the annual consumption of dairy products (per capita basis) is projected to increase to 119 kg on a fresh milk equivalent basis (Alexandratos and Bruinsma 2012, Britt *et al*. 2018) [2, 17]. The expected higher global demand for dairy products will be primarily due to population growth, urbanisation, increasing incomes, and globalisation. Fulfilling this expected demand with the current amount of cultivated land poses a challenge (Melak *et al*. 2024) [70]. Meanwhile, climate change poses a significant threat to livestock production due to its multifaceted impact. In addition to climate change, drivers of development change will contribute to a formidable set of challenges for the dairy sector. Given the impending challenges, it is essential for the dairy sector to proactively address these critical issues by enhancing its productivity and resource utilization efficiency effectively (Clay *et al*. 2020, Shine and Murphy 2022) [21, 97]. Enhancing efficiency and productivity in dairy farming requires continuous monitoring and evaluation of various aspects of the production cycle. As herd size and production efficiency increase, farms generate more data. Typically, farmers rely on their observations and experiences, but it is often impractical for them to monitor every activity and process all the raw data on a commercial scale (Slob *et al*. 2021) [100]. Therefore, there is a need for technological innovations to collect, analyse and integrate these data sources into the decision-making processes so that farmers can be advised to implement appropriate corrective actions promptly for more efficient herd management and to minimise losses.

Lately, there has been a notable increase in the use of AI technology options to support dairy farms (Vries *et al*. 2023) [108]. This trend can be attributed to the ability of AI applications to handle complex, non-linear relationships, automatically extract features, scale extensive data, adapt to new information, and process unstructured data. Moreover, AI models typically offer improved accuracy, versatility, and automation potential, while traditional methods are effective for simpler tasks. AI's role in dairy farming is extensive and multifaceted, spanning multiple areas such as enhancing productivity, improving animal health, promoting environmental sustainability, increasing operational efficiency, and addressing critical challenges. With the advancement of these technologies, their impact on dairy farming will grow, which will drive more innovation and contribute to the industry's sustainability and success. This review aims to give summarised information to the researchers, farm owners, readers, and other stakeholders about advances in various domains of AI, its applicability, limitations, and prospects in dairy farming.

What is Artificial Intelligence (AI)

McCarthy (1956) [69] defined AI as "the science and engineering of making intelligent machines, especially intelligent computer programs." Vries *et al*. (2023) [108] defined AI "as the ability of a digital computer or computer-controlled robot to perform tasks commonly associated with intelligent beings." AI can perform tasks such as learning, reasoning, perception, problem-solving, and understanding language. AI integrates various technologies and methodologies to achieve these capabilities. Based on capabilities, AI can be categorized into narrow or weak AI, general and strong AI. Further, it could be classified into reactive machines, limited memory, theory of mind, and self-awareness based on functionality (Ghosh and Thirugnanam 2021) [38]. Broadly, the major domains of AI and related models/algorithms have been depicted in Figure 1 and discussed in the subsequent paragraphs.

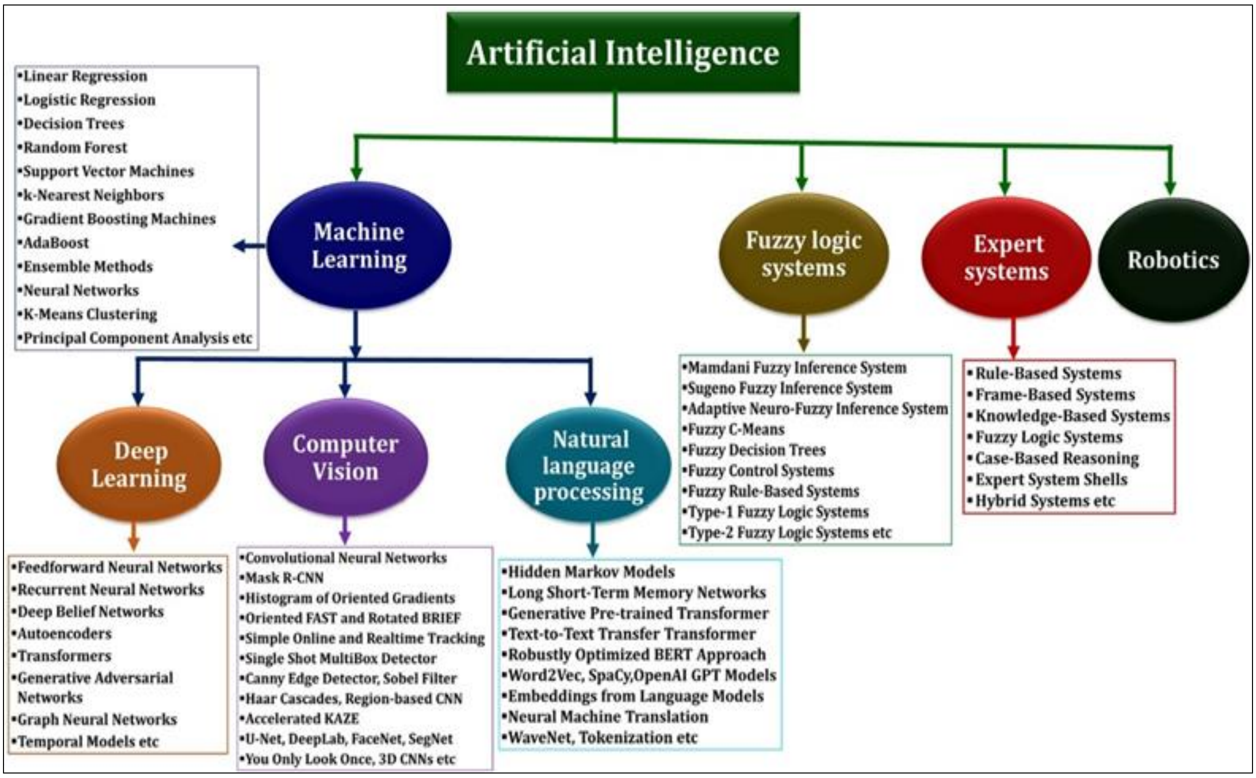

Fig 1: Major domains of AI with related algorithms

Applications and prospects of artificial intelligence in dairy farming

Artificial intelligence is revolutionizing dairy farming by improving efficiency and productivity across a wide array of practices, including feeding, breeding, health monitoring, milking, housing, behavior analysis, estrus detection, calving, animal identification, body weight estimation, and body condition score prediction, record keeping and other farm management tasks. In this review, we will focus on the integration of fundamental AI technologies, starting with Machine Learning (ML), which forms the foundation for data-driven decision-making. We will explore Deep Learning (DL), a subset of ML that enhances the capabilities of applications like Computer Vision (CV) and Natural Language Processing (NLP). Robotics combines engineering and AI, where AI enables robots to process information, make decisions, and learn from their environments. Additionally, we will discuss Fuzzy Logic Systems (FLS) for managing uncertainty in decision-making and Expert Systems (ES) for providing comprehensive decision support in dairy farming.

AI-driven feeding solutions can tailor diets to meet cows' individual nutritional needs, utilizing precision feeding systems that minimize waste and ensure optimal health (Martin *et al*. 2021, Saar *et al*. 2022) [66, 91]. AI significantly benefits breeding practices using advanced genetic analysis to identify optimal mating pairs based on desired traits, improving herd genetics and productivity (Ehret *et al*. 2015) [30]. AI can analyze data from biometric sensors, health records and environmental conditions to identify potential health issues like mastitis (Ebrahimi *et al*. 2019) [29] and ruminal acidosis (Wagner *et al*. 2020) [109] early, allowing for targeted interventions. Automated AI systems in milking can analyze yield data to optimize schedules, enhancing milk quality and quantity while reducing labor costs (Liseune *et al*. 2021) [61]. AI technologies can improve housing practices by employing smart sensors and cameras to monitor cow comfort and auto-adjust barn ventilation, temperature, humidity, lighting, etc. AI can analyze behavior data to incorporate timely corrective measures to promote better health and welfare (Benaissa *et al*. 2019, Guo *et al*. 2020) [13, 44]. Estrus detection is vital for successful breeding, with AI accurately identifying when cows are in heat, enhancing insemination timing and conception rates (Wang *et al*. 2022) [110]. AI also helps predict calving due dates and reduce complications (Fenlon *et al*. 2017, Zaborski *et al*. 2019) [34, 119]. Advanced facial recognition systems can track individuals (Amjed *et al*. 2019) [5]. In dairy farming, they ensure accurate record-keeping and facilitate tailored management strategies, particularly in large herds (Bergman *et al*. 2024) [14]. Cattle bioacoustics helps to identify individual cattle, assess welfare, and predict respiratory illnesses, particularly in young calves (Green *et al*. 2018) [43]. Computer vision techniques can accurately estimate an animal's weight and body condition scores based on visual data, allowing farmers to monitor growth rates and adjust feeding strategies (O'Leary *et al*. 2020, Xu *et al*. 2024) [82]. Record keeping, an essential part of dairy management, can be streamlined through AI systems that automate data entry and analysis. This improves accuracy and allows farmers and veterinarians to focus on strategic decision-making based on comprehensive insights.

As these technologies continue to advance and become more attainable, dairy farmers of all scales will have the ability to embrace innovative solutions. The emphasis on sustainability will drive demand for AI applications that optimize resources, improve animal welfare, and lessen environmental impacts. With ongoing progress in AI, the future of dairy farming holds the potential to be more efficient, sustainable, and productive, ushering in a new era in dairy farming. In the following paragraphs, we will discuss the different domain of AI and their applicability in dairy husbandry practices.

Machine Learning (ML)

Machine learning is a fundamental component of AI, involving the creation of algorithms that allow computers to learn from data and make predictions (Al-Jarrah *et al*. 2015) [4]. ML algorithms can identify patterns in large datasets with multiple variables, forecast the beginning of events, and learn from the given data (Mueller and Massaron 2016) [74]. Some statisticians suggest that machine learning algorithms generally produce better results because they learn from the provided data, whereas the researcher's hypothesis influences traditional analysis methods (Gorczyca and Gebremedhin 2020) [42]. ML approaches include i) Supervised learning, which involves training models on labeled data to predict outcomes (Ashour *et al*. 2020) [8]. Recent advancements in supervised learning techniques include improved algorithms for classification (Ashour *et al*. 2019) [9] and regression tasks (Sen *et al*. 2019) [96]. Some of the well-known supervised learning algorithms include linear regression, logistic regression, decision trees, random forest, support vector machines (SVM), K-nearest neighbors (KNN), gradient boosting machines (GBM), AdaBoost, and neural networks. ii) Unsupervised learning focuses on discovering patterns or groupings in unlabelled data. K-means clustering, hierarchical clustering, principal component analysis (PCA), t-Distributed Stochastic Neighbour Embedding (t-SNE), Density Based Spatial Clustering of Applications with Noise (DBSCAN), Locally Linear Embedding (LLE), and Eclat, etc. are some of the unsupervised learning algorithms. iii) Reinforcement learning involves models learning to make sequences of decisions by receiving rewards or penalties. Deep reinforcement learning has gained prominence for training AI systems in complex environments (Mnih *et al*. 2015) [73]. Some of the reinforcement learning algorithms are Q-learning, deep Q-networks (DQN), state-action-reward-state-action (SARSA), actor-critic methods, etc.

In machine learning, a prediction model is created by training algorithms using a specific dataset and then validating the model with a separate dataset (Khalid *et al*. 2022) [52]. The dataset contains features, which are the independent variables, and the corresponding outcome, which is the dependent variable. The process of using machine learning models is relatively simple. However, to create a highly accurate prediction model, it is essential to correctly identify which features & algorithms to use, properly tune hyperparameters, and address the complexities associated with large amounts of data (Slob *et al*.2021) [100].

Recently, there has been an increased use of ML algorithms as research tools in dairy farm management, providing new opportunities for advanced data-driven discoveries (Cockburn 2020, Shine and Murphy 2022) [97, 22]. These algorithms have various applications in dairy farming. They can predict feed intake (Glatz-Hoppe *et al*. 2019, Salleh *et al*. 2023) [39, 94]. In milking operations, they optimize yield predictions (Jensen *et al*. 2018) [49] and facilitate improved herd management by identifying behavioral patterns (Benaissa *et al*. 2019) [13]. Additionally, machine learning aids in estrus detection (Aungier *et al*. 2015, Wang *et al*. 2020) [10, 111] and reproductive success (Fenlon *et al*. 2016) [33]. It can predict calving instances (Fenlon *et al*. 2017) [34], detect dystocia (Zaborski *et al*. 2019) [119], and estimate live body weight (Gomez-Vazquez 2024) [41], ultimately leading to more informed decision-making. Machine learning models have also proven effective in assessing metabolic status (Wagner *et al*. 2020, Heirbaut *et al*. 2022) [109] and detecting disease incidences such as lameness (Post *et al*. 2020) [86], mastitis (Ebrahimi *et al*. 2019, Ghafoor and Sitkowska 2021, Roberta *et al*. 2023) [29, 37, 67], and bovine viral diarrhea (Machado *et al*. 2015). Furthermore, these algorithms can identify farm-specific risk factors (Probo *et al*. 2018) [87] and predict physiological responses to environmental heat stress (Gorczyca and Gebremedhin 2020) [42]. Some of the other and most recent ML studies have been depicted in Table 1.

Deep Learning (DL)

Deep learning is a specialized field of machine learning that utilizes neural networks to automatically learn and extract features from extensive datasets, mimicking the function of the human nervous system. A typical deep learning architecture comprises an input layer, one or more hidden layers, and an output layer. As the number of layers increases, it is called deep learning or a deep neural network (Zhang *et al*. 2023) [123]. For a given task, the input layer receives raw data, and the output layer makes predictions. Hidden layers extract features through interconnected neurons. Various specialized layers can be integrated within the hidden layer section to improve the model's capabilities and performance. Convolutional layers are responsible for identifying spatial patterns in images, while recurrent layers manage sequential data by retaining the memory of past inputs. Fully connected layers combine features to make final predictions. Pooling layers are included to reduce dimensionality and retain essential features, while activation layers introduce non-linearity. Dropout layers prevent overfitting by randomly deactivating neurons, and normalization layers standardize inputs (Srivastava *et al*. 2014) [102]. Deep learning comprises various algorithms, such as Feedforward Neural Networks (FNNs), which are the basic architecture for supervised tasks, while Convolutional Neural Networks (CNNs) excel in image processing. Recurrent Neural Networks (RNNs), along with Long Short-Term Memory Networks (LSTMs) and Gated Recurrent Units (GRUs), are designed for sequential data. Autoencoders are used for unsupervised learning and data compression, while Generative Adversarial Networks (GANs) generate new data through adversarial training (Liu *et al*. 2024a) [62]. Transformer Networks, known for their effectiveness in natural language processing, leverage attention mechanisms (Liu *et al*. 2024b) [63]. Other algorithms include Self-Organizing Maps, Capsule Networks for object recognition, and Graph Neural Networks for graph-structured data, showcasing the diverse capabilities of deep learning in various fields. A simple and deep-learning neural network has been depicted in Figures 3 & 4.

The performance of deep learning models is evaluated on specific metrics tailored to the task at hand. For classification tasks, accuracy, precision, recall, and F1 score are commonly used to gauge prediction quality. For regression tasks, mean absolute error (MAE), mean squared error (MSE), and R-squared tare are generally used to measure prediction accuracy. In segmentation tasks, metrics like Intersection Over Union (IoU) and the dice coefficient assess model performance in object detection (Kakumani *et al*. 2022) [51]. Additionally, confusion matrices provide a detailed overview of true positives, false positives, and negatives. Computational metrics, such as training and inference time, are also vital in assessing model efficiency and feasibility. The deep learning process involves several key steps. These include understanding the problem, collecting and preprocessing data, and selecting the appropriate algorithm. The method also entails training the model using training data, validating its performance on a validation set, testing it on unseen data, and iteratively tuning hyperparameters to enhance performance before deploying it in real-world applications (Kiran and Ozyildirim 2022, Alfarisy *et al*. 2023) [57, 3]. Deep learning offers several key advantages. It excels at handling large and complex datasets, making it highly effective in big-data scenarios. DL models can learn relevant features automatically, reducing the necessity for extensive pre-processing and minimizing human error.

Table 1: Machine learning models used for disease detection, voice recognition, genetic improvement, prediction of ESTRUS, calving incidences in dairy farming

References	**Model architecture and dataset**	**Findings**
Bushby *et al*. (2024) [18]	Random forest, elastic net, and gradient-boosting machine; social, feeding, movement behaviors, and location data of pre-weaned dairy calves.	A moderate to high accuracy (0.761-0.774) of prediction for the incidence of bovine respiratory disease was achieved using a gradient-boosting machine algorithm.
Gavojdian *et al*. (2024) [36]	Explainable framework tree-based pipeline optimization tool, XGboost, and deep-gated recurrent unit neural network model; vocal parameters of multiparous lactating cows.	The classification accuracy for the low- and high-frequency calls was 87.2 and 89.4%, and the accuracy of individual cow identification tasks was 68.9 and 72.5% for explainable and DL models, respectively.
Perneel *et al*. (2024) [85]	Multiple linear, ridge & lasso regression, PCA followed by linear regression on the first and first 100 principal components, PCA+lasso, random forest, boosting tree, SVM regression with radial kernel and polynomial kernel; genetics, environment, and management data to predict the lifetime production of dairy cows immediately after birth.	About 47% of the variance in lifetime production was explained by the best model (*PCA + lasso*). Additionally, the model for surplus animal selection led to a 9.4% greater lifetime production in the retained animals in comparison with the present Dutch cow average lifetime production.
Nadeem and Anis (2024) [76]	Random forest, XGBoost, logistic regression, and single perceptron; activity, eating, resting, and walking time data.	The Random Forest classifier exhibited an average accuracy of 91.60, 95.89, 92.96, 91.47, and 79.88% for predicting incidences of estrus, calving, mastitis, lameness, and acidosis, respectively.
Neupane *et al*. (2024) [80]	Random forest, Naive Bayes, logistic regression, and random convolutions kernel transformation (ROCKET); lying time, daily steps count, daily change, and claw treatment incidences.	ROCKET classifier outperformed other ML algorithms used in the study in classifying cows that needed corrective and therapeutic claw treatment with more than 90% accuracy.

Deep learning models often outperform traditional machine learning algorithms when it comes to handling high-dimensional data like images or audio. In addition, deep learning enables transfer learning, allowing a model trained for one task to be adapted for another, which facilitates quicker deployment in new applications (Sun *et al*. 2021, Kimutai and Förster 2022, Khalid and Romle 2024) [103, 56, 54].

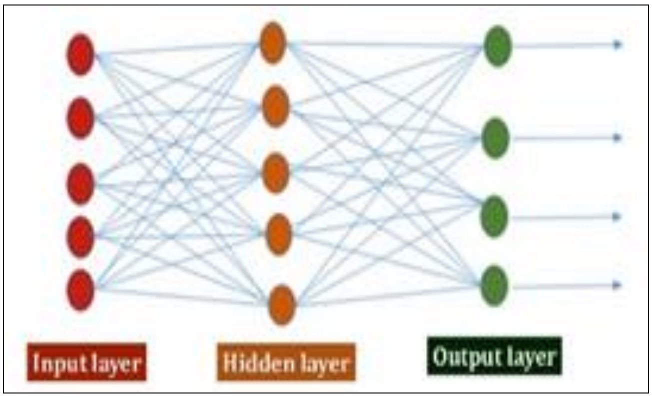

Fig 3: A simple neural network

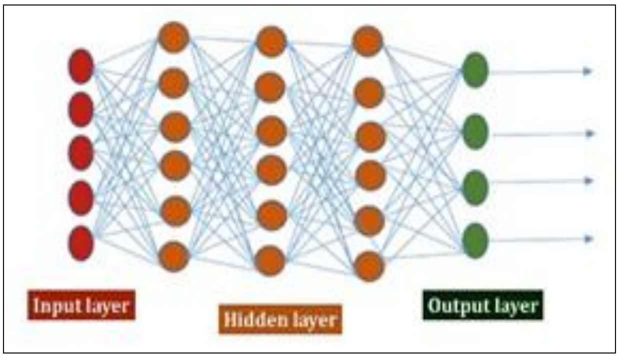

Fig 4: A deep learning neural network

Deep Learning (DL) is transforming dairy farming through various innovative applications. In this section, we will explore DL models other than CNN, as we have already discussed these algorithms in the CV section of this review. In dairy farming, various DL-based models have been employed in feeding, breeding, housing, behavior, and disease diagnosis to advise timely corrective measures and classification of vocal sounds to enable real-time livestock monitoring systems (Jung *et al*. 2021) [50]. Deep neural networks (DNNs) have been applied to predict milk yield (Liseune *et al*. 2021) [61] and prediction of lifetime profit estimates of dairy cattle (Naghashi and Diallo 2022) [78]. Further, DNNs have been used for behavioral analysis using wearable movement monitoring devices (Wu *et al*. 2022) [113], which can detect various behavioral episodes and signs of stress and, therefore, may assist in enhancing the living environment for the herd. One significant area is health monitoring, where DL algorithms analyze data from sensors to detect health issues such as mastitis (Naqvi *et al*. 2022) [79] and predict the bovine tuberculosis status of individual cows using milk MIR spectral data (Denholm *et al*. 2020) [26]. A deep learning model has also been used to establish pregnancy status from routinely collected milk MIR spectral data (Brand *et al*. 2021) [16]. Some of the most recent DL studies have been depicted in Table 2.

Computer Vision (CV)

Computer vision is an interdisciplinary field that combines computer science, artificial intelligence, mathematics, image processing, photometry, signal processing, robotics, cognitive science, physics, human-computer interaction, neuroscience, statistics, and augmented/virtual reality. It aims to understand visual information from the world and replicate human visual perception. CV aims to automate tasks involving visual inputs, such as recognizing objects, segmenting images, and analyzing scenes, which facilitates various applications from autonomous vehicles to medical imaging (Minaee *et al*.2021) [72]. Broadly, components of computer vision include 1. Image acquisition, where images or video are captured using cameras and sensors, 2. pre-processing, which enhances image quality through techniques like noise reduction and normalization; 3. Feature extraction, where critical attributes are identified using methods such as edge detection or texture analysis, 4. modelling, which involves applying algorithms to understand the features extracted, 5. Post-processing, where results are refined and interpreted, and 6. Visualization, presenting the output in an accessible format. Various algorithms play a crucial role in these processes, including SIFT (Scale-Invariant Feature Transform) and SURF (Speeded Up Robust Features) for key point detection, Canny edge detector and Sobel operator for identifying image boundaries and the Hough Transform for shape detection (Zhang 2020, Chekanov *et al*. 2022) [123, 19]. In recent years, deep learning has revolutionized computer vision. It has led to the development of Convolutional Neural Networks (CNNs) that can automatically learn hierarchical feature representations from images. This has significantly improved image classification and object detection performance (Khalid *et al*. 2020) [8]. Several CNN architectures, including AlexNet, VGGNet, GoogLeNet/Inception, ResNet, RefineDet, DenseNet, MobileNet, Xception, etc., have set benchmarks in various competitions and real-world applications. Furthermore, modern object detection algorithms like YOLO (You Only Look Once) and Mask R-CNN provide real-time capabilities for recognizing and segmenting multiple objects in images. Integrating traditional algorithms with deep learning techniques has improved accuracy and efficiency. Additionally, advancements in hardware and the availability of extensive datasets have accelerated research and deployment in computer vision applications across diverse domains like robotics, agriculture, animal husbandry, security, and healthcare. The Relationship between AI, ML, DL, and CV is depicted in Figure 2.

CV is playing an increasingly important role in transforming dairy farming by improving productivity, animal welfare, and operational efficiency through advanced monitoring and analysis techniques. This innovative aspect of computer vision, supported by state-of-the-art two-dimensional (Roberta *et al*. 2023) [67] and three-dimensional (Xavier *et al*. 2022, Cominotte *et al*. 2023) [114, 23] systems makes traditional human observations replaceable. It promotes a contactless and efficient approach to improving livestock management.

Table 2: Deep learning models used for genomic prediction, detecting estrus, predicting dairy cow behavior, and calving time in dairy farming

References	Model architecture and dataset	Findings
Pedrosa *et al*. (2024) [84]	Feed-forward neural networks, convolutional neural networks; milking refusals (MREF) and milking failures (MFAIL) as behavioral traits of Holstein cows in automatic milking systems (milking robots).	The mean square error for MREF and MFAIL was 0.36 (0.09) and 0.32 (0.09) for MLP, 0.37 (0.08) and 0.30 (0.09) for CNN. Hence, deep learning methods may be used to improve the accuracy of genomic prediction for behavioral traits in cows.
Chen *et al*. (2024) [115]	LSTM neural network; eating, activity, and resting times throughout the day of dairy cows.	The LSTM model achieved an area under the receiver operator characteristic curve of 0.89, demonstrate an excellent performance in estrus detection for dairy cows.
Balasso *et al*. (2023) [12]	Convolutional neural networks; manual behavior recording and accelerometer data (moving, standing, feeding, ruminating, and resting) as an indicator for detecting the early onset of disease in dairy cows.	The CNN model (8-layer) outperformed classical ML models and achieved an overall accuracy and F1 score of 0.96. For the single behavior, the precision, sensitivity/recall, and F1 score ranged between 0.93-0.99.
Yildiz *and ÖZGÜVEN* (2022) [117]	Feed-forward neural network model; cow age, lactation number, and number of days after estrus, movement, temperature, and humidity data	The two-layer network predicted estrus in dairy cows with an accuracy of 0.99. The model's sensitivity, precision, and F1 score were 0.10, 0.63 and 0.17, respectively.
Rahman *et al*. (2022) [89]	Forest deep neural network; lying time, the number of steps, stand-ups & head moves, and rumination time of cattle.	The model showed accuracy, sensitivity and specificity values of 98.38, 88.19 & 98.41 for predicting daily calving time and 97.93, 97.40, and 89.42, respectively, for predicting hourly calving time.

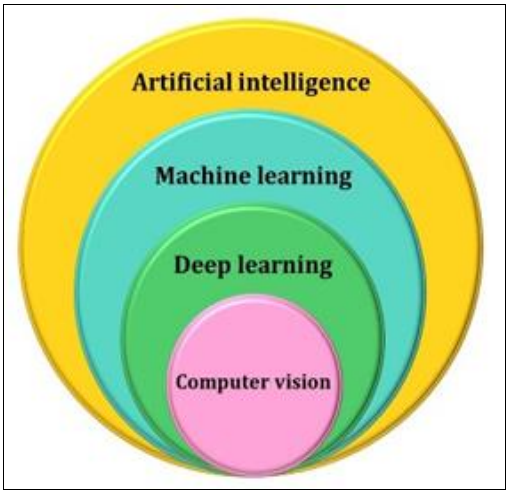

Fig 2: Relationship between AI, ML, DL and CV

CV techniques are being used to identify dairy animals based on coat pattern analysis (Andrew *et al*. 2016, Zhao *et al*. 2019) [6, 124], muzzle pattern analysis (Singh *et al*. 2024) [99], iris imaging (Sun *et al*. 2013) [104], tailhead images (Li *et al*. 2017) [60], and facial features (Wang *et al*. 2020, Xu *et al*. 2021) [116, 111]. This makes monitoring specific cows for health, breeding, and milking schedules easier. CV techniques are also used for cattle breed identification (Weber *et al*. 2020) [112] and determining the dairyness of cows (Dahiya *et al*. 2024) [25]. Researchers have explored the applicability of CV techniques to predict live body weight (Dohmen *et al*. 2021) [17] to provide insights into the animals' growth patterns and overall health. Another significant application of CV techniques is the prediction of body condition scores (Li *et al*. 2024) [59] to determine their health and nutritional status, allowing farmers to adjust feeding practices accordingly. In breeding management, CV aids in estrus detection (Arago *et al*. 2020) [7] and the prediction of optimal artificial insemination timing in cows (Nagahara *et al*. 2024) [77], thus improving conception rates. CV systems also play a crucial role in monitoring individual cow feed intake (Bezen *et al*. 2020, Yu *et al*. 2022) [15, 118], prediction of milk yield using visual images of cows (Jembere and Chimonyo 2024) [48], and automated detection of horn flies on cattle (Psota *et al*. 2021) [88]. Some of the most recent CV studies have been depicted in Table 3.

Natural Language Processing (NLP): Natural Language Processing (NLP) is a branch of artificial intelligence that focuses on the interaction between computers and human language. In essence, NLP allows computers to comprehend, interpret, and produce human language in a meaningful and useful way. NLP utilizes statistical modeling, machine learning, and deep learning to process and generate language. It relies on large annotated datasets for training. Some common examples of NLP in everyday life include voice assistants (Google Assistant, Alexa, and Siri), autocorrect and predictive text features on smartphones and email, text and speech translation between different languages, spam filters, chatbots, voice-to-text conversion, and summaries of lengthy articles and papers.

Compared to other AI techniques, limited reports are available on the applicability of NLP methods in dairy farming. NLP tools can analyze and interpret history sheets, feeding schedules and breeding records, veterinary notes and health records, sensor data, and operational reports, extracting valuable insights to optimize practices. Data extraction from documents, transcription of spoken data, and literature review for innovation tracking are the areas where dairy farms can utilize textual data to gain valuable insights and streamline their operations through the integration of NLP with existing technologies and systems.

Fuzzy Logic Systems (FLS)

Fuzzy Logic Systems are computational systems that utilize fuzzy logic to process and interpret data, make decisions, and control systems based on approximate reasoning instead of exact calculations. The main idea behind fuzzy set theory is to handle degrees of membership. A degree of 1 denotes full membership, 0 denotes no membership, and any value in between represents a degree of partial membership. Fuzzy logic uses these principles to translate human-like reasoning into machine operations, employing verbal and numerical information containing uncertainties (Mikail and Keskin 2009) [71]. Further, fuzzy logic provides simple and understandable solutions for controlling various non-linear and time-varying systems (Saday 2019) [92]. The main components of a fuzzy system typically include: 1. Fuzzifier translates crisp, quantitative inputs into fuzzy sets, 2. The inference engine applies the fuzzy rules to the fuzzified inputs to derive fuzzy outputs, 3. The fuzzy knowledge base encompasses both the rule base and the membership functions, and 4. The defuzzifier converts the combined fuzzy output into a precise value, yielding a clear and actionable result. The general structure of the Fuzzy logic system is depicted in Figure 5.

Table 3: Computer vision models used for individual cattle identification, estrus detection, prediction of body weight, and body condition score in dairy farming

References	Model architecture and dataset	Findings
Bergman *et al*. (2024) [14]	YOLOv5, vision transformer, Visformer, DenseNet, MobileNet, ResNet, EfficientNet; facial images of cows	YOLOv5 algorithm achieved a mean average precision of 97.8% for facial detection, while the vision-transformer model showed a facial classification accuracy of 96.3%.
Feng *et al*. (2024) [32]	ShuffleNet-SHE; images of the tail area of cows	In the constructed motion blur test ShuffleNet-SHE performed excellently and achieved an accuracy rate of 98.2% and a precision rate of 98.5%.
Islam *et al*. (2024) [47]	Contrast-limited adaptive histogram equalisation, YOLO, FaceNet; images of the muzzle of cattle	The model achieved an accuracy of 96.489% for identifying cattle based on their muzzle pattern.
Ninphet *et al*. (2024) [81]	Artificial immune system (AIS) algorithm and YOLOv5; estrus related images of cows	The AIS algorithm yielded an accuracy of 98.36%, while YOLOv5 detected estrus with an accuracy of nearly 99.50%.
Xu *et al*. (2024) [115]	ResNet-101-D, Atrous spatial pyramid pooling module, back propagation neural network, support vector machine, decision tree, multiple linear regression, and Gaussian regression; top-and back-view digital images of cows	An MAE of 13.11 pounds and an RMSE of 22.73 pounds were obtained using a backpropagation neural network, which was a superior performance in weight prediction accuracy compared to other models used in the study.

FLS, with their practicality and ease of use, offer valuable applications in dairy farming. They can effectively manage complex and variable conditions, providing farmers with a user-friendly and reliable tool for their operations. Many accessible reports are available for applying FLS in dairy husbandry, and some recent reports are discussed here. Zaninelli *et al*. (2016) [122] developed a fuzzy logic model to monitor the udder health status (UHS) of goats using a milk electrical conductivity (EC) signal for each gland by a sensor. They also considered bacteriological analyses and somatic cell count (SCC) to define the UHS of the glands. The researchers reported that EC indexes derived from the Fourier frequency spectra of gland milk EC signals recorded by EC sensors could improve the performance of a fuzzy logic model in monitoring mammary gland health status.

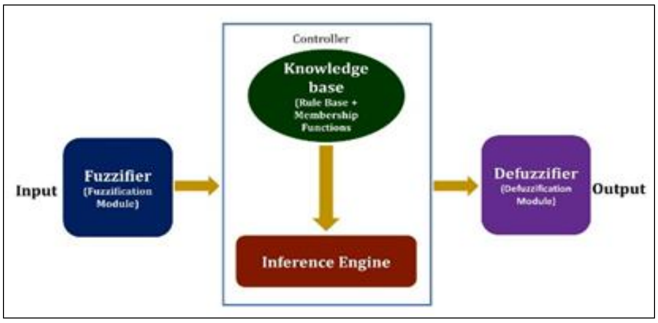

Fig 5: General structure of the fuzzy logic system

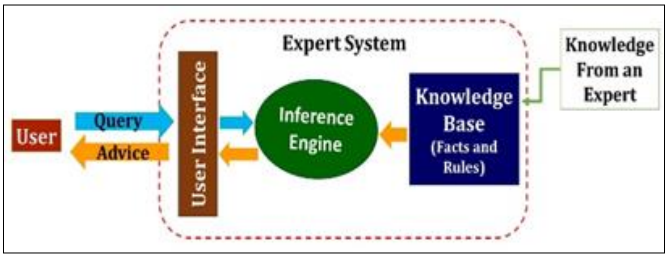

Fig 6: General structure of an expert system

Ağaoğlu *et al*. (2021) [1] assessed cow breeding efficiency using first calving age, calving interval, and number of seeding per pregnancy as input variables in a fuzzy system. They reported a success rate of 94% and calving interval as the most critical variable affecting accuracy. Kibar *et al*. (2024) [55] developed a fuzzy system to evaluate stress using environmental temperature, humidity, and THI values as input variables. They noticed that the impact of heat stress is higher as THI values increase and lower as THI values decrease in the fuzzy expert system. In 2024, Maziero *et al*. [68] created software for farmers to input data and receive insights to enhance their management practices. The software utilizes body mass and height as input variables and generates a fuzzy body mass index as the output variable.

Expert system Expert systems in dairy farming are a traditional application of AI. They are developed by gathering insights from human experts in a specific domain and then translating their expertise into computer code (Vries *et al*. 2023) [108]. These systems tackle intricate problems by using if-then rules or knowledge bases to reason through bodies of knowledge. They apply these rules to draw conclusions or make decisions (Slob *et al*. 2021) [100]. The general structure of an expert system is depicted in figure 6.

As early as 1988, Spahr *et al*. highlighted the potential use of expert systems in dairy farming and extension services. Reports indicate that expert systems could analyze feeding, health, milking, environmental conditions, breeding, finance, and operational efficiency data to provide actionable insights. After that, several researchers tried different ES to address various issues in dairy farming. Samer *et al*. (2012) [95] created an expert system using eleven simulation models that could plan and design housing systems, roof materials, concrete bases, cooling systems, milking parlors, fodder storage, and manure management systems. Additionally, it could suggest the machines and equipment required, as well as the water and electricity requirements for the planned facility. They further validated and evaluated the developed expert system's performance, and the developed system's accuracy was 94.5%. In 2014, Ravisankar *et al*. [90] developed a rule-based expert system for dairy cattle management. This system functions as an online guide, allowing users to interact using a set of rules consisting of if/then statements gathered from veterinary experts. The rules were utilized to create a knowledge base, and the programming codes were written in VB Net. The expert system offers immediate access to essential knowledge regarding milking, feeding, breeding, shed management, fodder cultivation, and disease and health management. Muhamediyeva *et al*. (2023) [75] developed a software tool that uses a fuzzy model to predict disease etiology, its progression, and the probability of clinical symptoms in cattle. The researchers utilized fuzzy set theory and fuzzy rule derivation algorithms in their approach. They concluded that the developed expert systems could be a valuable tool for veterinarians in diagnosing, treating, and preventing diseases in cattle, as well as in processing and analyzing disease data. Dairy farmers can achieve better productivity, reduce costs, and enhance animal welfare by leveraging these systems. Overall, the applicability of expert systems in dairy farming enhances operational efficiency and supports sustainable farming practices.

Robotics

As a subfield of artificial intelligence, robotics focuses on creating machines capable of autonomously or semi-autonomously performing tasks by integrating AI techniques with physical robots. The use of robots or humanoids is a rapidly growing trend that is gaining widespread recognition and adoption worldwide. The most common use of robots in dairy farming is robotic milking machines, also known as milk bots (Melak *et al*. 2024) [70]. Automated milking systems (AMS) typically consist of a milking stall, a sensor system to detect teats, a robotic arm for teat attachment, a teat cleaning system, software, and monitoring technologies for productivity, behavior, health, welfare, and the milking equipment (Filho *et al*., 2020, Eastwood *et al*., 2022) [35, 28]. It may be the feed-first or the milk-first system. These systems are efficient and save time, and they can also reduce labor costs (Silva *et al*. 2019) [98]. Additionally, autonomous mobile robot scrapers are increasingly used for routine cleaning and sanitization, which improves hygiene and greatly lowers the risk of disease transmission and contamination (Patel *et al*. 2022) [83]. Besides, these farm operations robots are also used for automatic feed delivery (Kumari and Dhawal, 2021) [58] and vaccine delivery (Ezanno *et al*. 2021) [31].

Limitations of AI systems in dairy farming

Adopting Artificial Intelligence (AI) in dairy farm management presents numerous opportunities but also faces several limitations that must be addressed. Following are the limitations or challenges in the adoption of AI technologies in dairy farming

- **Availability of quality and precise livestock datasets:** AI systems rely on complete, consistent, and accurate livestock datasets to make precise predictions and informed decisions. However, collecting and managing high-quality data from different sources can be costly, complicated, and sometimes impractical due to various limitations (Salamone *et al*. 2022, Trapanese *et al*. 2024) [93, 104].

- **The initial cost of AI technologies:** The expenses of acquiring AI hardware (such as sensors, cameras, and computers) and software can be substantial, particularly for small to medium-sized farms (Zambon *et al*. 2019, Bahn *et al*. 2021) [120, 11]. Additionally, ongoing system maintenance, updates, troubleshooting, and staff training costs will contribute to the overall expenditure, creating a financial burden for the farmer.
- **Technical complexity in implementation:** Implementing AI systems often requires specialized knowledge and skills that may not be readily available on all farms (Hassoun *et al*. 2023) [45]. Integrating AI systems with existing farm infrastructure is another significant hurdle.
- **Data privacy and security:** The storage and processing of extensive amounts of sensitive farm data pose a significant risk of data breaches and cybersecurity threats (Goller *et al*. 2021) [40]. This could potentially disrupt farm operations or lead to data loss. Compliance with privacy regulations and ensuring robust cybersecurity measures are essential, but they can be complex and costly, and requirements may vary by region.
- **Territorial location of the farm**: It is tough for dairy farmers to utilize new technologies in many rural areas due to the unavailability of digital infrastructure and connectivity (Zambon *et al*. 2019, Dadi *et al*. 2021) [120, 24].
- **Digital divide between farms:** In all countries, larger farms will have a competitive advantage over smaller farms due to their larger resource base, enabling them to invest in new technologies. This will widen the digital divide between smaller and larger farms (Hassoun *et al*. 2023) [45].
- **Risks of over-reliability on AI models:** AI models may have limitations in accuracy, contextual understanding, and may face disruptions from technical failures. Therefore, excessive reliance on AI may reduce human oversight, leading to issues in unexpected scenarios.
- **Adaptability and scalability issues:** The problem arises when customized AI solutions specific to a farm's conditions are applied to another farm or scaled to larger operations, which can be resource-intensive and time-consuming.
- **Lack of interoperability of data through prevailing AI systems:** Sharing datasets among farms would enhance algorithm development for better farm management (Lokhorst *et al.*, 2019) [64]. However, it is not easy to achieve because most of the sensor systems in vogue aim to accomplish certain purposes only and are manufacturer-specific, which invokes limitations due to vendor lock-in (Sykuta 2016) [105]. Thus, resulting in multiple data entries and lacking multifactorial analysis and decision-making (Cockburn 2020) [22].
- **Ethical and social implications:** The use of AI for automation may decrease the need for manual labor, potentially resulting in job loss or displacement of farm workers. Additionally, a transition to high-tech solutions could widen the digital divide and affect rural communities that lack access to advanced technologies.
- **Regulatory and compliance issues:** Navigating and complying with dairy farming data protection, and AI-specific regulations can be complex. These regulations vary by region, and the lack of standards can lead to inconsistent practices, making it difficult to ensure interoperability. Furthermore, determining legal responsibility in the event of AI-related errors or failures can be challenging.

Conclusion
The integration of AI systems is revolutionizing dairy farming by offering data-driven, real-time insights to farmers, enabling them to make informed and advantageous decisions. Machine learning analyzes vast datasets, while deep learning enhances image recognition for health assessments. Computer vision monitors animal behavior, and natural language processing allows intuitive interaction with farm management systems. Fuzzy logic assists in decision-making, and expert systems provide guidance on best practices. However, the adoption of AI in dairy farming also faces several limitations. Despite these challenges, the ongoing evolution of AI technologies presents significant opportunities for the dairy sector, paving the way for innovative practices to address sustainability and efficiency goals.

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Reference
1. Ağaoğlu B, Comba B, Koyun H. Evaluate of the reproductive efficiency of cows with fuzzy logic. Int J Appl Math Electron Comput. 2021;9:19-25.
2. Alexandratos N, Bruinsma J. World agriculture towards 2030/2050: the 2012 revision. ESA Working paper No. 12-03. Rome: FAO, 2012.
3. Alfarisy G, Malik O, Hong O. Quad-channel contrastive prototype networks for open-set recognition in domain-specific tasks. IEEE Access. 2023;11:48578-48592.
4. Al-Jarrah O, Yoo P, Muhaidat S, Karagiannidis G, Taha K. Efficient machine learning for big data: a review. Big Data Res. 2015;2:87-93.
5. Amjed N, Khalid F, Rahmat RWO, Bint MH. An efficient non-occluded face area detection method under unconstrained environment of smartphone database. In: 2019 IEEE Int Conf Signal Image Process Appl (ICSIPA), 2019. p. 291-295.
6. Andrew W, Sion H, Neill C, Tilo B. Automatic individual Holstein Friesian cattle identification via selective local coat pattern matching in RGB-D imagery. In: Proc Int Conf Image Process (ICIP), 2016 Aug. https://doi.org/10.1109/ICIP.2016.7532404
7. Arago NM, Chris IA, Angelita GM, Charl GL, Nicole ER, Rodney RAR, Timothy MA. Automated estrus detection for dairy cattle through neural networks and bounding box corner analysis. Int J Adv Comput Sci Appl. 2020;11(9):303-311.
8. Ashour MW, Khalid F, Halin AA, Darwish SH, Abdulrazzaq MM. A review on steel surface image features extraction and representation methods. In: Int Conf Emerg Technol Comput. Cham: Springer Int Publ, 2020. p. 239-250.
9. Ashour MW, Khalid F, Abdul Halin A, Abdullah LN, Darwish SH. Surface defects classification of hot-rolled

steel strips using multi-directional shearlet features. Arab J Sci Eng. 2019;44:2925-2932.
10. Aungier SPM, Roche JF, Duffy P, Scully S, Crowe MA. The relationship between activity clusters detected by an automatic activity monitor and endocrine changes during the periestrous period in lactating dairy cows. J Dairy Sci. 2015;98:1666-1684.
11. Bahn RA, Abed AKY, Rami Z. Digitalization for sustainable agri-food systems: Potential, status, and risks for the MENA region. Sustainability. 2021;13:3223.
12. Balasso P, Cristian T, Lorenzo S, Luisa M, Igino A, Giorgio M. Uncovering patterns in dairy cow behaviour: a deep learning approach with tri-axial accelerometer data. Animals. 2023;13:1866.
13. Benaissa S, Frank AMT, David P, Toon DP, Jens T, Emmeric T, *et al*. On the use of on-cow accelerometers for the classification of behaviours in dairy barns. Res Vet Sci. 2019;125:425-433.
14. Bergman N, Yitzhaky Y, Halachmi I. Biometric identification of dairy cows via real-time facial recognition. Animal. 2024;18:101079.
15. Bezen R, Yael E, Ilan H. Computer vision system for measuring individual cow feed intake using RGB-D camera and deep learning algorithms. Comput Electron Agric. 2020;172:105345.
16. Brand W, Wells AT, Smith SL, Denholm SJ, Wall E, Coffey MP. Predicting pregnancy status from mid-infrared spectroscopy in dairy cow milk using deep learning. J Dairy Sci. 2021;104:4980-4990.
17. Britt JH, Cushman RA, Dechow CD, Dobson H, Humblot P, Hutjens MF, Jones GA, Ruegg PS, Sheldon IM, Stevenson JS. Invited review: Learning from the future: A vision for dairy farms and cows in 2067. J Dairy Sci. 2018;101:3722-3741.
18. Bushby EV, Matthew T, Vázquez-D JA, Francesca O, Jasmeet K. Early detection of bovine respiratory disease in pre-weaned dairy calves using sensor-based feeding, movement, and social behavioural data. Sci Rep. 2024;14:9737.
19. Chekanov M, Shipitko O, Skoryukina N. Study of key points detectors and descriptors performance on X-ray images compared to the visible light spectrum images. IEEE Access. 2022;10:38964-38972.
20. Chen YR, Chen PY, Su CK. An LSTM neural network for estrus detection in dairy cows. In: 2024 10th Int Conf Appl Syst Innov (ICASI-IEEE), 2024, p. 196-198.
21. Clay N, Tara G, Jamie L. Dairy intensification: drivers, impacts and alternatives. Ambio. 2020;49:35-48.
22. Cockburn M. Review: Application and prospective discussion of machine learning for the management of dairy farms. Animals. 2020;10:1690.
23. Cominotte A, Arthur F, João D, Guilherme R, Rodrigo T, Guilherme P, *et al*. Use of biometric images to predict body weight and hot carcass weight of Nellore cattle. Animals. 2023;13:1679.
24. Dadi V, Suryadevara RN, Rahul SM, Tripti A, Sapna A. Agri-food 4.0 and innovations: revamping the supply chain operations. Prod Eng Arch. 2021;27(2):75-89.
25. Dahiya NK, Bajaj SB, Ruhil AP, Jaglan V. Udderly accurate: A deep learning based modelling for determination of dairyness of Sahiwal cow using computer vision. Indian J Anim Sci. 2024;94:83-87.
26. Denholm SJ, Brand W, Mitchell AP, Wells AT, Krzyzelewski TS, Smith L, *et al*. Predicting bovine tuberculosis status of dairy cows from mid-infrared spectral data of milk using deep learning. J Dairy Sci. 2020;103:9355-9367.
27. Dohmen R, Cagatay C, Qingzhi L. Image-based body mass prediction of heifers using deep neural networks. Biosyst Eng. 2021;204:283-293.
28. Eastwood CR, Dela Rue B, Edwards JP, Jago J. Responsible robotics design-A systems approach to developing design guides for robotics in pasture-grazed dairy farming. Front Robot AI. 2022;9:914850.
29. Ebrahimi M, Dehcheshmeh MM, Ebrahimie E, Petrovski KR. Comprehensive analysis of machine learning models for prediction of sub-clinical mastitis: deep learning and gradient-boosted trees outperform other models. Comput Biol Med. 2019;114:103456.
30. Ehret A, Hochstuhl D, Gianola D, Thaller G. Application of neural networks with back-propagation to genome-enabled prediction of complex traits in Holstein-Friesian and German Fleckvieh cattle. Genet Sel Evol. 2015;47:1.
31. Ezanno P, Picault S, Beaunée G, Bailly X, Muñoz F, Duboz R, *et al*. Research perspectives on animal health in the era of artificial intelligence. Vet Res. 2021;52:1.
32. Feng T, Guo Y, Huang X, Wu J, Cheng C. A method of body condition scoring for dairy cows based on lightweight convolution neural network. J ASABE. 2024;67:409-420.
33. Fenlon C, O'Grady L, Dunnion J, Shalloo L, Butler S, Doherty M. A comparison of machine learning techniques for predicting insemination outcome in Irish dairy cows. In: CEUR Workshop Proc. 2016;1751.
34. Fenlon C, O'Grady L, Mee JF, Butler ST, Doherty ML, Dunnion J. A comparison of 4 predictive models of calving assistance and difficulty in dairy heifers and cows. J Dairy Sci. 2017;100:12.
35. Filho LMS, Lopes MA, Brito SC, Rossi G, Conti L, Barbari M. Robotic milking of dairy cows: a review. Semin Cienc Agrar. 2020;41:2833.
36. Gavojdian D, Mincu M, Lazebnik T, Oren A, Nicolae I, Zamansky A. Bovine Talk: Machine learning for vocalization analysis of dairy cattle under the negative affective state of isolation. Front Vet Sci. 2024;11:1357109.
37. Ghafoor NA, Sitkowska B. MasPA: A machine learning application to predict risk of mastitis in cattle from AMS sensor data. Agric Eng. 2021;3:3.
38. Ghosh M, Thirugnanam A. Introduction to artificial intelligence. In: Introduction to Artificial Intelligence. Singapore: Springer, 2021. p. 23-44. https://doi.org/10.1007/978-981-16-0415-7_2
39. Hoppe GJ, Mohr E, Losand B. Use of milk recording data for characterization of dairy cow supply situation. Second part: Evaluation scheme for the assessment of milk ingredients at farm level. Zuchtungskunde. 2019;91:6.
40. Goller M, Caruso C, Harteis C. Digitalisation in agriculture: Knowledge and learning requirements of German dairy farmers. Int J Res Vocat Educ Train. 2021;8:2.
41. Vazquez GA, Silva DTP, Ítavo VLC, Herrera GRA, Rojas MD, Camacho HJ, *et al*. Relationship between body weight and dorsal area in female buffaloes. Rev Colomb Cienc Pecu. 2024;37:243-250.
42. Gorczyca MT, Gebremedhin KG. Ranking of environmental heat stressors for dairy cows using machine learning algorithms. Comput Electron Agric. 2020;168:105124.

43. Green AC, Johnston IN, Clark CEF. Invited review: The evaluation of cattle bioacoustics and application of advanced dairy systems. Animals. 2018;12:1250-1259.
44. Guo Y, He D, Chai L. A machine vision-based method for monitoring scene-interactive behaviors of dairy calf. Animals. 2020;10:2.
45. Hassoun A, Garcia-Garcia G, Trollman H, Jagtap S, Parra-López C, Cropotova J, *et al*. Birth of Dairy 4.0: Opportunities and challenges in adoption of fourth industrial revolution technologies in the production of milk and its derivatives. Curr Res Food Sci. 2023;7:100535.
46. Heirbaut S, Jensen DB, Jing XP, Stefańska B, Lutakome P, Vandaele L, *et al*. Different reticuloruminal pH metrics of high-yielding dairy cattle during the transition period in relation to metabolic health, activity, and feed intake. J Dairy Sci. 2022;105:6880-6894.
47. Islam HZ, Khan S, Paul SK, Rahi SI, Sifat FH, Sany MMH, *et al*. Muzzle-based cattle identification system using artificial intelligence. arXiv. 2024;2407.06096v1.
48. Jembere L, Chimonyo M. Prediction of milk yield using visual images of cows through deep learning. S Afr J Anim Sci. 2024;54:47-58.
49. Jensen DB, Van der Voort M, Hogeveen H. Dynamic forecasting of individual cow milk yield in automatic milking systems. J Dairy Sci. 2018;101:10495-10507.
50. Jung DH, Kim NY, Moon SH, Jhin C, Kim HJ, Yang JS, *et al*. Deep learning-based cattle vocal classification model and real-time livestock monitoring systems with noise filtration. Animals. 2021;11:357-373.
51. Kakumani A, Sree L, Kumar B, Rao S, Garrepally M, Chandrakanth M. Segmentation of cell nuclei in microscopy images using modified ResUNet. 2022 IEEE 3rd Global Conf Adv Technol (GCAT), 2022, p. 1-6.
52. Khalid F, Abdullah AH, Abdullah LN. Smartflora mobile flower recognition application using machine learning tools. 2022 IEEE 18th Int Colloq Signal Process Appl (CSPA). 2022:204-209.
53. Khalid F, Amjeed N, Wirza RWO, Madzin H, Azizan I. Face recognition for varying illumination and different optical zoom using a combination of binary and geometric features. IEEE Access. 2020;8:129774-129784.
54. Khalid F, Romle AA. Herbal plant image classification using transfer learning and fine-tuning deep learning model. J Adv Res Appl Sci Eng Technol. 2024;35:16-25.
55. Kibar M, Aytekin İ, Özkan İA. Fuzzy logic model for determining optimal temperature-humidity index values in dairy farms in temperate climate. J Appl Anim Welf Sci. 2024;10:1-13.
56. Kimutai G, Förster A. An instance-based deep transfer learning approach for resource-constrained environments. Proc ACM SIGCOMM Workshop Netw Sens Syst Sustain Soc, 2022. https://doi.org/10.1145/3538393.3544938.
57. Kiran M, Ozyildirim M. Hyperparameter tuning for deep reinforcement learning applications. arXiv. 2022;abs/2201.11182.
58. Kumari M, Dhawal K. Application of artificial intelligence (AI) in animal husbandry. Vigyan Varta. 2021;2:27-29.
59. Li K, Teng G, Wang J, Zhang Y, Gao L, Feng H. Body condition scoring of dairy cows based on feature point location. IEEE Access. 2024;12:5270-5283.
60. Li W, Ji Z, Wang L, Sun C, Yang X. Automatic individual identification of Holstein dairy cows using tailhead images. Comput Electron Agric. 2017;142:622-631.
61. Liseune A, Salamone M, Van den Poel D, Van Ranst B, Hostens M. Predicting the milk yield curve of dairy cows in the subsequent lactation period using deep learning. Comput Electron Agric. 2021;180:105904.
62. Liu Y, Khalid B, Binti F, Mustaffa MR, Azman BA. Dual-modality learning and transformer-based approach for high-quality vector font generation. Expert Syst Appl. 2024;240:122405.
63. Liu Y, Khalid B, Wang F, Binti C, Mustaffa MR, Azman BA. An end-to-end Chinese font generation network with stroke semantics and deformable attention skip-connection. Expert Syst Appl. 2024;237:121407.
64. Lokhorst C, De Mol RM, Kamphuis C. Invited review: Big data in precision dairy farming. Anim. 2019;13:1519-1528.
65. Machado G, Mendoza MR, Corbellini LG. What variables are important in predicting bovine viral diarrhea virus? A random forest approach. Vet Res. 2015;46:21.
66. Martin MJ, Dórea JRR, Borchers MR, Wallace RL, Bertics SJ, DeNise SK, *et al*. Comparison of methods to predict feed intake and residual feed intake using behavioral and metabolite data in addition to classical performance variables. J Dairy Sci. 2021;104:9054-9069.
67. Roberta M, Leopoldo A, Gianluca N, Angela S, Francesco B, Maria TV, *et al*. Reliable use of smart cameras for monitoring biometric parameters in buffalo precision livestock farming. ACTA IMEKO. 2023;12:1-7.
68. Maziero LP, Chacur MGM, Cremasco CP, Bordin D, Putti FF, Gabriel Filho LRA. Software based on fuzzy logic for the classification of body mass cattle. Soft Comput. 2024;28:8151-8165.
69. McCarthy J. What is artificial intelligence, 1956. Available from: http://www-formal.stanford.edu/jmc/whatisai.html
70. Melak A, Aseged T, Shitaw T. The influence of artificial intelligence technology on the management of livestock farms. Int J Distrib Sens Netw. 2024;2024:8929748. https://doi.org/10.1155/2024/8929748.
71. Mikail N, Keskin İ. Fuzzy logic applications in animal breeding. Selçuk J Agric Food Sci. 2009;23:89-95.
72. Minaee S, Boykov Y, Porikli F, Plaza A, Kehtarnavaz N, Terzopoulos D. Image segmentation using deep learning: A survey. IEEE Trans Pattern Anal Mach Intell. 2021;44:3523-3542.
73. Mnih V, Kavukcuoglu K, Silver D, Rusu AA, Veness J, Bellemare MG, *et al*. Human-level control through deep reinforcement learning. Nature. 2015;518:529-533.
74. Mueller J, Massaron L. Machine learning for dummies. New Jersey, United States: John Wiley & Sons, 2016.
75. Muhamediyeva DT, Safarova LU, Ruzikulov RF. Expert systems for diagnostics of infectious diseases in cattle. BIO Web Conf. 2023;71:1073.
76. Nadeem G, Anis MI. Investigation of bovine disease and events through machine learning models. Pak J Agric Res. 2024;37:102-114.
77. Nagahara M, Tatemoto S, Ito T, Fujimoto O, Ono T, Taniguchi M, *et al*. Designing a diagnostic method to predict the optimal artificial insemination timing in cows using artificial intelligence. Front Anim Sci. 2024;5:122.

78. Naghashi V, Diallo AB. A model for the prediction of lifetime profit estimate of dairy cattle (Student abstract). Proc 36th AAAI Conf Artif Intell (AAAI 2022). 2022;36:13021-13022.
79. Naqvi SA, King MTM, Matson RD, DeVries TJ, Deardon R, Barkema HW. Mastitis detection with recurrent neural networks in farms using automated milking systems. Comput Electron Agric. 2022;192:106618.
80. Neupane R, Aryal A, Haeussermann A, Hartung E, Pinedo P, Paudyal S. Evaluating machine learning algorithms to predict lameness in dairy cattle. PLoS One. 2024;19(7):e0301167.
81. Ninphet W, Amdee N, Sangsongfa A. Adaptive deep learning for image-based estrus prediction and detection in dairy cows. PriMera Sci Eng. 2024;5:12-37.
82. O'Leary N, Leso L, Buckley F, Kenneally J, McSweeney D, Shalloo L. Validation of an automated body condition scoring system using 3D imaging. Agric (Switzerland). 2020;10:246.
83. Patel H, Samad A, Hamza M, Muazzam A, Harahap MK. Role of artificial intelligence in livestock and poultry farming. Sinkron. 2022;7:109-114.
84. Pedrosa VB, Chen SY, Gloria LS, Doucette JS, Boerman JP, Rosa GJM, *et al*. Machine learning methods for genomic prediction of cow behavioral traits measured by automatic milking systems in North American Holstein cattle. J Dairy Sci. 2024;107:4758-4772.
85. Perneel M, De Smet S, Verwaeren J. Data driven prediction of dairy cattle lifetime production and its use as a guideline to select surplus youngstock. J Dairy Sci, 2024. https://doi.org/10.3168/jds.2023-23660.
86. Post C, Rietz C, Büscher W, Müller U. Using sensor data to detect lameness and mastitis treatment events in dairy cows: A comparison of classification models. Sensors. 2020;20:3863.
87. Probo M, Bogado Pascottini O, LeBlanc S, Opsomer G, Hostens M. Association between metabolic diseases and the culling risk of high-yielding dairy cows in a transition management facility using survival and decision tree analysis. J Dairy Sci. 2018;101:9271-9285.
88. Psota ET, Luc EK, Pighetti GM, Schneider LG, Fryxell TRT, Keele JW, *et al*. Development and validation of a neural network for the automated detection of horn flies on cattle. Comput Electron Agric. 2021;180:105927.
89. Rahman MM, Rana EA, Tamzi NN, Saha I, Siddiqui FH. A deep learning approach-FDNN: Forest deep neural network to predict cow's parturition date. J Appl Artif Intell. 2022;3:61-74.
90. Ravisankar H, Naidu VSGR, Sivaraju K, John Babu B, Sivarao PVVS. Expert system for dairy cattle management. Indian J Anim Sci. 2014;84:946-949.
91. Saar M, Edan Y, Godo A, Lepar J, Parmet Y, Halachmi I. A machine vision system to predict individual cow feed intake of different feeds in a cowshed. Anim. 2022;16:77-85.
92. Saday F. Developing a gender determination method with fuzzy logic approach in cattle [Master's thesis]. Konya, Turkey: Karatay Univ, Inst of Science, 2019.
93. Salamone M, Adriaens I, Vervaet A, Opsomer G, Atashi H, Fievez V, *et al*. Prediction of first test day milk yield using historical records in dairy cows. Anim. 2022;16:100658.
94. Salleh SM, Danielsson R, Kronqvist C. Using machine learning methods to predict dry matter intake from milk mid-infrared spectroscopy data on Swedish dairy cattle. J Dairy Res. 2023;90:42-50.
95. Samer M, Hatem M, Grimm H, Doluschitz R, Jungbluth T. An expert system for planning and designing dairy farms in hot climates. Agric Eng Int CIGR J. 2012;14:1-9.
96. Sen P, Hajra M, Ghosh M. Supervised classification algorithms in machine learning: A survey and review. In: Advances in Intelligent Systems and Computing. 2019;199012244:99-111.
97. Shine P, Murphy MD. Over 20 years of machine learning applications on dairy farms: A comprehensive mapping study. Sensors. 2022;22:52.
98. Silva GR, Lopes MA, Lima AL, Costa GM, Damasceno FA, Barros VP, *et al*. Analysis of rentability of milk production systems in compost barn and free stall: A comparative. Semina Cienc Agrar. 2019;40:1165-1184.
99. Singh Rana R, Khalid F, Ahlawat TR, Sankanur MS, Azman A, Agrawal A, *et al*. Individual buffalo identification through muzzle dermatoglyphics images using deep learning approaches. J Adv Res Appl Sci Eng Technol, 2024, p. 59. https://doi.org/10.37934/araset.59.2.178191
100. Slob N, Catal C, Kassahun A. Application of machine learning to improve dairy farm management: A systematic literature review. Prev Vet Med. 2021;187:105237.
101. Spahr SL, Jones LR, Dill DE. Expert systems their use in dairy herd management. J Dairy Sci. 1988;71:879-885.
102. Srivastava N, Hinton G, Krizhevsky A, Sutskever I, Salakhutdinov R. Dropout: A simple way to prevent neural networks from overfitting. J Mach Learn Res. 2014;15:1929-1958.
103. Sun Q, Bai C, Chen T, Geng H, Zhang X, Bai Y, *et al*. Fast and efficient DNN deployment via deep Gaussian transfer learning. In: 2021 IEEE/CVF Int Conf Comput Vis (ICCV). 2021:5360-5370.
104. Sun S, Yang S, Zhao L. Noncooperative bovine iris recognition via SIFT. Neurocomputing. 2013;120:372-379.
105. Sykuta ME. Big data in agriculture: Property rights, privacy and competition in AG data services. Int Food Agribus Manag Rev Spec Issue. 2016;19(A):1-20.
106. Trapanese L, Hostens M, Salzano A, Pasquino N. Short review of current limits and challenges of application of machine learning algorithms in the dairy sector. Acta IMEKO. 2024;13(1):1-7.
107. United Nations. World population prospects: 2024. United Nations Population Division, 2024. Available from: https://population.un.org/dataportal/data/indicators/49/locations/900/start/2024/end/2067/table/pivotbylocation?df=93c725be-2cf1-4f48-914e-136fa21c98d1
108. Vries AD, Bliznyuk N, Pinedo P. Invited review: Examples and opportunities for artificial intelligence (AI) in dairy farms. Appl Anim Sci. 2023;39:14.
109. Wagner N, Antoine V, Mialon MM, Lardy R, Silberberg M, Koko J, *et al*. Machine learning to detect behavioural anomalies in dairy cows under subacute ruminal acidosis. Comput Electron Agric. 2020;170:105233.
110. Wang J, Zhang Y, Wang J, Zhao K, Li X, Liu B. Using machine-learning technique for estrus onset detection in dairy cows from acceleration and location data acquired by a neck-tag. Biosyst Eng. 2022;214:103-112.

111. Wang Z, Wang E, Zhu Y. Image segmentation evaluation: A survey of methods. Artif Intell Rev. 2020;53:4937-496.
112. Moraes WVAD, Lima WFD, Costa GRD, Silva OAD, Menezes GV, *et al*. Prediction of Girolando cattle weight by means of body measurements extracted from images. Rev Bras Zootec. 2020;49:e20190110.
113. Wu Y, Liu M, Peng Z, Liu M, Wang M, Peng Y. Recognising cattle behaviour with deep residual bidirectional LSTM model using a wearable movement monitoring collar. Agric (Switzerland). 2022;12:1237.
114. Xavier C, Le Cozler Y, Depuille L, Caillot A, Lebreton A, Allain C, *et al*. The use of 3-dimensional imaging of Holstein cows to estimate body weight and monitor the composition of body weight change throughout lactation. J Dairy Sci. 2022;105:4508-4519.
115. Xu B, Mao Y, Wang W, Chen G. Intelligent weight prediction of cows based on semantic segmentation and back propagation neural network. Front Artif Intell. 2024;7:1299169.
116. Xu B, Wang W, Guo L, Chen G, Wang Y, Zhang W, *et al*. Evaluation of deep learning for automatic multi-view face detection in cattle. Agric. 2021;11:1062.
117. Yildiz AK, Özgüven MM. Hareketlilik ve çevre verileri kullanılarak yapay sinir ağları ile sığırlarda kızgınlık tespiti. J Agric Fac Gaziosmanpasa Univ. 2022;39:40-45.
118. Yu Z, Liu Y, Yu S, Wang R, Song Z, Yan Y, *et al*. Automatic detection method of dairy cow feeding behaviour based on YOLO improved model and edge computing. Sensors. 2022;22:327.
119. Zaborski D, Proskura WS, Grzesiak W, Różańska-Zawieja J, Sobek Z. The comparison between random forest and boosted trees for dystocia detection in dairy cows. Comput Electron Agric. 2019;163:104856.
120. Zambon I, Cecchini M, Egidi G, Saporito MG, Colantoni A. Revolution 4.0: Industry vs. agriculture in a future development for SMEs. Processes. 2019;7:36.
121. Zaninelli M, Tangorra FM, Costa A, Rossi L, Dell'Orto V, Savoini G. Improved fuzzy logic system to evaluate milk electrical conductivity signals from on-line sensors to monitor dairy goat mastitis. Sensors (Switzerland). 2016;16:1079.
122. Zhang J, Liu T, Tao D. Going deeper, generalizing better: An information-theoretic view for deep learning. IEEE Trans Neural Netw Learn Syst. 2023;16:1-13.
123. Zhang W. Combination of SIFT and Canny edge detection for registration between SAR and optical images. IEEE Geosci Remote Sens Lett. 2020;19:1-5.
124. Zhao K, Xin J, Jiangtao J, Jun W, Hao M, Xuefeng Z. Individual identification of Holstein dairy cows based on detecting and matching feature points in body images. Biosyst Eng. 2019;181:128-139.

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