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Board Invited Reviews

BOARD INVITED REVIEWS

ASAS-NANP SYMPOSIUM: Applications of machine learning for livestock body weight prediction from digital images

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Abstract

Monitoring, recording, and predicting livestock body weight (BW) allows for timely intervention in diets and health, greater efficiency in genetic selection, and identification of optimal times to market animals because animals that have already reached the point of slaughter represent a burden for the feedlot. There are currently two main approaches (direct and indirect) to measure the BW in livestock. Direct approaches include partial-weight or full-weight industrial scales placed in designated locations on large farms that measure passively or dynamically the weight of livestock. While these devices are very accurate, their acquisition, intended purpose and operation size, repeated calibration and maintenance costs associated with their placement in high-temperature variability, and corrosive environments are significant and beyond the affordability and sustainability limits of small and medium size farms and even of commercial operators. As a more affordable alternative to direct weighing approaches, indirect approaches have been developed based on observed or inferred relationships between biometric and morphometric measurements of livestock and their BW. Initial indirect approaches involved manual measurements of animals using measuring tapes and tubes and the use of regression equations able to correlate such measurements with BW. While such approaches have good BW prediction accuracies, they are time consuming, require trained and skilled farm laborers, and can be stressful for both animals and handlers especially when repeated daily. With the concomitant advancement of contactless electro-optical sensors (e.g., 2D, 3D, infrared cameras), computer vision (CV) technologies, and artificial intelligence fields such as machine learning (ML) and deep learning (DL), 2D and 3D images have started to be used as biometric and morphometric proxies for BW estimations. This manuscript provides a review of CV-based and ML/DL-based BW prediction methods and discusses their strengths, weaknesses, and industry applicability potential.

Key words: biometrics, body weight, computer vision, digital images, machine learning, morphometrics

Abbreviations

AI	artificial intelligence
ANN	artificial neutral network
CNN	convolutional neural network
CV	computer vision
DL	deep learning
ENR	elastic network regression
IA	image analysis
LASSO	least absolute shrinkage and selection operator
BW	body weight
LR	linear regression
MAE	mean average error
ML	machine learning
MLP	multilayer perceptron
MLR	multiple linear regression
PLS	partial least square
RAM	recurrent attention model
RCNN	recurrent convolutional neural network
RF	random forest
RMSE	root mean squared error
RNN	recurrent neural network
SVM	support vector machine

Introduction

In animal production, livestock body weight (BW) is a very important and widely used feature that has a significant impact on feed consumption (Putnam et al., 1964), breeding potential (Buckley et al., 2003; Ghotbaldini et al., 2019), social behavior (Bouissou, 1972; Hong et al., 2017), energy balance (Thorup et al., 2012), and overall farm management (Halachmi et al., 2019). It may be used indirectly in the assessment of health and welfare status (Dikmen et al., 2012), and in the determination of time-to-market for animals (Mc Hugh et al., 2011). Large or abrupt changes in BW might indicate the presence of a disease (Frigo et al., 2010; Yin and König, 2018), improper housing conditions (Heins et al., 2019), welfare problems (Neveux et al., 2006), feeding errors (Meyer et al., 1960) or inefficient genetic selection (Freetly et al., 2020). There are currently two main approaches to measure the BW in livestock: 1) direct approaches using scales, and 2) indirect approaches based on relationships between body part measurements and BW.

Direct weighing methods rely on weighing technologies such as partial-weight or full-weight industrial scales capable to support small, medium, or large livestock. These devices are typically placed in a designated location on a farm such as passageways or next to feeders and drinkers, and animals are physically moved to that location and placed on the weighing scale one at a time. Some companies provide passive-weighing solutions that integrate sensor-rich scaling systems such as GrowSafe (Canada), the Bosch Precision Livestock Platform (Germany), Rice Lake Weighing Systems (USA), and Diverseco Industrial Scales and Weighing Systems (Australia) capable to measure, log results and transmit information over wired or wireless networks. Other companies such as Arvet CIMA Control Pig and CIMA Control Cow Scaling Systems (Spain) and the GEA iNTELIWEIGH Walk Over Weigh System (Germany) as well as research groups that developed custom-made scales (Cveticanin, 2003; Pastell et al., 2006) provide dynamic-weighing systems where animals are weighed while in motion using walk-through or step-over weighers (Rousing et al., 2004). While these devices are very accurate, their acquisition, intended purpose and operation size, repeated calibration and maintenance costs associated with their placement in high-temperature variability, and corrosive environments are significant and beyond the affordability and sustainability limits of small and medium size farms and even of commercial operators (Banhazi et al., 2012; Dickinson et al., 2013). Removing animals from paddocks and holding areas and leading them to weighing stations is a costly, stressful and potentially harmful activity for animals and handlers alike and could also inadvertently lead to animal weight loss or even death (Augspurger and Ellis, 2002; Grandin and Shivley, 2015; Faucitano and Goumon, 2018). Moreover, since the weighing process is very laborious, the frequency of measurements is not sufficiently high to permit the use of BW as indicator for other traits. However, since affordability of direct weighing methods may be an impediment for small producers (Dickinson et al., 2013), researchers have developed indirect weighing methods represented by regression models that relate morphometric measurements and image features to BW in livestock. The direct acquisition of morphometric measurements can be accomplished with the aid of technologies with various degrees of complexity, from measuring tapes and tubes to specialized software or manual, semi-automatic or automatic measurements extrapolated from images obtained with electro-optical devices such as mono-2D (Li et al., 2014), stereo-2D (Rudenko, 2020), 3D (Miller et al., 2019), ultrasound, and infrared sensors. A review and comparison of five different low-level indirect weighing techniques (Rondo tape, Weigh tape, Weighbridge equation, Schaeffer's formula, and Agarwal's formula) to estimate BW is provided in Wangchuk et al. (2018). Nevertheless, these low-level technologies are affected by animal breed, feeding method, animal satiety level, and the elasticity or plasticity of the measuring tapes or tubes (Joo, 2010). A paradigm shift in morphometric estimations via advanced systems can be observed in recent years, when computer vision (CV) and deep learning (DL) techniques are increasingly applied to this problem and more abstract image features, such as body area and texture patterns (Gjergji et al., 2020) that are not directly connected to previously applied morphometric measurements are used to predict BW with increasing success.

From a modeling standpoint, we can distinguish four modeling approaches for BW prediction with different complexity levels (Figure 1). For all models we can identify three major components/mechanisms such as feature extraction/acquisition, feature selection (for modeling), and the regression/learning model that could be automated.

The first one is a **Traditional Approach**, where preliminary models for BW prediction are based on the manual collection of morphometric measurements. Some of the most popular morphometric measurements include heart girth circumference, wither height, hip width/height, and body length. These measurements are manually selected and used as features for traditional regression models, which result in predictive equations with one or more variables based on the number of selected measurements in various species, such as cattle (Heinrichs et al., 1992; Franco et al., 2017; Goopy et al., 2018), pigs (Groesbeck et al., 2002; Mutua et al., 2011; Sungirai et al., 2014; Al Ard Khanji et al., 2018), sheep (Sowande and Sobola, 2008; Kunene et al., 2009; Chay-Canul et al., 2019; Canul-Solis et al., 2020), goats (Sebolai et al., 2012), camels (Fadlelmoula et al., 2020; Meghelli et al., 2020), and yaks (Yan et al., 2019).

To decrease the animals stress levels and the significant costs and labor associated with the traditional approach, the second approach (CV approach) employs CV systems and uses images

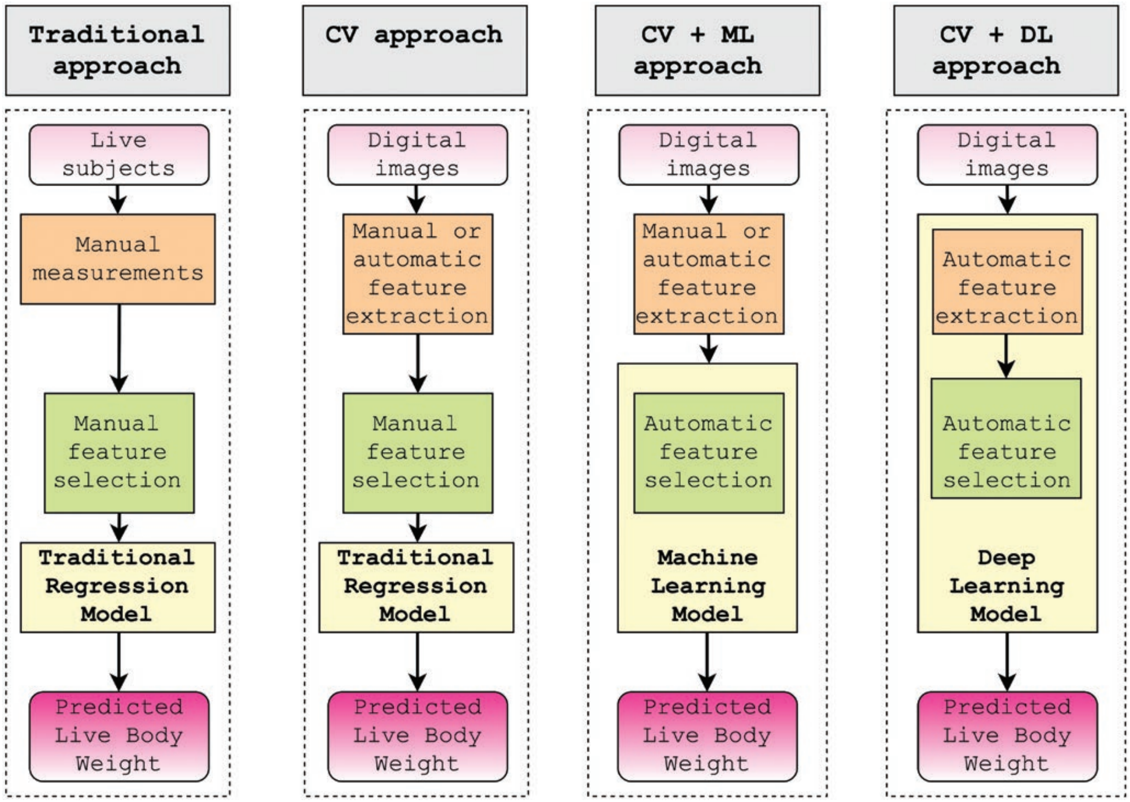

Figure 1. A schematic representation of 4 generic and increasingly complex BW prediction approaches.

acquired with 2D (e.g., RGB and thermal cameras) or 3D (e.g., depth and Microsoft Kinect sensors, stereo systems) electro-optical sensors as an alternative way to capture morphometric measurements. These approaches include an additional step consisting in the manual or automatic preprocessing of the acquired images and manual selection of animal biometric and morphometric measurements, which are then used as predictor variables in statistical models for BW prediction. When 2D images are acquired for pre-processing from single cameras, the third dimension is absent and limits what morphometric measurements can be captured and selected for modeling. For example, the HG circumference is reduced to an HG diameter or replaced with chest depth measurements when extrapolated from either lateral or top images (Ozkaya, 2013). This limitation can be addressed by using 3D cameras, but their excessive cost and more complex data processing steps represent a current bottleneck for a larger scale adoption. Alternatively, the use of 2D images as sources for morphometric measurements supports the use of perimeter- and area-based measurements that can serve as model features and cannot be easily estimated with manual measurements.

Since feature selection can be a tedious task particularly when the number of morphometric measurements is large, it is preferable to automate the process. Therefore, the third approach (CV+ML approach) includes systems that use CV techniques as described in the CV approach and machine learning (ML) methods for feature selection automation (Tasdemir and Ozkan, 2019; de Moraes Weber et al., 2020; Rudenko, 2020). Both, the CV approach and the CV+ML approach, enlist some level of manual operations, such as image and feature selection, image segmentation, and morphometric measurement extractions. Since the manual steps will impede the integration of such approaches in high-throughput applications capable to process thousands of animals, full automation is the key factor for commercial solutions.

The fourth approach based on CV and DL (CV+DL approach) represents a first step toward the full automation of the BW prediction process using digital images. The DL modeling component typically includes image selection, morphometric feature extraction, and feature selection as part of complex neural network architectures such as convolutional neural networks—CNNs (Fukushima, 1980), recurrent convolutional neural networks—RCNNs/RNNs (Spoerer et al., 2017), recurrent attention models—RAMs (Mnih et al., 2014), and RAMs with CNNs (Ba et al., 2014). Preliminary livestock studies implementing this approach reported significant improvements for BW prediction when compared with more traditional approaches (Fernandes et al., 2019, 2020a; Gjergji et al., 2020), nevertheless there is plenty of space for improvements particularly on the precise automatic segmentation of animals from images with complex backgrounds, confounding backgrounds (similar colour as the subjects) or multiple subjects. This task can be addressed using various approaches such as the active shape model proposed by (Cootes et al., 1993) and successfully applied by (Wirthgen et al., 2011) using infrared thermography or a texture-based segmentation approach using a semi-supervised learning method proposed by (Shukla and Anand, 2016).

The remaining of this review is structured as follows. First typical biometric and morphometric measurements used for livestock BW estimation is provided. The next section discusses CV methods that are typically used for digital image processing and feature extraction, whereas the latter section will review work related to ML methods applied to the BW prediction problem. The Conclusions section summarizes the reviewed work and identifies new avenues of research in the area.

Biometric and Morphometric Measurements for BW Prediction

While animal biometrics is an emerging field focused on quantification and detection of the phenotypic appearance of species, individuals, behaviors, and morphological traits (Kühl and Burghardt, 2013), animal morphometrics (Rohlf, 1990; Adams et al., 2004; Doyle et al., 2018) is almost exclusively focused on landmark-based methods (and less on outline-based methods) using quantitative analysis of form relying on measuring the size and shape of animals, and the relation between size and shape (allometry). Estimation of livestock BW using biometric and morphometric measurements has been studied in detail for various species, such as cattle (Taşdemir et al., 2011a,b; Miller et al., 2019; Tasdemir and Ozkan, 2019; Gjergji et al., 2020; de Moraes Weber et al., 2020; Rudenko, 2020), pigs (Brandl and Jørgensen, 1996; O'Connell et al., 2007; Mutua et al., 2011; Sungirai et al., 2014; Al Ard Khanji et al., 2018), sheep (Eyduran et al., 2015; Huma and Iqbal, 2019), goats (Sebolai et al., 2012; Eyduran et al., 2017; Temoso et al., 2017), camels (Fadlelmoula et al., 2020; de Moraes Weber et al., 2020), yaks (Yan et al., 2019), poultry (Mendeş and Akkartal, 2009), and fish (Fernandes et al., 2020b). This process is typically applied to avoid drawbacks associated with manually performed individual animal weighing such as: 1) the animal and manual laborer stress associated with animal relocation, 2) the costs associated with this labor-intensive process, and 3) the significant cost associated with acquiring and maintaining industrial scales. Biometric and morphometric measurements capture a plethora of body dimensions and body characteristics that can be used as parameters in BW predictive models. A summary of biometric and morphometric measurements for six species is included in Table 1. Some of these measurements are species-specific and have been used for BW predictive purposes only in one species such as paunch girth, face length, length between ears, ear length, tail length, and tail width in sheep. Other measurements such as heart-girth circumference, body length, shoulder width, shoulder height, and wither height are more generic and can be used for BW prediction in more than one species. It is important to note that the manual acquisition of such measurements is by no means less laborious than using a scale and the "easiness" of the operation depends on the age and the ability to restrain the animals because larger and older animals are typically harder to isolate, restrain, and handle.

CV Methods for Morphometric Measurements Extraction

An alternative way to acquire morphometric and behavior-based biometric measurements of livestock animals consists in using contactless optical systems, which overcome difficulties arising from direct measurements. Different types of 2D and 3D optical sensors have been successfully used mostly for morphometric measurements and in a limited way for biometric identification of animal behaviors (Porto et al., 2013; Banhazi and Tscharke, 2016; Nasirahmadi et al., 2017; Li et al., 2019). The 2D sensors include regular 2D digital cameras, thermal cameras (Stajnko et al., 2008), and systems of cameras capable to extrapolate 3D models from a series of 2D images. Such systems include multiple calibrated 2D cameras (Taşdemir et al., 2011a,b), Structure-from-motion systems or hybrid systems that include a combination of 2D cameras and laser projectors such as the Morpho 3D system (Le Cozler et al., 2019). The 3D sensors use a wide variety of technologies, such as time-of-flight cameras, consumer triangulation sensors, and infrared sensors such as Microsoft Kinect (Kongsro, 2014; Gomes et al., 2016; Nir et al., 2018; Pezzuolo et al., 2018a; Fernandes et al., 2019; Cominotte et al., 2020; Martins et al., 2020).

Animal subjects are typically imaged from the top or the side and the acquired images are processed by specialized (and sometimes custom-made) CV software that extracts a predefined set of features such as lengths, areas, volumes (for 3D images), colors, and textures.

The position, orientation and motility of the animals captured in images vary with each species. Some species, such as sheep have more joints, are more flexible, exhibit a more variable posture, and have more complex behaviors when compared with larger livestock such as cattle (Zhang et al., 2018b). These can cause various artifacts such as tilted or incomplete views of body parts and blurs and directly affect the subsequent image processing and segmentation steps. Two other factors that affect the quality of the BW prediction results are the presence of more than one animal in a camera's field of view and the background. These problems become more prominent in automatic systems that select images from continuous or motion sensor-triggered video feeds (Fernandes et al., 2020a) and can be addressed by carefully choosing, limiting, and customizing the space available for animals' movement in the proximity of the camera system.

One of the most important aspects of applying CV for BW prediction in livestock animals is the image segmentation and processing stage, which consists of three main steps: 1) the detection stage, where a decision is made if an animal is present or absent from an image, 2) the segmentation stage, where the boundaries of an animal's body or the body parts are identified and extracted from the image, and 3) the feature extraction stage, where prespecified body parts dimensions and characteristics (e.g., lengths, areas, shapes, colors, textures) are calculated.

Step 1

The detection stage typically relies on weaker or stronger assumptions related to what is expected to be in front of the cameras, depending on the position of the cameras. For example, a camera placed on top of a feeding station in a dairy, beef or pig farm would rely on the assumption that only the desired target animals can be present in the frame and the object with the largest area represents the animal. Alternative approaches for animal detection include a wide variety of technologies. Low-level technologies consist of tagging individual animals with unique markers, such as chalk, paint, markers, or wax markings (de Moraes Weber et al., 2020). More advanced technologies include face detection (Yao et al., 2019), muzzle detection (Noviyanto and Arymurthy, 2013; Tharwat et al., 2014), automatic detection via ML, and DL approaches applied to surveillance videos (Zhang et al., 2018a) or hybrid systems that combine radio-frequency identification sensors and CV technologies (Velez et al., 2013). A review of cattle detection methods is presented by Awad (2016). When 3D cameras are used, the distance between the sensor and the subject (depth) is proportional to the intensity of the pixels in the image and serves as a great classifier for foreground or background image components. Moreover, 3D images include depth information

Table 1. Summary of biometric and morphometric measurements and corresponding references used in the literature for BW estimation in six livestock species.

Measurement	Camel	Cattle	Goat	Pig	Sheep	Yak
Biometric						
Backfat thickness (BF)				Al Ard Khanji et al., 2018; O'Connell et al., 2007		
Body Condition Score (BCS)			Temoso et al., 2017; Tsegaye et al., 2013			
Morphometric						
Abdomen Circumference (AC)		de Moraes Weber et al., 2020				
Automatically Derived via ML or DL (AD)		Rudenko et al., 2020				
Arm Length (AL)	Fadlelmoula et al., 2020					
Barrel Girth (BG)	Fadlelmoula et al., 2020					
Belly Sprung (BS)			Eyduran et al., 2017			
Body Area (BA)		Cominotte et al., 2020; Kashiha et al., 2014		Fernandes et al., 2020a		
Body Contour (BC)		Gjergji et al., 2020				
Body Diagonal Length (BDL)						Yan et al., 2019
Body Length (BL)	Meghelli et al., 2020; Fadlelmoula et al., 2020; de Moraes Weber et al., 2020	Miller et al., 2019; Gjergji et al., 2020; Heinrichs et al., 1992; de Moraes Weber et al., 2020; Tasdemir et al., 2019, 2011a,b; Cominotte et al., 2020; Vanvanhossou et al., 2018; Lukuyu et al., 2016	Sebolai et al., 2012; Eyduran et al., 2017	Mutua et al., 2011; Sungirai et al., 2014; Fernandes et al., 2020a	Sowande et al., 2008; Eyduran et al., 2015; Huma et al., 2019; Topal et al., 2004; Sabbioni et al., 2020	
Body Side Area (BSA)		de Moraes Weber et al., 2020; Bozkurt et al., 2007		Brandl et al., 1996		Yan et al., 2019
Body Side Perimeter (BSP)		de Moraes Weber et al., 2020				
Body Volume (BV)		Cominotte et al., 2020				
Breadth at Back (BB)		Miller et al., 2019		Brandl et al., 1996		
Breadth at Middle (BM)		Miller et al., 2019		Brandl et al., 1996		
Chest Depth (CD)		Vanvanhossou et al., 2018			Sabbioni et al., 2020	
Chest Girth (CG)	Meghelli et al., 2020	Vanvanhossou et al., 2018			Eyduran et al., 2015; Sabbioni et al., 2020	
Chest Width (CW)			Tsegaye et al., 2013		Topal et al., 2004; Sabbioni et al., 2020	
Croup Height (CrH)					Sabbioni et al., 2020	
Croup Width (CrW)					Sabbioni et al., 2020	

Table 1. Continued

Measurement	Camel	Cattle	Goat	Pig	Sheep	Yak
Distance between Ears (DEA)	Meghelli et al., 2020					
Distance between Eyes (DEY)	Meghelli et al., 2020					
Dorsum Perimeter (DP)		de Moraes Weber et al., 2020				
Ear Length (EL)			Tsegaye et al., 2013		Eyduran et al., 2015	
Eccentricity (EC)				Fernandes et al., 2020a		
Face Length (FL)					Eyduran et al., 2015	
Flank-to-Flank Distance (FF)		Miller et al., 2019				
Head Girth (HeG)			Eyduran et al., 2017			
Head Length (HeL)	Meghelli et al., 2020				Sowande et al., 2008	
Head Width (HeW)					Sowande et al., 2008	
Heart Depth (HD)					Topal et al., 2004	
Heart-Girth Circumference (HG)	Fadlelmoula et al., 2020	Heinrichs et al., 1992; Goopy et al., 2018; de Moraes Weber et al., 2020; Lukuyu et al., 2016	Sebolai et al., 2012; Temoso et al., 2017	Al Ard Khanji et al., 2018; Mutua et al., 2011; Sungirai et al., 2014; O'Connell et al., 2007	Sowande et al., 2008; Huma et al., 2019; Topal et al., 2004	
Height at Back (HB)				Brandl et al., 1996		
Hindquarter Length (HiL)					Sowande et al., 2008	
Hindquarter Width (HiW)					Sowande et al., 2008	
Hip Girth (HG)	Fadlelmoula et al., 2020					
Hip Height (HH)	Fadlelmoula et al., 2020	de Moraes Weber et al., 2020; Tasdemir et al., 2019, 2011				
Hip Width (HW)		Heinrichs et al., 1992; de Moraes Weber et al., 2020; Tasdemir et al., 2019, 2011a,b				
Horn Length (HL)			Tsegaye et al., 2013			
Leg Length (LL)	Fadlelmoula et al., 2020					
Length Between the Ears (LBE)					Eyduran et al., 2015	
Loin Depth (LD)				Al Ard Khanji et al., 2018		
Loin Girth (LG)					Sowande et al., 2008	
Neck Girth (NG)	Meghelli et al., 2020					
Neck Length (NL)	Meghelli et al., 2020; Fadlelmoula et al., 2020		Eyduran et al., 2017			

Table 1. Continued

Measurement	Camel	Cattle	Goat	Pig	Sheep	Yak
Occipito-Ischial Length (OIL)		de Moraes Weber et al., 2020				
Paunch Girth (PG)					Eyduran et al., 2015	
Pelvic Width (PeW)			Tsegaye et al., 2013			
Pump Width (PW)					Topal et al., 2004	
Rib Height (RiH)		Gjergji et al., 2020; de Moraes Weber et al., 2020				
Rump Height (RH)		Miller et al., 2019; Gjergji et al., 2020	Eyduran et al., 2017; Tsegaye et al., 2013			
Rump Length (RL)			Tsegaye et al., 2013			
Rump Width (RW)		Miller et al., 2019; Gjergji et al., 2020; Vanvanhossou et al., 2018				
Sacrum Height (SaH)		Vanvanhossou et al., 2018				
Scrotal Circumference (SC)			Tsegaye et al., 2013		Huma et al., 2019	
Scrotal Diameter (SD)					Huma et al., 2019	
Scrotal Length (SL)					Huma et al., 2019	
Shank Circumference (ShC)			Eyduran et al., 2017			
Shoulder Width (SW)		Miller et al., 2019	Sebolai et al., 2012	Brandl et al., 1996		
Shoulder Height (SH)		Miller et al., 2019	Temoso et al., 2017	Brandl et al., 1996		
Snout to Shoulder (SS)				Brandl et al., 1996		
Tail Length (TL)	Meghelli et al., 2020				Eyduran et al., 2015	
Tail to Scapula (TS)		de Moraes Weber et al., 2020		Brandl et al., 1996		
Tail Width (TW)					Eyduran et al., 2015	
Testicular Length (TeL)			Keith et al., 2009; Gemeda et al., 2017		Huma et al., 2019	
Wither Height (WH)	Meghelli et al., 2020; Fadlelmoula et al., 2020	Heinrichs et al., 1992; de Moraes Weber et al., 2020; Tasdemir et al., 2019, 2011a,b; Vanvanhossou et al., 2018; Lukuyu et al., 2016	Sebolai et al., 2012; Tsegaye et al., 2013		Sowande et al., 2008; Eyduran et al., 2015; Huma et al., 2019; Topal et al., 2004; Sabbioni et al., 2020	Yan et al., 2019

on the body surface of the subject, whereas 2D and thermal images are limited to information related to body contours and cross-sectional areas. A postprocessing step consisting of a number of quality control criteria is needed to select valid frames with correctly positioned animals that are completely included in the frame, not touching boundary walls and having a straight posture. Failing to control the quality of an image can lead to inaccurate image-based biometric morphometric measurements in the feature extraction stage.

Step 2

The segmentation stage can include a large number of methods that can be classified as manual and automatic. Manual methods are focused on application of software tools such as ImageJ (Schneider et al., 2012) and VIA Annotation Software (Dutta and Zisserman, 2019) to preprocess and select areas of interest from an image that can be used to directly infer morphometric measurements or to prepare training datasets for ML methods meant to build segmentation models capable to detect similar animals in new images.

Automatic methods are typically focused on specific body parts identification and span a wide complexity spectrum, from simple background subtraction approaches (Yang and Teng, 2007), edge detection (Senthilkumaran and Rajesh, 2009) via operators such as Prewitt (Prewitt, 1970), Canny (Canny, 1986), Sobel, Laplacian (Kimmel and Bruckstein, 2003), and masking (e.g. Kirsch, Robinson) to complex operations for shape recognition such as the use of Hough transform (Hough, 1962) for identification of round objects (Fernandes et al., 2019) and super-pixel methods such as the Simple Linear Iterative Clustering (Achanta et al., 2012). Postprocessing steps could include black and white or color-based masking, rotation, scaling and coordinate transformations (e.g., conversions to polar coordinates).

Step 3

The third stage is focused on *morphometric and biometric measurements extraction* and can be grouped into two categories as suggested by Fernandes et al. (2019): body measurements and shape descriptors. The body measurements include lengths, widths, areas, and volumes and can be calculated either manually as described in the segmentation stage or automatically via superposing a grid on top of the segmented animal and extracting equidistant measurements along a line, curve, contour, or an area. The volumetric measurements are rough approximations given the limited camera views of either the top or the side of an animal. The shape descriptors reported in the literature include generic ones such as Fourier descriptors (Fernandes et al., 2019) and fast point feature histograms (Huang et al., 2019).

Many factors related to environment, animal positioning, animal characteristics, and location affect the ability of CV methods to be efficiently applied for morphometric and biometric measurements extraction from digital images. For example, large group sizes, high stocking densities, unmarked individuals, variable lighting, different backgrounds, animals covered in dirt or feces, and the presence of dust, insects, ammonia, and water particles (from cleaning systems) in the air are typical challenges associated with operating CV equipment in commercial farming environments (Kim et al., 2017; D'Eath et al., 2018; Wurtz et al., 2019). Animal characteristics such as the presence of thick coat, wool, or long hairs; various colours; and textures and variable intrabreed anatomical landmarks (e.g., bone protuberances) pose further challenges for CV systems (Song et al., 2018). A summary of CV methods for processing images used in the prediction of BW in four livestock species (cattle, pigs, sheep, goats) is presented in Table 2. Moreover, a detailed species-specific review of CV methods for pigs' BW estimations is available in the literature (Li et al., 2014).

ML and CV Methods for BW Prediction

While predicting BW of farm animals from biometric and morphometric measurements observed at different growth periods in cattle, pigs, sheep, and goats has been the focus of many past research studies, which applied traditional statistical regression techniques such as linear, multiple, and ridge regression, their success was limited by the multicollinearity and complex relationships among measurements (variables). To capture and explain such complex inter-variable relationships, a limited number of recent studies have reported the successful application of various ML and DL methods for predicting BW using features extracted from 2D and 3D digital images (Table 3).

Successful applications of ML approaches on morphometric measurements extracted from 2D images via CV techniques have been reported in the literature for cattle. An early study carried out by Tasdemir et al. (2011b) employed a fuzzy rule-based model to estimate the BW of 115 Holstein cows using the body measurements obtained through *Image Analysis (IA)*. 2D digital images of each animal were synchronously acquired from various directions and wither height, hip height, body length, and hip width were measured with a laser meter and a measuring stick for validation purposes. A platform weighing scale was used to measure the BW of the cows and the data were automatically stored on a computer. The photos were analyzed in the second stage by the IA software developed in Delphi and body measurements were calculated. They noticed that values measured manually were very similar to IA outcomes. Finally, the MATLAB software was used to develop a fuzzy system using the acquired body measurements and the predicted BW values

Table 2. Summary of CV methods and corresponding references used in the literature for BW estimation in four livestock species

CV method	Cattle	Goat	Pig	Sheep
Single camera 3D imagery: TFNIR	Miller et al., 2019; Cominotte et al., 2020	Negretti et al., 2011	Fernandes et al., 2020a,b; Pezzuolo et al., 2018; White et al., 2004	
3D Structure-from-Motion (SfM)			Wirthgen et al. 2011	
Multi-camera 2D imagery	Gjergji et al., 2020; de Moraes Weber et al., 2020; Tasdemir et al., 2011a,b	Lerch et al., 2020		Dickinson et al. 2013; Menesatti et al., 2014
Multi-camera 3D imagery	Rudenko et al., 2020; Tasdemir et al., 2019			

Table 3. Summary of ML methods and corresponding references used in the literature for BW estimation in four livestock species

Reference	ML method	2D/3D Images	Breed	Num. of animals	R	R^2	ARE	MAE	RMSE
Tasdemir et al., 2011a,b	Fuzzy rule-based model	2D	Cattle (Holstein)	115	0.9922				
Tasdemir et al., 2019	ANN/MLP	2D	Cattle (Holstein)	115	0.9916				
de Moraes Weber et al., 2020	LR SVM regression Regression by discretization with RF	2D	Cattle (Girolando)	34	0.7100			38.4600	46.6900
Gjergji et al., 2020	CNN RNN/CNN RAM RAM with CNN	2D	Cattle (Nellore, Angus)	20				23.1900	
Miller et al., 2019	ANN	3D	Cattle (Aberdeen Angus, Limousin, Simmental, Charolais)	1,484		0.7000			42.0000
Cominotte et al., 2020	MLR LASSO PLS ANN	3D	Beef cattle	48		[0.79, 0.92]			[7.78, 18.14]
Fernandes et al., 2020b	MLR PLS ENR MLP DL image encoder model	3D	Pig	557		[0.03, 0.87]		[0.81, 5.20]	[1.05, 6.44]
Rudenko et al., 2020	Mask RCNN network and MLP	3D	Cattle (Ayrshire, Holstein, Jersey, Red Steppe)	500	[0.84, 0.92]		[0.1, 0.17]	[0.9, 2.5]	

were compared to those acquired with the platform scale. The authors obtained high correlation coefficients (R = 0.97) between predicted and measured BW values and concluded that the digital IA method and fuzzy rule-based system is a feasible, quick, and very realistic approach, which may be effectively used as a directly computerized and more reliable recording system.

Eight years later, Tasdemir and Ozkan (2019) used an artificial neural network (ANN) to estimate Holstein cows' BW using the same type of measurements obtained from digital images as in their previous work. Different ANN model architectures were generated, and the best performing model improved on their previous results leading to a correlation coefficient R equal to 0.99.

More recently, de Moraes Weber et al. (2020) investigated the BW prediction ability of three ML algorithms on a rather small number of Girolando cattle (34) using dorsal and lateral measurements extracted from digital images and their corresponding BW was measured with a scale. A set of 34 dorsal images and 34 lateral images was selected and manually processed with the ImageJ software (version 1.52, National Institutes of Health) and 10 measurements were extracted: hip width, body length, tail distance to the neck, dorsum area, dorsum perimeter, wither height, hip height, area of the body lateral area, the perimeter of the lateral area, and rib height. The data were divided into a training set (66%) and a testing set (34%) and three ML methods were applied: linear regression (LR), support vector machines (SVM), and random forests (RF). The highest correlation coefficient between measured and predicted BW for the test set was obtained with the LR method (0.71), followed by SVM (0.68) and RF (0.62). While the study is very interesting and shows how three ML methods can be successfully used to predict BW in cattle using manually extracted measurements from images, larger data sets would be necessary for the development of better models, especially when boosting/ensemble such as RF are considered. It is expected that models built on subsamples extracted from already small data sets would lead to lower performance, which could explain the poor performance of the RF models.

Since feature selection in previous work has been typically done manually and is prone to human error during the image processing stage, Gjergji et al. (2020) employed DL—a novel approach capable to automatically extract relevant features from digital images and known to outperform traditional ML models for both classification and regression problems for a large number of CV problems. The authors explored the prediction performance of CNN, RCNNs, RAMs, and RAMs with CNN to predict beef cattle weight using CV techniques. The images were collected from 10 male Nellore and 10 male Angus cattle using 2D cameras with a 720p standard High-Definition image quality (1,280 × 720 pixels resolution, 16:9 aspect ratio). Two cameras were fixed in the structure of the water trough to collect the dorsal image of the animal when drinking and two other cameras were installed in the trough cover structure to acquire the profile images of the animals going into the trough. The data set was divided into training (60%), validation (20%), and testing (20%) sets. The authors reported that CNNs achieved the highest performance with a top model mean average error (MAE) of 23.19 ± 1.46 kg, which was nearly half the error of the top LR models proposed by de Moraes Weber et al. (2020) with an MAE value of 38.46 kg. While it is not clear if the camera resolution influenced in any way the quality of the obtained results, the authors report that only models such as RNN/CNN that use partial parts of an image are capable to estimate correctly the BW, whereas the segmentation step of the other models is significantly influenced by the presence of stray subjects in an image.

Recent advances in imaging technologies combined with increasingly reduced costs for sensors (Wolfert et al., 2017; Benjamin and Yik, 2019) have enabled the use of 3D imaging technologies within CV systems in the livestock sector with direct applications in BW estimation in cattle (Fukuda et al., 2019), pigs (Wang et al., 2008), and chicken (Mortensen et al., 2016). Nevertheless, only a handful of studies have applied ML and DL methods on data acquired with 3D imaging systems. Miller et al. (2019) applied 3D imaging technology and ML algorithms to predict BW and carcass characteristics of live animals. Three-dimensional images and BWs were passively obtained from finishing steer and heifer beef cattle of a variety of preslaughter breeds either on-farm or after entering the abattoir. The sixty potential predictor variables obtained by an automated camera system and the bespoke algorithm were used to construct stepwise LR and ANN predictive models for BW and carcass characteristics. The predictor variables comprised various measurements (5 widths, 6 lengths, 5 heights, 2 diagonals, 20 ratios, 11 areas, and 11 volumes). The prediction performance of the ANN model for BW using 4,443 subjects was R^2 = 0.7 and RMSE = 42, whereas the performance of the stepwise LR model was lower with R^2 = 0.54 and RMSE = 51. They concluded that 3D imaging coupled with ML analytics can be used to predict LW and traditional carcass characteristics of live animals. This can provide an opportunity to reduce a considerable inefficiency in beef production enterprises through autonomous monitoring of finishing cattle on the farm and marketing of animals at the optimal time.

Rudenko et al. (2020) applied ANNs and CV to identify the cow's breed and estimate their BW. Cow images taken at different angles by synchronized cameras were fed to a Mask RCNN to determine the breed and position of each subject. Then, withers height, hip height, body length, and width of a cow were determined using the stereopsis method from 3D images acquired with an Intel RealSense D435i camera using the position of the cow detected by Mask RCNN in the previous step. Finally, the obtained data about the species and its size were fed to a multilayer perceptron (MLP) to estimate the live weight of the animals. Using an initial collection of 250 representative images for each of the three breeds and an augmentation system to increase the size of the training and testing sets, the ANN system predicted BW with an accuracy of 0.92, 0.88, 0.85, and 0.84, for Ayrshire, Red Steppe, Jersey, and Holstein, respectively. The authors concluded that the proposed method enables modern farmers to assess the animal's BW easily and accurately, as well as identify its breed, save time, and minimize effort without damaging the animals' welfare and disrupting the growth of livestock. The method can be applied in both corrals and pastures without interfering with animals' normal behavior. The authors also noted that the use of a 3D camera alone leads to poor results due to its low resolution and it is recommended to complement the technology with additional photogrammetric technologies.

Fernandes et al. (2020a) employed CV systems to predict the BW, muscle depth, and back fat in pigs from 3D images using multiple linear regression (MLR), partial least squares (PLS), elastic network regression (ENR), MLPs, and a DL image encoder model. The BW was measured with an electronic scale for 557 finishing pigs. The MD and BF were measured using an ultrasound device. The pig top view video records were acquired using a Microsoft Kinect V2 sensor and automatically processed in MATLAB for feature extraction, using the methodology described in Fernandes et al. (2019). The features extracted were: 1) body measurements, including apparent volume, surface area, length, height and width, and eccentricity; 2) 360 equidistant measurements of the polar shape contour of the top view image; and 3) the corresponding 360 Fourier descriptor features of the same polar shape contour. The body measurements were extracted from the 3D images and converted to metric scale values using the intrinsic focal length of the Kinect depth camera. The pig volume was calculated as the sum of pixels' volumes. The pig eccentricity was estimated as the ratio between the foci and the major axis of the ellipsis, which has the same major and minor axis as the pig area. The polar shape descriptors were measured as the distance from the centroid of the pig to points on its boundary contour. The obtained data were split into training and testing sets using a 5-fold cross-validation approach. The authors reported that the DL image encoder model with raw 3D images as direct inputs achieved the best BW prediction performance (R^2 = 0.86).

Cominotte et al. (2020) assessed the predictive quality of an automated CV system used to predict BW and average daily gain in beef cattle. The authors compared four different predictive approaches, including MLR, least absolute shrinkage and selection operator (LASSO), PLSs, and ANN using 3D images captured with a Kinect model 1473 sensor (Microsoft Corporation, Redmond, WA). The BW was measured using an electronic scale. The collect 234 3D images at four time points (weaning, stocker, beginning of feedlot, and end of feedlot) during the animal's life cycle. They collected 3D images from 62 animals for the first three time points and from 48 animals for the last time point. They preprocessed and segmented the animals from images using a combination of acceptance criteria based on the position of the cow in the image and removal of non-important parts such as head and tail. One final image was manually selected for each animal at each time point and further subjected to feature extraction, which resulted in a significant number of automatically determined body measurements, such as area, volume, maximum length, 11 widths (W1 to W11), and 11 heights (H1 to H11) at equidistant locations in the dorsal part of the animal from the shoulders to the hip. The ANN approach produced the best results for BW prediction with R^2 values between 0.79 (stocker phase) and 0.92 (beginning of feedlot phase) and RMSE values between 7.78 (beginning of feedlot phase) and 18.14 kg (end of feedlot phase).

Conclusions

When considering the global farming focus to increase animal density, productivity, and welfare and reduce feeding costs and greenhouse gas emissions, the prospect of replacing manual biometric and morphometric measurements with automatic noncontact measurements and integrating the outcomes into intelligent ML and DL systems is of great interest and aimed at optimizing livestock management and allowing individual animal health, welfare, and real-time growth monitoring.

While there is a large body of research literature describing BW prediction systems belonging to one of the generic approaches described in Figure 1, there are obvious limitations that must be overcome to be able to evaluate the true potential of each solution and make a fair comparison among them. These limitations include: 1) relatively small numbers of animals per study, 2) different species and breeds, 3) inconsistent use of result measures and metrics across studies (e.g., RMSE, MAE, r, r^2, R, R^2, accuracy, correlation coefficients), 4) different experimental settings, 5) different 2D and 3D sensors, 6) various calibration approaches, and 7) the factors impacting technology acceptance by producers.

Solutions that combine the uncanny ability of 2D and 3D CV technologies to capture livestock body dimensions and characteristics and intelligent ML and DL algorithms able to model the extracted information and create predictive systems for livestock BW have started to emerge in the past few years. Nevertheless, there is still a long way until such systems will reach industry-ready stages, both in terms of practical accuracy and affordability. While current research shows promising results predominantly in cattle and pigs, there are still many avenues to be explored for better automation of the whole BW estimation process, such as 1) the ability of CV and ML/DL hybrid BW predictive systems to cope with missing information possibly via imputation and data enhancement approaches as suggested by (Khan et al., 2019), 2) the generalization power and the breed-agnostic prediction for any given species, 3) the automatic detection and identification of an animal remotely, and 4) the automatic recognition and adaptability based on an animal's development stage, posture, and position within a sensor's field of view.

Current results are also limited by reduced dataset sizes, datasets of lower quality, reduced variability and lack of annotated information (ground truth), and most importantly by limited availability of shareable information. Therefore, the creation of publicly available repositories and databases that store 2D and 3D images and corresponding biometric/morphometric (and other complementary) measurements of livestock breeds are quintessential for the development and enhancement of current CV, ML and DL approaches that have a clear potential to improve contactless BW estimations.

Someone may easily envision a future where a new stage of technological development will include handheld or airborne mobile devices equipped with advanced and yet affordable vision systems and complex pretrained predictive models able to remotely detect, identify, estimate, and record an animal's BW and make current weighing technologies obsolete.

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Author Contributions

All authors improved and contributed to the editing of the manuscript. All authors read and approved the final manuscript.

Conflict of interest statement

The authors declare no real or perceived conflicts of interest.

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