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Role of computer vision and deep learning algorithms in livestock behavioural recognition: A state-of-the-art- review

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Abstract: The increasing demand for sustainable livestock products necessitates a re-evaluation of animal production and breeding practices. Contemporary breeding programs now integrate animal phenotypic behaviors due to their considerable influence on productivity, health, and welfare, which ultimately impact industry yield and economic outcomes. Monitoring animal behavior manually is challenging and subjective, especially in continuous or large-scale operations, as it is time-consuming and labor-intensive. Consequently, computer vision technology has attracted attention for its objectivity, non-invasiveness, and capacity for continuous monitoring. However, recognizing livestock behavior using computer vision remains difficult due to complex scenes and varying conditions, hindering its widespread adoption in the industry. Deep learning technology has emerged as a promising solution, mitigating some of these challenges and enhancing the recognition of livestock behaviors. This paper reviews recent advancements in computer vision methods for detecting behaviors in livestock such as cattle with an emphasis on behaviors critical for health, welfare, and productivity. It investigates the development of both traditional computer vision and deep learning techniques for image segmentation, identification, and behavior recognition. The review explores the development of research trends in livestock behavior recognition, focusing on improvements in reliable identification algorithms, the analysis of behaviors at different growth stages, the measurement of behavioral data, and the design of systems to evaluate welfare, health, growth, and development.
Keywords: *Behaviour, Cattle, Computer vision, Deep learning, Livestock.*

1. Introduction

The increasing demand for sustainable animal products highlights the significance of livestock breeding and diligent animal management in enhancing productivity within the livestock industry [1]. Animal behavior is a critical indicator of welfare, growth, and health, directly affecting yield and economic benefits [2]. Key behaviors, including water and feed intake, social interactions, and maternal care, are essential for assessing the welfare and productivity of livestock [3]. From the earliest stages of animal domestication, humans have monitored livestock behavior and health through direct observation. This method involves spending significant time observing animals as they graze, mate, rest, and interact socially. Over time, herders and farmers have gained an intuitive grasp of what constitutes normal and abnormal behaviors, enabling them to make well-informed decisions about breeding, feeding, and treating illnesses in livestock [4]. For instance, aggressive behavior in cattle can cause injuries and infections, and excessive mounting can negatively impact welfare and lead to economic losses. On the other hand, behaviors such as interacting with enrichment objects can reduce negative behaviors and enhance animal welfare [5]. Furthermore, observing the movements of animal body parts can assist in detecting diseases, especially in identifying lameness issues that are common in the dairy industry and have a substantial impact on productivity and reproductive performance [6]. Additionally, precise estimation of livestock poses is essential for analyzing their behaviors and assessing their health, making

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it critical for sophisticated cattle breeding practices [7]. Therefore, recognizing and monitoring livestock behaviors is a crucial component in advancing precision livestock farming.

Traditionally, livestock farming has relied on the expertise of professionals, such as farmers, workers, and veterinary behaviourists, to observe animal behaviour and its connection to health. However, in intensive production systems where large groups of various species are managed, continuously monitoring individual animals in real-time is not practical. The integration of Industry 4.0 technologies into industrial automation has paved the way for systems that perform tasks with enhanced efficiency and autonomy. Artificial Intelligence (AI) has significantly transformed livestock farming, ushering in innovative concepts like "smart farming," "precision agriculture," and "precision livestock farming."[8]. AI is widely utilized in these areas to process data and develop sophisticated tools for tracking and managing animal behavior and health. These advancements have the potential to transform conventional livestock farming by empowering farmers to make informed, data-driven choices that enhance animal welfare, health, and productivity. Precision livestock farming (PLF) supports production efficiency, cost reduction, and environmental sustainability through the real-time monitoring and analysis of animal behavior [9]. Incorporating advanced technologies into livestock farming holds the promise of transforming the industry by encouraging sustainable and efficient practices that support both animal welfare and farmers. Such innovations are crucial in addressing issues related to infectious and endemic diseases, such as mastitis, which have profound effects on animal well-being and public health [10]. Computer vision (CV) involves analyzing, reconstructing, and extracting information from images to represent various aspects of the physical world, such as shapes, textures, densities, and distances[11]. It is also referred to as machine vision systems, visual imaging systems, or image analysis systems. Consequently, CV entails developing artificial systems to tackle visual challenges through techniques in image processing and analysis. Furthermore, CV is closely linked with Machine Learning (ML) and Pattern Recognition (PR).

Recently, CV technology has become increasingly prominent due to its ability to provide objective, non-invasive, and continuous monitoring. This technology is extensively employed for identifying various livestock behaviors such as lameness, aggressive behavior, pecking, drinking patterns, and feeding habits [4,12]. CV, a technique that mimics biological vision using computers, plays a pivotal role in AI. It involves processing images or videos to extract detailed scene information [13]. Conventional CV systems emphasize feature extraction from images using algorithms such as SIFT, SURF, and BRIEF [14]. However, the effectiveness of these algorithms' hinges on the type and quality of the input images, which presents difficulties in accurately identifying features. Moreover, applying CV to recognize livestock behavior encounters challenges such as complex environments, varying lighting conditions, and obstruction, adding further complexity to the process. Despite these challenges, advancements in refining algorithms offer potential solutions, though they often require manual adjustments tailored to specific applications [15]. Overcoming these hurdles is essential for achieving reliable CV in livestock behavior recognition.

Deep Learning (DL) plays a crucial role in PLF, being extensively applied for tasks such as identifying individual animals [16], recognizing body parts [17], identifying faces [18-19], monitoring health [20], tracking and counting animals [21], classifying breeds and species [22-23], and analyzing behaviour [4]. Deep learning (DL) employs deep neural networks (DNNs) to automatically learn patterns from raw data, allowing for accurate pattern recognition and feature extraction. Its capability to handle vast and complex datasets, as well as perform tasks like image classification, object detection, and spatiotemporal analysis, makes it highly effective. However, despite its wide-ranging applications, further research is necessary to comprehend the specific challenges that different DL models can tackle, underscoring the ongoing complexity in the design, development, and deployment of these intricate systems. DL technology has demonstrated significant potential as an effective solution for overcoming challenges in livestock behavior recognition [24]. Recent reviews in PLF have delved into areas such as sustainability, environmental effects, and socioeconomic considerations [25-26]. Additionally, there has been significant research into CV applications for dairy farm management [27] and DL applications specific to precision cattle farming [28]. The performance of DL models and networks is frequently task-dependent, even though these reviews offer valuable insights into the many uses of CV and DL in livestock farming. For instance, when dealing with more complicated tasks like behavior identification, a DL model that is designed for object categorization might not function as well. This emphasizes the necessity of doing a focused study to evaluate DL's potential for addressing behavior recognition issues in precision livestock farming (PLF). This review looks at current developments and new directions in behavior recognition using CV and DL technology. It delves into several key areas, such as the types of behavior recognition challenges tackled using these technologies, approaches to data collection focusing on quantity, quality, and data types, an examination of various DL models and networks created for behavior recognition, an assessment of their performance metrics, an analysis of challenges highlighted in existing research, and suggestions for overcoming these challenges. This paper is organized as follows: Section 2 provides an overview of research on cattle image segmentation, discussing techniques that range from segmenting the entire body to individual body parts. Section 3 focuses on studies related to cattle identification, highlighting approaches that involve both specific body parts and whole-body identification. Section 4 explores research on behavior recognition of cattle, transitioning from CV to DL methodologies. Section 5 discusses the limitations and the way forward of the related works. Section 6 concludes the review.

2. Segmentation

Image segmentation primarily aims to differentiate foreground objects from the background, directly influencing the accuracy of feature extraction and the recognition of livestock behaviors [29].

2.1. Whole-Body Segmentation

Initially, the primary focus of segmentation efforts for cattle was on the whole-body, with a particular emphasis on individual cattle. Fig. 1 shows the enhanced Mask R-CNN [30] for individual cattle segmentation using CV.

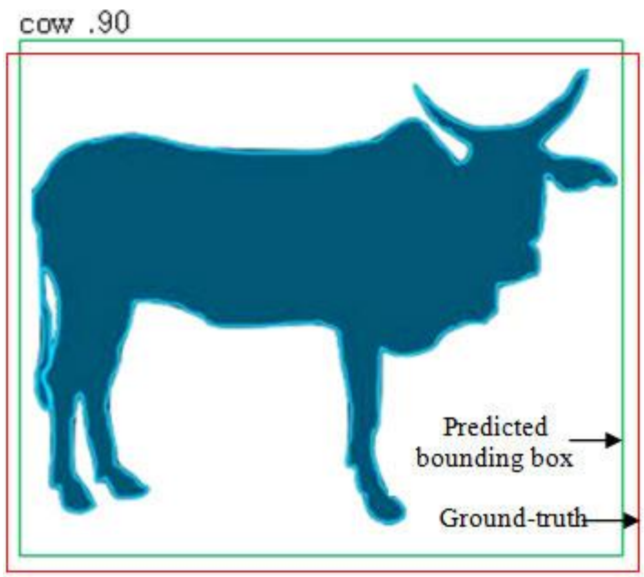

Figure 1.
Individual cattle segmentation using CV. [30].

Mask R-CNN was enhanced in [30] with an addition of subnetwork to the fully connected layers (FCLs) for an accurate mask generation. This research work effectively showcased the segmentation of foreground cattle in challenging ranch environment, handling situations such as sudden light changes, dynamic backgrounds, and stationary foreground elements. The goal was to accurately segment individual cattle in ranch under varying lighting conditions throughout the day and night.

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The work in Ren et al. [31], though targeted on sheep, was similar to the work in Bello et al. [32]. While [31] established an automated system capable of producing behavioral and localization data for individual sheep; by using DL, [32] carried out an experiment with cattle dataset to recognize behavior of group-ranched cattle from video sequences. The framework proposed by [32] for recognition of cattle behavior is shown in Fig. 2.

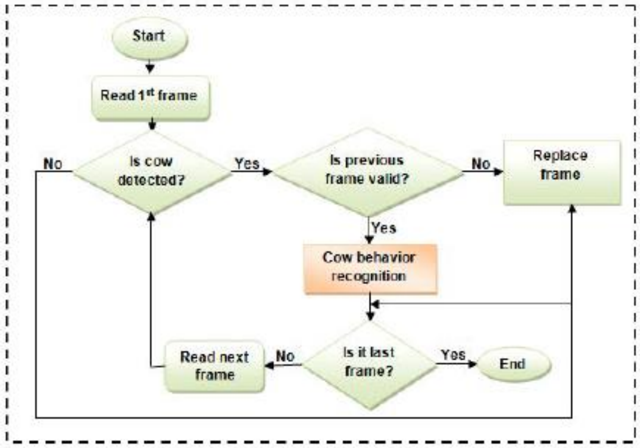

Figure 2.
Framework for recognizing cattle behavior. [32].

In [31], a sensor fusion system was devised to monitor sheep positions and detect their standing and lying behaviours. The ultra-wideband location system maintained a mean position error of 0.357 ± 0.254 m, and infrared radiation cameras combined with 3D CV achieved high sensitivities of 98.16% and 100% for detecting standing and lying behaviours, respectively. Ultimately, the system effectively generated real-time reports on individual sheep activities. The work in [33] explored feature extraction and ML algorithms to accurately classify behaviors in extensively grazed sheep using accelerometers attached to their ears. Nineteen movement characteristics were extracted and evaluated across three distinct time epochs (5, 10, and 30 seconds), employing four ML algorithms: Classification and Regression Trees (CART), Linear Kernel Support-Vector Machines (SVM), Linear Discriminant Analysis (LDA), and Quadratic Discriminant Analysis (QDA). Behavior classification encompassed three ethograms: (i) grazing, lying, standing, and walking; (ii) active versus inactive behavior; and (iii) body posture. SVM with a 10-second epoch achieved the highest accuracy (76.9%) in distinguishing mutually exclusive behaviors. CART with a 30-second epoch excelled in activity detection (98.1%), while LDA with a 30-second epoch demonstrated superior performance (90.6%) in posture classification. Effective classification relied on accurately discerning between different behaviors rather than identifying patterns within a single behavior. Alvarenga et al. [34] evaluated how well tri-axial accelerometers could identify sheep behaviors in various pasture settings, emphasizing accuracy, sensitivity, specificity, and precision. Two studies were conducted, one lasting six days and the other two days, involving South African Meat Merino × Merino ewes averaging 55 (±5) kg and 22 months old. The sheep were observed in either a semi-improved pasture (0.3 ha) or a small (30 m2) area with water access, engaging in five distinct behaviors: grazing, lying, running, standing, and walking. Each sheep wore a tri-axial accelerometer affixed to a halter beneath their jaw.

Behavior classification employed three different epochs (3s, 5s, and 10s) and forty-four features derived from accelerometer data. The study utilized random forest to identify the top five significant features for each epoch, followed by a decision-tree algorithm to classify behaviors and calculate model performance metrics. The decision-tree algorithm accurately classified grazing behavior with rates of 90.5%, 92.5%, and 91.3% for the 3 s, 5 s, and 10 s epochs, respectively. To achieve comprehensive segmentation of multiple cattle, Bello et al. [35], devised a technique employing the Enhanced Mask R-CNN DL framework to handle challenges associated with segmenting cattle and extracting contours in real-world feedlot settings. This method encompassed several critical stages: identifying key frames to capture substantial cattle movements, improving image quality to reduce the impact of lighting and shadow issues, segmenting cattle, and accurately extracting body contours. The study showed remarkable outcomes, achieving a remarkable and promising results. However, improvements are needed to enhance segmentation accuracy in areas where cattle overlap, and further work should explore explicit segmentation to differentiate various cattle body parts, such as the head, trunk, and legs. Bello and Oladipo [36] utilized the Mask YOLOv7-based drone vision system for automated cattle detection and counting, aiding in cattle counting across various environments such as extensive pastures and intensive feedlots. Fig. 3 illustrates the framework for cattle detection and counting. Performance evaluation confirmed the optimal Intersection over Union (IoU) threshold and validated the algorithm's effectiveness in full-appearance detection. The study highlighted the framework's consistent performance in offline drone vision systems, enabling accurate counting of cattle in both pasture and feedlot environments. Their method demonstrated enhanced counting accuracy and average precision compared to current algorithms, particularly in datasets with occlusion and overlapping instances.

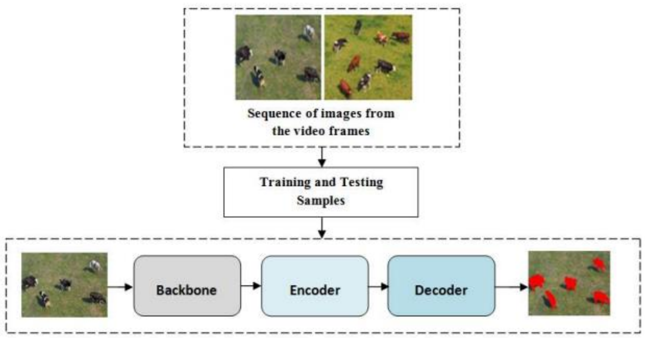

Figure 3.
Framework for cattle detection and counting. [36].

2.2. Segmentation of Body Parts

To improve the precision of traditional object detection algorithms in identifying crucial parts of dairy cattle, Jiang et al. [17] investigated the FLYOLOv3 deep learning framework, which incorporates FilterLayer (FilterLayer YOLOv3), for identifying key body parts like the head, trunk, and legs of dairy cattle in complex settings. During training, they addressed issues such as image instability and initialization noise in convolutional feature maps by applying a mean filtering algorithm and adding a leaky rectifier function (Leaky ReLU) to the custom FilterLayer, helping to minimize training disruptions. Artificial annotations delineated cow head, trunk, and leg boundaries in initial images, followed by training of the FLYOLOv3 network with these annotated samples. The trained model underwent evaluation on test images, comparing its performance with Faster R-CNN and YOLOv3 by means of metrics such as recall rate, accuracy, average precision and average frame rate. Results displayed that FLYOLOv3 algorithm achieved 99.18% accuracy, a 97.51% recall rate, an average frame rate of 21 f/s, and an average precision of 93.73%. While Faster R-CNN demonstrated high accuracy and recall rates with an average detection rate of 93.47%, it struggled in leg detection with some false positives and operated at a frame rate of 8 f/s, which was insufficient for real-time applications. YOLOv3, despite its high frame rate of 76 f/s, exhibited lower accuracy and recall rates, particularly for small objects, and faced challenges in detecting untrained nighttime cattle images, indicating weaker generalization capability.

In summary, FLYOLOv3 showed superior accuracy and recall rates; Faster R-CNN performed well in certain aspects but lacked real-time capability; and YOLOv3 offered speed advantages but lower accuracy under challenging conditions. Fig. 4 shows the results depicting the detection of critical parts in cattle.

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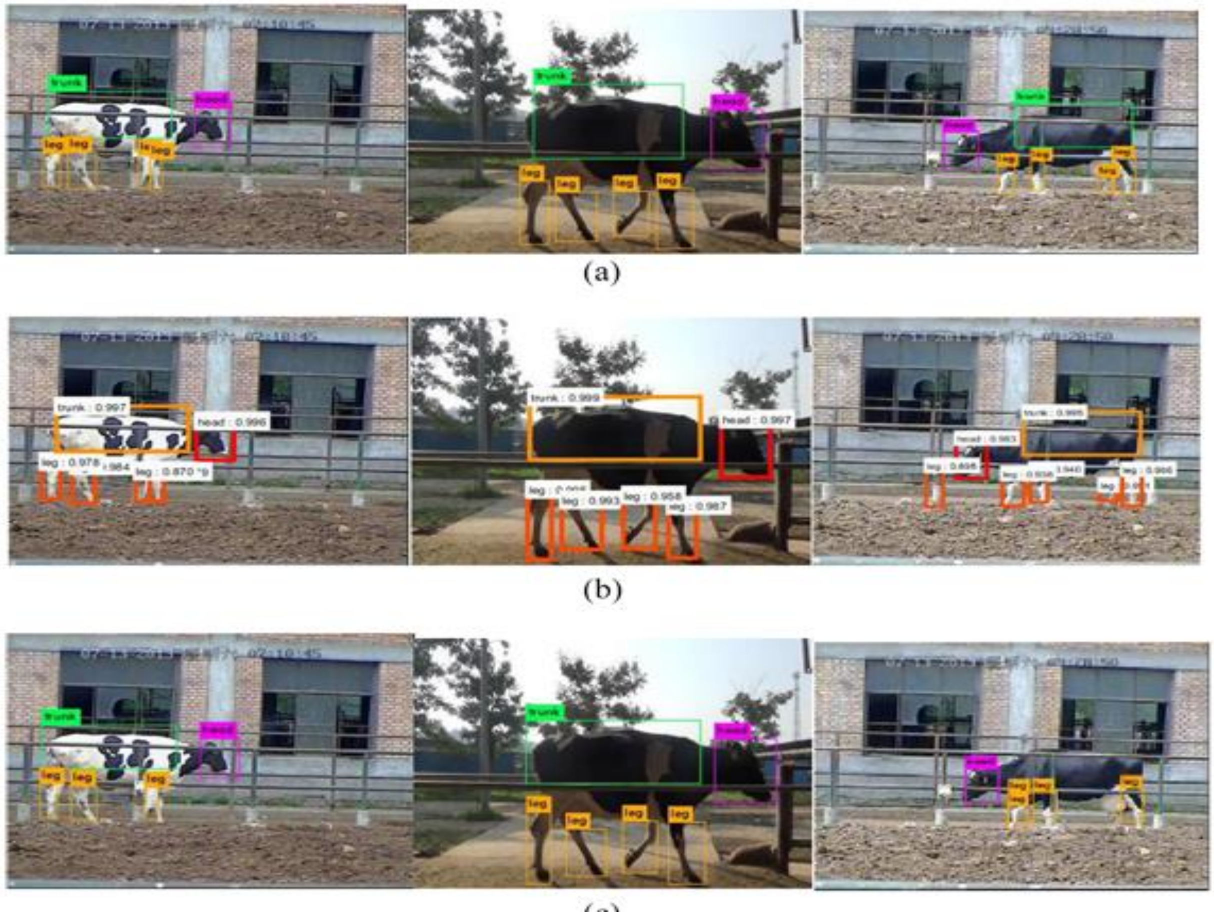

Figure 4.
Results depicting the detection of critical parts in cattle: (a) outcomes from the FLYOLOv3 algorithm, (b) outcomes from the Faster R-CNN algorithm, (c) outcomes from the YOLOv3 algorithm. [17].

Liu et al. [37] developed a structural model for cattle viewed from the side, detailing the spatial arrangement of key points representing the cattle's joints, and implemented a DL system to autonomously extract this model from videos. The system successfully identified multiple cattle within a single frame, demonstrating reliable performance in identifying body regions even under challenging conditions such as obstacles like fences and low lighting. These findings underscore the widespread adoption of DL in segmenting parts of cattle.

However, the study identifies the need for exploring new approaches to overcome limitations in their current system. Specifically, improving the robustness of leg and hoof key-point estimation is crucial. These key-points are challenging to detect due to motion blur and insufficient lighting conditions. Yet, accurately tracking these points is critical for detecting cow lameness effectively.

Similarly, Sun et al. [38] proposed a model based on SlowFast enhancements aimed at accurately recognizing fundamental yak behaviors. The backbone of their approach utilized the 3D ResNet50 network, achieving an average accuracy of 96.6% in recognizing basic behaviors. Challenges included difficulty in clearly distinguishing boundaries between different yak behaviors. For example, determining whether a behavior started when a yak's neck bent or when its head touched the grass during grazing was ambiguous. Another limitation was the inability to link individual yak identification with the recognition of basic daily behaviors, which hindered correlating behavior identification results with specific yaks. A new network named Open Pose (OP) Mask R-CNN was developed by Wang et al.

[39] to enhance individual cattle identification, improving accuracy and recognition speed across various environments. This network uses three main tactics to enhance cow identification by integrating OpenPose with the Mask R-CNN architecture. In the first, the convolutional layers in Mask R-CNN's ResNet101 backbone are optimized. The second extracts cattle skeletal characteristics using an OpenPose-based technique. In order to improve performance, the third presents a fusion mechanism that integrates the OpenPose module, Convolutional Block Attention Module (CBAM), ResNet101, and the attention module. The results demonstrated accuracy improvements of 5.6%, 7.3%, and 11.1% for each respective strategy, highlighting significant enhancements in identification performance.

Zhang et al. [40] introduced a technique for cascaded identification of individual dairy cattle employing DeepOtsu and EfficientNet. This approach involves segmenting and classifying body pattern images of dairy cows to overcome challenges such as similarity in body patterns, poor image quality, and numerous output terminals during group identification. The binarization segmentation achieved an accuracy of 0.932, with an overall identification accuracy reaching 0.985. The method processes a single image in 0.433 seconds, demonstrating superior efficiency and training speed compared to end-to-end methods for dairy cattle identification. Despite its advantages, further refinement of the cascaded approach is needed, particularly in enhancing the robustness of the binarization model through network optimization. This enhancement is crucial for adapting the method to complex farm environments where challenges like overexposed cattle trunk images may occur.

Shao et al. [41] introduced a Filter-Attention mechanism incorporating bilateral filtering and a soft pooling algorithm in the backbone feature extraction network to enhance the identification and localization of key parts in cattle. This mechanism aimed to mitigate particle and fragment noise from convolution operations and Gaussian noise from input images. Experimental results demonstrated a mean Average Precision (mAP) of 90.74%, improving F1 and AP values across all sections. Despite achieving successful segment identification, challenges like congestion, overlap, and varying lighting conditions in livestock environments hindered precise detection. Addressing these issues is critical for optimizing detection in cattle farms, especially in low-light conditions such as nighttime. Further refinement and optimization are essential to enhance detection speed and accuracy, ensuring robust performance in detecting key cattle parts.

3. Identification

The objective of identification is to establish a distinct identity within a collective, associating observed behaviours with specific animals. This linkage enables the transition from recognizing behaviours at a group level to identifying behaviours on an individual basis [42]. Iris analysis, which involves imaging, detecting and recognition the iris, was utilized by Lu et al. [43] to build a cattle identification system. The procedure involved evaluating image quality, delineating the iris through elliptical fitting based on edge images, applying geometric methods for normalization, and extracting features using the 2D complex wavelet transform (2D-CWT). This method demonstrated effectiveness but was limited by a small cattle iris database.

Gaber et al. [44], They employed a Weber Local Descriptor (WLD) to extract strong features from cattle muzzle prints and utilized the AdaBoost classifier for head identification based on these features. This method showed superior performance when compared to the k-Nearest Neighbor (k-NN) and fuzzy k-Nearest Neighbor (Fk-NN) algorithms, achieving an accuracy rate of approximately 99.5%. Previous identification methods focused on controlled environments for retinal patterns, eyes, or noses. Evaluation metrics such as AUC, accuracy rate Specificity, Sensitivity, and Equal Error Rate (EER) confirmed the efficacy of using WLD with AdaBoost. To identify cattle in different enviromental settings, Li et al. [45] focused on identifying cattle in various environments by analyzing the tailhead image as a Region of Interest (ROI) and employing Zernike moments to extract the shape features of the white pattern within this region. Four classification techniques were used after two sets of Zernike moments were taken out of the pre-processed images: Support Vector Machines (SVM), Artificial Neural Networks (ANN), Linear Discriminant Analysis (LDA), and Quadratic Discriminant Analysis (QDA). The findings demonstrated the excellent effectiveness of low-order Zernike moment characteristics for identifying individual dairy animals, especially when combined with QDA and SVM.

The QDA classifier achieved the highest accuracy rate at 99.7%, while the SVM classifier demonstrated the highest precision at 99.6%. QDA and SVM classifiers both performed quite well, each achieving an F1 score of 0.995. These findings demonstrate the potential of combining low-order Zernike moment characteristics with SVM and QDA algorithms as a successful method for managing animals precisely. The goal of the computer vision (CV) system created by Zhao et al. [46] was to detect Holstein animals and extract body images from side-view films of dairy cattle moving in a straight line. The system utilized an adaptive Self-Organizing Map (SOM) technique to detect cattle masks and define the body area by extracting the largest inscribed rectangle. The feature points from these body images were then compared with a template dataset to identify unknown cattle. The study evaluated several feature extraction and matching techniques, concluding that a combination of Oriented FAST and Rotated BRIEF (ORB) for feature extraction, along with BruteForce for matching, provided enhanced computational efficiency while maintaining high accuracy. This approach achieved a peak identification accuracy of 96.72%. The work highlights the application of CV techniques in cattle identification based on body parts, complementing DL approaches for similar tasks.

In Kumar et al. [47], a DL technique was created to recognize individual cattle based on patterns in their muzzle point images. This method utilized Convolutional Neural Network (CNN) and Deep Belief Network (DBN) architectures to extract unique texture features from muzzle images. These features were encoded using Stacked Denoising Autoencoders (SDAE). The approach surpassed competitive methods for cattle identification using muzzle point image databases, achieving identification accuracies of 75.98% with CNN, 88.46% with SDAE, and 95.99% with DBN.

In Hu et al. [48], a method was devised for cattle identification that integrates deep features extracted from various body parts. To identify cattle, side-view images of the cattle were collected and analyzed using the YOLO object detection technique. A part segmentation algorithm then divided each cow into distinct parts, including the head, trunk, and legs. Distinct CNNs were trained to extract deep features from the segmented regions, which were then combined through deep part feature fusion. In the final step, an SVM classifier was trained on the combined features to identify each cow. This method achieved an accuracy of 98.36% in identifying cattle from a dataset of side-view images of 93 cattle, demonstrating superiority over existing methods. The study underscores the advancement of cattle identification from body-part-based CV to DL approaches, resulting in improved identification accuracy and practical applicability. This approach holds potential for integration into various applications such as lameness detection, drinking behavior analysis, linear appraisal, mastitis detection, and individual localization. In the study by Okura et al. [49], a cattle recognition approach was created using RGB-D cameras that capture both color (RGB) and depth data to analyze 3D video footage of cattle walking. This approach leverages two key features: gait (walking style) and texture (markings on the cattle). In experiments conducted within a cow house, their integrated method achieved an accuracy (rank-1 identification rate) of 84.2%.

Qiao et al. [50], deep learning framework was proposed for identifying beef cattle using image sequences, integrating CNN and Long Short-Term Memory (LSTM) network methods. InceptionV3 was applied to extract features from rear-view videos of cattle, which were then used to train an LSTM model that captures temporal patterns to distinguish individual animals. This approach marks a departure from traditional CV methods towards DL for comprehensive cattle identification. The method achieved accuracies of 88% for 15-frame videos and 91% for 20-frame videos using a dataset of 516 rear-view videos from 41 cattle across three timepoints.

4. Behavioural Regognition

4.1. Feeding Behavioural Recognition

In Porto et al. [51], the Viola-Jones algorithm was utilized to detect cattle feeding and standing behaviors using a multi-camera video setup capturing panoramic top-view images of a barn area. The study demonstrated the system's effectiveness in calculating behavioral indices and detecting real-time behavioral changes in cattle, achieving high sensitivity rates of around 87% for feeding behavior and 86% for standing behavior. Achour et al. [52] focused on analyzing the upper section of dairy cattle head images in place of a Region of Interest (ROI). CNN classifiers were used to recognize feeding behaviour and identify individual cattle among seventeen Holstein dairy cows. The system demonstrated exceptional performance, achieving perfect accuracy (100%) in detecting and classifying food availability, 92% accuracy in distinguishing between standing and feeding behaviours, and 97% accuracy in identifying individual cattle. In Bezen et al. [53], a CV system was developed using deep CNNs and an affordable RGB-D camera to quantify the feed intake of individual cattle. This system integrated RGB and depth data to estimate feed intake, relying solely on RGB images for cattle identification. CNN models tailored for both tasks showed superior performance compared to depth-only models, achieving 93.65% accuracy in identifying cattle in an open cowshed. The system is promising as an alternative to RFID tags but requires retraining for varying feed compositions.

4.2. Lameness Recognition

Song XiangYu et al. [54] utilized computer vision techniques to monitor the "relative position of the hind hoof to the fore hoof" as a method for assessing lameness in cattle. Their method included background subtraction, binary image operations, and hoof separation to analyze the cattle's locomotion. The correlation coefficient between automated and manually labeled results averaged 94.8%, demonstrating promising accuracy. However, limitations include reliance on a small dataset, which may affect the system's generalizability. Additionally, variations in environmental conditions like lighting changes and uneven flooring could impact the reliability and accuracy of the vision-based analysis. Poursaberi et al. [55] presented a hierarchical method for separating background and foreground to isolate cattle in video frames and monitor their movements. The technique employed logarithmic and exponential functions, along with background subtraction and statistical filtering, to accurately outline the cattle's shape. The algorithm automatically extracted back postures while cattle stood or walked by identifying back curvature and fitting circles to points along the spine line. Using curvature metrics, the system generated automated lameness scores for cattle by computing the average inverse radius from frames showing the hind hoofs touching the ground. The system achieved over 96% accuracy in classifying lameness in 184 dairy cattle, demonstrating significant potential. However, adjustments are needed to account for behavioral influences when cattle walk closely together, ensuring the algorithm's robustness in practical milk production settings.

Previous studies have utilized population-wide thresholds for identifying lameness in cattle; Viazzi et al. [56] expanded on this by developing a personalized body movement pattern score that uses back posture to classify lameness into three categories. They compared both population-wide and individualized approaches in real farm conditions. However, using two-dimensional cameras on farms presents challenges like installation difficulties and issues with image segmentation due to shadows and background changes. The Bitmap (BMP) algorithm, designed for monitoring lameness in dairy cattle was tested on 223 randomly selected cattle videos under farm conditions, achieving a 76% classification success rate. However, distinguishing between closely related lameness classes was challenging due to high individual variability among cattle. Implementing individual-specific thresholds improved overall accuracy and true positive rates by 10 percentage points to 91% compared to the population-based model, while reducing the false positive rate by 4 percentage points to 6%. Moreover, the classification rates remained consistently high (>85%) across all three lameness categories. This individualized threshold approach shows promise for addressing individual variability in developing automated lameness detection systems based on image analysis. To address these challenges, Viazzi et al. [57] introduced a new CV approach using a three-dimensional camera to analyze the back posture of walking cattle from a top-view perspective. Their work showed that this method, comparable in accuracy to traditional side-view techniques, offers automation and processing efficiency benefits. The two-dimensional algorithm achieved 91% accuracy, while the three-dimensional approach reached 90% on the evaluation dataset.

Zhao et al. [58] applied CV techniques to analyze leg swing and developed an automated system for continuous cattle locomotion scoring, facilitating precise lameness detection and prediction. They opined that advancements in DL technology have transformed the detection of cattle lameness from conventional CV techniques to more advanced DL methodologies. They used image processing to extract leg movement positions and derived six gait symmetry features: speed, tracking, stance time, stride length, and tenderness. These features were analyzed across three lameness classes, demonstrating clear indicators of lameness progression. The system achieved a classification accuracy of 90.18%, with average sensitivity of 90.25% and specificity of 94.74%.

Wu et al. [59] introduced a method that employs the YOLOv3 deep learning algorithm along with relative step size characteristic vectors to differentiate between cattle affected by lameness and those that are not. The approach involved segmenting videos into frames, detecting cow leg positions with YOLOv3, and calculating relative step sizes for front and rear legs as characteristic vectors. These vectors were used to train an LSTM classification model for lameness detection. Validation across 210 videos demonstrated LSTM achieving 98.57% accuracy, surpassing SVM, KNN, and DTC by margins of 2.93%, 3.88%, and 9.25%, respectively.

Jiang et al. [60] aimed to capture and represent dairy cattle lameness behaviors, which are brief and exhibit unique spatiotemporal patterns, using CNNs. They addressed the limitations of conventional frame-level representations by exploring video representations through single-stream long-term optical flow convolutional networks. Their work indicated that including extended temporal scopes significantly improves the accuracy of identifying lameness actions in dairy cattle. They emphasized the importance of high-quality optical flow estimation in developing precise lameness action models, achieving state-of-the-art results with 98.24% accuracy on challenging benchmarks for dairy cattle lameness action videos. However, the study acknowledges limitations related to dataset availability and diversity, which could impact the model's generalization and robustness. Additionally, they highlighted the need for comprehensive evaluation metrics to ensure the model's effectiveness in practical applications.

4.3. Mounting Behavioural Recognition

Guo et al. [61] introduced a method for detecting mounting behavior in dairy cattle through computer vision techniques. They applied masking methods to remove irrelevant background features by transforming RGB images into the HSV color space and adjusting the coefficients to enhance the contrast between the cattle and their environment. The Background Subtraction with Color and Texture Features (BSCTF) algorithm detected cow regions, followed by extraction of geometric and optical flow characteristics for inter-frame differential processing. This yielded regional feature vectors with seven optimized features. A SVM classifier was trained on these vectors to distinguish mounting from non-mounting regions, achieving 98.3% accuracy and a 6.4% omission rate. The SVM showed an average recognition accuracy of 90.9% with a 4.2% false positive rate.

4.4. Posture Behavioural Recognition

To recognize cattle behavior and posture, Porto et al. [62] developed a CV system to automatically detect dairy cattle lying behavior in free-stall barns using multiple camera setups and the Viola-Jones algorithm. The system aimed to compute the cattle lying index, crucial for assessing cattle behavior in such environments. The approach demonstrated high sensitivity, approximately 92%, in accurately identifying cattle lying behavior. However, challenges remain in distinguishing between lying and other behaviors, potentially leading to false positives or negatives. The system's effectiveness may vary depending on the specific configurations of free-stall barns, highlighting the need for further refinement and adaptation across diverse farming environments.

Li et al. [63] developed three deep cascaded CNN models—convolutional pose machine, stacked hourglass, and convolutional heat map regression—to accurately predict cattle poses from RGB images in real farm environments. The stacked hourglass model demonstrated superior performance with a PCKh mean score of 90.39% for 16 joints at a threshold of 0.5. This evolution from traditional CV to DL signifies advancements in posture recognition methods for cattle. Fig. 5 shows the general scheme of cattle pose estimation.

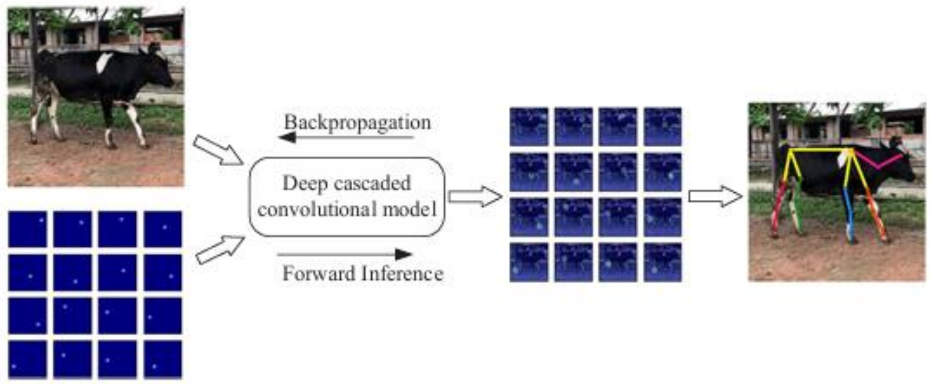

Figure 5.
The general scheme of cattle pose estimation. [63].

4.5. Multi- Behavioural Recognition

Conversely, DL has been applied to recognize various behaviors exhibited by cattle as well. Fuentes et al. [64] introduced a hierarchical DL approach for recognizing cattle behaviors, emphasizing spatial-temporal information integration. The approach combined appearance features with contextual and temporal data to detect and localize different cattle behaviors in video frames. The study demonstrated the system's effectiveness in recognizing 15 unique activities, encompassing both individual and group behaviors.

Yin et al. [65] proposed a method to identify different behaviors of dairy cattle, such as lying, standing, walking, drinking, and feeding. They leveraged EfficientNet for effective extraction of spatial features from video frames that display cattle behavior. To capture diverse behavior patterns, they applied BiFPN (Bidirectional Feature Pyramid Network) to combine features from layers 3 to 5 of EfficientNet. The behavior information was processed through a BiLSTM module with an attention mechanism to aggregate video frames over time, achieving swift and accurate behavior recognition. Experimental results demonstrated a behavior recognition accuracy of 97.87%, outperforming ResNet50-LSTM by 4.25%, with a processing speed of 134 frames per second (fps). By incorporating a sliding window approach, the algorithm successfully recognized behaviors in continuous single-target dairy cattle videos with a final accuracy of 95.20%. These findings highlight the algorithm's efficacy in enhancing dairy cattle management and health monitoring capabilities.

5. Discussions

In this review work, related works were reviewed on the applications of state-of-the-art CV and DL to livestock management. Several limitations were revealed in those related works reviewed that demand the attention of the present time researchers. Moreover, different suggestions were noticed, that were made by the individual authors as a way forward. In [36], it was suggested that future endeavors concentrate on evaluating Mask R-CNN's capability in species classification of livestock and investigating the influence of stocking density on animal well-being for more accurate results. In the future work of Lu et al. [43], they recommended validation and improvement of their proposed method's reliability across a larger dataset of cattle iris images. In the future work of Gaber et al. [44], they iterated the importance of evaluating their approach on a larger database of cattle images and exploring the potential of combining two cattle biometrics: muzzle and face. In their future work, Zhao et al. [46] suggested focusing on methods for extracting binary information from cow body patterns to further enhance the system's accuracy and efficiency. In [47], it was recommended as future work to expand the proposed cattle recognition system to identify different animals in real-time, in addition to the following points:

- Design a multi-modal cattle recognition system using both muzzle point and face images of cattle for accurate identification and verification in real-time.

- Enhance the performance of the proposed cattle recognition system by employing multi-modal systems and feature fusion techniques. This could involve combining the discriminative texture features of muzzle point images with facial images of individual cattle.
- Increase the size of the cattle database to validate experimental results against benchmark existing hand-crafted texture descriptor techniques and DL-based feature learning and representation techniques in CV.

In the future trajectory of Achour et al. [52], they considered employing the approach for individual cattle identification in a large-scale farm, where identification would be performed separately in each cluster. Additionally, they aimed to gather additional datasets comprising a larger number of cattle from various farms and over extended periods. In the future work of Viazzi et al. [57], they suggested employing individualized models that account for each cow's normal posture and detect deviations from the baseline posture on an individual basis. Additionally, further studies are suggested for assessing the system's performance when applied to a larger variety of animals, different breeds, and diverse farming conditions not limited to those in Israel, such as open cowsheds, non-cubicle housing, and non-concrete flooring. In their future studies, Zhao et al. [58] recommended the use of a solid color background and an electric fence to capture high-quality indoor videos of cattle walking. A solid color background would enhance the accuracy of extracting the back curve, while an electric fence would help minimize information loss. In the future endeavors of Guo et al. [61], they advised the incorporation of common behaviors of dairy cattle into their proposed model to enhance estrus detection accuracy and enable comprehensive monitoring of their daily activities. In the future work of Li et al. [63], they suggested employing a 3-D dataset derived from pose estimation holds promise for enhancing the accuracy and resilience of cattle pose estimation. This approach harnesses in-depth image information to glean more precise features, potentially resolving issues related to extensive occlusion. Additionally, delving into multi-cattle pose estimation poses a challenging yet promising avenue worthy of further investigation in future research.

6. Conclusion

Research on livestock behaviour focuses on identifying actions such as aggression, mounting, feeding, drinking, lameness, tail-biting, nursing, posture, and play. Drinking and feeding behaviours directly influence the growth of livestock, while behaviours like aggression, lameness, mounting, and tail-biting can result in injuries and negatively impact the overall health of the animals. Assessing animal health relies significantly on pose estimation, while nursing and playing behaviours provide insights into animal welfare. However, existing studies predominantly focus on recognizing individual behaviours rather than establishing a comprehensive link between behaviour recognition and indicators like growth, health, and welfare. Despite significant progress in integrating CV and DL technologies for livestock behaviour recognition, further research is necessary to address existing challenges. Enhancing algorithm robustness under diverse and complex conditions will be pivotal for broader adoption across the industry. Moreover, advancements in these technologies hold promise for improving the efficiency and effectiveness of livestock management practices, ultimately enhancing industry sustainability and productivity.

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