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Review

A systematic literature review on deep learning applications for precision cattle farming

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ABSTRACT

In animal agriculture, deep learning-based approaches have been widely implemented as a decision support tool for precision farming. Several deep learning models have been applied to solve diverse problems related to cattle health and identification. However, an overview of the state-of-the-art of deep learning in precision cattle farming is needed, for which we performed a systematic literature review (SLR). This study aims to provide an overview of the recent progress in deep learning applications for precision cattle farming, in particular health and identification. In the initial search, we retrieved 678 studies from different electronic databases. Only 56 studies qualify the selection criteria, which were then analyzed to extract the data to answer the research questions. The two major applications of deep learning for cattle farming were identified: identification and health monitoring. About 58% of the selected studies are dedicated to cattle identification and the rest for health monitoring. We identified 20 deep learning models that were used to solve different problems, and Convolutional Neural Networks (CNNs) is the most adopted model than others, including Long Short-Term Memory (LSTM), Mask-Region Based Convolutional Neural Networks (Mask-RCNN), and Faster-RCNN. We identified 19 training networks and of which ResNet is by far the most used. From our selection, 12 model evaluation parameters were determined, of which seven were used more than five times. The challenges most encountered with image quality, data processing speed, dataset size, redundant information, and motion of the cattle during data acquisition. In closing, we consider that this SLR study will pave the way for future research towards developing automatic systems for cattle farming.

1. Introduction

In the United States, cattle production is one of the most important agricultural industries, accounts for 18% ($66.2 billion) of the total cash receipts from agricultural commodities in 2019 (USDA-ERS, 2020). Cattle farming refers to the breeding of animals to obtain products such as meat, milk, and other dairy products for human consumption. Over the years, the cattle production system has been intensified in terms of productivity per animal, but many countries are undergoing a reduction in small farms, due to limited land for crop cultivation and slurry spreading (Fournel et al., 2017). The small cattle farms facing multiple difficulties to keep on the market intend to make efficient management decisions to ensure profitability (Cavaliere and Ventura, 2018). The intent of efficient decisions is driven by increasing food demand due to the growing population (Godfray et al., 2010). In traditional cattle farms, decisions such as what to feed, when to inseminate, and when to treat an animal, etc., are often based on the producer or worker's observations and experiences. However, observing every activity of the animals on a farm is impractical. The farmers usually focus on the production aspects, but as the farm dimensions increase, every animal's attention decreases (Meen et al., 2015).

Precision cattle farming is an emerging field that includes information and communication technologies (ICT), aims at real-time monitoring and management of the smallest production units (animals) to

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improve the farming process (Halachmi and Guarino, 2016). The research proves that using ICT has reduced investment costs and improved both production and animal health (Banhazi et al., 2012). Typical objectives include: to support individual cattle identification and counting, to improve animal welfare by early disease detection, to automate tasks such as milking, herding, and feeding, etc., and to identify the appropriate feeding and efficient resource management (O'Mahony et al., 2019; Pomar et al., 2011). In a precision cattle farm, management decisions rely on quantitative data. Different sensing technologies are used for data collection, which is then analyzed with advanced algorithms. Additionally, the real-time quantitative data can also be acquired using sensors such as accelerometers or gyroscopes worn by the cattle to monitor the behavior or movement. The Farm Management Information System uses the data to facilitate the farmers to make correct decisions. This information allows determining the animal's needs, providing individualized attention to benefit production (Banhazi and Black, 2009). However, to fully utilize the data and decision-support functionalities, various artificial intelligence/learning algorithms can be incorporated to automate the decision-making processes (Banhazi et al., 2012).

Deep learning (DL) is a subfield of artificial intelligence that solves complex problems using convoluted algorithms. The algorithms learn high-level features from the data, which makes DL better than traditional machine learning (Tan et al., 2018). It can automatically extract features by learning algorithms and has less burden on the users. The DL prediction model is a two-phase process. In the first phase, the algorithm is trained with a training dataset, and in the second phase, algorithm validation is performed using a different dataset. The algorithm and the trained parameters create a prediction model, which is then used to predict the outcome and support decision making. Although training, validating, and implementing DL prediction models are straightforward, accurate prediction models come with challenges like what algorithms to choose, what training network to choose, and how to deal with mass data. Recent advancements in computing technologies have shown promise in monitoring the needs and the behavior of animals. In the precision cattle farming sector, DL is already being implemented to address different problems, for example, to detect flies on cattle body (Psota et al., 2021), individual body parts (Jiang et al., 2019), breed (Weber et al., 2020), lameness (Kang et al., 2020), and mastitis (Zhang et al., 2020) using ground-based images and predicting body weight (Gjergji et al., 2020), and counting (Xu et al., 2020) using the unmanned aerial vehicle (UAV) images. Although a wide range of cattle farming problems is addressed using DL, there is still a lack of overview of the problems solved, DL model used, training network adopted, and the challenges faced in applying DL for cattle farming.

Previously available reviews cover machine learning applications for dairy farm management (Slob et al., 2021), precision livestock farming with a focus on sustainability: environmental, economic, and social aspects (Lovarelli et al., 2020), and machine learning for precision livestock farming (García et al., 2020). However, these available reviews lack the information on DL applications for precision cattle farming. Thus, an SLR is needed to determine DL status for precision cattle farming, particularly current DL models used in precision cattle farming and future challenges.

This review aims to present an overview of DL applications in cattle farming, including health monitoring and identification. This article's core contributions are the following: First, a summary of DL applications for cattle health monitoring and cattle identification. Second, we analyzed widely used DL models and networks for these applications. Third, we presented the model evaluation parameters used by the selected studies. Finally, an overview of the challenges involved in this domain, and future research directions are discussed.

The article is organized as follows. Section 2 covers the methodology of the SLR, including defining research questions and selection criteria. In Section 3, the review results, which includes the answers to the research questions, are presented. The general and research questions-based discussion is presented in Section 4. Finally, in Section 5, the overall conclusions of the SLR are presented.

2. Methodology

2.1. Review protocol

The review protocol was defined following the guidelines provided by Kitchenham et al. (2007) entitled "Guidelines for performing Systematic Literature Reviews in Software Engineering". The SLR process is categorized into three stages: planning, conducting, and reporting the review. Fig. 1 shows the steps involved in all stages of the SLR. In the planning stage, research questions, related keywords, and publication databases were determined. Once the research questions were ready, the search protocol was established, including what databases to search, and what search strings to use. Selected keywords were used to develop search strings for different databases. The databases used in this study include Science Direct, Google Scholar, Scopus, Web of Science, Wiley, and Springer Link. These databases were selected to extend review boundaries, to ensure good coverage of the target sector. In conducting review stage, relevant studies were selected by going through all the databases. Afterwards, selection criteria were defined to select the eligible studies. The papers that passed the selection criteria were collected, and essential data were extracted in response to the research questions. In the reporting stage, the research questions were addressed based on the extracted data, and the results were reported using supporting figures and summary tables. In addition, a brief discussion about the associated challenges is also presented.

2.2. Research questions

This SLR aimed to feature the studies that have been published in the field of cattle farming using DL approaches. The studies searched were scrutinized from multiple aspects, and the following six research questions (RQs) were defined.

RQ.1: What are the cattle farming problems solved using DL?
RQ.2: What are the imaging platforms/data acquisition systems used for DL applications in cattle farming?
RQ.3: What are the DL models and networks used for cattle farming?
RQ.4: What DL models and networks performed the best for a specific problem?
RQ.5: What are the evaluation parameters and approaches used for DL models in cattle farming?
RQ.6: What are the challenges associated with the application of DL-based cattle identification and health monitoring?

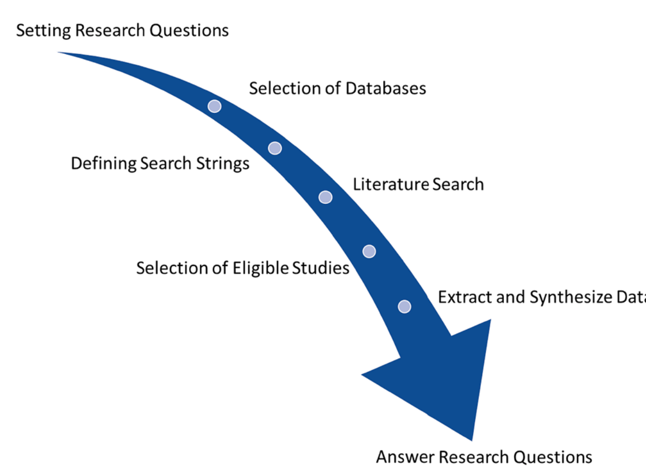

Fig. 1. Steps involved in planning the systematic literature review (SLR).

2.3. Search approach

A systematic approach was adopted to narrow down the search results to the papers that are directly related to the scope of the SLR. The initial search started with a broad search equation comprised of the basic keywords "deep learning" AND "cattle health" OR "cattle identification" to get the extended search results. A few related studies were retrieved from the search results to extract the synonyms and other keywords by reading through the title, abstracts, and authors keywords. The identified keywords resulted in the following general search string/equation: ("deep learning" OR "artificial intelligence") AND ("cattle" OR "cow" OR "livestock") AND ("identification" OR "recognition" OR "detection" OR "behavior" OR "health"). The search keywords were used for all six databases. A description of the search strings for each database are provided as follows:

Science Direct: the search string was ("deep learning" OR "artificial intelligence") AND ("cattle" OR "livestock") AND ("identification" OR "recognition" OR "detection" OR "behavior" OR "health"). The search string was used to search in the abstract, title, and keywords fields.

Google Scholar: the search string was ["deep learning" AND "cattle"] and [("deep learning" OR "artificial intelligence") AND ("cattle detection" OR "cattle recognition" OR "cattle behavior" OR "cattle health" OR "cattle identification")] (anywhere) and ["deep learning" AND "cow"] and [("deep learning" OR "artificial intelligence") AND ("cow detection" OR "cow recognition" OR "cow behavior" OR "cow health" OR "cow identification")] (anywhere).

Scopus: the search string was ("deep learning" AND "cattle") AND ("deep learning" OR "artificial intelligence") AND ("cattle" OR "cow" OR "livestock") AND ("identification" OR "recognition" OR "detection" OR "behavior" OR "health"). The search string was used to search in the abstract, title, and keywords fields.

Web of Science: the search string was AB = (("deep learning" OR "artificial intelligence") AND ("cattle" OR "cow" OR "livestock") AND ("identification" OR "recognition" OR "detection" OR "behavior" OR "health")) OR AK = (("deep learning" OR "artificial intelligence") AND ("cattle" OR "cow" OR "livestock") AND ("identification" OR "recognition" OR "detection" OR "behavior" OR "health")). The search string was used to search in the abstract (AB), and authors keywords (AK) fields.

Wiley: the search string was ("deep learning" OR "artificial intelligence") AND ("cattle" OR "cow" OR "livestock") AND ("identification" OR "recognition" OR "detection" OR "behavior" OR "health") (anywhere).

SpringerLink: the search string was ("deep learning" AND "cattle") AND ("deep learning" OR "artificial intelligence") AND ("cattle" OR "cow" OR "livestock") AND ("identification" OR "recognition" OR "detection" OR "behavior" OR "health") (anywhere).

The Science Direct database has a limit of maximum eight Boolean (AND/OR) operators in the advanced search. Thus, ("cattle" OR "cow" OR "livestock") was adjusted to ("cattle" OR "cow"), to reduce the size of the search equation. Google Scholar search has maximum character limits; thus, two search strings were used, and the search results of both were combined, and duplicates were removed. All the results were processed, and the above-mentioned search strings resulted in a total of 678 studies.

2.4. Selection criteria

The selection/inclusion and exclusion criteria (EC) were defined to set the boundaries for the SLR. The studies retrieved from all databases were scrutinized to select the relevant studies based on defined selection and exclusion criteria. The search results from different databases were added to a spreadsheet and checked against the selection criteria. For a study to be included, all the inclusion criteria must be true, and exclusion criteria must be false (Kitchenham et al., 2007). All the studies that could answer the research questions were considered relevant and selected upon passing the exclusion criteria. The ECs are shown as follows:

EC.1: Publication is not related to DL for cattle farming.
EC.2: Publication is duplicate or retrieved from another database.
EC.3: Publication is a survey or review paper.
EC.4: Full text of the study is not available.
EC.5: Publication is not peer-reviewed.
EC.6: The study is not published in the English language.

After applying EC1 to EC4, only 78 studies remained from the total search results. Applying EC1 to EC6, resulted in only 56 peer-reviewed studies, which were used for further analysis. In Fig. 2, we presented an overall search and selection process for SLR. Table 1 presents the database wise distribution of searched papers, selected paper, and representative percentage for SLR. As shown in Table 1, the majority of papers were retrieved from Science Direct, Google Scholar, Scopus, and Web of Science databases.

2.5. Data extraction

The required data from the selected studies were extracted and synthesized to address the research questions. Table 2 presents the selected studies that passed the selection criteria. The relevant data were extracted by reading all the selected studies in full. A spreadsheet application was used to summarize the extracted data. Each data parameter was added to a different column in the spreadsheet, and the studies were assigned in different rows. The data retrieval from all selected studies was focused on responding to the research questions, including objectives, DL models, training networks, reporting country, publication year, publishing journal, imagining systems, performance and evaluation parameters, and challenges. All the extracted data were categorized and synthesized into multiple classes to address the research questions accordingly. The results of this SLR are reported in the next section.

3. Results

3.1. Problems solved using deep learning

The problems that the articles solved using DL (RQ.1) were divided into two categories: health monitoring and identification. The categories were established after extracting and analyzing the information about the problems solved. Cattle health monitoring determines the status, well-being, and nutritional status of cows precisely and identifies possible bottlenecks. Automatic identification of cattle helps to optimize cow performance with successful management. The cattle problems related to health are explained through automated monitoring of behavior, activity, pose, body structure, body condition score, body weight, respiratory rate, and detection of lameness and mastitis, etc. The solution related to identification includes face detection and recognition, breed and race classification, cattle detection and tracking, and cattle recognition by muzzle point, etc. As shown in Fig. 3, the highest number of papers (33) were retrieved from the identification category, where the total number of screened articles was 23 for the health category. This result shows researchers approached cattle farming problems mostly in identifying and tracking using DL models. Year-wise distribution of the published articles is also presented (Fig. 3). This figure indicates that DL's application for cattle identification and health monitoring has increased incredibly from last year. We also presented the journal-wise distribution of the published articles in Fig. 4. The figure indicates that Computers and Electronics in Agriculture journal published the highest number (12) of automatic cattle identification and health monitoring papers.

To address RQ.2, we generated a Sankey chart (Fig. 5) to present the imaging platforms/data acquisition systems used for DL applications in

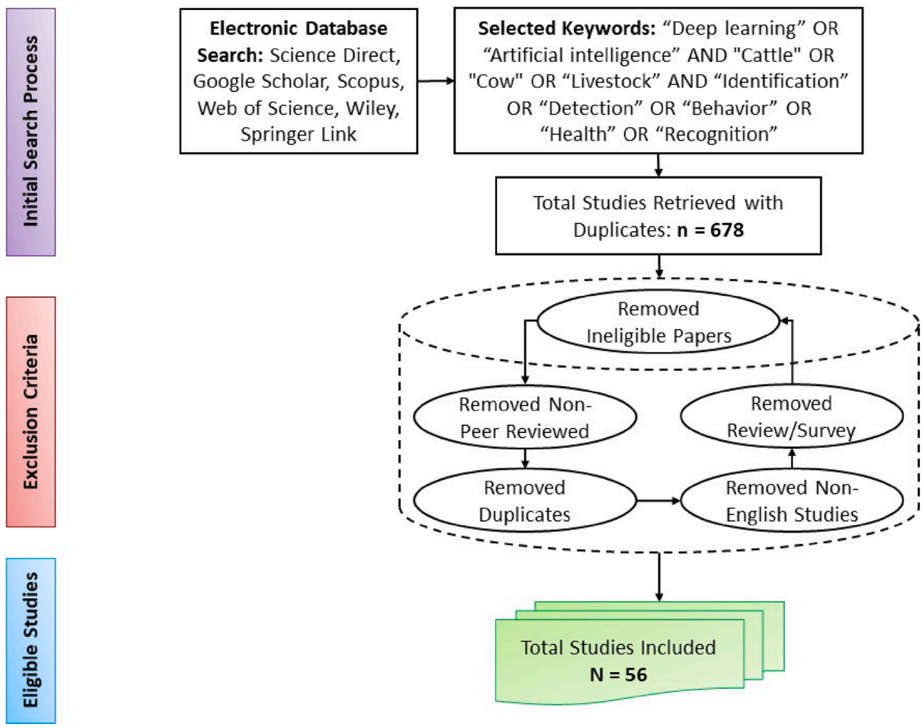

Fig. 2. Flowchart of the article selection process for systematic literature review.

Table 1
Database-wise distribution of the papers extracted for systematic literature review.

Source	Number of Papers in the Initial Search	Number of Eligible Papers	Percentage
Science Direct	31	18	32
Google Scholar	376	22	39
Scopus	54	8	14
Web of Science	63	5	9
Wiley	19	2	4
Springer Link	135	1	2
Total	**678**	**56**	**100**

cattle farming. Our research reported that ground-based datasets were the most used platform (45 times) for automatic cattle identification and monitoring. Different data acquisition systems were used with different sensors for the ground-based datasets such as red-greenblue (RGB), RGB-Depth, RGB with NIR, and thermal. The ground-based imaging captures images or videos from the cattle farms and processes the captured data to complete the decision-making process using DL for solving a specific problem. In addition, a few other sensors such as LiDAR, temperature, pressure, and bubble activity sensors were also used for ground-based datasets. In total, 11 studies used the aerial data acquisition system. Among aerial systems, the majority of the data was collected using RGB cameras integrated with unmanned aerial vehicles (UAVs)/multirotor, and one study reported the use of satellite images for counting the cattle. Fig. 5 also presents the country-wise distribution of the published articles and particular DL applications (specific areas). We analyzed that China has the highest number of DL papers (20) for cattle farming, where both Japan (5) and Brazil (5) hold second place.

3.2. Deep learning models and networks

Different deep learning models have been used, including CNNs, DNNs, R-CNNs, and SSD. Tables 3 and 4 present the model, network, dataset, class, and performance for specific cattle farming tasks in automatic health monitoring and identification (RQ.3). Based on our survey, the RGB images and videos were mainly used for forming the experimental training and testing dataset in health monitoring. Most of the experiments in cattle identification were also relied on RGB color images for establishing the dataset. About 80% of the research was conducted using not more than five classes to train DL models. A variety of networks were utilized for training the models; however, the Residual Network (ResNet) was the most widely used network for cattle health monitoring and identification (Fig. 6). The ResNet architecture was introduced to solve the vanishing/exploding gradient problem. When training a deep neural network with gradient-based learning and back-propagation, the numbers of n hidden layers are multiplied with n numbers of derivatives. When the derivatives are small, the gradient exponentially decreases as it propagates through the model until it eventually vanishes, called the vanishing gradient problem. When the derivatives are larger, the gradient increases exponentially cause the exploding gradient problem. In the ResNet, a skip connection approach is used to skip training from a few layers and connects directly to the output. The skip technique allows the network to fit the residual mapping instead of learning from the underlying mapping. The advantage of using the skipping method is that when any layer harms the network's performance, it will be skipped by regularization, which helps avoid vanishing/exploding gradient deep neural network problems. Among the various DL models tested for cattle identification and health monitoring, the CNNs model is more popular and used more than 40 times (counted from the retrieved articles), probably because it was developed at the beginning of the DL era (Fig. 7). Another reason could be that this model can be explained and implemented easily than the later ones. The CNNs model consists of three layers: convolutional layers, pooling layers, and fully connected layers. Convolution layers are comprised of filters and feature maps. Filters are the neurons of the layer, have weighted inputs, and create an output value. Feature maps are

Table 2
Titles of the selected studies from multiple databases for systematic literature review.

#	Source	Title of the Selected Studies	References
1	Science Direct	Automatic monitoring system for individual dairy cows based on a deep learning framework that provides identification via body parts and estimation of body condition score	(Yukun et al., 2019)
2		Accurate detection of lameness in dairy cattle with computer vision: A new and individualized detection strategy based on the analysis of the supporting phase	(Kang et al., 2020)
3		Deep cascaded convolutional models for cattle pose estimation	(Li et al., 2019a)
4		Development and validation of a neural network for the automated detection of horn flies on cattle	(Psota et al., 2021)
5		Cattle segmentation and contour extraction based on Mask R-CNN for precision livestock farming	(Qiao et al., 2019)
6		FLYOLOv3 deep learning for key parts of dairy cow body detection	(Jiang et al., 2019)
7		Computer vision system for measuring individual cow feed intake using RGB-D camera and deep learning algorithms	(Bezen et al., 2020)
8		Automated cattle counting using Mask R-CNN in quadcopter vision system	(Xu et al., 2020)
9		Video analytic system for detecting cow structure	(Liu et al., 2020)
10		Deep learning-based hierarchical cattle behavior recognition with spatiotemporal information	(Fuentes et al., 2020)
11		Single-stream long-term optical flow convolution network for action recognition of lameness dairy cow	(Jiang et al., 2020)
12		Automatic recognition of dairy cow mastitis from thermal images by a deep learning detector	(Zhang et al., 2020)
13		Deep learning framework for recognition of cattle using muzzle point image pattern	(Kumar et al., 2018)
14		Lameness detection of dairy cows based on the YOLOv3 deep learning algorithm and a relative step size characteristic vector	(Wu et al., 2020a)
15		Detection of the respiratory rate of standing cows by combining the Deeplab V3+ semantic segmentation model with the phase-based video magnification algorithm	(Wu et al., 2020b)
16		Assessment of dairy cow heat stress by monitoring drinking behaviour using an embedded imaging system	(Tsai et al., 2020)
17		Image analysis for individual identification and feeding behaviour monitoring of dairy cows based on Convolutional Neural Networks (CNN)	(Achour et al., 2020)
18		Cattle Race Classification Using Gray Level Co-occurrence Matrix Convolutional Neural Networks	(Santoni et al., 2015)
19	Google Scholar	Using an EfficientNet-LSTM for the recognition of single Cow's motion behaviours in a complicated environment	(Yin et al., 2020)
20		Deep Learning-based Cattle Activity Classi cation Using Joint Time-frequency Data Representation	(Noorbin et al., 2020)
21		Bootstrapping Labelled Dataset Construction for Cow Tracking and Behavior Analysis	(Ter-Sarkisov et al., 2018)
22		Cow Body Condition Score Estimation with Convolutional Neural Networks	(Li et al., 2019b)
23		Recognition method of dairy cow feeding behavior based on convolutional neural network	(Chen et al., 2020)
24		Image-based Individual Cow Recognition using Body Patterns	(Bello et al., 2020a)
25		Image Technology based Cow Identification System Using Deep Learning	(Zin et al., 2018)
26		Recognition of Pantaneira cattle breed using computer vision and convolutional neural networks	(Weber et al., 2020)
27		Cow identification based on fusion of deep parts features	(Hu et al., 2020)
28		Counting Cows: Tracking Illegal Cattle Ranching From High-Resolution Satellite Imagery	(Laradji et al., 2020)
29		FSSCaps-DetCountNet: fuzzy soft sets and CapsNet-based detection and counting network for monitoring animals from aerial images	(Sundaram & Loganathan, 2020)
30		Cow Individual Identification Based on Convolutional Neural Network	(Li et al., 2018)
31		Cow Face Detection and Recognition Based on Automatic Feature Extraction Algorithm	(Yao et al., 2019)
32		A Hybrid Rolling Skew Histogram-Neural Network Approach to Dairy Cow Identification System	(Phyo et al., 2019)
33		Multi-views Embedding for Cattle Re-identification	(Bergamini et al., 2018)
34		Data Augmentation for Deep Learning based Cattle Segmentation in Precision Livestock Farming	(Qiao et al., 2020b)
35		Instance Segmentation with Mask R-CNN Applied to Loose-Housed Dairy Cows in a Multi-Camera Setting	(Salau & Krieter, 2020)
36		Cattle detection and counting in UAV images based on convolutional neural networks	(Shao et al., 2020)
37		Cattle Detection Using Oblique UAV Images	(Barbedo et al., 2020a)
38		Now You See Me: Convolutional Neural Network Based Tracker for Dairy Cows	(Guzhva et al., 2018)
39		Counting Cattle in UAV Images—Dealing with Clustered Animals and Animal/Background Contrast Changes	(Barbedo et al., 2020b)
40		Automatic Cow Location Tracking System Using Ear Tag Visual Analysis	(Zin et al., 2020)
41	Scopus	Deep Learning Techniques for Beef Cattle Body Weight Prediction	(Gjergji et al., 2020)
42		Cattle Identification and Activity Recognition by Surveillance Camera	(Guan et al., 2020)
43		A computer vision approach to improving cattle digestive health by the monitoring of faecal samples	(Atkinson et al., 2020)
44		Cattle Face Recognition Method Based on Parameter Transfer and Deep Learning	(Wang et al., 2020)
45		Object detection algorithm based AdaBoost residual correction Fast R-CNN on network	(Lin et al., 2019)
46		Visual Localization and Individual Identification of Holstein Friesian Cattle via Deep Learning	(Andrew et al., 2017)
47		Aerial Animal Biometrics: Individual Friesian Cattle Recovery and Visual Identification via an Autonomous UAV with Onboard Deep Inference	(Andrew et al., 2019)
48		BiLSTM-based Individual Cattle Identification for Automated Precision Livestock Farming	(Qiao et al., 2020c)
49	Web of Science	Deep Learning-Based Architectures for Recognition of Cow Using Cow Nose Image Pattern	(Bello et al., 2020b)
50		An Improved Single Shot Multibox Detector Method Applied in Body Condition Score for Dairy Cows	(Huang et al., 2019a)
51			

(continued on next page)

Table 2 (*continued*)

#	Source	Title of the Selected Studies	References
		Body Dimension Measurements of Qinchuan Cattle with Transfer Learning from LiDAR Sensing	(Huang et al., 2019b)
52		A Study on the Detection of Cattle in UAV Images Using Deep Learning	(Barbedo et al., 2019)
53		Detection of Cattle Using Drones and Convolutional Neural Networks	(Rivas et al., 2018)
54	Springer Link	Individual identification of dairy cows based on convolutional neural networks	(Shen et al., 2020)
55	Wiley	Machine learning to classify animal species in camera trap images: Applications in ecology	(Tabak et al., 2019)
56		Improving the accessibility and transferability of machine learning algorithms for identification of animals in camera trap images: MLWIC2	(Tabak et al., 2020)

considered the filter's output (one feature map = one filter) (Brownlee, 2019). Pooling layers are used to down-sample the previous layer's feature map, generalize feature representations, and reduce the overfitting. For the predictions, fully connected layers are mostly utilized at the end of the network. The overall example for CNN models is that a pooling layer follows at least one convolutional layer, and this structure is repeated a few times; lastly, fully connected layers are applied (Brownlee, 2019).

We examined the performance column of Tables 3 and 4 to address RQ.4. Based on our research, most studies used one model and indicated it as the best model for their specific purposes. Few studies compared two or more DL models for a specific objective to compare their performances. For example, Wu et al. (2020a) compared YOLOv3 and LSTM for lameness detection of dairy cows. The study concluded that LSTM performed better than YOLOv3 and achieved 98.57% of accuracy. Huang et al. (2019a) reported that the SSD-based DL model achieved 98.46% accuracy (mAP) compared to 88.84% using YOLO-v3 for cow body condition score estimation. Qiao et al. (2020c) compared three DL

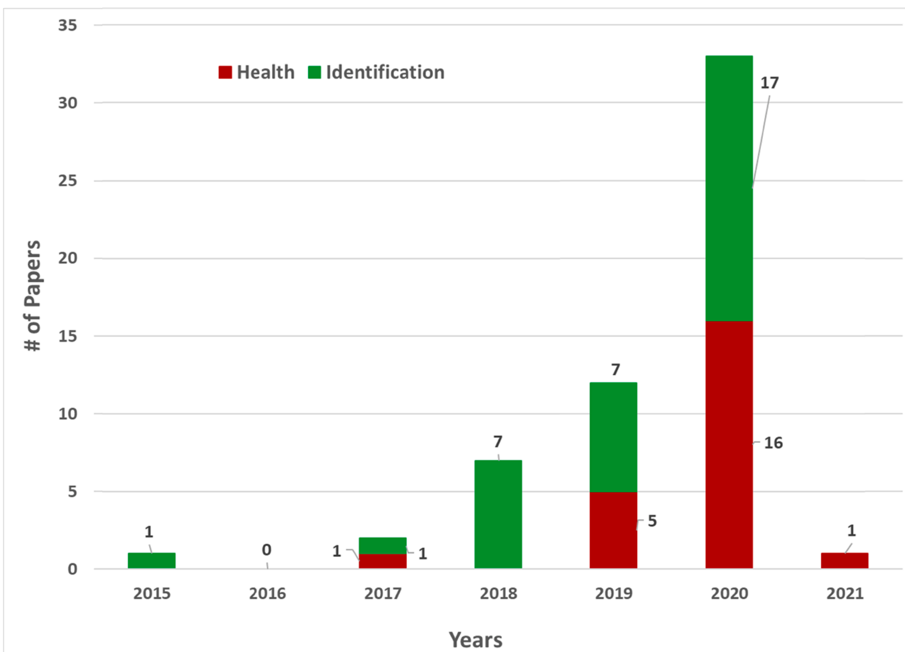

Fig. 3. Year-wise distribution of papers for deep learning applications in precision cattle farming.

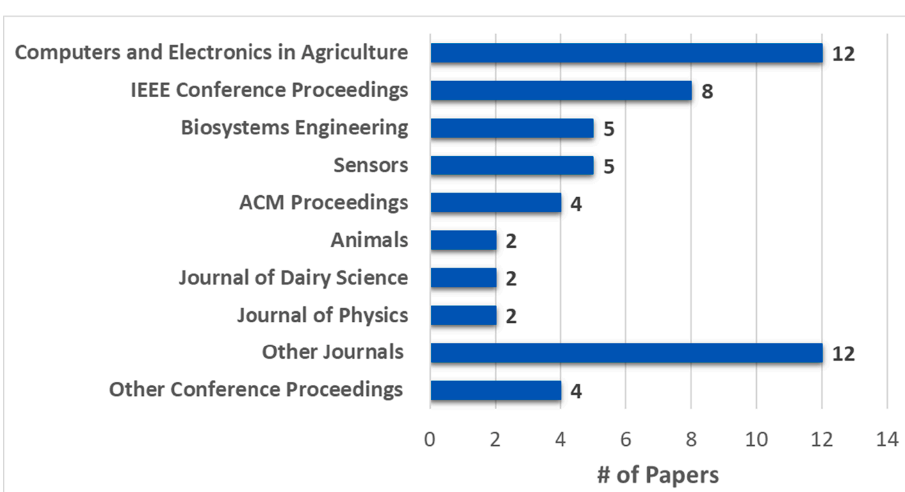

Fig. 4. Journal-wise distribution of papers for deep learning applications in precision cattle farming.

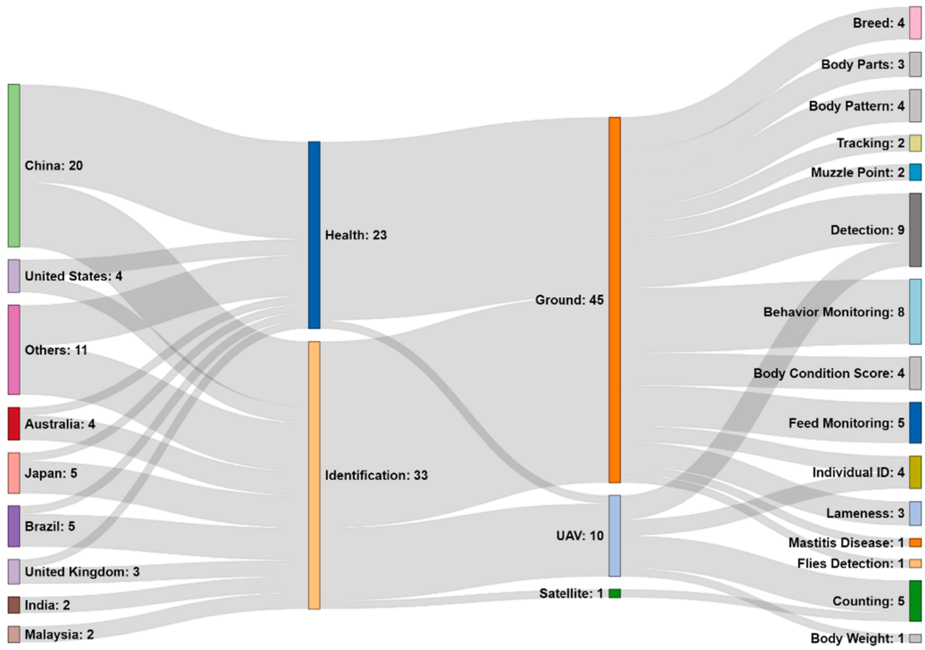

Fig. 5. A global overview of the deep learning applications for cattle farming.

models: Inception-V3, BiLSTM, and LSTM for cattle identification. They found that BiLSTM was best suited for their application and achieved the highest 91% identification accuracy. Jiang et al. (2019) also used three DL models (FLYOLOv3, Faster R-CNN, and YOLOv3) for cow body detection. The study reported that the best performance was achieved using FLYOLOv3 with 93.73% of average accuracy. Through the observation of our data, we noticed that the models, including SSD, RNN, CRFasRNN, and LSTM, were primarily used for cattle health monitoring purposes (Fig. 7). The DL models, including RCNN, SDAE, DBN, and InceptionV3, were mainly utilized for cattle identification experiments (Fig. 7). Similar to DL models, researchers used only one network in about 80% of the studies and presented it as the best network. Based on our search, we found that few networks including EfficientNet, ShapeNet, DeepLabCut, and RefineDet were primarily used for cattle health monitoring, where GoogleNet, AlexNet, NasNet, CapsNet, LeNet, and ERFNet are mainly utilized for cattle identification purposes (Fig. 6). We tried to observe which model was used the most with which network. In Fig. 8, we presented a matrix plot between models and networks considering their combination been used more than once. According to our results, CNN models were used the most with ResNet, second next was DenseNet. The YOLO models were used the most with the DarkNet network. Like CNNs models, RCNN models were also used the most with the ResNet network.

3.3. Evaluation parameters

Based on our survey, we identified 12 evaluation parameters that were used in the articles (RQ.5). The evaluation parameters including accuracy, errors, precision, mean average precision (mAP), specificity, sensitivity, mean absolute error (MAE), mean squared error (MSE), root mean square error (RMSE), R-Squared, false-positive rate (FPR), and F1 score, were primarily used for automatic cattle health monitoring and identification (Fig. 9). The accuracy was used the highest number of times as an evaluation parameter for both cases (health: 17 times and identification: 23 times). Accuracy is defined as the proximity of estimation results to the correct/right value. Figs. 10a and 10b) presents the performance of widely used deep learning models and networks in terms of a similar metric. The highest and lowest reported accuracy and precision values are presented for each model and network from all selected studies. The following evaluation parameters were used at least five times: sensitivity, precision, mAP, specificity, and F1 Score for either health or identification or both cases; the rest were used less than five times. Although 40 studies utilized accuracy as their evaluation parameter, the sensitivity, precision, mAP, specificity, and F1 Score would be best to present, especially the identification results. Because these evaluation parameters consider true positive, true negative, false positive, and false negative for the calculation, the accuracy is calculated simply with the ratio of correctly predicted observation to the total observations. The R-Squared, RMSE, MAE, and FPR could be suitable for automatic health monitoring applications for cattle farming.

3.4. Challenges identified

The retrieved articles identified various challenges they had to deal with while conducting their research (RQ.6). Some of the challenges were very specific to their experiments, and some were common for DL applications for cattle farming. Therefore, we decided to discuss the common challenges associated with DL models for cattle farm management. Poor image quality is identified as one of the significant performance-limiting factors for DL applications. However, when the researchers improved the quality of images, a few studies identified longer data processing time as another major challenge. Some researchers have enhanced the data processing speed by reducing the size of images or dividing images into small pieces. Several studies reported their accuracy lowered due to the lack of information, small dataset, and unbalanced dataset. Some attempts were observed to increase the dataset size using the data augmentation technique. Some studies experienced overfitting or overestimating problems during their data processing. A large amount of redundant information in the video dataset is another challenge identified by few studies on health monitoring research. For real-time counting, few studies noticed that the performances are descended when counting fast-moving cattle. Researchers also noticed that when the DL model trained with the image or video dataset captured at low motion, the model could not perform well in the cattle farm condition. The performance could be improved by training DL models with a larger and more complex image or video dataset suggested by a few studies. Besides, the results of the models can also be unsatisfactory when the cattle are in clusters. Studies indicated that the DL model's performance could be enhanced by improving segmentation ability for the overlapping cattle regions.

Table 3
Summary of studies for deep learning applications in cattle health monitoring.

References	Tasks	Dataset Type	Dataset Source	Learning Models	Networks	Candidate Objects	Classes	Performance
(Yin et al., 2020)	Behavior recognition	Videos: 1,009	RGB (Sony HDR-CX290) camera inside the cow shed	LSTM	EfficientNet, VGG16, ResNet50, DensNet169	BiFPN[a]	5	Overall recognition accuracy was 97.87% using EfficientNet-LSTM
(Ter-Sarkisov et al., 2018)	Cow behavior analysis	Video: 99.2 hrs	From Irish National Agriculture and Food Development Authority	CRFasRNN[b]	FCN-8	N/A	N/A	Average precision was 81.44%
(Noorbin et al., 2020)	Cattle behavior and activity classification	Video: 19 hrs	Taken from DATA61 (CSIRO) in Armidale, Australia	DNNs	Custom	N/A	N/A	F1 Score of 94:9% achieved for 3 classes
(Guan et al., 2020)	Cattle activity recognition	Video: 18 hrs	Surveillance camera in cow shed	CNNs	RefineDet	N/A	4	Average recognition rates were 64.4% and 84.1% for active and static modes
(Liu et al., 2020)	Cow structure detection	Video: 1,495 frames	Internet protocol (IP) camera in cow shed	Two CNNs models	DeepLabCut, ResNet	N/A	2	F1 scores were 0.71 and 0.59 for body and leg-hoof region segmentations
(Fuentes et al., 2020)	Cattle behavior recognition	Videos: 350 with an average duration of 12 min each	RGB cameras in cow shed	YOLOv3 Faster R-CNN	Darknet53 VGG16	RPN	15	The accuracy (mAP) was 0.856 for spatio-temporal behavior recognition
(Wu et al., 2020b)	Detection of respiratory rate	Images: 3,000	RGB (Sony HDR-CX290) camera in cow shed	Deeplab V3+	ResNet-101	ASPP[c]	2	Detection accuracy was 98.69%
(Li et al., 2019a)	Cattle pose estimation	Images: 2,134	a smartphone (iPhone8 Plus) https://github.com/MicaleLee/ Database	Cascaded CNNs (CPMs[d])	VGG-16	N/A	7	The highest mean score achieved was 90.39%
(Li et al., 2019b)	Cow body condition score estimation	Images: 2,231	2D industrial cameras in cow shed	YOLOv2	ResNet50	N/A	5	Accuracy of 94.5% within 0.5 units of difference from true values
(Gjergji et al., 2020)	Cattle body weight prediction		UAV- AHD 720p	Combination RNN/CNN	EfficientNet-B1, ResNet18	N/A	N/A	Top model averages an MAE of 23.19 kg
(Yukun et al., 2019)	Cow body condition score estimation	Images: 3,430	RGB-Depth (Intel RealSense D435) camera in cow shed	CNN	DenseNet	N/A	9	Average precision was 0.90 with 0.5 range error
(Huang et al., 2019b)	Cattle body dimension measurement	LiDAR data: 15,990 samples of PCD files	LiDAR sensor indoor	CNNs	ShapeNet	N/A	16	An error of body dimensions was close to 2%
(Huang et al., 2019a)	Cow body condition score estimation	Images: 8,972	RGB camera	SSD, YOLO-v3	VGG-16, DenseNet Inception-v4	N/A	5	Accuracy values were 98.46% and 88.84% for SSD and YOLO-v3
(Chen et al., 2020)	Cow feeding behavior recognition	Activity collector log data	Microcontroller (MCU), bubble activity sensor, ZigBee and wireless transceiver module	CNNs, RNNs	Custom	N/A	4	Recognition accuracy was 89.5%,
(Atkinson et al., 2020)	Monitoring digestive health	Images: 100 samples	Point Grey Grasshopper camera (color and monochrome NIR)	DCNN	ResNet-101	N/A	3	Yield results over 90% in certain cases
(Tsai et al., 2020)	Cow drinking behavior monitoring	Images: 1,000	RGB (Raspberry Pi V2) camera with temperature and humidity sensors	YOLOv3	Darknet	N/A	1	F1 Score was 0.987, and true positive rate was 0.983 for cow head detection
(Achour et al., 2020)	Feeding behavior monitoring	Images: 7,265	RGB (webcam) camera in cow shed	Four CNNs models; DeepLab	Xception	N/A	2	Average precision was 90.84% for feeding and standing
(Bezen et al., 2020)	Feed intake estimation of cows	Images: 994	RGB-Depth camera	CNN, Faster R-CNN	Resnet, Resnet50	RPN	10	Identification based on cows eating was 93.65%
(Psota et al., 2021)	Horn flies detection on cattle	Images: 375	RGB (Nikon Coolpix P1000) camera	DeepLabV3 +	ResNet18	N/A	2	Precision was approximately 0.9
(Kang et al., 2020)	Detection of lame cows and lame hooves	Images: 1,500 from video dataset	Digital camera (DC-GH5S)	RFB_NET_ SSD[e]	Custom	N/A	3	Accuracies were 96% and 93% for lame cows and lame hooves identification
(Jiang et al., 2020)	Action recognition of lameness cows	Videos: 1,080	RGB (webcam and SONY HDR-CX290E) cameras	CNNs[f], BiLSTM	DenseNet-201	N/A	4	mAP was 98.24% using combined dataset

(continued on next page)

Table 3 (*continued*)

References	Tasks	Dataset Type	Dataset Source	Learning Models	Networks	Candidate Objects	Classes	Performance
(Wu et al., 2020a)	Lameness detection of dairy cows	Videos: 210 (15 to 20 s each)	RGB (DS-2DM1-714) dome cameras	YOLOv3, LSTM	Darknet53 ResNet-18	N/A	3	Lameness detection accuracy was 98.57% using LSTM
(Zhang et al., 2020)	Cow mastitis recognition	Thermal images 6,000	Thermal imaging camera (FLIR-A615)	EFMYOLOv3[g]	MobileNetV3	N/A	4	Overall mAP was 96.8%

[a] Bidirectional Feature Pyramid Network.
[b] Conditional Random Fields as Recurrent Neural Network.
[c] Atrous Spatial Pyramid Pooling.
[d] Convolutional Pose Machines.
[e] Receptive Field Block Net Single Shot Detector.
[f] single-stream long-term optical flow convolution network.
[g] Enhanced Fusion MobileNetV3 You Only Look Once v3.

4. Discussion

General discussion: this type of SLR study is susceptible to threats to validity. Potential threats to validity are construct validity, external validity, internal validity, and reliability (Šmite et al., 2010). Construct validity assesses whether the SLR shows the level to which it measures what it claims. We used different automated search queries to evaluate the insights from the published available studies from various databases for this purpose. A database is an essential tool for searching published studies but very sensitive to query phrasing. A little change in the query can give a massive difference in the search results. Query format is different across databases; therefore, modification is required to search with various databases. This may result in missing some of the relevant studies. Several discussions among the scholars (authors and experts) were conducted for the query design to address these threats, and multiple trials were executed to test its feasibility. We checked the abstract of the searched papers manually to ensure that the search result is correct and valid. When we found irrelevant studies in the search results, modification is performed in the query, and the search is accomplished again. There might be another threat related to the process of result screening. Even though we used our predefined criteria and research questions for screening the papers, this might be possible that some of the studies were not determined based on our subjective personal decisions. This is because DL is widely used in the last two years for different livestock management operations. Another threat could be data extraction. We applied a predefined data extraction form, and some of the valuable information might likely be missed in this extraction form. We updated the data extraction form regularly during the SLR process to ensure that all the relevant information is extracted. We added new data by checking two criteria: i) the data was useful to answer the research question, ii) it was possible to extract from most articles. We removed some unnecessary data to avoid misleading.

We formulated the research questions to carefully investigate the necessary components of using DL models for cattle farming to address internal validity. As DL components are well-defined in this SLR, the relationship between research questions and research goals is adequately explained.

This SLR only investigates published articles, which applied DL approaches for cattle health monitoring and identification. There may be other innovative techniques of DL, which have not been used for cattle health monitoring and identification, that have a potential for usage, but we did not discuss this in this SLR since they have not been published yet.

This SLR follows the guidelines provided by Kitchenham et al. (2007) to ensure its reliability. The research query design, searching process, screening method, and quality evaluation were performed using Kitchenham et al. (2007) protocol. In this SLR, conclusions are derived based on the information extracted from the selected articles to avoid subjective interpretation of animal research scientists' results.

Problem studies: to the best of the authors' knowledge, identification (or tracking in real-time) and monitoring health are the two essential operations for cattle farming, which require meticulous observations. The advancement of the technologies has gained the researcher's interests in automatic cattle monitoring. DL-based artificial intelligence is increasingly used in various cattle farming operations for the last two years.

Imaging platforms: Ground-based imaging is the most used imaging platform for cattle identification and health monitoring; however, some applications were observed using a UAV, especially for identification. It is worth noting that monitoring cattle health requires high quality and clear images, therefore, the ground-based imaging platform is suitable and used for this operation. Besides, it is possible that a UAV based system can detect and track the cattle successfully from a certain height because the cattle are large. But if we want to track body parts of the cattle, then the UAV should run at a close height enough to capture or record good quality images or videos. Good quality data shows better performance in detection and monitoring using DL models. UAVs have been tested and proven successful for other agricultural operations, including crop scouting, site-specific spraying and crop yield monitoring. The major advantage of using UAVs for cattle farming could be tracking and monitoring cattle without human involvement for a large-scale farm. But more research and developments into UAV based technologies based on advanced DL models are needed to develop efficient systems for precision cattle farming.

Deep learning models and networks: DL algorithms are classified into three main categories based on learning: supervised, semi/partially supervised, and unsupervised. However, most of the articles considered in this study implemented supervised DL models. The supervised DL algorithms deal with labeled data, and the agent repeatedly updates them to gain an improved estimation for the desired outputs. These DL algorithms are simpler than others (semi-supervised and unsupervised) in the way of learning with high performance. The major advantage of using the supervised DL approaches is their ability to collect or generate data outputs from prior knowledge. One downside of these algorithms is that the decision boundary may be overstrained when the training set does not own the samples in a class. The CNNs are the most used DL models for both cattle identification and health monitoring, according to Tables 3 & 4 and Fig. 6. Although CNNs models are used in many articles, it does not mean that it is the best performing DL model. It should be interpreted carefully because "most usages" do not explicitly suggest that CNNs is a "best model" for cattle farming. This may be because CNNs is the oldest DL model, and it can be explained and implemented easily than the later ones. The large-scale network implementation with CNNs is much easier and provides better accuracy than traditional neural networks, which is one of the primary reasons for using CNNs in cattle farming. Nevertheless, a few studies have reported problems using CNNs, including vanishing gradient, longer processing time, overfitting, underfitting, lower accuracy, etc. To prevent these problems, batch normalization of the dataset could be a potential solution. Batch normalization standardizes the data inputs to a layer for each mini-

Table 4
Summary of studies for deep learning applications in cattle identification.

References	Tasks	Dataset Type	Data Source	Learning Models	Networks	Candidate Objects	Classes	Performance
(Yao et al., 2019)	Cow face detection and recognition	Images: 68,000	RGB camera for a period of two months	Faster R-CNN	VGGNet, InceptionV2, ResNet50, and ResNet101; PnasNet-5 and LeNet-5	RPN	2	Accuracies (mAP) were 98.3% for detection using Faster R-CNN + ResNet101 and 94.1% for face recognition using PnasNet-5
(Weber et al., 2020)	Pantaneira cattle breed recognition	Images: 27,849	Digital Video Recorder (DVR) set MIDI MD-1004NS MD-DVR41 at the exit outlet of cow shed	CNNs	DenseNet-201, Resnet50 and Inception-Resnet-V	N/A	7	99% in all Networks (mAP)
(Wang et al., 2020)	Cattle face recognition	Images: 1,087	RGB camera	CNNs	VGG-16	N/A	3	93% of recognition accuracy (mAP)
(Santoni et al., 2015)	Cattle race classification	Images: 1,351	RGB camera	GLCM-CNN[a]	Lenet-5	N/A	5	The best Kappa value of 0.979 was achieved with the energy image feature
(Laradji et al., 2020)	Tracking and counting cattle	Satellite images: 903	Maxar Technologies Satellite dataset	CSRNet and LCFCN	VGG16 FCN8 and ResNet-50	FCN	2	Highest F-score of 0.676 was achieved using CSRNet with VGG16 FCN8 network
(Sundaram & Loganathan, 2020)	Cattle detection and counting	Aerial images: 2,771	The aerial elephant dataset and the livestock dataset https://zenodo.org/record/3234780#.XueiE0UzbIU	FSSCaps-DetCountNet	CapsNet[b]	N/A	2	Average precision was 99.84% for livestock dataset
(Shao et al., 2020)	Cattle detection and counting	Aerial images: 670	UAV DJI Phantom 4 with RGB camera	YOLOv2	Darknet	N/A	1	F-measure of 0.952 for detection and counting accuracy over 90%
(Barbedo et al., 2020b)	Cattle counting	Images: 19,097	DJI Mavic 2 Pro with 20-MPixel camera	CNNs	NasNet	N/A	2	Accuracies were over 90% under a wide variety of conditions and backgrounds
(Xu et al., 2020)	Cattle detection and counting	Aerial images: 750	Mavic 2 Pro drone with an PTZ camera	Mask R-CNN	Resnet101	RPN	3	Best average precisions were 0.96, 0.92 and 0.94 for full-appearance detection, head detection in the pastures and full-appearance detection
(Salau & Krieter, 2020)	Segmentation of dairy cows	Images: 575	Eight Axis M3046-V internet protocol (IP) dome cameras	Mask R-CNN	ResNet50	RPN	1	Averaged precision scores for bounding boxes (0.91) and segmentation masks (0.85)
(Barbedo et al., 2020a)	Cattle detection	Aerial Images: 15,400	Mavic 2 Pro drone equipped with 20-MPixel camera	CNNs	Xception	N/A	2	F1 Score of 0.87 was achieved with 224 × 224 block size
(Qiao et al., 2020b)	Cattle segmentation	Images: 400	ZED (RGB-Depth) camera	Bonnet	ERFNet	N/A	2	99.5% of mean accuracy; precision of 99.70% for background and 97.73% for cattle
(Lin et al., 2019)	Cattle face position determination	Images: 900	RGB camera	Fast R-CNN	AlexNet	RPN	2	Target detection accuracy was 96.76% with resolution of 866 × 652 (pixels) images
(Qiao et al., 2019)	Cattle segmentation	Images: 1188	ZED cameras	Mask R-CNN	ResNet-101	RPN	1	Achieved 92% of mean pixel accuracy (MPA)
(Tabak et al., 2019)	Classify animal species	Images: 3,367,383	Camera trap images (https://github.com/mikeyEcology/MLWIC)	CNNs	ResNet-18	N/A	27	Precision of 0.99 was achieved for cattle
(Tabak et al., 2020)	Identification of animals	Images: 3 million	Camera trap images https://github.com/mikeyEcology/MLWIC2	CNNs	ResNet-18	N/A	58	Precision of 0.98 was achieved for cattle
(Rivas et al., 2018)	Cattle detection	Images: 13,520	Multirotors drone with RGB camera	CNNs	Custom	N/A	2	Accuracy of 91.8% was achieved
(Barbedo et al., 2019)	Cattle detection	Aerial Images: 1,853	DJI Phantom 4 Pro equipped with 20 MPixel camera	CNNs	VGG-16 VGG-19 ResNet-50 v2 ResNet-101 v2 ResNet-152 v2 MobileNet MobileNet v2 DenseNet 121 DenseNet 169 DenseNet 201	N/A	2	Highest F1 Score of 0.995 was achieved with NASNet Large

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Table 4 (*continued*)

References	Tasks	Dataset Type	Data Source	Learning Models	Networks	Candidate Objects	Classes	Performance
					Xception Inception Inception ResNet v2 NASNet Mobile NASNet Large			
(Qiao et al., 2020c)	Cattle identification	Videos: 363 rear-view	Two stereo ZED (RGB-Depth) cameras	Inception-V3, BiLSTM[c] LSTM[d]	Custom	N/A	2	Highest 91% of identification accuracy was achieved with BiLSTM
(Andrew et al., 2017)	Visual bovine identification of cattle	Drone Images: 940 Drone Videos: 34	Dataset: FriesianCattle2017 and AerialCattle2017 (http://data.bris.ac.uk)	R-CNNs, Inception V3	GoogLeNet	RPN	23	Average mAP of 86.07% was reported for identification and localization. Accuracy was 99.3%
(Andrew et al., 2019)	Cattle detection and localization	Images: 11,384	Drone with RGB camera (two day-long recording sessions)	YOLOv2, InceptionV3 LSTM	AlexNet	N/A	17	Detection accuracy was 92.4% and 93.6% for YOLOv2 and InceptionV3, respectively
(Shen et al., 2020)	Identification of dairy cows	Images: 82,633	RGB (Asus Xtion2) camera	YOLO	AlexNet	N/A	4	Accuracy of 96.65% in cow identification
(Hu et al., 2020)	Cow parts identification	Images: 4,353	RGB (Asus Xtion2) camera	YOLO	AlexNet	N/A	3	98.36% of cow identification accuracy after fusing with SVM
(Li et al., 2018)	Identification of cow	Images: 21,600	RGB camera for video recordings	InceptionV3	Custom	N/A	1	Recognition rate of single image was 90.55%, and video segment was 93.33%
(Jiang et al., 2019)	Cow body detection	Images: 1,000	Two RGB (webcam and SONY HDR-CX290E) cameras	FLYOLOv3[e] Faster R-CNN YOLOv3	Darknet (for YOLO), Caffe framework (for Faster R-CNN)	RPN (for Faster R-CNN), FPN (YOLOv3)	3	A best average accuracy of 93.73% was achieved using FLYOLOv3
(Bello et al., 2020a)	Cow identification using body patterns	Images: 1,000	RGB camera	DBN[f]	Custom	N/A	10	Accuracy was 89.95%
(Zin et al., 2018)	Cow identification using body patterns	Videos: 15	RGB camera for video recordings	CNNs	Custom (Caffe framework)	N/A	45	97.01% for cow's pattern identification
(Phyo et al., 2019)	Detection of cow body patterns	Images: 13,603	RGB camera	3D-DCNN[g]	Custom	N/A	60	Overall accuracy was 96.3%
(Bergamini et al., 2018)	Cattle re-identification	Images: 17,802	RGB camera	CNNs	Custom	N/A	N/A	Average accuracy was 85.4% with the close dataset
(Guzhva et al., 2018)	Cow tracking	Images: 64,953	RGB (M3006-V) camera	CNNs	VGGNet		5	Accuracy was 88.46% for tracking
(Zin et al., 2020)	Cow head detection for location tracking	Images: 10,793	RGB camera	YOLO	MobileNetV2	N/A	1	Accuracy was 100% for head detection
(Kumar et al., 2018)	Cattle recognition by muzzle point image	500 muzzle point images	RGB camera close images with a 30-megapixel	CNNs[h], DBN, SDAE[j]	Custom	N/A	N/A	Highest identification accuracy was 98.99% using DBN
(Bello et al., 2020b)	Cow recognition using nose image pattern	4,000 cow nose images	RGB dataset from Ministries of agriculture, forestry, and wildlife, Nigeria	CNN, DBN, SDAE	Custom	N/A	N/A	Approximately 98.99% accuracy using DBN

[a] Gray Level Co-occurrence Matrix Convolutional Neural Networks.
[b] Capsule Network.
[c] Bidirectional Long Short-Term Memory.
[d] Long Short-Term Memory.
[e] FilterLayer YOLOv3.
[f] deep belief network.
[g] Three Dimensional Deep Convolutional Neural Network.
[h] a combination of Stacked Denoising Sparse Auto-encoder (SDSA) and Deep Boltzmann machine (DBM) learning techniques.
[j] Stacked Denoising Auto-encoder (SDAE) is encoding.

batch. To improve the algorithm performances, data augmentation to expand the dataset, application of transfer learning, regularization, and increasing hyperparameter tuning and depth of the model should be considered. Several studies applied YOLO and SSD based single-stage object detection models. Compared to SSD, the YOLO is 2.2 times faster, but the accuracy of both models is less than two-stages detection models such as Faster-RCNN and Mask-RCNN, especially for small symptoms detection of cattle. The Faster-RCNN is a modified version of

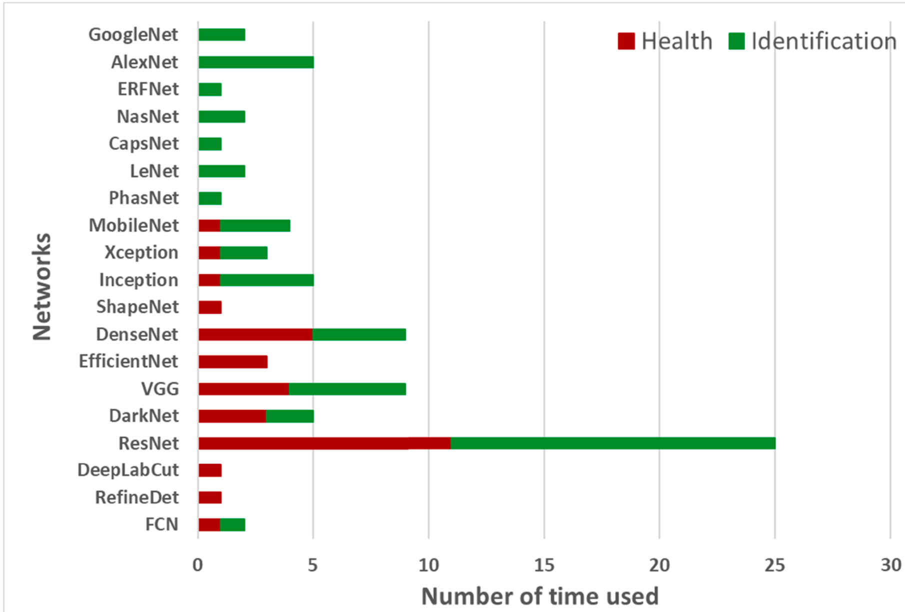

Fig. 6. Distribution of different deep learning training networks used precision cattle farming.

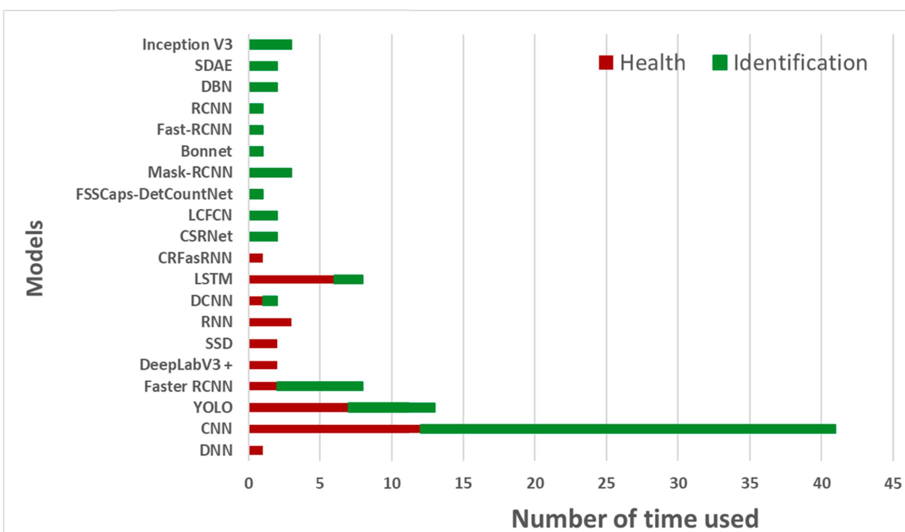

Fig. 7. Distribution of different deep learning models used for precision cattle farming.

Fast-RCNN that uses RPN (Region Proposal Network) instead of a selective search algorithm for generating regions of interest and performs faster detection than older RCNN models. The Mask-RCNN combines Faster-RCNN and FCN (Fully Convolution Network) in one mega architecture to generate a mask over targeted object after detection. Both models have the advantage of high accuracy and could improve the traditional detection algorithms by 50%, even for tiny visible symptoms. Additionally, we identified some other promising DL models, including LSTM, Mask-RCNN, DeepLabV3+, and Inception V3, which could have a better use than CNNs for cattle farming. For example, an LSTM can process and make predictions given sequences of data; Mask-RCNN solves instance segmentation problems, and DeepLabV3+ is used for semantic segmentation problems, etc. The LSTM models were introduced to address the problem of short memory and have four times more memory than neural networks. These models could be the best use for the timely forecasting of cattle behavior and monitoring health. It requires four multi-linear perceptron layers per cell to run, requiring a large amount of memory bandwidth to be computed. DeepLabV3+ is a state-of-art semantic segmentation approach where the aim is to assign semantic labels (e.g., head, body, legs, and tail of cattle) to every pixel in the captured input image. Inception V3 makes several improvements, including label smoothing, factorizing convolutions, and achieving the lowest error rates for cattle detection and monitoring. Among the study surveyed, two types of procedures mainly identified to carry out deep learning algorithms for cattle farming: (1) combination of image processing and DL techniques; (2) finetuning in DL algorithms. Finetuning/transfer learning of DL algorithms could be the best usage for precision cattle farming since the pre-trained model (trained with different datasets) may have better detection accuracies than the DL model developed from scratch. Application of advanced deep learning models is still inadequate for cattle compared to crop research. We expect more research to be conducted in automatic cattle farming using advanced and novel DL models in the future due to its promising potentials and superior performance in other agricultural applications.

Networks are the backbone of many DL models to compute features from the inputs (images or videos) using multiple complex layers. The

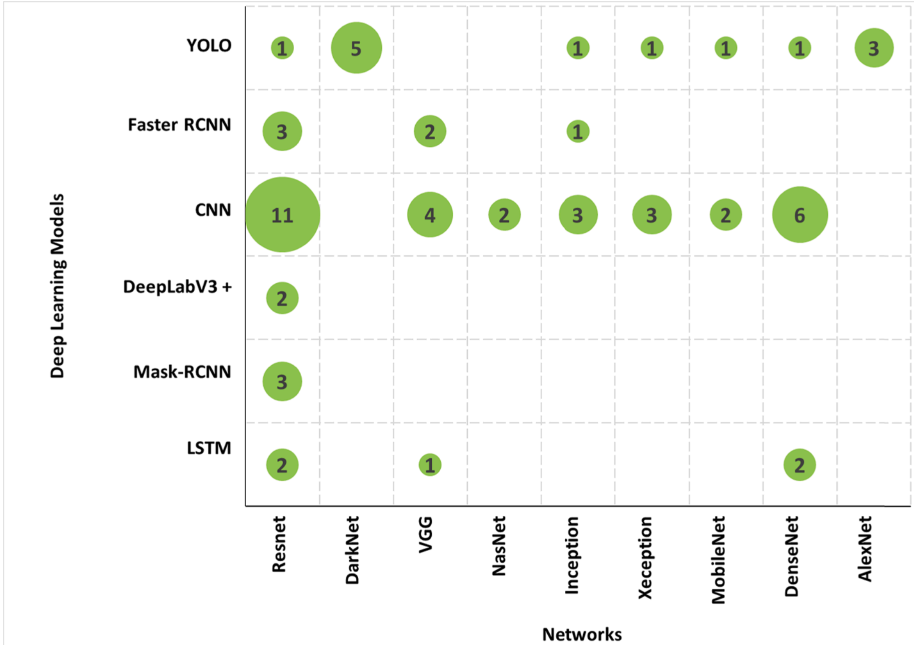

Fig. 8. Distribution of widely used deep learning models and networks for precision cattle farming.

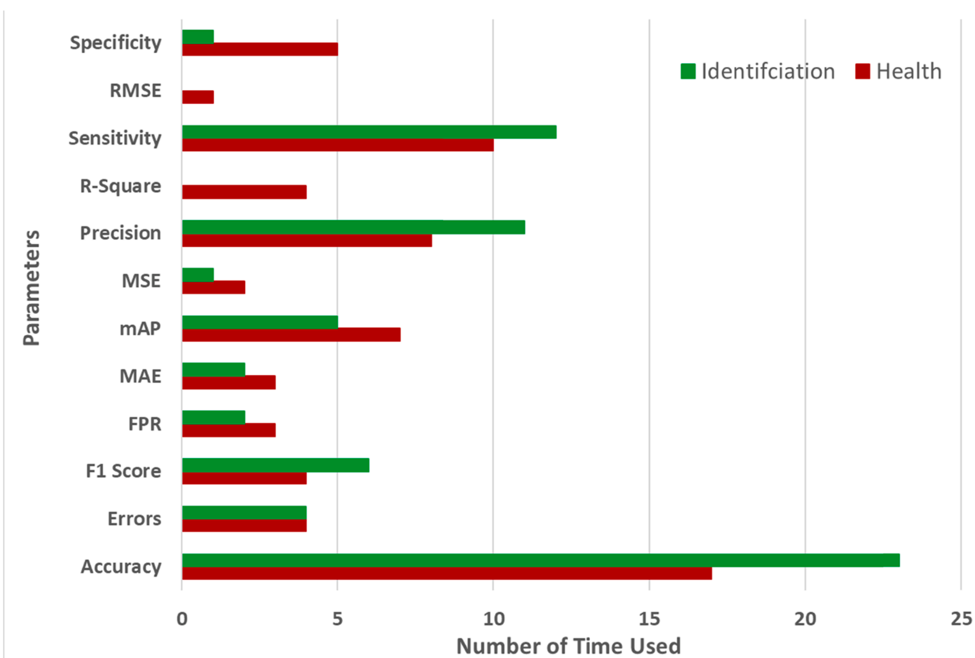

Fig. 9. Distribution of deep learning model evaluation parameters for precision cattle farming.

architecture of the DL algorithm is considered as a network for this study, is a critical factor in improving the performance of precision cattle farming. Table 5 presents a brief overview of major DL networks used for cattle research. Based on our search, the most used network is ResNet for cattle identification and health monitoring. Similar to the models, most uses do not mean the best network. However, ResNet can solve the vanishing/exploding gradient problem caused during the training phase of the DL models. Although several types of ResNet (Residual Network) have been tested for cattle farming, the ResNet50, which consisted of 49 convolutional layers and a single fully connected layer, is the most common type. Apart from ResNet, some networks showed promising results, including VGGNet, Inception V3, MobileNet, and DenseNet. The VGG (Visual Geometry Group) is a multilayer model architecture that decreases the number of parameters by using small-size filters and has low computational complexity compared to AlexNet, but the computational cost is higher than other recent networks such as Inception V3, MobileNet V2, and DenseNet. The motivation behind Inception V3 development was to accelerate the network training by using residual connections. It brings the advantage of faster training. Compared to Inception V3, the MobileNet V2 usages fewer number parameters and therefore, the accuracy could be slightly lower than Inception V3 and ResNet50. On the other hand, DenseNet was developed to solve the problem of vanishing gradient-like ResNet. This network is more efficient in terms of parameters and computation, provides the

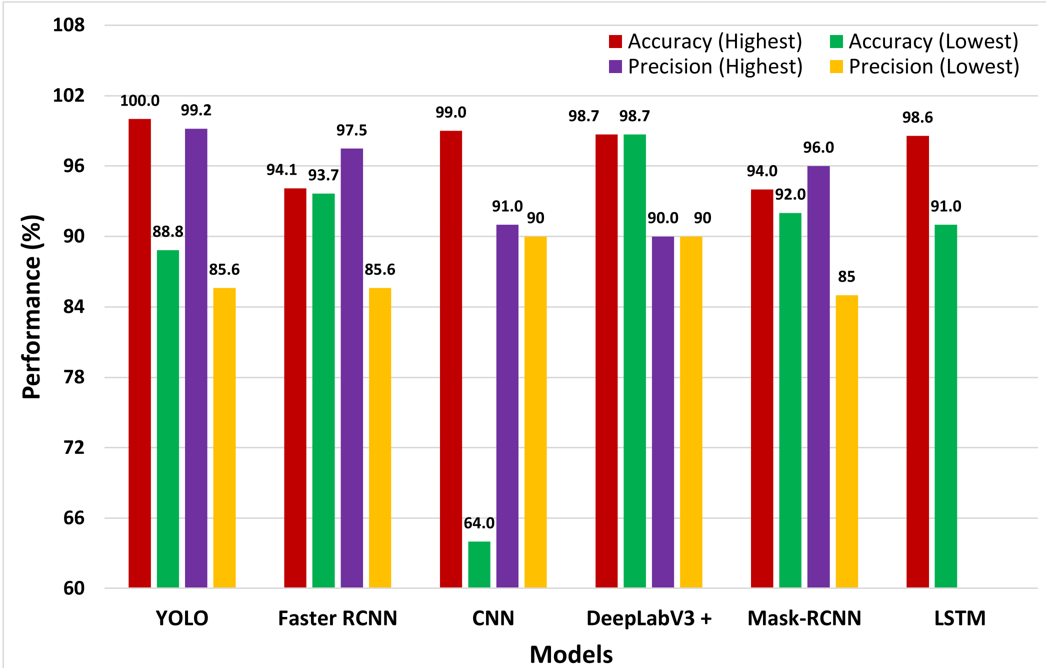

Fig. 10a. Performance reported for widely used deep learning models for precision cattle farming.

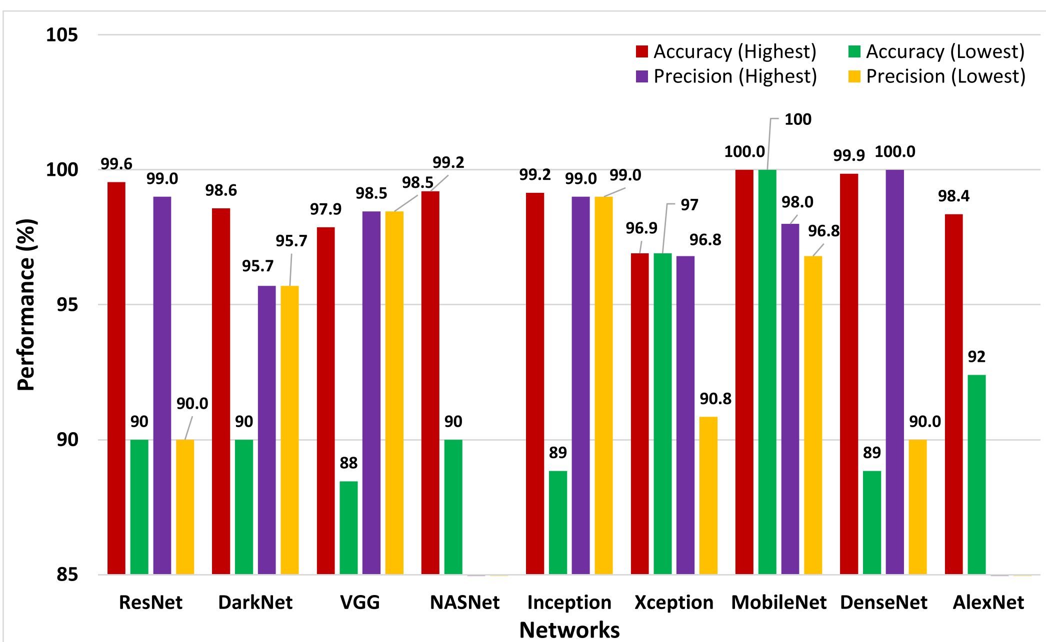

Fig. 10b. Performance reported for widely used deep learning network for precision cattle farming.

same level of performance compared with ResNet. So far, cattle research has experimented with few DL networks. Some advanced networks, including CapsuleNet and Xception being used for crop management, should be tested for cattle farming. Hence, more applications are desired to validate these cutting-edge networks' performances for specific cattle farming operations considering different conditions.

Evaluation parameters: a total of 12 evaluation parameters were reported in the retrieved articles. About 70% of the studies used accuracy as one of their evaluation parameters. Some of the evaluation parameters, including RMSE and R-Square, were used only in health monitoring studies. Some of the parameters (precision and sensitivity) were used mainly in identification problems. Most of the articles reported the outcomes with high accuracy values for their evaluation parameters, which means their technique made correct identification or monitoring. As discussed in the result section, the sensitivity, precision, mAP, specificity, and F1 could be better used for identification and R-Squared, RMSE, MAE, and FPR for automatic health monitoring applications.

Challenges: we found that most of the challenges are associated with image quality, data processing speed, dataset size, redundant information, and motion of the cattle during data acquisition. However, there might be additional challenges that were not discussed in the retrieved articles. Few studies have mentioned the challenges as future improvement scopes. It was seen that some studies identified difficulties

Table 5
Overview of DL networks used for precision cattle farming.

DL Network	Input Size	Dataset	Depth	Error Rate	Advantages
VGGNet	224 × 224 × 3	ImageNet	16, 19	7.3	Increased depth; small filter size
ResNet	224 × 224 × 3	ImageNet	152	3.57	Robust against overfitting
Inception V3	229 × 229 × 3	ImageNet	48	3.5	Usages small filter size; better feature representation
MobileNet V2	224 × 224 × 3	ImageNet	53	–	Inverted residual structure
DenseNet	224 × 224 × 3	ImageNet, CIFAR-10, CIFAR-100	201	3.46, 17.18, 5.54	Blocks of layers; connected layers

in their experiments that were solved by other research groups/studies. Some research stated the unbalanced data problem, but some studies address this problem using more data to train DL models. A few studies solved cattle's motion problem using high frame per second (FPS) cameras. In general, the DL models learn unique features from the input data themselves; thus, gathering a large dataset to train and test could give high accuracy of the models. Improving accuracy is not enough to implement the DL techniques for real-time cattle farm management; there might also be other challenges researchers will have to deal with during this process.

5. Conclusions

This SLR explicitly discuss the applications of DL for cattle farming. Numerous important insights can be derived from this SLR. DL has been increasingly utilized to automate several cattle farming operations. In recent years, DL techniques have shown to be useful and effective for automatic identification and health monitoring of cattle. However, many challenges still exist and need to be addressed, among which motion of the cattle during tracking and real-time health monitoring of cattle in the farm condition are identified as two critical fields. The results of this study indicate that the applications of DL models have been gaining tremendous attention in recent years due to their own ability to learn unique object features and provide higher precision. No conclusion can be derived as to what the best DL model is, however, some DL models, including CNNs, LSTM, Mask-RCNN, and Faster-RCNN, used more than the others. The studies used various networks, but ResNet, DenseNet, VGGNet, Inception V3, and MobileNet were used several times. Although CNNs and ResNet are the most used model and network, other models and networks are also applied to these areas. As we stated, implementing the real-time applications require addressing the current challenges and further improvements of the DL models and networks. We consider that these studies will guide future research towards developing the automatic system for cattle tracking and health monitoring systems.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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