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REVIEW ARTICLE

Computer vision-based weight estimation of livestock: a systematic literature review

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ABSTRACT

Body weight measurement of animals is often labor-intensive for farmers and stressful for animals. To this end, several methods have been researched and implemented to automate this process. In this study, we performed a Systematic Literature Review to identify and synthesise the published studies on the body weight estimation approaches for livestock (i.e. cattle and pigs). Information about features of models, underlying methods, performance evaluation parameters, challenges, and solutions using computer vision-based weight estimation, and characteristics of the future vision-based weight estimation models were presented based on the identified scientific papers. We found 151 papers, of which 26 papers were selected as primary studies that we analyzed in detail. We identified that: (1) seven features, namely top view body area, withers height, hip height, body length, hip-width, body volume, and chest girth are widely used in approaches; (2) 3D Time of Flight camera is the most preferred one; (3) the linear regression is the most used algorithm; (4) the application of Deep Learning algorithms is still very limited; and (5) coefficient of determination is the most used evaluation parameter for weight estimation. In addition to these observations, 13 challenges, 22 solutions, and guidelines for future research direction were presented.

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KEYWORDS
Animal body weight estimation; systematic literature review (SLR); machine learning; livestock; computer vision

1. Introduction

Over the years, modern dairy farms all over the world increased in size (Lowder et al. 2016), and the number of farms continued to decrease (NASS 2017; Shearer 2019). According to the 2017 Census of Agriculture report, which is completed every five years and provides information on land and activities on U.S. farms, 2.04 million farms (down 3.2% compared to the 2012 Census of Agriculture report) with an average size of 178 ha (up 1.6% compared to the 2012 Census of Agriculture report) exist in the U.S. In addition, in the Netherlands from 2005 to 2015, the total number of dairy cows increased by 13%, but the number of dairy farms decreased by 29% (Netherlands 2016). In general, the increase in farm size makes it more difficult for farmers to give enough attention to animals individually. This trend has led to the increasing adoption of precision dairy farming technologies by dairy farmers (Bikker et al. 2014).

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Most existing technologies focus on monitoring the activity of livestock. However, body weight of livestock, which is highly related to the digestive and health conditions, attracts less attention. For example, it is essential for young livestock to have a good start in life to develop their immune systems and grow to be a healthy animal. This is especially important for calves that are less than three weeks of age due to digestive limitations. They must develop a good digestive tract and sufficient body weight to produce high-quality dairy products without getting sick of lame (Heinrichs et al. 1995). Therefore, proper monitoring and estimating of the weight of livestock is of high importance to detect deviation from the optimal growth and to adapt management decisions, such as weaning and dehorning (Frizzo et al. 2011). However, it is inefficient for large farms to measure the weight of each livestock using traditional physical weighing methods. An exception might be with the milking robots because they are generally equipped with a weighing system. Moreover, to monitor the important growth stage of the livestock, it is necessary to measure the body weight regularly, such as the first years of young livestock (Swanson 1960).

The method to determine the weight of animals using a weighing scale is the most accurate one because it determines the real weight by placing the animal on a scale. Another method is the estimation using empirical relationships between morphology traits and body weight (Heinrichs and Losinger 1998). The weight of the animals can be estimated by measuring the chest girth (Mourits et al., 2013), withers height, hip height (Heinrichs and Lammers 1998) or the body weight using an electronic scale (Dingwell et al. 2006). However, the measures of body dimensions are mostly time-consuming and could be dangerous if the procedure is not automated and properly handled. Also, it should be noted that these manual measurement procedures could potentially have a negative influence on the growth of the young stock (Heinrichs et al. 1992). The weight of livestock animals can be used to determine whether the growth of the animal is within the expected margins. It is also possible to analyze the perturbations of growth curve, which requires more precision than accuracy. This can be used to see if the animal is on track with the growth needed to reach the optimal weight for starting lactation after 24 months.

Among all the livestock animals, the weight estimation of cattle and pigs is the most important one in the livestock industry because they provide most of the meat products to the world population (Nasirahmadi et al. 2017). In addition to the cattle weight estimation studies, researchers published several articles on the weight estimation of pigs (Wang et al. 2008; Kashiha et al. 2014; Fernandes et al. 2019). Due to the rapid growth of the cattle and pig enterprises that provide meat products to the growing world population (Nasirahmadi et al. 2017), the monitoring of the weights of cattle and pigs became more and more important. Therefore, in this review study, we focused on the weight estimation of cattle and pigs.

To overcome the limitations that are inherent to the conventional weight measurement methods, machine learning and computer vision techniques are used as non-intrusive approaches for animal weight measurements (Mollah et al. 2010). Determining the body weight by using computer vision methods combined with machine learning algorithms can deliver frequent data acquisition without creating too much stress for the animals (Wang et al. 2008).

To the best of our knowledge, no Systematic Literature Review (SLR) paper has been published yet on the weight estimation of livestock (i.e. cattle and pigs) by using computer vision and machine learning. As such, we planned to carry out this timely research. The main objective of this article is to identify, evaluate, and synthesise the relevant studies regarding the weight estimation of cattle and pigs. For practitioners, this research consists of valuable information because it presents the state-of-the-art in this domain. For researchers, this paper synthesises and presents the challenges and possible solutions, which can be focused on future studies. Also, the characteristics of the future computer vision-based weight estimation models are presented.

2. Materials and methods

2.1. Review protocol

The review protocol for the SLR is based on the study of Tummers et al. (Tummers et al. 2019), which is created using the guidelines of Kitchenham et al. (2009). This review protocol is depicted in Figure 1.

2.2. Research questions

Based on the objective of this study, the following five research questions (RQ) were derived:

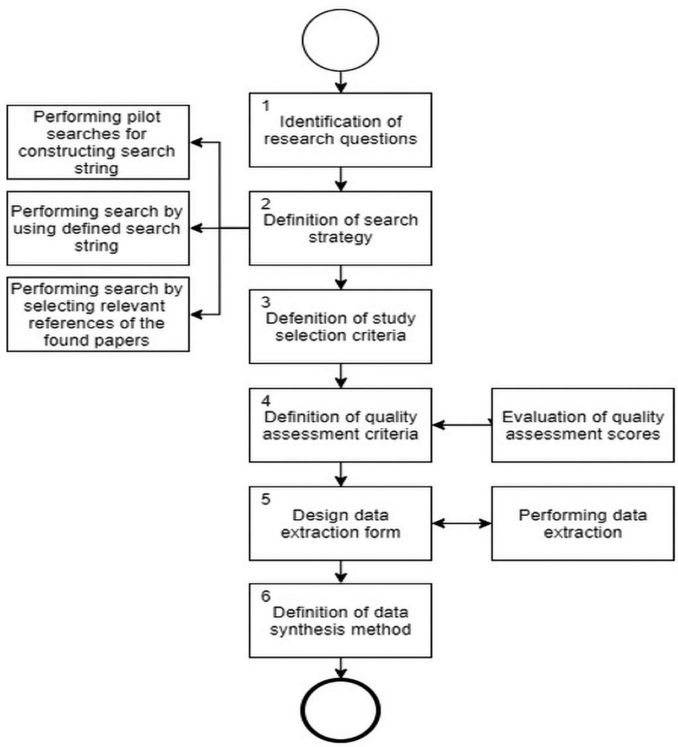

Figure 1. SLR review protocol.

- RQ1: What body features are used in vision-based weight estimation models?
  [In RQ1, we aim to identify the features of the weight estimation models. The feature is a measurable property or characteristic of the animal being analyzed. In machine learning and computer vision, we need discriminating and independent features such as withers height and hip height].
- RQ2: What kind of computer vision techniques are applied for detecting livestock in an image?
- RQ3: Which machine learning algorithms are used for the body weight estimation of livestock?
- RQ4: What are the challenges and possible solutions for determining the body weight of livestock from images?
- RQ5: What evaluation parameters are used to test the quality of the estimation models?

The answers to these research questions were found by analyzing the primary studies that were selected after a thorough search process followed by a quality assessment.

2.3. Search strategy

We searched in the following digital libraries: IEEE Xplore, ACM Digital, Science Direct, and Web of Science. We selected the studies published after 2008. The search was followed by applying the snowballing approach. For backward snowballing, we checked the reference lists of the identified papers to find additional relevant papers. For forward snowballing, we checked the articles that have cited the identified article (Jalali and Wohlin 2012). We searched in Scholar Google to determine which papers have cited the identified article. Our search resulted in a total of 151 studies. The distribution of papers per source is presented in Table 1. Finally, we had 27 papers after applying the selection criteria. As explained in Section 2.6, we also performed a quality assessment on these 27 papers, and this process resulted in 26 papers for further analysis because one paper has been excluded due to its low-quality score. Details of the quality assessment are explained in Section 2.6.

Research questions of this SLR study were answered based on these 26 papers.

2.4. Search strings per database

The following search string has been identified after several iterations because we aimed to find papers that are about the weight estimation of livestock.

'(cow OR heifer OR cattle OR pig) AND image* AND (weigh*)'

Table 1. Overview of the search results.

Source	After Automated Search	After Selection Criteria	After Quality Assessment
Science Direct	66	10	10
ACM Digital	9	1	1
IEEE Explore	56	5	4
Web of Science	6	1	1
Snowballing	14	10	10
Total	151	27	26

Table 2. Selection criteria.

No.	Criterion
IC1	The article is focused on the weight measurement of cattle or pigs
IC2	The article uses computer vision to estimate the weight of the animal
EC1	The article is not a full paper (only abstract is given)
EC2	The article is not written in English
EC3	The article is already accessed from another database
EC4	The article is not related to the application of computer vision approaches
EC5	The article is a secondary study, not a primary study (e.g. survey, SLR, or systematic mapping study)

2.5. Selection criteria

The following selection criteria shown in Table 2 were used for the study selection. IC acronym indicates the inclusion criterion, and EC represents the exclusion criterion. In Table 2, two inclusion criteria and five exclusion criteria are presented.

2.6. Study quality assessment

Twenty-seven studies were assessed with respect to their quality. In order to assess the quality of the studies, the criteria described in Table 3 were used to score these studies. Each of these eight criteria were answered as follows: yes = 1, somewhat = 0.5, No = 0. These points were summed for each paper to calculate the final score of the paper.

To maintain a high quality of the primary studies, the studies that scored less than 4 points were excluded from our study. This threshold is depicted in Figure 2 with a red line, which shows that only one study has less than 4 quality scores. Therefore, that study was excluded from the primary studies list, which results in a total of 26 primary studies.

2.7. Data extraction

The 26 resulting primary studies were used for the data extraction. The data extraction was performed based on the research questions. All the data were combined in an excel file to respond to the research questions.

2.8. Data synthesis

During the data synthesis process, data resulting from the data extraction step was synthesised in such a way that the information gathered could be combined and compared.

Table 3. Quality assessment criteria based on Kitchenham et al. (2009).

No.	Question
Q1	Are the aims of the study clearly stated?
Q2	Are the scope and context and experimental of the study clearly defined?
Q3	Are the variables in the study likely to be valid and reliable?
Q4	Is the research process documented adequately?
Q5	Are all the study questions answered?
Q6	Are negative findings presented?
Q7	Are the main findings stated clearly? Regarding credibility, validity, and reliability?
Q8	Do the conclusions relate to the aim/purpose of the study?

Figure 2. The quality score distribution of the 26 studies.

Since every study may describe its information differently, it is necessary to identify the meaning of the terms used in different studies.

3. Results

In this section, we first discuss the relevant statistics about 26 primary studies (Table 4). In the second part of this section, we present the results corresponding to five research questions.

3.1. Main statistics

The publication year of these studies ranges from the years 2008–2020. The yearly distribution of these studies is presented in Figure 3. It is shown that the number of studies per year varies a lot, but in recent years, there are more studies. This figure indicates that there is an increasing demand for vision-based weight estimation of livestock, particularly cattle and pigs within the last three years (i.e. 11 articles in total, 42% of all identified papers). The data regarding 2020 is not complete yet due to our search period.

In Figure 4, the number of primary studies resulting from different sources is presented. In this figure, it can be seen that Science Direct and IEEE Xplore are the most popular primary sources for the primary studies, which include 10 and 4 studies, respectively. The other main source for the primary studies is the snowballing approach, which resulted in the same number of studies as the Science Direct database. This figure shows that the snowballing approach increases the coverage of SLR studies.

3.2. Response to research questions

In this section, we present the responses to the research questions explained in Section 2.2.

RQ1: What body features are used in vision-based weight estimation models?

Table 4. 26 primary studies used in this SLR study.

Reference	Year	Reference	Year	Reference	Year
(Anglart 2014)	2010	(Ozkaya and Bozkurt 2008)	2008	(Suwannakhun and Daungmala 2018)	2018
(Hansen et al. 2018)	2018	(Pezzuolo et al. 2018)	2018	(Tasdemir et al. 2011a)	2011
(Jun et al. 2018)	2018	(Pradana et al. 2016)	2016	(Wang et al. 2008)	2008
(Kashiha et al. 2014)	2014	(Shi et al. 2016)	2016	(Wongsriworaphon et al. 2015)	2015
(Kongsro 2014)	2014	(Song X et al. 2018)	2018	(Yamashita et al. 2017)	2017
(Kuzuhara et al. 2015)	2015	(Song et al. 2014)	2014	(Martins et al. 2020)	2020
(Nishide et al. 2018)	2018	(Stajnko et al. 2008)	2008	(Le Cozler et al. 2019)	2019
(Cominotte et al. 2020)	2020	(Fernandes et al. 2019)	2019	(Tasdemir et al. 2011b)	2011
(Gomes et al. 2016)	2016	(Cang et al. 2019)	2019		

The features that were identified in the primary studies are presented in Table 5. This table shows that there are three features that are widely preferred by researchers. The most used feature is the body length (BL). This feature has been used in 11 primary studies. The second most used feature is the hip height (HH), which has been used in

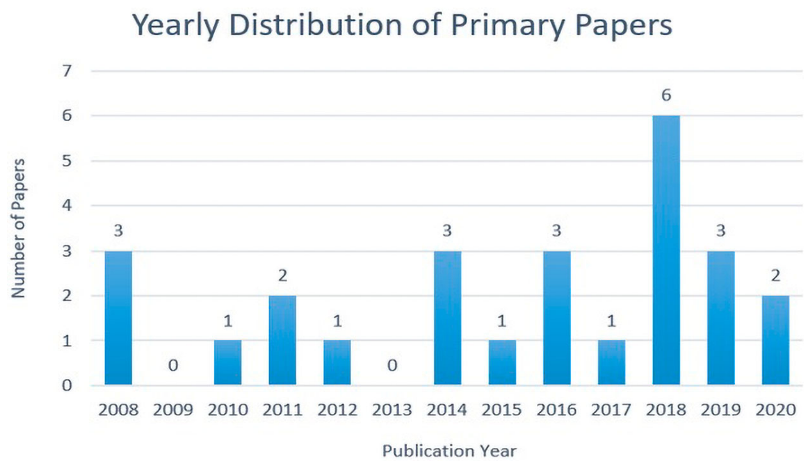

Figure 3. Yearly distribution of primary papers.

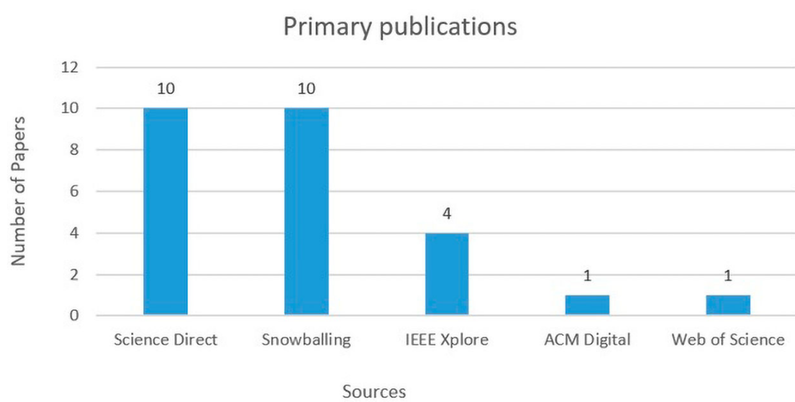

Figure 4. Distribution of studies per source.

Table 5. The features mentioned in the studies.

Source	geodesic lines	Top view body area	withers height	hip height	body length	hip width	body volume	convex area	perimeter	eccentricity	chest girth	waist girth	days in milking	SD height	side view body area	average body boundary distance	parity
(Kuzuhara et al. 2015)*	X																
(Shi et al. 2016)		X															
(Hansen et al. 2018)*		X															
(Kashiha et al. 2014)		X															
(Tasdemir et al. 2011a)*			X	X	X	X											
(Kongsro 2014)		X	X				X										
(Wang et al. 2008)		X			X			X	X	X							
(Nishide et al. 2018)*											X	X					
(Pradana et al. 2016)*					X						X				X		
(Suwannakhun and Daungmala 2018)		X			X					X							
(Wongsriworaphon et al. 2015)									X							X	
(Jun et al. 2018)		X															
(Anglart 2014)*		X	X	X	X	X											
(Ozkaya and Bozkurt 2008)*															X		
(Pezzuolo et al. 2018)			X	X	X						X						
(Song X et al. 2018)				X									X				X
(Song et al. 2014)				X			X							X			
(Stajnko et al. 2008)*			X	X													
(Yamashita et al. 2017)*					X		X										
(Martins et al. 2020) *				X		X	X				X	X					
(Le Cozler et al. 2019)*			X			X					X						
(Cominotte et al. 2020)*			X	X	X	X	X										
(Fernandes et al., 2019)			X	X	X	X	X										
(Tasdemir et al. 2011b)*			X	X	X	X											
(Gomes et al. 2016)*					X						X						
(Cang et al. 2019)																	
Total	1	8	9	10	11	7	6	1	2	2	6	2	1	1	2	1	1

* Primary studies focused on cattle weight production.

10 studies. The third feature is the withers height (WH) which has been used in 9 studies. Furthermore, it was observed that most studies use more than one feature in the corresponding weight estimation model. In deep learning algorithms, there is no need to measure the features directly because features are automatically discovered from the data. As such, in one of the studies (Cang et al. 2019) shown in Table 5, there is no specific feature because features were discovered automatically with the help of the deep learning algorithm and then, the weight estimation was performed using these features.

In Table 6, descriptions of these features and corresponding livestock species are presented. Since some features are used in more than one study, there might exist several species in the corresponding column.

RQ2: What kind of computer vision techniques are applied for detecting livestock in an image?

To estimate the weight of animals using computer vision, images need to be collected and processed. These techniques for collecting images can be divided into two main categories, namely, 2D and 3D vision-based techniques. Several techniques are available to gather the image data that is needed as input data for weight estimation models.

In Figure 5, four techniques that were used in the primary studies are presented. 3D Time of flight (3D ToF) is mostly preferred for cattle. The least used techniques are 3D stereo imaging and thermal 2D for cattle. For the research of pigs, 2D camera imaging is the most used technique followed by 3D ToF. The Thermal 2D technique has not been used for pigs. Also, it is observed that the total number of studies that use 3D vision techniques is higher than the number of studies that use 2D vision. There are 16 studies that use 3D vision techniques and 10 studies that use 2D vision techniques.

RQ3: Which machine learning algorithms are used for the body weight estimation of livestock?

The main part of the weight estimation is the model that is able to translate the input data to estimated weight values. Figure 6 shows that the linear regression algorithm is the widely used algorithm in this domain. For the pigs, other approaches have also been applied. However, for both cattle and pig, the least used modelling algorithm is the transfer function SISO (single input single output) and fuzzy logic. Although deep learning, which is a special form of Neural Network algorithm, has achieved state-of-the-art results in many other domains and problems, its application for body weight estimation of cattle and pigs is still limited. However, we may see more research on the use of deep learning for the weight estimation of livestock in the future.

RQ4: What are the challenges and possible solutions for determining the body weight of livestock from images?

In the primary studies, several challenges were identified and presented in Table 7. Most of the challenges are about the quality of the data collection and the data preparation for training and testing of the estimation models. These challenges range from the data collection to data processing and animal posture. We classified these challenges into several categories. The hardware and data categories include the most challenges (i.e. 5 and 4 challenges, respectively). In Table 8, we present the challenge categories, each of these challenges, and solutions. In Table 9, we present some of the commercial systems that can be used for the weight estimation of livestock.

Table 6. Features and their descriptions.

Features	Species	Description
Geodesic lines	Holstein cows	Lines that represent the shortest path over a surface from one point to another, in the study the lines were used to measure the distance between several bones in the back of the animal
Top view body area	Holstein Friesian cows, Dairy cows (Swedish Holstein and the Swedish Red Breed), Pigs (Landrace), Pigs (Rattlerow Seghers x Piétrain Plus), Pigs (Duroc and Landrace boars), Pigs (Crossbreed of Yorkshire and Landrace)	The area of the silhouette that the animal represented on a flat surface when viewing from above.
Withers height	Holstein cows, Dairy cows (Swedish Holstein and the Swedish Red Breed), Nellore beef cattle, Pigs (Duroc and Landrace boars), Pigs (Crossbreed of Large White and Landrace), Simmental bulls	The shortest distance between the surface the animal is standing on and the ridge between the shoulder blades of an animal.
Hip height	Holstein cows, Dairy cows (Swedish Holstein and the Swedish Red Breed), Holstein cows, Holstein Friesian calves, Nellore beef cattle, Simmental bulls, Pigs (Crossbreed of Large White and Landrace)	The shortest distance between the surface the animal is standing on and the top of the hips.
Body length	Holstein cows, Dairy cows (Swedish Holstein and the Swedish Red Breed), Beef cattle, Black calves, Pigs (Crossbreed of Large White and Landrace), Pigs (Crossbreed of Yorkshire and Landrace)(Yamashita et al. 2017)	The distance between the front of the shoulders and the start of the tail bone.
Hip width	Dairy cows (Swedish Holstein and the Swedish Red Breed), Holstein cows, Nellore beef cattle, Pigs	The distance between the two hip bones
Body volume	Pigs (Duroc and Landrace boars), Holstein Friesian calves, Black calves, Holstein cows, Nellore beef cattle	A proxy of the animal volume with some partial projection from the top to the ground, of from a side to the virtual wall
Convex area	Pigs (Crossbreed of Yorkshire and Landrace)	The area of the smallest convex polygon that contains the animal in the top view image.
Perimeter	Pigs (Crossbreed of Yorkshire and Landrace), Pigs (Crossbreed of Largewhite, Lancerace, and Duroc)	The perimeter of the animal in the top view image
Eccentricity	Pigs (Crossbreed of Yorkshire and Landrace)	The ratio between the foci of a fitted ellipse and its major axis length. This is between 0 and 1.
Chest girth	Japanese Black cattle, Beef cattle, Holstein cows, Pigs (Crossbreed of Large White and Landrace)	The circumference of the animal when measured directly behind the front legs.
Waist girth	Japanese Black cattle, Holstein cows	The circumference of the animal when measured directly in front of the hind legs.
Days in milking	Holstein cows	The number of days that a dairy cow has given milk since the birth of her calf.
SD height	Holstein Friesian calves	The standard deviation of the height in the hip region. This gives an indication of the amount of fat on the animal.
Side view body area	Holstein, Brown Swiss, and Crossbred cattle, Beef cattle	The area of the silhouette that the animal represented on a flat surface when viewing from the side.
Average body boundary distance	Pigs (Crossbreed of Largewhite, Lancerace, and Duroc)	The average distance of a point on the perimeter of the animal to the centre line.
Parity	Holstein cows	The number of different times a female animal has had offspring.

RQ5: What evaluation parameters are used to test the quality of the estimation models?

In Figure 7, evaluation parameters and their occurrences in the papers are presented. In this figure, it is shown that three parameters are mostly preferred. The most used parameter is the coefficient of determination (R^2), which is used as a statistical measure to represent the proportion of the total variance of the predicted weights ($W_i^{estimated}$)

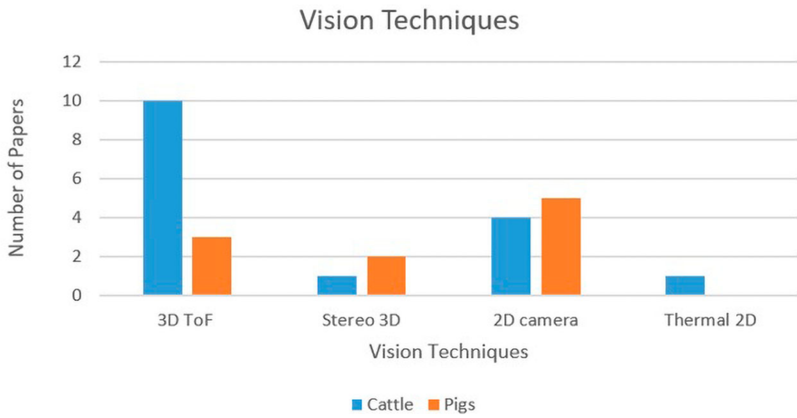

Figure 5. The vision techniques for cattle and pig weight detection.

of the test dataset. The second most used parameter is the Root Mean Square Error (RMSE). The third parameter is the Mean Absolute Percentage Error (MAPE), it is the relative estimation error of each estimated weight. Formulas 1, 2, and 3 shown present how to calculate these evaluation parameters.

In Table 10, we also present the accuracy values of each body weight estimation models presented in the selected publications. Since some publications used different evaluation parameters, the values were presented in terms of the selected evaluation parameter.

$$R^2 = 1 - \frac{\sum (W_i^{predicted} - W_i^{real})^2}{\sum (W_i^{real})^2} \tag{1}$$

$$RMSE = \sqrt{\frac{\sum (W_i^{predicted} - W_i^{real})^2}{N}} \tag{2}$$

$$MAPE = \sum \left| \frac{W_i^{predicted} - W_i^{real}}{W_i^{real}} \right| \times \frac{100}{N} \tag{3}$$

4. Discussion

4.1. Characteristics of the future vision-based weight estimation models

After we investigated the papers in detail, we identified the following characteristics for the future vision-based weight estimation models of livestock:

- *Transfer Learning-based Estimation Models:* All the papers on image-based weight estimation rely on pre-set cameras. However, if the camera angle or position changes after the training process, the accuracy of the models is adversely affected. As such, we need a system that can use any images of animals for training. Also,

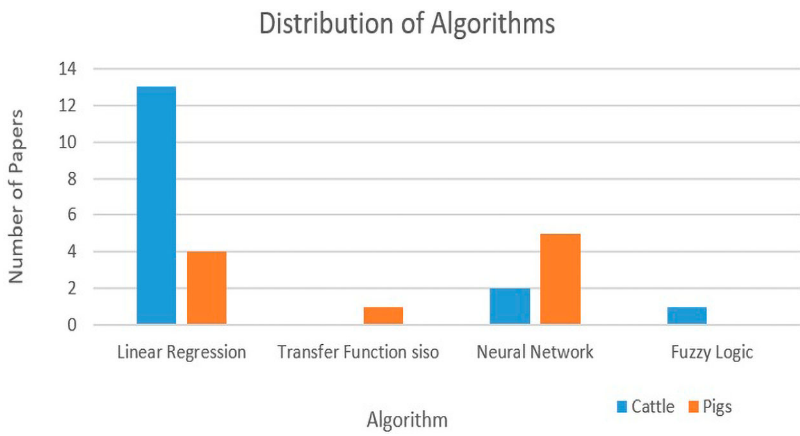

Figure 6. Distribution of algorithms.

the training stage is time-consuming and the collection of data is expensive. From the machine learning perspective, we expect to see new models that utilise transfer learning approaches. In transfer learning, a previously developed model for a task can be applied to a different but related task.

Table 7. The main challenges for the weight estimation of livestock.

ID	Challenge	Description
C1	Incomplete image viewpoint of the animal	To get an accurate measurement of certain features, the correct orientation of the camera with respect to the animal should be used.
C2	Image quality	For the image segmentation, images should be high quality that means the acquired image should avoid the factors such as illumination changes, shadows, and background noises as much as possible (Shi et al. 2016)
C3	Insufficient measurement period	To get a good representation of the weight of an animal, different measurement periods are required.
C4	Anomalies in edge detection	Errors may arise in body edge detection due to unclear backgrounds.
C5	Sensor interference	Sensors can interfere with the dust and sunlight. Infrared lasers beams can interfere with the dust particles, which might result in a shorter measured distance than it should be. Sunlight also contains infrared radiation which can be detected by the infrared sensor in the camera so that the sensor cannot distinguish the infrared beam from the surrounding infrared light.
C6	Camera position	Camera should be placed too high. Sometimes this might be appropriate for dairy cow barns if the ceiling height is low.
C7	Camera estimation problems related to the black animals	Camera may not estimate the shape of the black animals properly.
C8	Illumination and other environment conditions	Illumination is important for the identification and segmentation of the images. Also, dust can decrease the quality of the 3D measurements.
C9	Calibration of the camera	Calibration of the binocular vision camera is important.
C10	The selection of the image segmentation approach	The image segmentation approach should be more sensitive.
C11	Animal posture	For the extraction of certain features, the animal should stand in a particular position to enable the most accurate measurement of these features.
C12	Dirt on the animal or fading paint patterns	Dirt on the pig or fading paint patterns might cause a low identification rate.
C13	Partial results	Results cannot be generated for all cows because of cow aberrant behaviour or RFID tag detection problem.

Table 8. The challenge categories, challenges, and possible solutions.

Category	Challenges (C1 to C13)	Proposed Solutions (S1 to S21)	Reference
Data	C1. Incomplete image viewpoint of the animal	S1. Animals can be guided through a corridor	(Stajnko et al. 2008)
	C2. Image quality	S2. Instead of 2D techniques, 3D techniques can be applied if quality is an important concern for the model.	(Anglart 2014)
		S3. Images can be rejected or accepted based on the posture of the animals and the drinking posture work best.	(Kongsro 2014; Gomes et al. 2016; Le Cozler et al. 2019)
		There is a need to develop an objective image quality selection approach.	(Kongsro 2014)
	C3. Insufficient measurement period	S4. Each animal can be measured 10 times at different times	(Wongsriworaphon et al. 2015)
	C4. Anomalies in edge detection	S5. The edge of the pig is selected by the user instead of using edge detection algorithms.	(Wongsriworaphon et al. 2015)
Hardware	C5. Sensor interference	*There is not a complete solution yet, but intense light conditions due to the radiation from the sun radiation are limited in typical indoor feeding areas.*	(Pezzuolo et al. 2018)
		S6. Depth data is affected by the bright sunlight and depth camera can be used unless there is too much sunlight and shadows do not appear in the images.	(Nishide et al. 2018)
	C6. Camera position	S7. More than one camera can be used. S8. A camera with a wider angle can be used.	(Anglart 2014)
		S9. The cattle can be moved in front of the camera. This requires extra work.	(Yamashita et al. 2017)
		No solution provided for the limitation of the camera view	(Song X et al. 2018)
	C7. Camera estimation problems related to black animals	S10. Kinect using depth map can segment dark coloured breeds from its background	(Kongsro 2014)
		S11. The thermal camera can separate the Simmental brown-red-white bulls from the background on RGB images	(Stajnko et al. 2008)
		The contrast between white and black challenged the body condition score (BCS) program to find the selection points and as such, improvements are needed.	(Martins et al. 2020)
		There is not a complete solution yet, but some researchers excluded the images of the black cows (i.e. Swedish Low Land Breed – SLB)	(Anglart 2014)
	C8. Illumination and other environment conditions	S12. A range of light intensity of 40–150 lux is suggested according to the experiments.	(Kashiha et al. 2014)
		S13. 3D measurements can be done during the morning feeding time when cows do not move.	(Kuzuhara et al. 2015)
	C9. Calibration of the camera	S14. Kinect and other 3-D cameras can be used to avoid the complex calibration of binocular vision camera.	(Shi et al. 2016)
Technique	C10. The selection of the image segmentation approach	*More sensitive approaches are required; however, a possible solution has not been presented.*	(Pradana et al. 2016; Cominotte et al. 2020)
Animal	C11. Animal posture	S15. Novel features can be used, namely the curvature and the deviation.	(Jun et al. 2018)
		S16.Cattle can be fixed in the squeeze chute.	(Ozkaya and Bozkurt 2008)
		S17. Location of the camera and poor lighting condition can deal with this challenge.	(Suwannakhun and Daungmala 2018)

(*Continued*)

Table 8. Continued.

Category	Challenges (C1 to C13)	Proposed Solutions (S1 to S21)	Reference
		S18. The system can be located on the passing ways of the cows (i.e. entrance and exit of milking parlours, in front of the automatic feeding unit).	(Tasdemir et al. 2011a; Tasdemir et al. 2011b)
		S19. The walk-through weighing protocol can be applied or a scale can be positioned inside the pig pen to avoid the need of moving.	(Wang et al. 2008; Cang et al., 2019; Cominotte et al. 2020)
		S20. Certain pigs standing on their back feet present a reduced area, these images are excluded by thresholding the minimum body area.	(Kashiha et al. 2014)
		S21.Younger and/or nervous animals can be restrained in a feed fence during image acquisition.	(Le Cozler et al. 2019)
		S22. For pigs, the best option to mount the cameras can be the drinking areas.	(Shi et al. 2016)
	C12. Dirt on the animal or fading paint patterns	*There is not a solution yet, and image illumination and capturing techniques can help*	(Kashiha et al. 2014)
Results	C13. Partial results	*There is not a complete solution, but erroneous data is removed from the analysis.*	(Hansen et al. 2018)

Table 9. Commercial systems.

ID	Product Name	Company	Country	Website
1	Weight-Detect	PLF-Agritech Europe	UK	https://plfag.com/technology/
2	eYeScan	Fancom BV	The Netherlands	https://www.fancom.com/
3	Pigwei	Ymaging	Spain	http://www.ymaging.com/projects-2/pigwei
4	optiSCAN	Hölscher + Leuschner Gmbh	Germany	https://www.hl-agrar.de/hl+englisch/products/optiscan/index.html
5	GrowthSensor	GroStat	UK	http://grostat.com/growth_sensor.php
6	WUGGL One Gmbh	WUGGL Gmbh	Austria	http://www.wuggl.com/
7	QSCAN	Innovent	UK	http://www.qscan.co.uk/

- *Dynamic Vision:* Most of the existing solutions use fixed cameras to take images, and then train the model based on these images. However, in the future, in order to observe livestock more carefully, we need to deploy these cameras on drones or robots and perform the measurements at any time and location. The reason for these measurements at any time and location is that weight variation and other changes of livestock can be determined quickly with the help of accurate and timely measurements. For instance, such a weight variation can be an early warning of some diseases (Segerkvist et al. 2020), so that the corresponding treatment plan can be adopted quickly. However, the use of drones and robots for this purpose involves several challenges such as accurately predicting the weight of livestock from a certain distance. While counting the number of livestock is relatively easier, the determination of the weight variation of livestock is more challenging. Also, the identification of particular livestock is not easy from a certain distance because ear tags might not be detected clearly in some cases. As such, we will need some solutions to capture, filter, and process videos from mobile devices in the future.

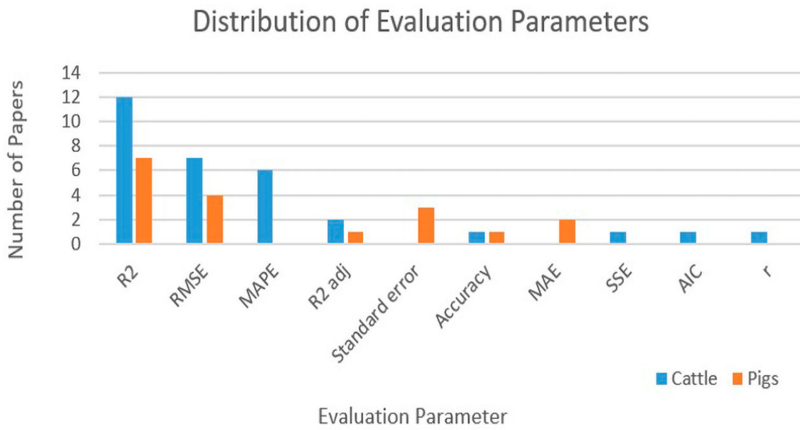

Figure 7. Distribution of evaluation parameters.

- *Integrated Data*: Our review study focused on the weight estimation of livestock, however, there is another review study on machine vision with livestock that has been recently published (Wurtz et al. 2019). Wurtz et al. (2019) presented an overview of studies that automatically detect indoor-housed farm animal behaviour activity by using machine vision technology. For future research in precision agriculture, we consider that different kinds of data can be integrated for building high-quality models and different components in precision agriculture. For example, sensing networks and localisation can coordinate and communicate to achieve this higher performance. In such a system, the position tracking data from animals can be used to estimate the calorie consumption and further, calibrate the weight changing trend. As such, we need solutions that are able to integrate data from multiple sources.
- *New Technologies and New Opportunities:* Recently, new technologies have been introduced such as Kinect and 3D Scanners. Kinect device has been used in several studies. Scanning technology that uses several cameras, each paired with a laser projector is also emerging (Le Cozler et al. 2019). We expect to see new models that apply scanning technology for accurate models. Also, the construction of the estimation models is expected to be faster compared to the existing approaches.
- *Resilient and Sustainable Systems:* New systems should be adaptive to the environment conditions such as sunlight and dust, and they should not affect the performance of the systems. Once the system is deployed to the site, it should require minimal maintenance.
- *Fully Automated Systems:* Many reported systems require some manual steps that prevent full automation. New systems should avoid the involvement of a person and automate the whole process.
- *Deep Learning-based Techniques:* Deep Learning (DL) that is a sub-branch of machine learning provided remarkable results in many different domains. Object segmentation approaches based on deep learning such as Mask R-CNN already exist and DL algorithms can be applied for regression tasks such as weight estimation. DL algorithms discover the features and as such, the manual measurement of features are no longer needed. We expect to see novel models based on different DL algorithms such as

Table 10. Performance of weight estimation models in terms of reported evaluation metrics.

ID	Reference	Performance of Models
1	(Anglart 2014)	The correlation between body weight measured by scale and estimated by camera is high (R = 0.87). No other metric
2	(Hansen et al. 2018)	The regression score is 0.81, MAPE is 3.1%
3	(Jun et al. 2018)	The coefficient of determination (R^2) is 0.79, RMSE is 3.82 kg, MAE is 3.15 kg
4	(Ozkaya and Bozkurt 2008)	The coefficient of determination (R^2) is 0.851 for Brown Swiss cattle, 0.796 for crossbred, and 0.353 for Holstein cattle
5	(Pezzuolo et al. 2018)	The coefficient of determination (R^2) is 0.9942, SEE is 0.68 kg, MAE is 0.48 kg, R^2 adj is 0.9934
6	(Pradana et al. 2016)	The accuracy is 73.21%, MAPE is 26.78%
7	(Suwannakhun and Daungmala 2018)	The accuracy is 82.72%. No other metric
8	(Tasdemir et al. 2011a)	The coefficient of determination (R^2) is 0.94, RMSE is 19.87 kg
9	(Wang et al. 2008)	The coefficient of determination (R^2) is 0.9925 and the average relative error is 3%
10	(Kashiha et al. 2014)	The coefficient of determination (R^2) is 0.962 on the individual level, standard error is 1.23 kg
11	(Kongsro 2014)	The coefficient of determination (R^2) is 0.99, RMSE is in between 3.3 and 3.4 kg for different pig races
12	(Kuzuhara et al. 2015)	The coefficient of determination (R^2) is 0.80, RMSE is 42.6 kg, AIC is 0.96
13	(Nishide et al. 2018)	The coefficient of determination (R^2) is 0.9525, MAPE is 8.42%
14	(Shi et al. 2016)	The coefficient of determination (R^2) is 0.9931, MAE is 1.759 kg
15	(Song X et al. 2018)	The mean absolute percentage error (MAPE) is 5.2%, RMSE is 41.2 kg
16	(Song et al. 2014)	The mean relative error is 6.5%, RMSE is 6.2 kg
17	(Stajnko et al. 2008)	The coefficient of determination (R^2) is 0.747, R^2adj is 21.76kg
18	(Wongsriworaphon et al. 2015)	The coefficient of determination (R^2) is 0.82, maximum relative error is 9%
19	(Yamashita et al. 2017)	The coefficient of determination (R^2) is 0.8679, MAPE is 21.46%
20	(Martins et al. 2020)	The coefficient of determination (R^2) is 0.96, MAE is −0.61, RMSE is 26.89 for dorsal perspective, MARE is −0.13
21	(Le Cozler et al. 2019)	The coefficient of determination (R^2) is 0.93, RMSEP (root mean square error of prediction) is 2.72% (18.2 kg)
22	(Cominotte et al. 2020)	The coefficient of determination (R^2) is 0.91 for weaning phase, RMSEP (root mean square error of prediction) is 4.26% (8.6 kg)
23	(Fernandes et al. 2019)	The coefficient of determination (R^2) is 0.92 for younger animals and MAE is 3%
24	(Tasdemir et al. 2011b)	Mean relative percentage accuracy is 98.93% and correlation coefficient is 0.99
25	(Gomes et al. 2016)	The models to estimate body weight of Angus and Nellore have R^2 between 0.69 and 0.84 ($P < 0.001$)
26	(Cang et al. 2019)	Average absolute error is 0.644 kg and average relative error is 0.374%

Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM) Networks, Deep Belief Networks (DBN), Autoencoder, Hybrid models, and Generative Adversarial Networks (GAN). Also, DL algorithms provide better performance compared to the other traditional machine learning algorithms (a.k.a., shallow learning) when more data is provided for the models. However, there are some disadvantages. Most of the time they require more data (i.e. images) and there is a risk of overfitting. Furthermore, building a high-performance prediction model takes a longer time and the required computing power is much more compared to the machine learning-based models (i.e. shallow learning). Also, finding the optimal parameter values is more difficult and time-consuming because there might exist millions of possible parameter values in a large DL-based model. One of the challenging issues with DL-based models is that they are mostly black-box models and therefore, Explainability in Artificial Intelligence (XAI) research field aims to provide some model agnostic solutions to explain the logic behind these prediction results.

- *Research Infrastructure:* A better research infrastructure will help to develop better estimation models and systems. Currently, there are either no public datasets or very limited public datasets on the weight estimation of livestock. Some data repositories can be created to store these public datasets and for repeatability of the experiments, public datasets can be preferred during the experiments. Although there are different techniques for weight estimation, there is no benchmarking framework to compare all the available models and techniques. Evaluation approaches and validation parameters are very different across studies and as such, benchmarking of the existing models is not easily performed in this domain. The researcher should consider designing new benchmarking frameworks to address this problem.

- *Other Issues and Observations:* Complete images are required instead of partial images to build the weight prediction models because the performance is adversely affected when partial images are utilised. A 'partial image' is an image of the livestock that shows only a part of the body, such as heads and legs. The resolution of the image is also important for accurate estimation, and most of the devices such as Kinect already present acceptable resolution. More research is needed on the full automation of vision-based weight prediction systems.

4.2. Threats to validity

In this study, we focus on the weight estimation of livestock (i.e. cattle and pigs). Studies that address other types of animals such as wild animals might be using different types of approaches and estimation models because camera traps that are motion-sensor cameras take millions of images (Norouzzadeh et al. 2018), and extracting knowledge from this huge amount of data might require additional steps. Also, there might exist a very limited number of images for some endangered species and building models on these very limited datasets might be challenging and researchers might not apply deep learning algorithms. Therefore, researchers who want to include studies that also cover the weight prediction of wild animals might prefer different search strings and come up with different papers.

In this study, we only used high-quality research articles, and no grey literature such as blogs, company websites was preferred. Sources that can address the grey literature such as blogs and company websites might provide additional insights and present other features and models to estimate the weight of livestock. For instance, some software and equipment vendors might be using different techniques and approaches, but in this study, we preferred to focus on the state-of-the-art instead of including grey literature in this study. Another limitation of our study is that we searched papers on well-known databases, but it is possible that we missed some databases that address relevant papers. To minimise the effect of this issue, we performed snowballing and added additional papers.

5. Conclusion

The increasing popularity of vision technologies in recent years, such as ML-based image recognition, encourages researchers to explore new dimensions in precision agriculture. Among all these researches, much research effort has been focused on automatic image analysis for body parameter estimation such as weight and height, of livestock. In this paper, we have conducted a survey on vision-based techniques applied in the weight estimation of livestock. Specifically, we have identified 26 relevant papers and performed a comprehensive review. Based on these papers, we have provided analysis, categorisation, and summary of the techniques from multiple viewpoints. First, we have described the animal features that are commonly used in vision-based weight estimation models. Subsequently, we have summarised the computer vision techniques that are applied to recognising and filtering animals in images. After that, we have discussed the primary algorithms and models used for estimating the bodyweight of livestock. Then, we have classified the challenges in the measurements and calculations, and in addition, summarised a series of solutions for each challenge. Finally, we have reviewed the evaluation metrics that are used in this research field. Besides, we have discussed the drawbacks in the existing solutions and provided guidelines for future research direction.

It was observed that Neural Network-based models are still fairly unexplored approaches for vision-based weight estimation models. As such, deep learning algorithms that are based on Neural Networks present a lot of opportunities for further research in this domain. One of the promises of deep learning in computer vision-based estimation studies is the better performance of the deep learning-based models that require more data. Also, less digital signal processing expertise is needed to build computer-vision based models when deep learning algorithms are used (Brownlee 2019). Instead of using a feature extraction algorithm such as Scale-Invariant Feature Transform (SIFT), Gabor filters, Histogram of Oriented Gradients (HOG), features are automatically discovered in deep learning algorithms. Another promise of deep learning is model reuse, which means that pre-trained models can be used for different problems (a.k.a., transfer learning). For many challenging problems such as object detection, deep learning-based models have provided state-of-the-art results so far. Therefore, we can expect more research on the use of deep learning algorithms in this domain. However, there are also some drawbacks. For instance, they might require high-performance data processing equipment, such as Graphics Processing Unit (GPU) hardware, to train on big data, and model training can be time-consuming due to the model hyperparameter tuning. Also, the performance of the deep learning model highly relies on the quality of training data. We encountered only two studies (Suwannakhun and Daungmala 2018; Cang et al. 2019) that applied deep learning algorithms for the weight estimation of pigs. We expect to see more studies that apply different deep learning algorithms for the weight estimation of cattle as well soon.

We believe that this survey study will motivate researchers to leverage vision-based techniques for solving various vision-related problems in precision agriculture. At the same time, in spite of a number of research studies, some technical issues such as recognition of moving livestock, do not have efficient and mature solutions yet. Therefore, we expect more research effort will be engaged in this area to strengthen the application of vision-based livestock detection in precision agriculture.

Disclosure statement

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