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Enhancing cattle production and management through convolutional neural networks. A review

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Abstract: The rise in demand for animal products associated with global population growth has driven the world toward precision livestock farming, where convolutional neural networks (CNN) have gained increasing attention due to their potential to enhance animal health, productivity, and welfare. However, the effectiveness and generalizability of CNN applications in cattle production are limited by several challenges and limitations, which require further research and development to address. This systematic literature review aims to provide a comprehensive overview of the applications of CNN in cattle production. It identified some potential applications of CNN in this field and highlighted the challenges and limitations that need to be addressed to improve the effectiveness and efficiency of CNN applications in cattle production. It also provides valuable insights for researchers, practitioners, and policymakers interested in the use of CNN to enhance cattle production practices, animal welfare, and sustainability. Additionally, it also provides the reader with a summary of the literature on the fundamental concepts of convolutional neural networks and their commonly used model architectures in cattle production. This is because agriculture digitalisation is going more multidisciplinary and people from different areas of expertise may find it helpful to learn more from a combined source.

Keywords: Agriculture 4.0; agriculture digitalization; cattle health monitoring; cattle identification; precision livestock farming; stables technologies

According to the most recent estimate of the United Nations, the global population is predicted to exceed 8.5 billion in 2030, 9.7 billion in 2050, and 11.1 billion by 2100 (Sadigov 2022). The rise in demand for animal products associated with global population growth and food demand (in-

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cluding animal products) is forecast to increase by 59% to 98% by 2050, where 2.6 billion cattle are expectedto be produced (Yitbarek 2019). Cattle production is among the critical components of the global food supply chain, providing meat, dairy products, and other animal products for human consumption (Tona 2021). To keep up with the growing demand for animal products and controlling various factors that may affect animal health and productivity, the development of precision livestock farming technologies that can enhance the monitoring and management of animal health and productivity is essential for the sustainability of the industry. This allows the opportunity to increase animal productivity and early detection of health concerns (Schillings et al. 2021). Convolutional neural networks (CNN), one of the deep learning algorithms, provedto be a cutting edge for image processing and has shown promising results in several aspects where it has been applied (Kamilaris and Prenafeta-Boldu 2018). In recent years, CNNs have emergedas a promising tool for improving cattle production practices by enabling the automation of tasks, including cattle identification, disease detection, behavior analysis, and feed optimization. However, the successful application of CNN in cattle farming requires addressing several challenges related to data collection, processing, and model transferability.

In this systematic literature review, we aim to provide an overview of the current state of knowledge regarding the applications of CNN in cattle production and to identify the benefits, challenges, and future directions of CNN applications in this field. The findings of this review can inform future research and guide the development of CNN applications in cattle production to enhance animal health, productivity, and welfare. Other authors, including Gikunda and Jouandeau (2019) and Kamilaris and Prenafeta-Boldu (2018), have previously reviewed the broad applications of CNN in smart farms and agriculture in general, but mostly focused on plant production rather than animal farming. Others such as Mahmud et al. (2021), Bao and Xie (2022), Chen et al. (2021), Cockburn (2020), Garcia et al. (2020) and Qiao et al. (2021a) have reviewed various applications of artificial intelligence (AI) and deep learning in animal farming. Other reviews of convolutional neural networks were also provided for some computer vision tasks like image classification by Rawat and Wang (2017) and object detection by Zhao et al. (2019). Also, some other researchers like Li et al. (2021b) have reviewed the application of CNN in animal farming in general and partially for some animal species, such as poultry by Okinda et al. (2020), goats by Jiang et al. (2020b), etc. However, there was no comprehensive review that covers in a specific way CNN applications in cattle production were found to the best of the authors' knowledge.

Basic concepts of CNN and commonly used model architectures in cattle production

Convolutional neural networks are part of the most common artificial neural networks today for nearly all Artificial Intelligence tasks related to computer vision and image processing. They are mainly used to perform image analysis and classification, group images with respect to their similarity, and perform object recognition within a frame. In 1959, two neurophysiologists, Hubel and Wiesel (1959), introduced artificial neural networks while working on the cat's main visual cortex. After that, their approach effectively became one of the core principles of deep learning (Ghosh et al. 2020). Based on their work, in 1980, Neocognitron, a multilayered and autonomous neural network with hierarchical visual pattern recognition capabilities through learning, was proposed by Fukushima (1980), and hence the convolutional neural network got his first theoretical model based on this architecture. In 1989, a significant improvement to Neocognitron architecture was made by LeCun et al. (1989) by developing LeNet, a CNN framework that was able to recognize the MNIST handwritten digits dataset with success. Even though CNN did not perform well in a variety of complex tasks after the discovery of LeNet due to numerous limitations, such as the shortage in algorithm innovation, large training data, and insufficient computer processing capacity, but it started the era of CNN in Computer Vision. Later in 2009, the use of graphics processing units (GPUs) was launched by Raina et al. (2009) to boost the training speed of the network, which was up to 72.6 times faster than using only the central processing unit (CPU). Again in 2009, ImageNet, one of the world's largest openly accessible datasets with annotation, was developed to promote the advancement of CNN in computer vision (Deng et al. 2009).

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Thanks to these advancements, AlexNet was designed by Krizhevsky et al. (2012) and achieved an outstanding accuracy rate on the ImageNet Large-Scale Visual Recognition Challenge. Following AlexNet's breakthrough, CNN experienced significant admiration in object detection, classification, and segmentation tasks, and numerous advanced CNN models have been developed throughout the years (Ghosh et al. 2020).

With the target of further deepening the CNN architecture, Simonyan and Zisserman (2015) introduced VGGNet in 2014. At that time, VGG-16 was proposed to have a total of 16 layers, and compared to the performance of earlier networks, it showed great results. The in-depth study provided in their work had a big impact on CNN, where it was confirmed that performance may be improved significantly by deepening the model. The Inception network, also known as GoogleLeNet, was also developed by Szegedy et al. (2016a) in the same year. It was the largest and most effective deep learning convolutional neural network architecture at the time, with the goal of reducing the computational costs of very deep CNN by applying a 1 × 1 convolution and concatenating the channels (Szegedy et al. 2015a).

As the development of CNN-based architectures has been growing, there was a common trend in the research community that the network architectures needed to go deeper and deeper, and hence the addition of more layers in a deep neural network was preferred for every subsequent winning architecture. However, simply stacking the layers to increase the depth of CNN was associated with the common issue of vanishing or exploding gradient in deep learning, which increases the training errors. As solution, He et al. (2016) proposed Residual Network or ResNet in 2015, to address the issue of the necessity for a deep network without a vanishing gradient. The outstanding performance of Inception and ResNet has led to the idea of combining the two technologies to develop Inception-ResNet, a convolutional neural network architecture that expands on the Inception family of architectures while also including residual connections (Szegedy et al. 2016b).

Another important CNN architecture is YOLO, a convolutional neural network architecture introduced by Redmon et al. (2016) to detect multiple objects present in an image in real-time while drawing bounding boxes around them. As per its name, it passes the image through the CNN algorithm only once to get the output, which means that prediction in the entire image is processed in a single algorithm run, which accounts for its popularity due to its speed and accuracy (Redmon et al. 2016). The YOLO algorithm was upgraded until today that different versions are being introduced. To ensure maximum information flow between network layers, Huang et al. (2017) introduced DenseNet, a convolutional neural network in which each layer is connected to all other layers that are deeper in the network, resulting in several compelling advantages such as relieving the vanishing gradient problem, enhancing feature propagation, stimulating the reuse of features, and significantly reducing the number of parameters (Huang et al. 2017). As convolutional neural networks (CNN) were getting very popular, modern CNN architectures were becoming deeper and increasingly complex to achieve a higher degree of accuracy; however, such networks could not be used in real-time applications such as augmented reality, self-driving cars, and robotics. Alternatively, Howard et al. (2017) presented a lightweight model that makes useof a depthwise separable convolution, a new type of convolutional layer. Considering their compact size, it was uncertain that these models were particularly appropriate for mobile and embedded devices, and hence the name of MobileNet (Howard et al. 2017). Chollet (2018) also introduced an Inception-inspired deep convolutional neural network architecture in 2017 by substituting Inception modules with depth-wise separable convolutions. The model was given the name Xception, which stands for "Extreme Inception" and was based on the success of depth-wise separable convolution in the MobileNet and the relative lightness compared to traditional convolution (Chollet 2018).

Performance metrics commonly used to evaluate CNN models in cattle production

Model evaluationis a major part of building an effective deep learning model. The four key classification metrics, accuracy, precision, recall, and F1 score, have been used mostly by the identified studies for both the evaluation and testing of their CNN models. The total number of correct predic-

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Table 1. Possible classification outcomes: TP, FP, FN, TN

		Real situation	
		positive	negative
Model prediction	positive	true positive (TP)	false positive (FP)
	negative	false negative (FN)	true negative (TN)

tions over the total number of input samples ratio is known as accuracy, while the model's ability to accurately identify targets is known as precision. Recall reflects the model's ability to detect targets, and the F1 score is the harmonic means of precision and recall. All four of the indicators mentioned above range from 0 to 1, with a high number indicating the good predictive capacity of the model (Qiao et al. 2019b). Classification metrics and confusion matrices which can be defined as the result of classification problems are very closely connected and dependent on each other. There usually exist four possibilities of the result: True Positive, False Positive, False Negative, and True Negative. The possible classification outcomes are shown in Table 1.

The number of correctly detected objects is referredto as the True Positive (TP), which means that there was an object (the result should be positive) and the algorithm detects it (returned positive). The Missed object detections are referred to as False Negatives (FN), which simply means that there was an object (the result should be positive), but the algorithm did not detect it (and, therefore, returned negative). Moreover, the number of false detection of objects is referredto as the False Positive (FP), which means that there was no object (the result should be negative), but the algorithm seems to detect the object (returned positive). A true negative simply means that there was no object (the result should be negative), and the algorithm correctly states that the checked area does not hold an object (returned negative).

The following metrics were foundto be the most used to evaluate CNN models in the analysed studies:

$$\text{Accuracy} = \frac{\text{All corrects}}{\text{All predictions}} = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

$$\text{Precision} = \frac{\text{True positives}}{\text{Predicted positives}} = \frac{TP}{TP + FP} \quad (2)$$

$$\text{Recall} = \frac{\text{True positives}}{\text{Predicted positives}} = \frac{TP}{TP + FN} \quad (3)$$

$$F1 - \text{score} = \frac{2}{\dfrac{1}{\text{Recall}} + \dfrac{1}{\text{Precision}}} \quad (4)$$

Review reports

This systematic literature review identified 52 studies that used convolutional neural networks in cattle production, covering a wide range of applications. Following the scope of this work and after going through the identified studies, the cattle production issues classified into two categories were taken into consideration, as they were foundto be among the highly addressed using CNN. These are cattle identification and cattle health monitoring. Identification is among the key management techniques to keep animal records to make more informed management decisions (Qiao et al. 2021a). In cattle production, it contributes greatly to the tracking of cattle performance. While associated with continuous health monitoring, it enables the opportunity to improve well-being, productivity, and early detection of health concerns (Mahmud et al. 2021). Various cattle health-related issues were addressed using different approaches such as automated monitoring of cattle behavior and activities, cattle pose estimation, measurement of cattle body condition score, desease detection such as mastitis and lameness, heat stress evaluation, Breathing Pattern Analysis, body weight and structure estimation, etc. Identification-related issues included cattle detection and tracking, cattle face detection, cattle breed recognition and classification, etc. A total of 28 papers were identified in the category of cattle health monitoring while 24 papers were identified in the category of cattle identification. This result shows that both aspects were addressed almost equally. Figure 1 displays the distribution of the identified papers by year for each category. It shows that research based on CNN application in cattle identification and health monitoring has grown gradually each year, with the highest number of publications identified for the year 2020.

Additionally, in Figure 2 we present the distribution of the identified papers by country. China took first place with the most papers (20 out of 52), fol-

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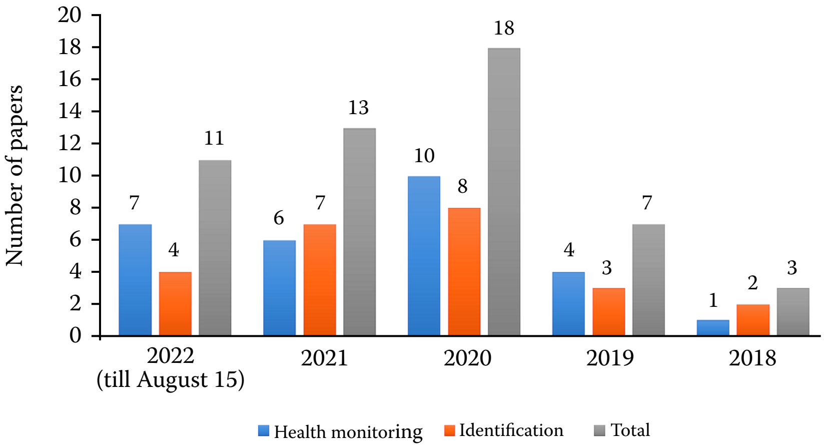

Figure 1. Identified papers in each category by year

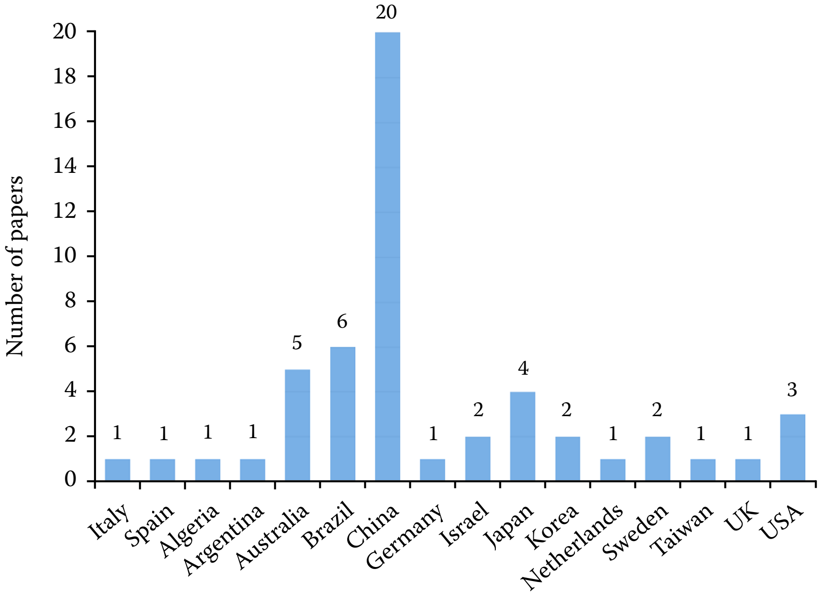

Figure 2. Distribution of identified papers by country

lowed by Brazil (6), and Australia (5). The summary of the main findings of the studies are summarized in Table 2.

Challenges and future research directions

Through this systematic literature review, this paper identified three key challenges to the application of CNN in cattle production in general: (1) the lack of standardization in data collection and processing, (2) the need for large and diverse datasets, and (3) the limited transferability of models across different populations and farming systems. The lack of standardization in data collection and processing refers to the challenge of developing CNN models using heterogeneous data that have been collected and processed differently across different farms or regions. This can result in inconsistent data quality and format, which can make it difficult to develop accurate and reliable CNN models. The reviewed studies proved that data were collected from various sources, such as cameras and sensors under different settings, environmental and lighting conditions, etc. Additionally, different studies may use different methods for data processing, such as image cropping, resizing, or normalization and different label-preserving transformations techniques for data augmentation (Kalouris et al. 2019; Li et al. 2021a). These methods can affect the distribution and range of features in the data, which can in turn affect the performance of CNN models. Generally, this lack of standardization in data collection and processing canbe a challenge for the practical application of CNN in cattle farming, as it requires developing models that can handle and learn from heterogeneous data, which can

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Table 2. Summary of the identified studies that applied CNN in cattle production

Issue	Dataset	Model architecture	Performance	Reference
Individual identification and feeding behaviour monitoring	7 801 RGB images captured by authors	Xception	accuracy was 96.55% for individual identification; average precision was 90.84% for feeding behaviour analysis	Achour et al. (2020)
Cows feed intake estimation	994 RGB images captured by authors	ResNet	identification accuracy was 93.65% while the amount of feed consumed, resulting in the mean absolute and square errors (MAE and MSE) of 0.127 kg, and 0.034 kg^2 respectively	Bezen et al. (2020)
Cow tracking	annotations from Ardo et al. (2018), (2 200 frames consisting of 9 279 images)	VGGNet	cows were successfully tracked for over 20 min	Guzhva et al. (2018)
Cow rump identification	3 057 rump images acquired by authors	MobileNet	identification accuracy was 99.76%	Hou et al. (2021)
Cattle identification	363 rear-view videos from 50 cattle	Inception	identification accuracy was 93.3%	Qiao et al. (2021b)
Segmentation of dairy cows	575 Holstein Friesian images captured by authors	ResNet	averaged precision scores for bounding boxes were 91% and 85% for segmentation masks	Salau and Krieter (2020)
Identification of dairy cows	82 633 cow images captured by authors	AlexNet	cow identification accuracy was 96.65%	Shen et al. (2020)
Cattle breed recognition	27 849 images of the Pantaneira cattle breed	Resnet DenseNet Inception-Resnet-V	the accuracy was 99% in all networks	de Lima Weber et al. (2020)
Recognition of basic behaviors of cows	18 h of videos captured by authors	VGGNet	the average recognition accuracy of 97.6% was obtained	Wu et al. (2021)
Cattle identification and activity recognition	18 h of videos captured by authors	RefineDet	average recognition accuracy of 84.1% and 64.4% for active and static modes	Guan et al. (2020)
Cow structure detection	1 495 video frames captured by authors	ResNet	for body and leg-hoof region segmentations F1scores were 0.71 and 0.59	Liu et al. (2020)
Cattle behavior recognition	350 videos (12 min each)	YOLO	the accuracy of 0.856 was obtained	Fuentes et al. (2020)
Lameness detection	210 videos (15 to 20 s each)	YOLO, DarkNet ResNet	an accuracy of 98.57% was obtained	Wu et al. (2020)
Cattle pose estimation	2 134 images captured by authors	VGGNet	average mean score of 90.39% was achieved	Li et al. (2019)

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Table 2 to be continued

Issue	Dataset	Model architecture	Performance	Reference
Action recognition of lameness cows	1 080 dairy cow videos captured by authors	DenseNet	the mAP was 98.24%	Jiang et al. (2020a)
Cattle face recognition	1 087 images captured by authors	VGGNet	recognition accuracy was 93%	Wang et al. (2020)
Cattle detection and counting	750 aerial images captured by authors	ResNet	an accuracy of 94% for cattle on pastures and 92% in feedlots	Xu et al. (2020)
Cattle segmentation	1 188 images collected by authors	ResNet	mean pixel accuracy (MPA) of 92% was achieved	Qiao et al. (2019c)
Cow parts identification	4 353 images collected by authors	YOLO, AlexNet	a cow identification accuracy of 98.36% was achieved	Hu et al. (2020)
Cow head detection and tracking	10 793 images collected by authors	YOLO, MobileNet	an accuracy of 100% for head detection and 92.5% for ear tag digit recognition	Zin et al. (2020)
Detection of dairy cows	25 200 frames were sampled	YOLO	the mean average precision of the detection was 64–66%	Tassinari et al. (2021)
Cows' activities and social behaviors monitoring	18 640 video frames collected by the authors	Inception	an accuracy of 93.2% was achieved	Ren et al. (2021)
Cattle detection and counting	670 f UAV images collected by the authors	YOLO	the detection performance achieved a precision of 95.7%	Shao et al. (2020)
Cattle detection	13 520 images collected by the authors	VGGNet	an average accuracy of 97.1% has been obtained	Rivas et al. (2018)
Cattle detection	19 097 images were collected by the authors	15 CNN architectures were tested including VGGNet, Xception, ResNet-50 v2, ResNet-101 v2, Inception v3, ResNet-152 v2, DenseNet 201 MobileNet, MobileNet v2, DenseNet 121, DenseNet 169, Inception ResNet v2, MobileNet, etc.	most models were able to reach accuracies above 95%	Barbedo et al. (2019)
Cattle detection	15 400 images collected by the authors	Xception	average detection accuracy of 83% was obtained	Barbedo et al. (2020)
Cattle vocal classification	a total of 12 000 recorded files were collected	CNN-MFCCs	an accuracy of 91.38% in recognizing cattle sounds	Jung et al. (2021)
Cattle segmentation	a total of 22 cattle videos were recorded by the authors	Xception	a contour accuracy of 80.8% was achieved	Qiao et al. (2022)

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Table 2 to be continued

Issue	Dataset	Model architecture	Performance	Reference
Cattle identification	4 738 images from MVCAID100 and MVCAIDRE datasets both produced by authors	Inception-ResNet	the average accuracy after verification on OpenCattle2020 was 98.39% with Inception V3 and 98.80% with ResNet50	Zhao and Lian (2022)
Body condition estimation	a dataset of 1 661 cow depth images was built by the authors	SqueezeNet	the overall accuracy within 0.50 units was 94%	Rodriguez Alvarez et al. (2018)
Cattle identification	a total of 516 cattle videos were collected by authors	Inception	a maximum accuracy of 91% was achieved	Qiao et al. (2019a)
Breathing pattern analysis	1 400 images were collected	Mask R-CNN, ResNet	an accuracy of 76% was achieved	Kim and Hidaka (2021)
Cow body condition score estimation	3 430 images collected by the authors	DenseNet	average precision was 90% with a 0.5 range error	Yukun et al. (2019)
Cow identification	a total of livest images were collected	AlexNet, Vgg, ResNet, MobileNet and GoogLeNet	an accuracy of 97.95% was achieved	Li et al. (2021a)
Drinking behaviour monitoring	1 000 images collected by the authors	YOLO and Darknet	F1 score of 0.987 was achieved	Tsai et al. (2020)
Digital dermatitis (DD) detection	3 500 DD lesion images produced by the authors	YOLO	an accuracy of 88% was achieved	Cernek et al. (2020)
Classification of teat-end condition	1 589 digital images of dairy cow teats were taken by authors	GoogLeNet	an overall accuracy of 77.4% was achieved	Porter et al. (2021)
Cattle identification	OpenCows2020 dataset also developed by these authors	RetinaNet and YOLO	an accuracy of 93.8% was achieved	Andrew et al. (2021)
Cattle detection and counting	5 058 images collected by the authors	Inception -Resnet	an accuracy of 92,8 % was achieved for cattle detection	Soares et al. (2021)
Cattle recognition	3 694 images were collected by the authors	MobileNet, Xception, DenseNet	an average accuracy of 99.71% was obtained	Bhole et al. (2022)
Lameness detection	456 videos were recorded	YOLO DenseNet	a detection accuracy for lameness in cows was 98.50%	Kang et al. (2022)
Cow identification	12 000 images of 48 cows were used as the dataset	ResNet	the proposed method achieves a 98.67% cow identification accuracy	Xiao et al. (2022)
Cattle face recognition	18 200 cow faces images were collected by the authors	AlexNet, VGGNet, GoogLeNet, ResNet	an average accuracy of 99.69% was obtained	Weng et al. (2022)

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Table 2 to be continued

Issue	Dataset	Model architecture	Performance	Reference
Cow feed intake prediction	the model was trained using a data-set of 40 000 tensors	EfficientNet	a mean absolute error of 0.14 kg per meal, and a root mean square error of 0.19 kg per meal were achieved	Saar et al. (2022)
Cattle face recognition	10 239 cattle face images were collected	YOLOv3	the accuracy of 98.37% was achieved	Li et al. (2022a)
Lameness detection	a total of 680 cows' monitoring videos	VGGNet	the best accuracy was 97.20%	Li et al. (2022b)
Thermal condition classification	36 990 thermal images were used	$CNN_{F\text{-}RR}$, $CNN_{F\text{-}RT}$, $CNN_{O\text{-}RR}$ and $CNN_{O\text{-}RT}$	average accuracy of 73.5% was obtained	Pacheco et al. (2022)
Motion behaviours recognition	1 009 videos containing 2 270 250 frames	EfficientNet	the behaviour recognition accuracy of the algorithm was 97.87%	Yin et al. (2020)
Feeding behaviour monitoring	10 288 images were collected.	DenseResNet-YOLO (DRN-YOLO)	the precision, recall, mAP and F1 score of 97.16%, 96.51%, 96.91% and 96.83%, were achieved respectively	Yu et al. (2022)
Mastitis detection	1 200 thermal images containing cow eyes or cow udders were collected	MobileNet, YOLO	average accuracy of 96.8% was obtained for key parts detection, and 83.33% for mastitis classification	Xudong et al. (2020)
Individual classification of the thermal condition of dairy cows	3 732 thermal images were collected and multiplied to 73 960 images	not specified	the highest accuracy of 76% was achieved	Pacheco et al. (2022)

be more complex and challenging than working with standardized data. Additionally, it may affect the scalability and interoperability of CNN models across different farms or regions, and it may affect the validity and reliability of their predictions. Therefore, this can be addressed by collaboration between researchers, farmers and industry stakeholders to share data and develop standardized data collection protocols to improve the quality and consistency of data and help to develop more robust CNN models. The need for large and diverse data sets was also highlighted in multiple studies and it seemsto be one of the striking challenges to CNN applications. Gathering high-quality labelled data for training CNN can be challenging in the context of dairy herd management. Developing accurate and reliable CNN models requires a large and diverse data set of labelled images that capture a wide range of variations in cattle appearance, behaviour, and environment (Russakovsky et al. 2015; Riaboff et al. 2022). However, obtaining such data sets can be challenging,as it may require significant time and resources for data collection, labelling, and verification. Additionally, there may be limited availability of labelled datasets, particularly in regions or countries with smaller cattle populations or lower levels of technological development which can lead to poor performance of CNN models. The limited transferability of models across different populations and farming systems was identifiedas a third challenge.

In reviewed studies, it was identified that CNN models are usually trained on large data sets of labelled images, and they learn to recognize patterns and features that are specific to the images in the training dataset. However, these patterns and features may not be generalizable to other populations or farming systems where the images have

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different characteristics, such as different breeds of cattle, lighting conditions, or environmental factors (Alzubaidi et al. 2020). CNN models developed for one population or farming system may not be suitable for another due to differences in genetics, management practices, and environmental factors. This limited transferability of models canbe a challenge for the practical application of CNN in cattle herd management, health and productivity,as it requires developing and fine-tuning models for specific populations and farming systems, which can be time-consuming and expensive (Bloch et al. 2023). Additionally, it can limit the scalability of CNN models in different regions and countries, and it may affect the accuracy and reliability of their predictions. The limited transferability of models across different populations and farming systems underscores the need for more research to develop context-specific models that are tailored to the unique characteristics of different cattle populations and farming systems.

Besides the above-mentioned major challenges, other specific challenges were also identified taking into account the specific applications of CNN addressing the issues directly related to herd management, health and productivity of dairy cows. These include the real-time monitoring of dairy cows' health and productivity which requires addressing challenges related to processing speed, hardware, and power consumption. On the other side, interpretability, and trust of CNN-based decisions in a way that farmers and stakeholders can understand, and trust, is crucial for the successful adoption of these technologies in herd management. Another challenge concerns the integration of CNN-based applications into existing herd management and productivity systems, which might use traditional methods, in terms of compatibility and data integration. Above all, collaborations between researchers, dairy farmers, veterinarians, and technology developers to ensure that CNN applications align with the practical needs and realities of the dairy industry is strongly encouraged.

CONCLUSION

This systematic literature review provided several contributions that can advance the knowledge and understanding of the applications of CNN in cattle production. These include: (1) Identifying and synthesizing the current state of knowledge: It provides a comprehensive and up-to-date overview of the applications of CNN in cattle farming. Several potential applications of CNN in cattle farming, including disease detection, behaviour analysis, and feed optimization were identified. (2) Overview of CNN architectures: it provided an overview of the most common CNN architectures used in cattle farming and their performance. The basic concepts of several CNN architectures, including YOLO, ResNet, VGGNet, DenseNet, MobileNet, Xception, and Inception, that are commonly used in cattle farming applications were described. (3) Identifying limitations and challenges: This review identified several limitations and challenges related to the application of CNNs in cattle farming, including the need for large and diverse datasets, lack of standardization in data collection and processing, and limited transferability of models. (4) Providing recommendations for future research: This review provided recommendations for future research to overcome the challenges and improve the effectiveness and efficiency of CNN applications in cattle farming. These recommendations include developing standardized data collection and processing protocols, enhancing the transferability of models across different populations and farming systems, and exploring the potential of using transfer learning and other techniques to reduce the need for large datasets. Finally, it is worth mentioning that the application of artificial intelligence methods in livestock (among which CNN is included) requires multidisciplinary collaborations and Industry involvement among computer science and animal science researchers to pool their knowledge together for enriched research and prevent the issues which may arise from the knowledge, time, and resources limitations from single disciplines.

The review highlights the potential benefits of CNN in enhancing the monitoring and management of animal health and productivity in cattle production. However, the limitations and challenges identified in the review indicate that further research and developments are needed to address the issues of standardization, data availability, and transferability requirements of CNN applications in cattle production.

The findings of this review could inform the development of more effective and context-specific CNN models that could contribute to the sustain-

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able intensification of cattle farming and improve the livelihoods of farmers and the welfare of animals. Moreover, CNNs offer transformative potential in revolutionizing dairy farming practices. By leveraging advanced technologies like CNN for image analysis, dairy farmers can enhance herd management, monitor cow health, optimize productivity, and ultimately improve the overall sustainability and efficiency of dairy operations. These advancements can lead to a significant positive impact on the dairy industry, ensuring the welfare of cows and the economic viability of dairy farms.

Conflict of interest

The authors declare no conflict of interest.

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