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Review

Progress of Machine Vision Technologies in Intelligent Dairy Farming

Yongan Zhang [1,*], Qian Zhang [2], Lina Zhang [3], Jia Li [1], Meian Li [1], Yanqiu Liu [1] and Yanyu Shi [1]

[1] College of Computer and Information Engineering, Inner Mongolia Agricultural University, Hohhot 010018, China; lijia@imau.edu.cn (J.L.); 20071036@imau.edu.cn (M.L.); liuyq@imau.edu.cn (Y.L.); syy@emails.imau.edu.cn (Y.S.)
[2] Department of Biosystems Engineering, University of Manitoba, Winnipeg, MB R3T 5V6, Canada; qiang.zhang@umanitoba.ca
[3] College of Physics and Electronic Information, Inner Mongolia Normal University, Hohhot 010022, China; 20061113@imnu.edu.cn
* Correspondence: zhangya@imau.edu.cn

Featured Application: Application of machine vision technology in intelligent breeding of cows.

Abstract: The large-scale and precise intelligent breeding mode for dairy cows is the main direction for the development of the dairy industry. Machine vision has become an important technological means for the intelligent breeding of dairy cows due to its non-invasive, low-cost, and multi-behavior recognition capabilities. This review summarizes the recent application of machine vision technology, machine learning, and deep learning in the main behavior recognition of dairy cows. The authors summarized identity recognition technology based on facial features, muzzle prints, and body features of dairy cows; motion behavior recognition technology such as lying, standing, walking, drinking, eating, rumination, estrus; and the recognition of common diseases such as lameness and mastitis. Based on current research results, machine vision technology will become one of the important technological means for the intelligent breeding of dairy cows. Finally, the author also summarized the advantages of this technology in intelligent dairy farming, as well as the problems and challenges faced in the next development.

Keywords: machine vision; dairy cow behavior recognition; intelligent farming; animal welfare

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1. Introduction

Milk is an important source of protein in human diets, and its demand is expanding year by year. World milk production in 2022 reached around 930 million tons, up by 0.6 percent from 2021 [1]. The resulting scale of dairy cows farming is also increasing rapidly. By the end of 2022, the number of dairy cows in the world reached 140 million. Figure 1 shows the number of dairy cows in the world's major dairy farming countries in 2022 [2]. The changes in the scale of dairy cow farms have also led to changes in feeding methods. With the development of information technology, dairy cow feeding methods are also moving toward large-scale and intelligent development. Intelligent breeding can improve breeding efficiency, reduce breeding costs and manpower investment, and benefit the welfare of cows. Therefore, it is also the main development direction of cow breeding in the future. In the process of intelligent breeding, the automatic acquisition of dairy cow behavior is a prerequisite for achieving intelligence. Back in the 1960s, Allden et al. began using the pendulum principle and the mechanical device of a clock to record the grazing time and frequency of cattle and sheep [3]. By around 2000, research on monitoring cow behavior using mature sensor technology had become extremely common, and nearly 10,000 related articles could be obtained using similar subject headings [4–9]. As a result, the intelligent era of dairy cow farming has gradually begun.

Figure 1. Main wearing methods of touch sensors on the body of dairy cows.

For a long time, using various touch sensors to obtain cows' motion behavior, physiological indicators, body size parameters, and so on has been the main means of the intelligent breeding of dairy cows. Balasso et al. used triaxial acceleration sensors to monitor the resting, feeding, and ruminating behaviors of dairy cows [10]. Haladjian et al. used wearable motion sensors to identify the lameness of cattle [11]. Maatje and Morais et al. used a resistive sensor implanted in the cow's obstetric canal to monitor the estrus behavior of dairy cows [6,12]. Gardner and Strutzke et al. used pressure sensors to calculate the frequency of breaths of cattle [7,13]. Chelotti monitored the feeding and rumination of dairy cows by recording their mandibular acoustic signals [14]. Bewley et al. also used an animal activity monitor sensor to score the body condition of dairy cows and milk yield [15].

On the other hand, while using sensors to obtain physiological and physical data from dairy cows, this direct touch method (such as the wearing method shown in Figure 1) can cause stress reactions in dairy cows, which is not conducive to their animal welfare. According to research, the welfare status of dairy cows is closely related to their health status, milk yield, and milk quality [16–18]. The traditional method of obtaining cow growth data using sensors is facing challenges, and the use of sensors also has the following drawbacks.

- High cost

In order to obtain information about each dairy cow, it is necessary to wear sensors for each cow. As the number of farmed cows increases, the overall cost of the sensors increases.

- Easily damaged

Due to the presence of corrosive substances such as cow excreta and food residues in the breeding environment, sensors can be easily damaged. In addition, when cows experience stress reactions, they can also rub against the wearing parts, increasing the probability of sensor damage.

- Waste of human resources

The battery life of the small and portable sensors is poor, requiring manual periodic replacement of the battery. When some devices are not working properly, they also require manual removal and maintenance, which requires significant human resource costs throughout the sensor's use process.

- Single function

Each sensor can only measure a desired parameter. When multiple behaviors of cows need to be identified, multiple sensors are required, or when multiple sensors are integrated into a single device, integrated sensors will increase the volume, weight, and power consumption of the sensor, which will further highlight the shortcomings of sensor measurement methods.

The rapid development of artificial intelligence and image processing technology has provided new means for the perception of cow behavior. Machine vision technology mainly based on image and video processing has gained many mature applications in human behavior recognition, industrial product detection, medical fields, and agricultural fields. Machine vision has the advantages of being non-contact, stress-free, and low-cost, and having easy traceability having multiple behavior monitoring. Through one or more camera devices, machine vision can make real-time responses and judgments to various animal behaviors. This technology is also gradually being applied to the intelligent breeding of dairy cows. This technology can not only obtain cow behavior data, but also well meet the needs of animal welfare, becoming an important technical means for the intelligent breeding of dairy cows. In order to gain a deeper understanding of the application of machine vision in dairy farming, this paper deeply analyzes the main applications and effects of current machine vision technology in cow behavior recognition, and puts forward relevant suggestions, aiming to provide new methods and ideas for intelligent dairy farming.

2. Application of Machine Vision in Dairy Cow Identification

Dairy cow identity information can be used to establish individual profiles in the cow management information system and is also a prerequisite for conducting research on other aspects of dairy cows farming. Traditional cow identification is a manual labeling method for cows, such as wearing ear tags and collars. Later, it was developed into RFID (Radio-Frequency Identification) electronic tags [19,20]. RFID electronic tag technology is currently mature. Based on the mature application of machine learning in face recognition, many scholars have begun to recognize cow identities using cow facial information, muzzle print information, and body contour features, and these studies have achieved certain results.

Table 1 shows the current main research results of dairy cow identification based on machine vision and deep learning technology.

Kumar et al. published a paper titled 'Face recognition of cattle: can it be done?' [21]. The paper reviewed identity recognition methods based on cow facial features, proving the feasibility of cow identity recognition based on facial information.

Table 1. Research of dairy cow identification based on machine vision.

Reference	Identify Features	Recognition Methods	Accuracy
Xu et al. [22], 2022	Cow facial features	Integrated light-weight Retina Face-mobilenet with Additive Angular Margin Loss (ArcFace)	91.3%
Weng et al. [23], 2022	Cow facial features	Improved Convolutional Neural Network (ResNet)	94.5%
Chen et al. [24], 2022	Cow facial features	a novel unified global and part feature deep network (GPN)-framework-based ResNet50	97.4%
Guo et al. [25], 2022	Cow facial features	YOLO V3-Tiny Deep Learning Algorithm	90.0%
Awad Aet al. [26], 2013	Cow muzzle print features	SIFT (Scale-Invariant Feature Transform), RANSAC (Random Sample Consensus) algorithm	93.3%
Tharwat et al. [27], 2014	Cow muzzle print features	LBP (Local Binary Pattern), Naive Bayes, SVM, and KNN	99.5%
Kaur et al. [28], 2022	Cow muzzle print features	SIFT (Scale-Invariant Feature Transform), SURF (Speeded-up Robust Features), MLP(Multilayer Perceptron Network), RF (Random Forest), and DT (Decision tree)	83.35%
Sian et al. [29], 2020	Cow muzzle print features	WLD (Weber Local Descriptor), SVM (Support Vector Machine)	96.5%
Kumar et al. [30], 2018	Cow muzzle print features	CNN (Convolution Neural Network) and DBN (Deep Belief Network)	98.99%
Kosana et al. [31], 2022	Cow muzzle print features	InceptionResnetV2 + MLP (Multilayer Perceptron Network)	98.21%
Zhao et al. [32], 2019	Cow body features	FAST (Features from accelerated segment test) + SIFT (Scale-invariantfeature transform)+FLANN(Fast Library for Approximate Nearest Neighbors)	96.72%
Bhole et al. [33], 2022	Cow body features	Combination of Receptive Fields (CORF) + Convolution Neural Network (ConvNet) + linear SVM	99.64%
Qiao et al. [34], 2019	Cow body features	InceptionV3 + LSTM (Long Short-Term Memory)	91%
Yukun et al. [35], 2022	Cow body features	CNN (Convolution Neural Network) + LRM (Linear Regression Model)	93.7%
Hu et al. [36], 2022	Cow body features	YOLO (You Only Look Once) + CNNs (ConvolutionalNeural Networks) + SVM (Support Vector Machine)	98.36%

Xu et al. integrated Additive Angular Margin Loss (ArcFace) into lightweight Retina Face-mobilenet, and created a novel cow facial recognition framework called Cattle-FaceNet [22]. This framework had a recognition accuracy of 91.3% and a fast recognition speed, capable of recognizing 24 images per second. According to the idea of a residual network, Weng et al. proposed an improved convolutional neural network (Res_5_2Net) method for individual dairy cow recognition based on dairy cow facial images [23]. The recognition accuracy can reached 94.53%. Chen et al. proposed a novel unified global and part feature deep network framework (GPN) based on the feature maps from the backbone network ResNet50.This network could framework can capture both the global feature and the local detail to enhance the feature representation discriminability [24]. Finally, the recognition accuracy in rank-5 and rank-10 network depth can reach 95.9% and 97.4%, respectively. Guo et al. also used facial features to identify cow individuals when developing an automatic cow temperature measurement platform [25].They used the three layers of the YOLO V3-tiny recognition algorithm to achieve a recognition accuracy of 90%.

The texture information of a cow's muzzle print does not change during its growth. Therefore, many scholars use the cow muzzle print as a feature to identify cows.

As early as 2013, Awad et al. used the Scale-Invariant Feature Transform (SIFT) to extract the feature points of the cow's muzzle print image, and coupled the Random Sample Consistency (RANSAC) algorithm with the SIFT output to remove outliers and achieve higher robustness, and obtaineding a recognition accuracy of 93.3% [26]. Tharwat used the Local Binary Pattern (LBP) to extract features from cow muzzle print images, and classified them using Naive Bayes, Support Vector Machine (SVM), and K-Nearest Neighbor (KNN) algorithms, obtaining a recognition accuracy of 99.5% [27]. In addition, this method can also achieve high-precision recognition when the test images were is rotated at different angles or is partially occluded. Kaur et al. also used the SIFT algorithms and Speeded-Up Robust Features (SURFs) to extract cows' muzzle print features, and used Multi-Layer Perceptron (MLP), Random Forest (RF), and Decision Tree (DT) algorithms for image classification [28]. The recognition rates of these three algorithms, respectively, were 69.32%, 74.88%, and 79.60%.Finally, they improved the accuracy to 83.35% through integrated adaptive enhancement methods. Sian et al. used the Weber Local Descriptor (WLD) and LBP to extract cows' muzzle print features, and then used SVM to identify the cow's identity from the fusion features [29] and achieved a recognition accuracy of this method was 96.5%. Kumar et al. have also published several articles in recent years that use deep learning to identify cow identity through cow muzzle print features. By improving the deep learning algorithm, the recognition accuracy can reached 98.99% [30]. Kosana used a multi-level framework combination method and utilizedthe Inception Resnet V2 model to extract feature values, achieving a recognition accuracy of 98.21% [31].

It is interesting to note that many other scholars have used machine learning algorithms to identify cattle based on their mouth and nose texture images, but the main applications were for cattle information traceability, lost cow retrieval, and insurance claims. Due to the small area of the face and muzzle print images of cows and the irregular head movement of cows, it is difficult to obtain real-time face and muzzle print image data in on-farm conditions. For the automatic, real-time, and continuous on-site identification of cows required in precision breeding, this method still cannot meet the needs of large-scale and automated breeding. A relatively large area of body image information is undoubtedly a good choice for cow identification using machine vision.

The body pattern of cows contains rich individual information, such as the white-black pattern of Holstein cows. By extracting the body pattern features of cows, a precise identification of cow identity can be achieved. Zhao et al. extracted Holstein cows' body pattern from 528 segments of recorded video information, and then used a deep learning algorithm of FAST + SIFT + FLANN, achieving a recognition rate of 96.72% [32]. Bhole et al. also extracted body contours from the side view of Holstein cows, using the novel CORF3D contour maps to suppress environmental noise, resulting in an average recognition accuracy of 99.64%. However, this method works better for cows with special body patterns; the recognition rate for pure-colored cows is poor [33]. In addition to the side view, images of the back and rear-view of cows can also be used as feature information for identity recognition. Qiao extracted features from 516 rear-view cows' videos and used the LSTM model trained with video data to identify cattle identity [34]. The accuracy of this method can reach 88% and 91% when the video length is 15 frames and 20 frames, respectively.Yukun et al. obtained a back-view of the cow from the top camera to determine the cow's identity information when evaluating cows' Body Condition Score (BCS) [35]. Utilizing convolutional neural networks and linear regression models, they achieved a recognition rate of 93.7%. Hu et al. separated the head, trunk, and legs of the cow's body from the original image, and then fused these three features;finally, a support vector machine classifier was used to classify the fused features to identify the identity of cattle [36], achieving a 98.36% accuracy.

The comparison of the accuracy of three types of cow identity recognition is shown in Figure 2. From the figure, it can be seen that the recognition accuracy of muzzle print features and body features is slightly better than that of facial features.

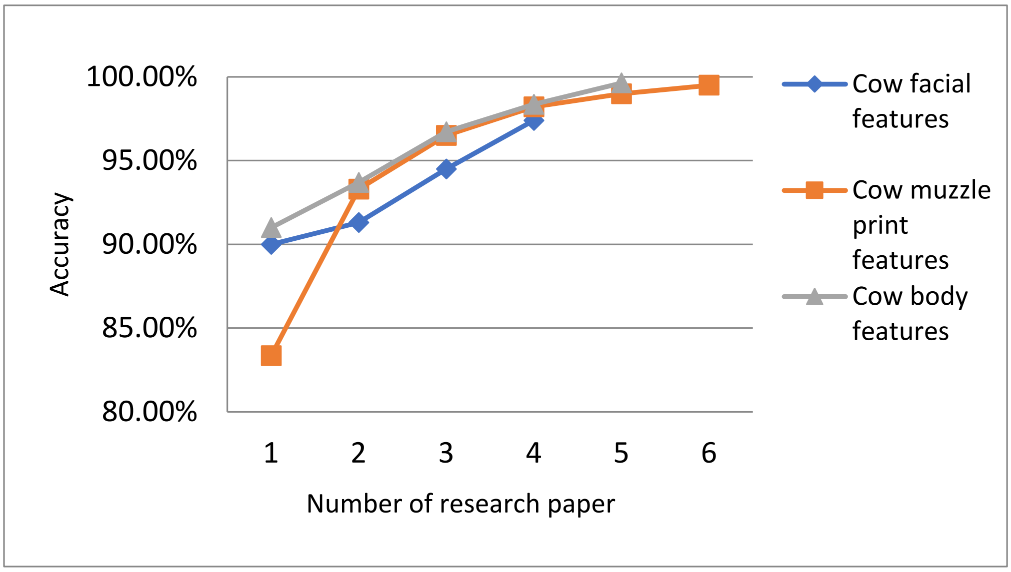

Figure 2. Accuracy of identification of cows with different features.

Cow identity recognition based on body features includes side-view, rear-view, back-view, and multi-part fusion, all of which have high recognition accuracy. The body feature is more applied to the Body Condition Score (BCS), and this part of the content is not discussed in this paper.

The above research sufficiently proved the feasibility of machine vision in dairy cow identification. Moreover, machine vision, with its advantages of being non-invasive and low-cost, and having multi-behavior recognition, will have a broader application prospect in dairy cow identification.

3. Application of Machine Vision in Main Behavior Recognition of Dairy Cows

The motion behavior of dairy cows mainly includes walking, standing, lying, feeding, breathing, attacking, ruminating, estrus, and so on. These behaviors of dairy cows are closely related to animal welfare, health, and milk production. Research on the motion behavior of dairy cows can provide data support for the formulation of precise breeding plans for dairy cows, as well as provide information for the prediction of some diseases, reducing economic losses caused by disease or death. The current research method is used in different types of sensors, such as acceleration sensors, pressure sensors, and pedometers [37–39]. On the other hand, machine vision methods have increasingly become an important research direction for the behavior recognition of dairy cows. Table 2 shows the main research results of machine learning methods in cow motion behavior recognition in recent years.

Table 2. Research on Machine Vision in Motion Behavior Recognition of Dairy Cows.

Reference	Behavior	Recognition Methods	Results
Ma et al. [40], 2022	Lying, standing, walking	Rank eXpansion Network 3D (Rexnet 3D), Resnet101, Mobilev2, Mobilev3, Shufflev2, C3D and S3D	lying and walking: 97.5%, standing: 90%
Guo et al. [41], 2020	Entering, leaving, turning, resting, feeding, and drinking of calves	Gaussian mixture model, ViBe, and the new integrated background model (combine background-subtraction and inter-frame difference methods)	Entering: 94.38%, leaving: 92.86%, staying: 96.85%, turning: 93.51%, feeding: 79.69%, drinking: 81.73%.
Wu et al. [42], 2021	drinking, ruminating, walking, standing and lying	VGG16 feature extraction network, Bi-LSTM (bidirectional long short-term memory) classification model	Average precision, recall, specificity, and accuracy were 0.971, 0.965, 0.983, and 0.976, respectively
Yin et al. [43], 2020	Lying, standing, walking, drinking, and feeding	EfficientNet for feature extraction, BiFPN (bidirectional feature pyramid network) for feature fusion, C3D, VGG16-LSTM, ResNet50-LSTM, and DensNet169-LSTM for behavior recognition	97.87%
Nguyen et al. [44], 2021	Drinking, grazing	Cascade R-CNN, Temporal Segment Networks (TSNs)	drinking: 84.4%, grazing: 94.4%
Wang et al. [45], 2023	lying, standing, walking, drinking, and feeding	ECA (Efficient Channel Attention) for channel information filtering, E3D (Efficient 3D CNN) algorithm for the spatiotemporal information processing of the video	Precision, recall, parameters, and FLOPs of the E3D were 98.17%, 97.08%, 2.35 M, and 0.98 G, respectively
Ayadi et al. [46], 2020	Rumination behavior of dairy cows	VGG16, VGG19, and ResNet152V	average accuracy: 95%, recall: 98%, precision: 98%
Wang et al. [47], 2022	Rumination behavior of dairy cows	YOLO algorithm combined with the Kernelized Correlation Filter (KCF)	91.87%
Mao et al. [48], 2019	Rumination behavior of dairy cows	optical flow method	Highest accuracy was 87.80%, average accuracy was 76.46%
Song et al. [49], 2022	Rumination behavior of dairy cows	Horn–Schunck optical flow method	Highest filling rate was 96.76%, the lowest filling rate was 25.36%.
Arago et al. [50], 2020	Estrus behavior of dairy cows	SSD (Single Shot Detector) + Inception V2, Faster R-CNN	90%
Pasupa et al. [51], 2019	Estrus behavior of dairy cows	SVM (Support Vector Machine)	90%
Dolecheck et al. [52], 2015	Estrus behavior of dairy cows	Random Forest, Linear Discriminant Analysis, and Neural Network	65.6%
Guo et al. [53], 2019	Estrus behavior of dairy cows	Background Subtraction with Color and Texture Features (BSCTF), SVM	98.3%
Noe et al. [54], 2022	Estrus behavior of dairy cows	Mask R-CNN, Kalman filter and Hungarian algorithm	95.5%

Basic motion behaviors of dairy cows contain abundant health information. Timely and accurate identification of cow motion behavior is helpful for precise breeding and disease prevention of cows. In order to accurately and effectively recognize the basic movement behavior of cows, Ma et al. added the time dimension to the Rank eXpansion Network 3D algorithm (Rexnet 3D) network, and the recognition accuracy of dairy cow motion behavior in natural scenes reached 95.00% [40]. Guo et al. monitored more behaviors of calves including entering or leaving, stationary and turning behaviors in the resting area, and feeding and drinking [41]. Then, they integrated the frame difference method, background subtraction, Gaussian mixture model, and ViBe model to generate an integrated background model, which can effectively recognize the above behaviors, avoiding the defect that the previous single model has low recognition accuracy for static behavior or moving behavior. Wu et al. realized accurate behavior classification in complex environments involving low-quality surveillance videos, complex illumination, and weather variations [42]. They used the VGG16 network for feature extraction, the Bi LSTM (Bidirectional Long Short-Term Memory) classification model had good stability, and even in the presence of interference, the difference in behavior recognition accuracy could still be less than 0.02.Yin et al. used four algorithms (C3D, VGG16-LSTM, ResNet50-LSTM, and DensNet169-LSTM) to recognize the five basic behaviors (lying, standing, walking, drinking, and feeding) of cows, obtaining an average accuracy of 97.87% [43]. Nguyen et al. used the same video dataset to identify the identity information and behavior of cows. Due to being pure-colored cows, they brushed red numbers on their brown fur to distinguish their identity [44]. At the same time, they achieved recognition rates of 84.4% and 94.4% for their drinking and grazing behaviors, respectively. Deep learning has a significant drawback, which is the conflict between recognition rate and computational complexity. When it is necessary to improve recognition accuracy, the computational complexity of the computer will also increase exponentially. Thus, the algorithm cannot be used on an edge device with insufficient computing power. In response to this situation, Wang et al. proposed an E3D (Efficient 3D CNN) algorithm [45]. The precision, recall, parameters, and FLOPs of the E3D were 98.17%, 97.08%, 2.35M, and 0.98G, respectively. Compared with the Improved Renext network, ACTION-Net, and C3D-ConvLSTM, the E3D algorithm is more suitable for deployment on portable mobile edge devices.

The basic motion behavior of cows is closely related to their health. In addition, there are also some special behaviors that are closely related to the health and economic value of cows, such as rumination and estrus behavior.

Ayadi et al. used a compacted representation of a video in a single 2D image to capture long-term dynamic rumination behavior [46]. The average accuracy and recall rate of this method in rumination behavior recognition were 95% and 98%, respectively. Wang et al. used the frame difference method to recognize the dairy cow rumination behavior [47]. To verify the feasibility of this method, the algorithm was tested on multi-object dairy cow rumination videos, the rumination time and chewing frequency were calculated, then a comparison was made with the results of manual observation. The result was a lower error rate, the rumination time average error was 5.902%, and the average error in the number of chews was 8.126%. Mao et al. used the optical flow method to calculate the relative motion speed of each pixel in the video frame images, then extracted the real area of cows' mouth [48]. The author validated the feasibility of this method using six video files with a total length of 96 min. The research obtained the highest accuracy of 87.80% and an average accuracy of 76.46%. Song et al. also used the Horn–Schunck optical flow method to detect the cow's mouth area, and took the filling rate (the proportion of the observation frame to the cow's mouth area) as its detection target [49]. By studying eight videos of cows' mouths, the result showed that the highest filling rate was 96.76%, the lowest filling rate was 25.36%, and the average true filling rate was 63.91%. Due to the small area of the mouth area of cows, it is still difficult to identify rumination behavior under the influence of illumination and obstructions. Wearable sensors are more suitable for identifying this behavior.

Traditional dairy estrus detection mainly depends on manual observation, which is time-consuming and laborious, and the detection efficiency is low. Accurate judgment of cow estrus behavior can improve the pregnancy rate, prolong the lactation period, and enhance the benefits of cow breeding. Arago et al. extracted estrus features of cow videos through the Faster R-CNN and Single Shot Detector models with the Inception V2 [50]. The confidence scores of the SSD algorithm exceeded 90% in visualizing bounding boxes on the single class objects. Faster R-CNN had poor accuracy in identifying objects with color differences between subjects and barn surface area, and it achieved a 50% detection efficiency.However, this system still has certain application value in detecting cow feeding behavior. Pasupa et al. used a set of discriminative features to detect cattle estrus. The author extracted the positions of key points in the body of cows to identify the behavioral feature of estrous cows [51]. The classification model adopted. Support Vector Machine with the Radial Basis Function, the maximum accuracy of the global model of this method was 90.0%, and the maximum accuracy of the cattle-specific model could rise to 92.0%. Earlier, Doleck et al. used machine vision to detect the estrus behavior of cows from different perspectives [52]. They continuously observed the estrus behavior and abnormal daily behavior of cows through machine vision after injecting them with estrus drugs. Random Forest, Linear Discriminant Analysis, and Neural Network were applied to automatically analyze the estrus behavior of 18 standing cows, and the accuracy of the results was between 91% and 100%. When comparing visual observation with progesterone profiles of all 32 cows, the accuracy was 65.6%. Guo et al. used Background Subtraction to extract detection regions, and then utilized the Support Vector Machine (SVM) classifier to identify mounting behavior, obtaining accuracy and omission rates of 98.3% and 6.4%, respectively [53]. Noe et al.proposed an estrus detection approach that tracks and identifies cattle mating postures individually based on video inputs [54]. They used the Mask R-CNN deep learning framework and a lightweight tracking algorithm as a post-processing step to detect mounting behaviors of the dairy cow, achieving a 95.5% detection accuracy in identifying the estrus behaviors of cattle. Finally, Reith reviewed the detection of dairy cows' estrus behavior, especially the application of automated detection techniques in cow estrus. This method embraces multiple technologies and included pressure sensing systems, activity meters, video cameras, recordings of vocalization, as well as measurements of body temperature and mill progesterone concentration. The method of integrating multiple technologies will achieve better results in detection sensitivity and specificity and has enormous research potential in the future [55].

The recognition of walking, lying down, and other behaviors of dairy cows is relatively simple and has a high recognition rate. However, the recognition of rumination and estrus has certain difficulties. Because the rumination behavior is not obvious, it is difficult to recognize in the case of insufficient light or occlusion. Although the estrus and mounting behavior is easy to identify, cows have a latent estrus phenomenon; in this case, the estrus behavior of cows is no different from their daily behavior, and there will be no mounting phenomenon. This situation can lead to missed detection when purely using machine vision as a means of identification. Therefore, when recognizing these special behaviors, other methods, such as specific sensors, should also be combined to ensure the accuracy of recognition.

4. Application of Machine Vision in Disease Prevention and Treatment of Dairy Cows

In addition to its extensive application in the motion behavior recognition of dairy cows, machine vision also has prominent research results in disease prevention and the early warning of dairy cows. Table 3 shows the main research results of machine vision in recent yearsin the field of frequent cow diseases such as claudication and mastitis.

Table 3. Research on machine vision in cow disease prevention and control.

Reference	Behavior	Characteristic Extraction and Classification Model	Result
Wu et al. [56], 2020	Lameness Behavior	YOLO V3, Long Short-Term Memory (LSTM)	98.57%
Song et al. [57], 2018	Lameness Behavior	DSKNN (Distilling data of K-Nearest Neighbor) + LCCCT (Local Cyclic Center Compensation Tracking Model), SVM, Naive Bayes, KNN	SVM: 91.11%, Naive Bayes: 86.11%, KNN: 93.89%
Zheng et al. [58], 2023	Legs Tracking, Lameness Behavior	Siamese attention model (Siam-AM), SVM	94.73%
Li et al. [59], 2023	Lameness Behavior	Temporal aggregation network using micromotion features	98.89%
Wang et al. [60], 2022	Cow Mastitis	YOLO v5	85.71%
Cai et al. [61], 2017	Cow Mastitis	Linear Regression, Power Regression, Quadratic Regression, and Principal Component Regression	average relative error was 3.67%
Golzarian et al. [62], 2017	Cow Mastitis	Matlab and SPSS Tool Software	57.3%

Lameness is one of the common diseases in dairy cattle, which seriously affects the health of cows and can lead to a decline in milk production and reproductive capacity. The early-onset symptoms of lameness in dairy cows are not obvious from the perspective of artificial observation. When discovered later, it will make treatment more difficult, and some can only be eliminated and slaughtered, causing significant economic losses to farmers. Therefore, research on the detection of lameness in dairy cows has always been a hot topic in dairy industry research. Applying machine vision technology to the detection of lameness in dairy cows can achieve early detection and treatment, reduce cow pain, and increase cow welfare and breeding economic benefits.

Wu et al. detected the leg characteristics of cows in each frame of a video through YOLO V3, and used various classification algorithms to identify them. After comprehensively comparing the accuracy, true positive and false positive rates, and the algorithm's demand for hardware resources, they concluded that the comprehensive performance of the Long Short-Term Memory (LSTM) model was best [56]. Song et al. proposed a lameness detection method of dairy cows with the fusion of LCCCT (local circulation center compensation tracking) and DSKNN (distilling data of k-nearest neighbor) [57]. Then, the SVM, Naive Bayes, and KNN classification algorithms were used to perform classification and detection experiments on cow lameness, and the accuracy rates were 91.11%, 86.11%, and 93.89% respectively. The result proved that the KNN classification algorithm can achieve better detection results. Zheng et al. proposed a Siamese Attention Model (Siam-AM) fusion attention mechanism, which monitors cow legs to obtain the motion tracking of cows in large-scale farms [58]. The Support Vector Machine (SVM) classifier was trained to classify the lameness behavior of cows. The Siam-AM algorithm had a lameness detection accuracy of 94.73%. In order to identify the early claudication behavior of dairy cows, Li et al. introduced the micro-motion feature as a feature value into the spatiotemporal attention mechanism, which can detect the claudication of dairy cows earlier and provide evidence for the early treatment of claudication [59].

The above scholars used machine vision to identify the lameness behavior of cows from different perspectives, providing strong technical support for the early detection and treatment of cow lameness.

Dairy cows are prone to mastitis during long-term and mass milk production. Therefore, the detection and treatment of mastitis have become key concerns in dairy farming. Replacing traditional artificial physical and chemical testing methods, contactless and efficient machine vision methods have also been used in the detection of mastitis in cows in recent years.

Using the temperature difference between the eyes and udder of cows to identify mastitis is currently a common method for machine vision. Wang et al. proposed a new detection method of dairy cow mastitis based on infrared thermal images [60]. This method combined the improved left and right udder skin surface temperature (USST) with the ocular surface temperature. The improved detection method avoided effectively the effect of external factors. The results showed that the accuracy, specificity, and sensitivity of mastitis detection were 87.62, 84.62, and 96.30%, respectively. However, factors such as changes in the distance between the thermal imager and key parts of dairy cows and obstructions in this method can have a certain impact on the accuracy rate. Cai et al. used another method to study cow mastitis. Namely, the sample milk was dropped onto a pH test paper, and the number of milk somatic cells was calculated based on the color characteristics of the pH test paper [61]. The number of milk somatic cells was used to determine whether the cow has mastitis and the severity of the disease. Golzarian et al. also used a similar method to obtain cow udder temperature through cow udder thermal images to determine if there is mastitis [62]. However, the accuracy of this method was relatively low, only 57.3%. The above methods are currently the main research methods for non-contact machine vision in diagnosing cow mastitis.

From the results of the above research on mastitis, it can be seen that the recognition of mastitis based on thermal infrared images is susceptible to factors such as attachments, shielding, and different measurement distances during non-contact temperature measurement, resulting in certain errors in measurement, and its accuracy needs to be further improved.

Machine vision has further applications in precision and large-scale dairy farming, such as cow perinatal behavior recognition, measurement of cow body size parameters, cow health assessment, and evaluation of farm environmental comfort.

5. Conclusions

The large-scale and precise breeding of dairy cows is the main direction of development in the future, and large-scale breeding cannot be separated from the support of information and digital technology. With the development of computer technology, technologies such as machine vision and deep learning have been widely used in human life and production. Applying this technology to the behavior and diseases of dairy cows will contribute to the large-scale breeding of dairy cows. This article focuses on the application of machine vision in cow identification, behavior recognition, and disease recognition. From recent research results, it can be seen that machine vision has the following advantages in the precision breeding of dairy cows.

5.1. The Advantages of Machine Vision in Precision and Large-Scale Breeding of Cows

(1) Reduce farming costs

With the expansion of dairy farming scale, the traditional artificial management mode requires a large amount of breeding and management personnel. More personnel investment means an increase in breeding costs. Although sensor technology can achieve the rapid detection of cow behavior and replace manual operations, it is still expensive for each cow to wear corresponding sensors, considering their cost and maintenance costs. The machine vision technology represented by image and video information processing requires only a few camera devices to be deployed at the farm, which is not only low-cost, but also simple to maintain, so it can save a lot of labor costs and maintenance costs for the large-scale breeding of dairy cows. At the same time, machine vision can use a single visual device to recognize multiple behaviors of cows, which can also save a lot of costs compared to sensor technology.

(2) Improve breeding efficiency

Traditional farming methods exhibit such phenomena as forage waste, artificial errors, and delays in diseases and production management. These factors can prevent breeding personnel from timely obtaining the status of dairy cows, causing a decline in farming efficiency and resource utilization. Through the daily behavior monitoring method of machine vision, an abnormal status of dairy cows during the breeding process can be detected as early as possible, and measures can be taken in a timely manner to avoid further losses. Precision farming based on machine vision will greatly improve the efficiency of dairy farming and be an important direction for the development of dairy farming in the future.

(3) Improve animal welfare

The detection of cow health and diseases through artificial and sensor methods can cause stress reactions in cows. These methods are not conducive to the welfare of dairy farming. The contactless approach of machine vision has no impact on the daily activities of dairy cows, thereby improving their welfare. In addition, machine vision monitoring of the daily behavior of dairy cows can also provide reference data for the welfare-oriented breeding of dairy cows.

(4) Provide data support for precise breeding of cows

Through machine vision technology, the identity, behavior, diseases, and other information of cows can be digitized. These data are the foundation for the construction of a digital information platform for dairy farming. The establishment of a digital platform can provide decision-making support for intelligent and precise dairy farming.

From the research results described in this article, it can be seen that current machine vision has achieved outstanding research results in cow behavior recognition, disease diagnosis, and other aspects. Machine vision technology is gradually becoming one of the important auxiliary means for precision dairy farming. However, in the process of practical application and promotion of this technology, further research and mining are needed in the following aspects.

5.2. Challengess Faced by Machine Vision Technologies in the Application of Intelligent Dairy Farming

(1) Strengthen the promotion of research results to production applications

Although current research using machine vision to identify various behaviors of dairy cows has achieved high recognition rates, most of the research focuses on collecting image or video data for subsequent identification in the laboratory, which is still behind the practical application of farming. Due to the complexity of the environment in actual farms, such as lighting, corrosion, equipment pollution, shielding, and the rapid movement of cattle, it can have a significant impact on the recognition effect of machine vision. The promotion of industrialization also needs to consider practical issues such as product costperformance, system integration, and staff operability.

(2) Algorithms

The feature extraction and classification algorithm used in cow behavior recognition at this stage achieves high accuracy, but high-precision recognition requires a longer computing time. The behavior recognition of dairy cows requires a good real-time performance. Therefore, it is necessary to optimize current algorithms for the needs of dairy farming, and to try to simplify the algorithm model while ensuring accuracy, to achieve the purpose of improving the computing speed. In addition, some scholars often use data from a specific farm, which cannot meet diversified needs. When a model is transplanted to another farm, its recognition rate will decline significantly. Therefore, the generalization ability of the model can only be further enhanced through multi-agency cooperation and the establishment of large-scale public datasets for dairy cows.

(3) Research on Comprehensive Application of Multi-technology Mixing

In the application of farming, products with high accuracy, strong stability, and a high cost–performance ratio are required. A single technical means is often not achievable, so it is necessary to integrate multiple technologies, such as relatively mature sensor technology, big data technology, Internet of Things technology, and edge computing technology. With comprehensive consideration of product economy and applicability, it is necessary to design a highly versatile precision dairy farming information system to promote the intelligent and large-scale development of the dairy farming industry.

With the development of artificial intelligence technology, non-contact and low-cost machine vision technology, as one of the important technical means for large-scale and intelligent breeding of cows, will achieve more extensive and deeper applications.

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